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MOBILE INTERNET ADOPTION AND INCLUSIVE STRUCTURAL CHANGE: EVIDENCE FROM NIGERIAN NON-FARMING ENTERPRISES

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Mobile Internet Adoption and Inclusive Structural Change: Evidence from Nigerian Non-Farming Enterprises

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Abstract

This paper investigates the impact of mobile internet adoption on micro-level structural change and inclusion in Nigeria. Using the case of Nigerian non-farming household enterprises (NFEs), the paper examines how the adoption of mobile internet affect structural change at the micro level, measured in terms of NFE sales per worker, household sectoral transitions, and labour shifts from the household towards the market; and inclusion, measured by the creation of job creation and entrepreneurial opportunities. The analysis combines a panel dataset of Nigerian households (2010-2015) with district level data from the GSMA mobile internet coverage maps. A mobile adoption measure is constructed to estimate its effect on the labour productivity, employment, sector transition, and firm entry. As the roll-out of mobile internet is unlikely to be entirely random, the study adopts an identification strategy that uses the variation of lightning strikes in Nigerian districts, along with an event study approach. Findings indicate that mobile internet adoption bolsters NFE labour productivity, mainly in services. However, this effect is driven by growth in sales and a reduction in labour required by household enterprises, although NFE-owning households are able to reallocate excess labour outside the household. Entry into manufacturing is discouraged and firm entry is not facilitated, neither are households protected against market exit.

Keywords: Structural change, mobile internet, informality, inclusion, Nigeria
JEL Codes: J21, J46, L16, O14, O33

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1 Introduction

While the internet has diffused rapidly in high- and middle-income countries since the '90s, some areas in low- and middle-income countries have lagged behind. In particular, sub-Saharan Africa (SSA) and South Asia have experienced diffusion of the internet only since the mid-2000s (Figure 1). Increased access to the internet in Africa has been made possible by the rapid diffusion of mobile phones,[1] which, in addition to having radically and rapidly provided opportunities to connect distant individuals and markets in African economies (Aker and Mbiti, 2010), have now become the main means of accessing fast mobile internet services.

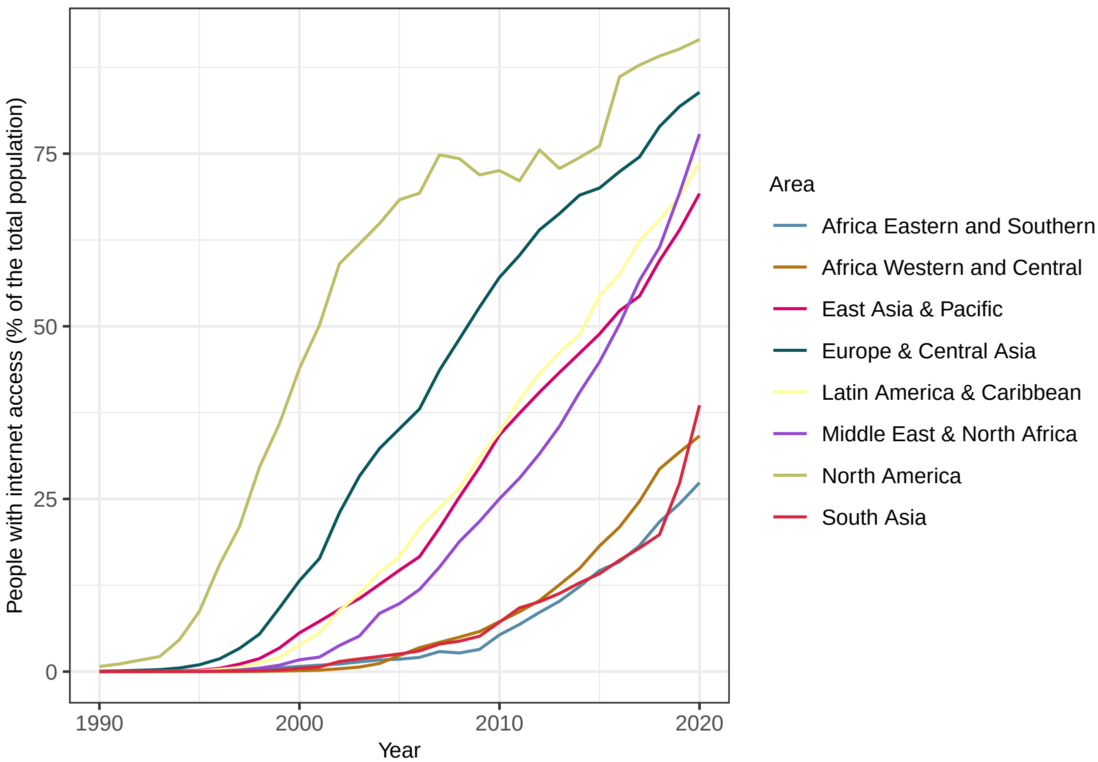

Figure 1: Percentage of population with access to internet services across the globe (1990-2020). Source: World Development Indicators.

It has been argued that the increased adoption of digital technologies, which allows access to internet services through mobile phones, creates a window of opportunity for low- and middle-income countries to undergo a process of structural change (Fagerberg et al., 2021; Kaplinsky and Kraemer-Mbula, 2022). However, the structural change experienced by SSA countries since the rapid diffusion of the internet has not always been virtuous (McMillan

[1]In 2015, 16% of the population in SSA was using internet, but there were only 1.1 fixed telephone subscriptions per 100 people, against 70 mobile phone subscriptions ("World Development Indicators", accessed on 8 May 2022).

et al., 2014), at times associated with labour moving away from more productive industries (de Vries et al., 2015), such as manufacturing (Rodrik, 2016), and adding to the pervasive presence of informal services and activities.

On the one hand, there is evidence that access to fast internet in sub-Saharan Africa has had a positive effect on employment (Hjort and Poulsen, 2019; Bahia et al., 2020, 2021; Caldarola et al., 2022), labour productivity growth (Hjort and Poulsen, 2019; Hjort and Tian, 2021), and firm entry (especially in the service sector), due to lower operation costs (Houngbonon et al., 2022). On the other hand, it has been acknowledged that digitalisation may lead to the concentration of benefits in larger firms, excluding smaller players (Altenburg et al., 2021), and that digital technologies can be labour saving or skill-biased technologies, favouring skilled workers over unskilled ones (Autor et al., 2003; Buera et al., 2021). Moreover, technical change and innovation can create new working opportunities in modern, emerging sectors, making 'old' jobs obsolete, through a process of "creative destruction" (Schumpeter, 1934; Aghion et al., 2019). Ultimately, as the trajectories of digital technologies co-evolve with the skills required to operate them, and with firms' innovation routines (Ciarli et al., 2021a), predicting the effect of their adoption on employment and productivity remains empirically challenging. It is for policy makers to single out the conditions under which the diffusion of digital technologies could yield a process of structural change that is inclusive for all (Ciarli et al., 2021b).

This paper contributes new evidence regarding the effect of internet access on firm performance and employment in low- and middle-income countries. The study is particularly interested in the extent to which such effects on performance and employment may lead to structural change and inclusion. Internet access can influence structural change through at least two channels. First, via an increase in labour productivity: complementing workers' skills, fostering human capital development, or improving firm-worker matching (Hjort and Tian, 2021). Second, the uptake of mobile internet can influence industrial composition, pushing labour and firms towards technologically intensive sectors. However, the effect of internet-driven structural change will depend on: whether it leads to increased job opportunities, and therefore on whether its adoption will complement or replace labour; and on whether it allows the entry of new firms, for instance by reducing entry costs, or instead, by raising market barriers and favouring the incumbents. In order to answer these questions, this study estimates the effect of internet adoption at the industry level on structural change (measured in terms of firms' performance and sector dynamics) and inclusion (measured by the creation/destruction of jobs and entrepreneurial opportunities). In so doing, the paper empirically investigates whether internet adoption results in inclusive structural change (Saha and Ciarli, 2018; Ciarli et al., 2021b).

Because most non-agricultural employment in SSA is concentrated in the informal sector (Haggblade et al., 2010; Nagler and Naudé, 2017), the focus here is on household Non-Farming Enterprises (NFEs). These firms conduct a considerable amount of innovation activity (Fu et al., 2018; Avenyo et al., 2020), playing a potentially central role in the process of structural change, given their potential to upgrade (Kraemer-Mbula and Monaco, 2020). However, most non-farming informal activities have low productivity levels (Diao and McMillan, 2018); in order to contribute actively to the process of structural change, informal activities would need to increase their productivity (Diao et al., 2018).

Within the focus of this thesis on structural change in SSA, the case of Nigeria is particularly relevant to the analysis of the impact of mobile internet adoption on informal economic activities for a number of reasons. First, the country is characterised by a "negative" or "growth reducing" structural transformation (McMillan et al., 2014; Benjamin and Mbaye, 2020), due to its increased dependency on the oil industry, and to the shift of labour from high to low productivity industries. This process has resulted in the enlargement of the informal sector: according to the International Labour Organisation, 89 per cent of its non-agricultural employment was informal in 2018 (International Labour Organization, 2018).

Second, in 2015 Nigeria ranked sixth[2] amongst sub-Saharan African countries for mobile services penetration, with 34 per cent of unique subscribers to either 2G or 3G services over the total population. Thirteen per cent of the population had a 3G subscription in 2015, whereas only 0.2 per cent had access to a fixed phone line in the same year (GSMA, 2015). Anecdotal evidence also indicates that the arrival of mobile internet has wiped out cyber-cafes – businesses that offered a shared space in which to connect to the internet and represented the only opportunity to do so before the diffusion of mobile internet. Most cyber-cafes either converted or closed down after the fast paced diffusion of mobile internet services.[3]

The analysis in this paper relies on data from a nationally representative panel survey of Nigerian households, collected in three rounds between 2010 and 2015, namely the Living Standard Measurement Survey data. The survey includes relevant information on household non-farming enterprises, most of which are informal, along with information on socio-demographic characteristics, household employment and asset ownership, including possession of mobile phones. The dataset is complemented by information on fast mobile internet coverage (3G)[4] across Nigerian Local Government Areas (LGA). Combining information on geographical

[2] After, in descending order, the Seychelles, South Africa, Kenya, Namibia.

[3] From Quartz Africa: https://qz.com/africa/412745/how-mobile-internet-killed-off-cyber-cafes-in-nigeria.

[4] From now on, the terms fast mobile internet and 3G internet will be used interchangeably.

mobile internet coverage and mobile phone ownership at the household level, a measure of mobile internet adoption is constructed.

The roll-out of mobile internet is likely to be correlated with a number of factors that may influence both mobile operators' choice of where to build their mobile cell towers, and informal business activity. In order to address the endogeneity between the availability of mobile internet and entrepreneurial decisions that remains after controlling for household and industry unobserved heterogeneity, year fixed effects, and a number of social, demographic, and geographical control variables, the analysis adopts two distinct identification strategies. First, a Two-Stage Least Squares (2SLS) estimation exploiting the differential and time-invariant exposure of Nigerian Local Government Areas (LGAs) to lightning strikes (following Andersen et al. 2012; Manacorda and Tesei 2020; Guriev et al. 2021). Second, because the instrumental variable (IV) approach illustrated above will correctly identify the relationship between mobile adoption, productivity, and labour only in the absence of parallel trends, it is complemented by an event study that further corroborates and expands on the findings provided by the 2SLS estimation.

The results indicate that the adoption of mobile internet at the household level has a positive and significant effect on the sales-to-workers ratio of non-farming enterprises, showing that the extant empirical evidence on the effect of the internet on labour productivity holds also for the informal sector.

However, interestingly, in terms of the effect on inclusive structural change, this paper finds that the positive impact on sales per worker is likely to occur only in service industries, providing an incentive to invest particularly in retail and wholesale trade activities. As a result, we find that internet adoption reduces the probability that households will switch towards manufacturing industries.

In relation to inclusion, the results first indicate that the growth in sales per worker driven by internet access is due to both higher sales and lower employment. More specifically, households are likely to reduce the number of household employees working in the NFE and to retain – or even increase – the number of workers from outside the household. This could be because NFEs need skills which may not be available within the household, or because household workers move to better jobs in the formal sector. However, the reduction of household labour in NFEs is likely to be offset by increased waged opportunities outside the household, neutralising the labour saving effect on household labour within NFEs.

Secondly, mobile adoption does not encourage the entry of new households into the market, indicating that only incumbent firms benefit from access to mobile internet. This last finding represents one possible exclusionary outcome of structural change: given the importance of entrepreneurship for innovation, employment creation, and structural transformation, the entry of firms will have to be encouraged and facilitated in order to foster employment creation and to sustain growth in productivity.

The remainder of the paper is organised as follows. Section 2 illustrates the Inclusive Structural Change framework adopted in the study to motivate the analysis (2.1) and reviews the extant literature on the economic effects of internet access on low- and middle- income economies (2.2); Section 3 describes the data and the empirical strategy adopted in this study, along with the two identification strategies; Section 4 summarises the results; Section 5 concludes.

2 Analytical framework and related literature

2.1 Inclusive Structural Change

Technical change is a powerful engine of structural transformation (Kuznets, 1973; Dosi, 1988). The diffusion of new technologies enables the emergence of new, modern sectors (Saviotti and Pyka, 2004), leading to productivity growth and the consequent reallocation of labour towards more productive sectors, sustaining economic growth and creating new opportunities to innovate. The mutually reinforcing relationship between innovation and structural change constitutes a well established empirical and theoretical concept. However, innovation is also disruptive (Schumpeter, 1934) due to its effect on the organisation of the productive structure. Technical change directly affects income distribution (Paunov, 2013) by changing the labour demand towards skilled occupations. This can lead to a process of skill-biased structural change (Buera et al., 2021), from which only the most productive firms benefit, and to higher market concentration (Autor et al., 2020). Therefore, in an unequal society, innovation might cause structural change that benefits only a few, perpetuating exclusion (OECD, 2015; Aghion et al., 2019). However, these outcomes are not inevitable, as innovation can also be inclusive (Chataway et al., 2014). For instance, structural change towards labour-intensive technologies may increase the labour share of the economy, and create working opportunities for those who previously did not participate in the workforce. The direction of the effect of innovation, especially when it is diffused via technology transfer in low- and middle-income countries, will also depend on its degree of appropriateness to the specific context (Fu et al., 2011; Hanlin and Kaplinsky, 2016).

Against this backdrop, the empirical evidence shows that labour-saving (and skill biased) technical change has been one of the major culprits in growth-reducing structural change in African countries (McMillan et al., 2014), leading to de-industrialisation (Rodrik, 2016) and pushing labour away from modern industries into the informal sector. Nevertheless, it has been argued that the transformative potential of digital technologies represents a major window of opportunity for developing countries and informal firms/workers to leapfrog from their historic productive structure (Kaplinsky and Kraemer-Mbula, 2022). While digital technologies – such as the internet – have often been considered General Purpose Technologies (GPTs) and linked to productivity growth (Cardona et al., 2013), it is not possible to know *a priori* whether they will result in inclusive outcomes based on their diffusion and adoption (Saha and Ciarli, 2018), and how the skills required to master new technologies will co-evolve with the technology itself (Ciarli et al., 2021a).

The relationship between innovation, structural change and inclusion should be analysed in a way that acknowledges the trade-offs and synergies that exist between them. The direction of structural change determined by the adoption of a new technology, and its effect on inclusion, will depend upon the underlying economic and social conditions, such as the structure of inequality, market concentration, and power relations, alongside the specific nature and trajectory of the technology itself. Ciarli et al. (2021b) have proposed a framework that offers analytical support to empirically testable hypotheses, with the aim of unpacking the conditions under which innovation leads to inclusionary or exclusionary structural change in low- and middle-income countries. The Inclusive Structural Change (ISC) framework posits that the impact of innovation on structural change and inclusion will depend on the actors involved in the process of diffusion or adoption of the innovation; on their interactions; and on the initial conditions within which the process unfolds. Focusing on the role of innovation in inclusion and structural change (Figure 2), the framework makes it possible to test the effect of innovation on structural change and inclusion, without making any assumptions about the direction of that effect. The adoption of a new technology may generate a trade-off between structural change and inclusion. For instance, the new technology may lead to labour productivity growth across industries, while replacing labour with capital, which in turn will exclude part of the (especially unskilled) workforce. Conversely, the adoption of the same technology may create working opportunities that allow previously unemployed individuals to take a labour-intensive, low-productivity job, reducing the productivity levels in the economy.

Using the lenses of the ISC framework, the next section reviews the available empirical evidence on the impact of the adoption of fast internet on inclusion and structural change in low- and middle-income countries.

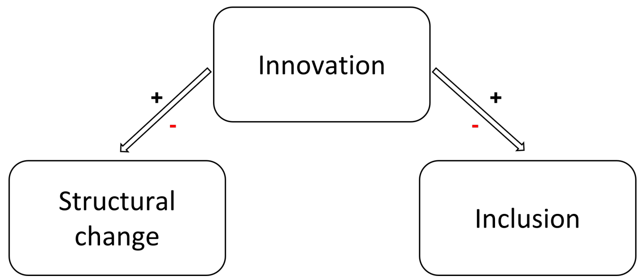

Figure 2: Inclusive Structural Change framework.

2.2 Internet and development in Africa

Internet adoption is associated with structural change via its positive effect on labour productivity across industries (Akerman et al., 2015; DeStefano et al., 2018; Hjort and Poulsen, 2019; Barrero et al., 2021), including agriculture (Gupta et al., 2020). The mechanisms underlying the relationship between internet adoption by firms and/or workers and labour productivity can be: direct, that is, via increased sales and/or labour replacement; via human capital development, allowing workers to acquire new skills; via better matching between firms and workers, allowing firms to identify the best and more skilled workers for their technology (Hjort and Tian, 2021). While this relationship appears to be rather uncontroversial in the empirical literature, the effects on inclusion of increased labour productivity induced by access to the internet are more mixed, as they seem to depend on the context, especially in low- and middle-income countries (Hjort and Tian, 2021) where evidence on the economic effects of internet diffusion is still scant.

Employment is one possible channel through which productivity gains induced by the diffusion of the internet can be associated with inclusion: if firms amend their labour requirements after adopting the internet, this will lead to exclusionary outcomes for the population in terms of working opportunities. Even with employment growth, firms may start to search for more skilled workers, leaving behind unskilled workers. Hjort and Poulsen (2019) exploit the staggered connection of fast internet submarine cables to the backbone networks of 12 African countries, and the differential timing in the connection of individual locations to those networks to estimate the effect of both internet access and speed on the individual probability of being employed. They find that individuals are more likely to be employed if they live in connected locations, although the effect on unskilled employment is only significant for individuals who had completed their primary education.

Focusing on mobile internet (3G), Caldarola et al. (2022) found a positive effect on aggregate employment across Rwandan districts. While both skilled and unskilled occupations grow, the former grow at a faster pace, while the latter grow more in absolute terms. Overall, the diffusion of fast mobile internet appears to steer structural change towards the creation of employment in the service sector, and to discourage employment creation in manufacturing. A positive effect of mobile internet diffusion on labour market participation has also been observed across Nigerian households (Bahia et al., 2020), who further benefit in terms of welfare and poverty reduction. A similar approach has been adopted to study Tanzanian households (Bahia et al., 2021), showing that labour force participation is increased for young and highly educated male individuals.

Other possible effects of internet access on inclusionary/exclusionary outcomes are the creation of business opportunities in new sectors, or the lowering of entry costs in existing ones. There is evidence that living in areas connected to broadband internet fixed lines has favoured the entry of firms in African countries, both formal (Hjort and Poulsen, 2019) and informal ones, although the latter mainly in the service sector, where operating costs are lower (Houngbonon et al., 2022). Moreover, the diffusion of fast mobile internet in Tanzania has allowed highly skilled women to leave farming to take up self-employment activities (Bahia et al., 2021). Overall, the literature suggests that, unlike other forms of structural change, the diffusion of the internet in SSA has had positive effects on inclusion, favouring both employment creation and entrepreneurship, and that these effects are more likely to occur in the service sector.

2.3 Gaps and contribution

A number of questions remain unanswered in the existing literature. First, there is little evidence of the effect of broadband internet on the performance of informal non-farming enterprises, which is where most of the population of SSA work. Houngbonon et al. (2022) found that, across African countries, the diffusion of fast land line internet increases the entry of non-farming household enterprises. However, to the best of our knowledge, there is no evidence on the impact of the internet on two major aspects of structural change, those of productivity growth and sectoral composition, in contexts where informality is prevalent over other forms of economic activity. In fact, the productivity of NFEs and their sectoral specialisations are a key driver of structural change in areas where informality is prevalent (Nagler and Naudé, 2017; Diao et al., 2018), because in these firms reside the capabilities that may or may not allow them to move to the productive formal sector and feed into the emergence of new economic industries.

Secondly, most of the firm-level evidence on the economic effect of internet access in Africa uses empirical strategies that look at the diffusion of land line internet. However, figures from sub-Saharan Africa show that the number of fixed phone subscriptions decreased from 1.6 per 100 inhabitants in 2009 to 0.7 in 2019. On the other hand, the penetration of mobile internet has grown exponentially: in 2015, 34 per cent of the Nigerian population subscribed to 2G mobile internet services, and 12 per cent had 3G subscriptions (GSMA, 2015). These figures indicate that mobile internet has had a much broader outreach in African countries than the land line.

Thirdly, the available evidence focuses on the diffusion, rather than the adoption of the internet. While the presence of the internet (whether land line or mobile) may encourage economic activity, more evidence is needed on the direct effect of internet adoption on the performance of firms, the industries in which they operate, and how these may impact structural change and inclusion.

In order to address these gaps, this paper first studies the effect of the adoption of fast mobile internet (3G services) on: i) the performance of Nigerian non-farming enterprises, measured as sales per worker; ii) the industry composition of such activities and their switches, or transitions, to other sectors. Second, it studies whether these effects on structural change (sales per worker and industry composition) positively or negatively influence inclusion measured in terms of: i) NFE labour, ii) household labour, and iii) firm entry. The next section illustrates the data and methods employed to achieve these goals.

3 Empirical strategy

3.1 Data

The analysis performed in this paper relies on a household panel dataset constructed by merging data from three sources – 1) the Nigeria Living Standard Measurement Survey (LSMS), for household and firm level data; 2) the Global System for Mobile Communications Association (GSMA) mobile coverage maps, for mobile internet diffusion; and 3) WWLLN Global Lightning Climatology and timeseries (WGLC). This is used to construct an instrumental variable based on lightning strikes (for more details, see Sections 3.1.3 and 3.3.1). Each data source is briefly discussed below.

3.1.1 Household data

The main source of information used for the construction of the dataset is the Nigeria Living Standard Measurement Survey - Integrated Survey for Agriculture (LSMS-ISA). The LSMS-ISA dataset is a nationally representative, geo-referenced panel data source at the household level, gathered as part of a broad data collection effort coordinated by the World Bank in several low- and middle-income countries in order to strengthen their household survey systems and to better inform development policies. Nigerian households were interviewed repeatedly across three waves (in 2010/11, 2012/13 and 2015/16), and each wave was collected in two rounds - a post-planting visit and a post-harvesting one.

The main reason for adopting this data source is that it includes a non-farming enterprise module. NFEs are defined as all economic establishments owned and run by household members, including self-employed individuals and excluding agricultural activities such as pre- and post-harvest activities on agricultural plots. Household NFEs can employ both household and external labour, and are active in many industrial sectors. In the survey, households were asked to self-report information on their household businesses, such as their sales, costs, capital, labour, and sector of activity. With respect to the latter, the dataset adopts the International Standard Industry Classification (ISIC) rev. 3.1. In the analysis, firms will be classified using the ISIC major groups: agriculture, business and real estate services, construction, education, electricity and water, finance, fishing, health, hospitality, manufacturing, mining, other services, public services, trade services,[5] and transport. The analysis will often refer to "services", a category that includes business and real estate, finance, hospitality, public, retail/wholesale trade, and other services. Following Behuria and Goodfellow (2019), the study also groups together a subset of services that have exhibited particularly high productivity growth in the same African context, such as finance, insurance and real estate services (henceforth, FIRE services).

The household modules of the survey include individual and household socio-demographic information, such as the age, gender, education, and employment status of individuals; and information on household-level asset ownership, consumption, expenditure, and non-farming businesses. The agricultural module includes information on all household agricultural plots. The geographical module holds information such as the coordinates of the Enumerator Area where the household is located (essentially the size of a village, or an urban neighbourhood), distance from the closest markets, roads and urban areas. Each NFE in the dataset can be associated with an owner and/or a manager, making it possible to merge firm-level data with relevant individual-level data about the NFE's owner, and related household-level information.

3.1.2 Mobile internet data

The data on mobile internet coverage is provided by the Global System for Mobile Communications Association (GSMA) in partnership with Collins-Bartholomew, a firm that specialises in map production.[6] The data used in this analysis gives the percentage of the population

[5] Henceforth, 'trade' refers to retail and wholesale trade services.

[6] The author is extremely grateful to Justin Tei Mensah for facilitating access to the data

with access to 2G, 3G, and 4G mobile services in each of the 775 Local Government Areas (LGA).[7] While 2G services do not allow to use fast mobile internet, the first technology that allowed to access fast mobile internet broadband services is the 3G technology, followed by the 4G, which improved the quality and speed of mobile internet. However, in the time period under consideration, there was no 4G coverage in Nigeria, and for this reason, the analysis will focus on the adoption of 3G mobile internet technology.

The original data comes from submissions by the four mobile operators offering 3G services in Nigeria: MTN, Airtel, Etisalat, and Glo (GSMA, 2015). In order to construct the measure of mobile services coverage in Nigeria, the analysis follows the approach elaborated by Mensah (2021) to obtain measures at the LGA level, as follows. The original disaggregated data takes the form of a raster map with separate layers for each technology (2G, 3G, and 4G). Each cell in the raster represents a 1 x 1 km area, with dichotomous information on whether the cell is covered by a mobile signal. The GSMA raster is overlaid with the Global Population of the World (GPW) data[8] (GPW) density raster (Centre for International Earth Science Information Network CIESIN Columbia University, 2018), in order to capture the number of people with access to each mobile service. Then cells are aggregated at the LGA level to compute the total population covered by mobile internet in each LGA; this number is divided by the total population of the LGA to obtain the share of population covered by each mobile technology in each LGA and year. The results of this exercise are shown in Figure 3, which describes the staggered roll-out of the 3G mobile internet across Nigerian LGAs and over time.

The main focus of this paper, however, is not to measure the effect of mobile 3G internet diffusion, but to capture the effect of technological adoption on firms and households. In order to identify the adoption of mobile internet at the household level, the district-level measure of 3G coverage has been weighted to reflect the number of mobile phones per capita in each household, obtained from the LSMS household data described in the previous subsection. In this way, a household in a district with high mobile internet coverage but where no one owns a mobile phone, is not counted as an adopter. This made it possible to refine the previously rather coarse measure of mobile internet diffusion at the LGA level, and to single out the effect of adoption of the new technology, as it is likely that some households will be covered by the infrastructure, but will not be able to access it due to income constraints.

[7] LGAs correspond to the Admin-2 subnational boundaries of Nigeria

[8] Population rasters are only available for 2010 and 2015. Therefore, the raster for 2012 is obtained from linear interpolation between the 2010 and 2015 measures. The population density data is publicly available at https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11/data-download#close

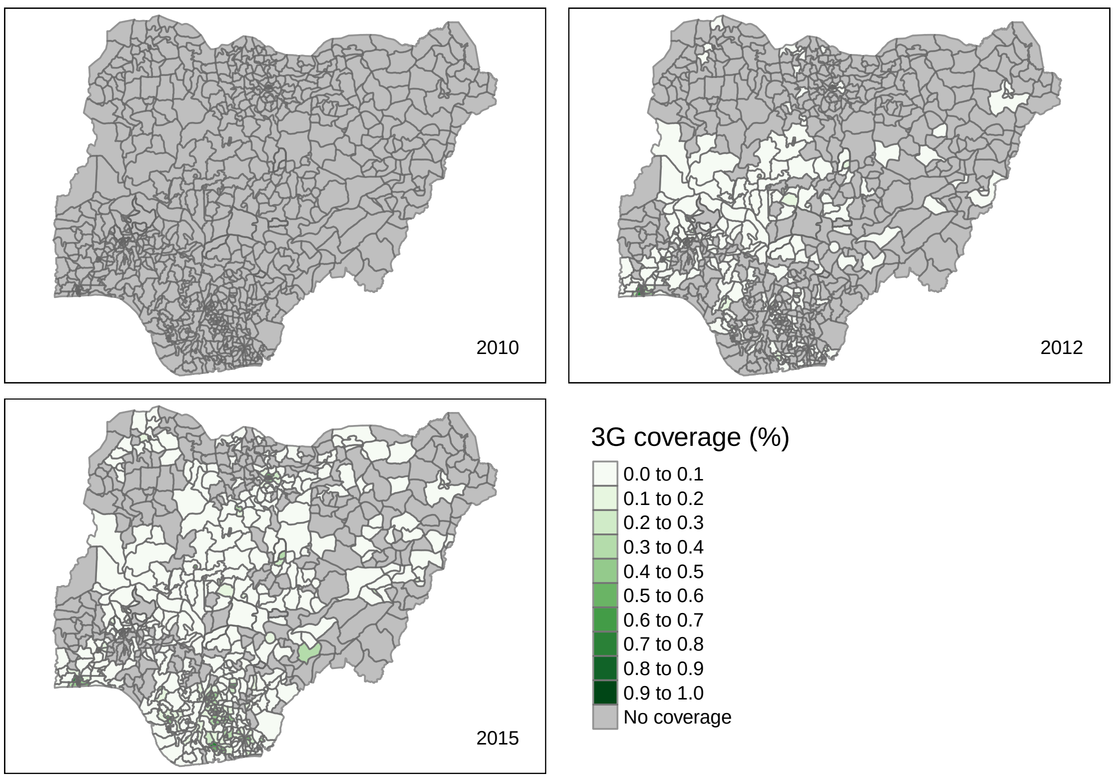

Figure 3: Mobile coverage in Nigeria in 2010-2015, based on GSMA Admin-2 (LGA) data. The colour indicates the percentage of 3G mobile internet coverage in each Nigerian LGA, in 2010, 2012, and 2015.

3.1.3 Additional data

Two additional sources have been added to the household data and the mobile internet coverage data. The first is the WWLLN Global Lightning Climatology and Timeseries (WGLC) data[9] (Kaplan and Lau, 2021), which is employed to construct a variable to instrument the main measure of interest – mobile internet adoption – to pursue the identification strategy described in Section 3.3.1. The WGLC data for Nigeria constitutes of rasters of 5 arc-minute resolution (around 8 km x 8 km at Nigeria's latitude) measuring the mean daily and monthly strike density (number of strikes per km^2) in each cell, for the period 2010-2020. In order to capture the exposure of each geographical unit to lightning, the series is averaged over time, resulting in a time-invariant measure of strike density. Similarly to the treatment of the mobile internet data, the strike density measure is weighted in terms of the GPW data (Centre for International Earth Science Information Network CIESIN Columbia University, 2018) for 2010, to obtain a time-invariant measure of strikes per capita, which is averaged for each LGA to obtain a subnational level measure of strikes per inhabitant.

The second additional source is the Armed Conflict Location and Event Data Project[10] (ACLED) (Raleigh et al., 2010), an extensive dataset that holds geo-coded information on conflict-related events around the world. This study relies on the Nigerian data on conflict events (battles, explosions, remote violence, and violence against civilians) to construct an LGA-level indicator of number of conflicts per capita. Based on the evidence that conflict events do affect economic activity (Collier and Duponchel, 2013; Ciarli et al., 2015), the information on conflict events is used as an additional control variable.

3.2 A descriptive picture of the data

The final dataset holds data for 3,459 NFEs in 2010, 4,446 in 2012, and 4,005 in 2015, owned by 3,443 unique households. All firms were operating at the time of the interview. A general description of the dataset is provided in Table 1, which shows that around 59 per cent of the NFEs are operated by male members of the household. Owners are approximately 42 years old on average. Only 5 per cent of the NFEs are formal (officially registered with the government), indicating that informality is the rule rather than the exception among Nigerian NFEs. Figure 4) shows a degree of sectoral heterogeneity across NFEs: the most common sector is retail and wholesale trade ("trade"), followed by manufacturing, and other services ("other"). Trade and manufacturing firms grew in both absolute and relative terms between 2010 and 2015.

[9] Open access data, available from https://zenodo.org/record/4882792#.YnIo89rP1hG

[10] The data is publicly available from https://acleddata.com/#/dashboard

While Figure 4) does not show any dramatic changes in the aggregate sectoral composition, Figure 5 indicates that both entry into a new sector and exit from the market are not infrequent among Nigerian households. The alluvial plot shows the aggregate number of households entering a new sector (all flows starting from any sector) or leaving the market (flows pointing to "none") over the time period available in the data.[11] The "None" block in 2010 groups together households that were not in the market in 2010, but entered at some point in either 2012 or 2015. To facilitate the visualisation, the flows starting from trade in 2010 are highlighted in blue, while those starting from manufacturing in the same year are highlighted in red; this makes it possible to trace the path of the households that started in the two largest sectors in 2010. It can be observed that households active in the manufacturing sector could enter the trade sector in the following time period (for instance, between 2010 and 2012), more than offsetting entry from trade into manufacturing. However, by 2015 almost half of the households that were active in trade services in 2010 had left the sector (mostly leaving the market, but also changing sector). Nevertheless, the new entries more than offset the exits in 2012, and almost did so in 2015.

Table 1: Non-farming enterprise dataset, descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
3G Adoption	11,900	0.037	0.126	0.000	1.852
Male owner	11,868	0.588	0.492	0	1
Age (owner)	11,807	40.199	14.054	15	65
# Members	11,910	7.441	3.521	1	35
# Members in work age	11,910	3.487	1.953	0	22
Household head is female	11,910	0.117	0.321	0	1
Household has agri. plot	11,910	0.568	0.495	0	1
Owner can read	11,716	0.633	0.482	0	1
Owner attended school	11,706	0.688	0.463	0	1
Formal	11,037	0.052	0.221	0	1
Dist. from road (miles)	11,910	7.863	11.620	0.000	102.100
Dist. from pop. centre (miles)	11,910	20.365	18.698	0.060	101.500
Dist. from market (miles)	11,910	66.636	44.253	0.370	214.340
Dist. from capital (miles)	11,910	61.484	52.209	0.180	442.700
3G coverage (%)	11,910	0.061	0.173	0.000	1.000
Mobile phones per cap.	11,900	0.430	0.402	0.000	12.000
# Conflict events (LGA)	11,910	0.694	4.380	0	77
Strike density	11,873	0.002	0.002	0.0004	0.014

Source: LSMS Nigeria, GSMA, ACLED, and WGLC.

[11] Households that owned more than one NFE in different sectors in the initial time period are shown twice; for instance, if a household owned a manufacturing firm and a retail firm in 2010, and it started a transport firm in 2012 without shutting down the firms active in 2010, that household would be counted in both flows going from manufacturing and trade in 2010 to transport in 2012. The figure excludes households that did not own an NFE across any of the survey waves.

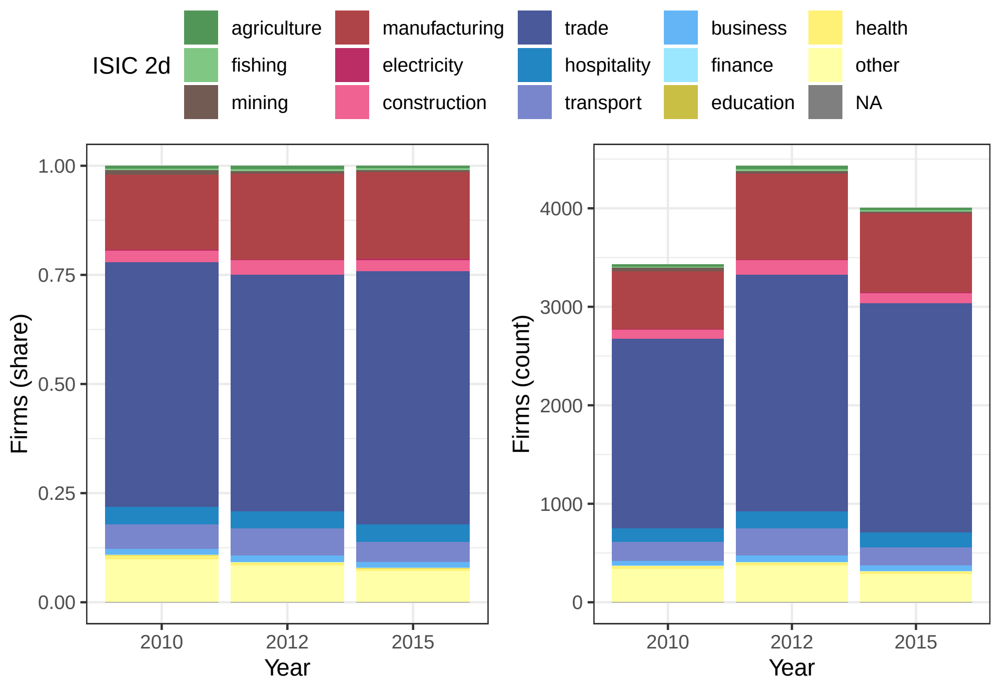

Figure 4: Non farming enterprises by sector over time: relative and absolute shares. Source: LSMS Nigeria.

Figure 6 describes the distribution of NFE sales per worker, over time. The log-normal shape persists across the three years; an interesting phenomenon is the fact that the mean logged measure of sales per worker moves slowly but steadily to the right between 2010 and 2015, and the right tail of the distribution – where the most productive firms are found – becomes progressively thicker, indicating that they have increased in number compared to previous years. Additionally, Table 2 reveals some interesting features of the data, which emerge after grouping firms according to the major categories of the International Standard Industrial Classification (ISIC rev. 3.1). Focusing on the two most numerous groups, trade and manufacturing, it can be observed that the former exhibits higher levels of productivity, while the latter is one of the least productive sectors in the sample. This description clashes somewhat with the idea that manufacturing firms are more productive than those active in the service sector, which here have significantly higher values of sales per worker; however, it must be noted that trade activities sustain higher costs, and require high capital investments to operate.

Looking at the sectoral differences in average mobile internet adoption (first column in Table 2), the data shows some heterogeneity across sectors, with education and the FIRE services exhibiting higher average mobile internet adoption when compared to other sectors. Overall, this heterogeneity highlights some possible correlations between the type of economic activities and the degree of mobile internet adoption. For instance, the presence of mobile internet

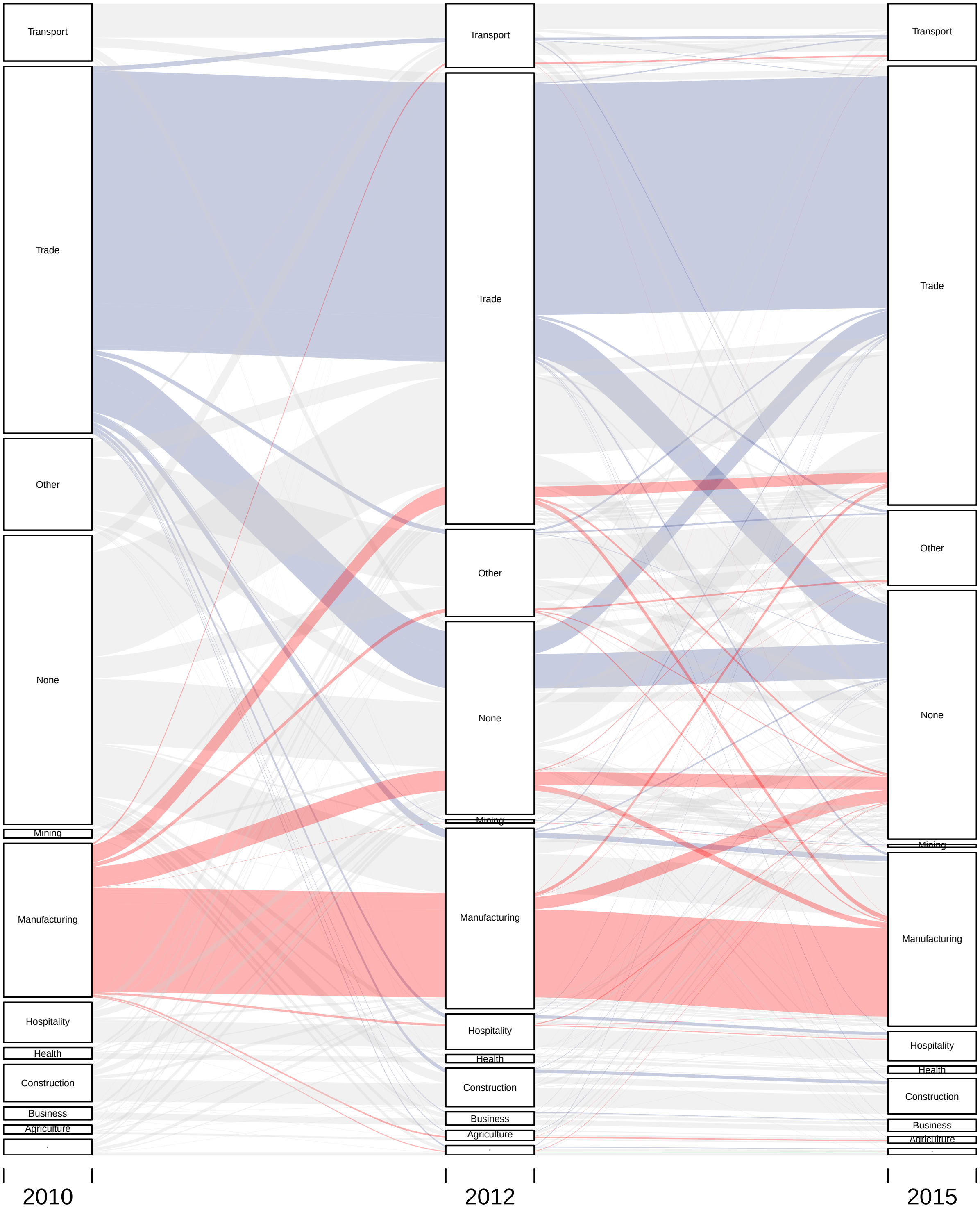

Figure 5: Household transition between sectors over time. The alluvial plot shows the flow of households across sectors; red(blue) flows identify households who had an NFE in the manufacturing (trade) sector in 2010, tracking their path over time. Source: LSMS Nigeria.

infrastructure may attract sectors that can benefit from its adoption. This issue will be dealt with in the identification strategy, described in section 3.3.1, by controlling for unobserved heterogeneity across major ISIC groups. Finally, Figure 7 provides grounds for an analysis of the effect of mobile internet adoption on NFE performance, showing a positive correlation between 3G adoption and the (logged) sales per worker of Nigerian NFEs. Bearing in mind that a causal interpretation of this relationship is not possible at this stage, the fitted lines indicate that the degree of positive correlation increases with time, presumably as a result of the progressive diffusion of 3G technology which allows higher adoption and an increasingly marked effect on economic activity. The next section illustrates the empirical strategy which will be employed to single out the effect of mobile internet adoption on NFE performance, sectoral dynamics, and on the inclusiveness of the transformation that accompanies the roll-out of fast mobile internet.

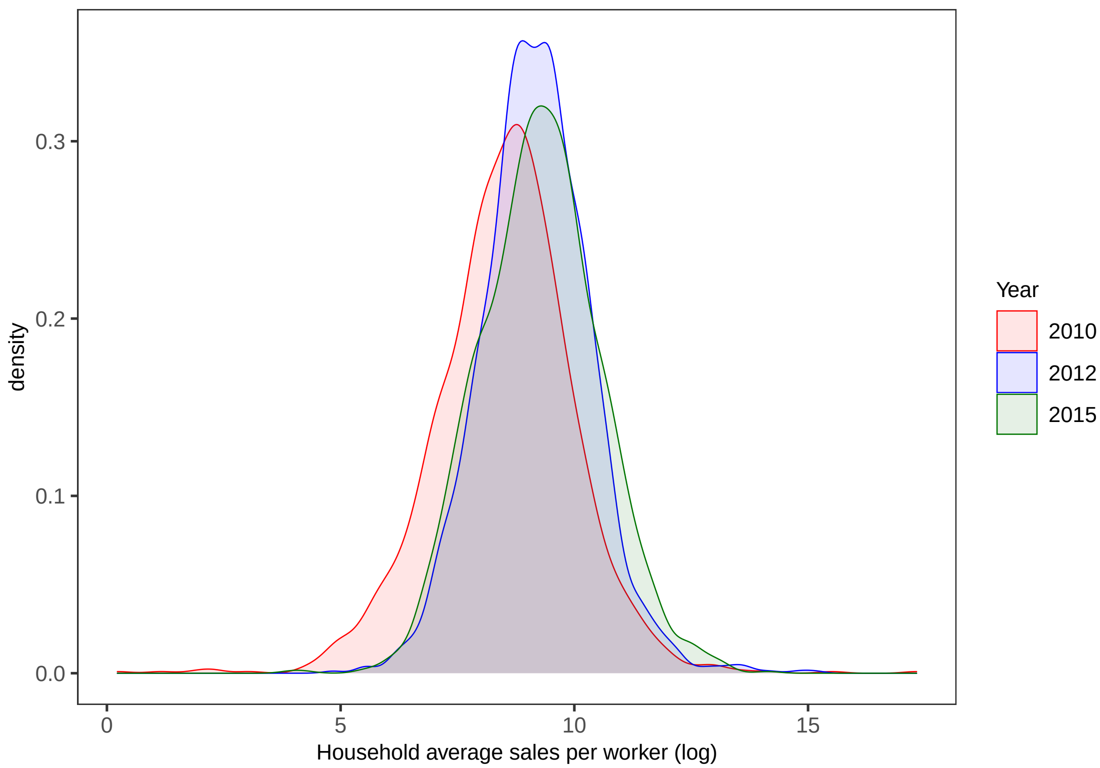

Figure 6: Kernel distribution of NFE sales per worker (logged), 2010-2015. Source: LSMS Nigeria.

3.3 Estimation strategy

The main goal of this study is to estimate the effect of mobile internet adoption by Nigerian households on structural change and inclusion, looking at their non farming enterprises. The baseline models can be outlined by Equation (1):

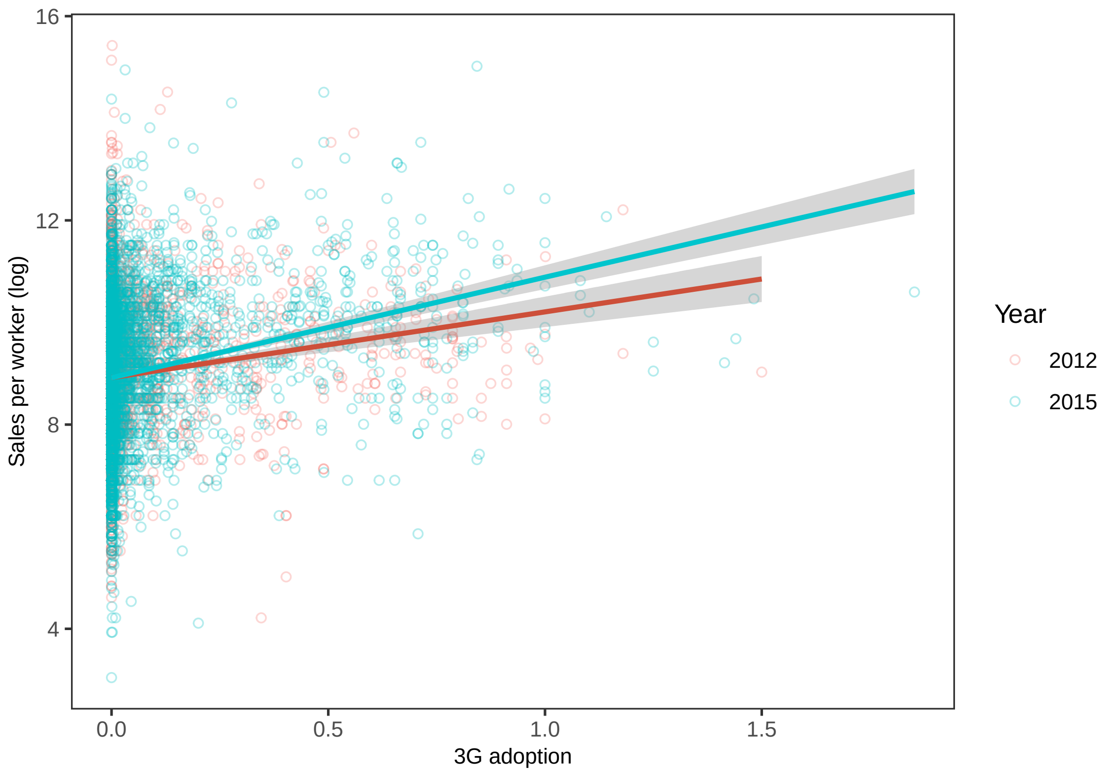

Figure 7: Correlation between mobile internet adoption (X axis) and logged sales per worker (Y axis). The fitted lines separately indicate the degree of correlation between the two variables, in 2012 (red) and in 2015 (blue). Source: LSMS Nigeria and GSMA.

Table 2: Descriptive statistics: averages by ISIC major groups

Industry	3G adop.	Sales PW	Costs	Capital	Sales	Labour	Formal	N
Agriculture	0.03	61.41	100.50	214.47	155.31	2.57	0.08	84
FIRE	0.09	42.18	99.06	900.54	124.93	2.98	0.22	175
Transport	0.03	35.33	117.53	872.40	157.57	2.55	0.23	642
Construction	0.03	25.89	34.67	191.49	96.28	3.00	0.07	348
Trade	0.04	23.55	59.50	182.36	56.37	2.58	0.03	6,646
Electricity	0.07	20.03	80.75	286.12	42.75	2.38	0.04	26
Mining	0.00	19.67	35.89	132.99	56.77	2.48	0.04	69
Health	0.06	19.55	35.20	525.87	55.78	2.64	0.27	85
Other	0.04	13.73	22.51	142.85	66.13	2.73	0.07	992
Education	0.15	12.95	89.48	2,566.82	164.32	9.41	0.65	17
Manufacturing	0.03	11.04	11.27	97.99	31.88	2.73	0.03	2,259
Hospitality	0.03	9.22	12.19	307.39	23.49	2.65	0.01	471
Fishing	0.01	7.96	15.91	76.44	19.98	2.79	0.17	52
Public	0.00	5.83	1.60	9.33	12.00	2.67	0.00	3

Note: All values are sector-wise means. 3G adoption is expressed as mean 3G coverage weighted by mobile phones per capita; sales per worker is expressed as average sales (in thousand Nairas) per worker; costs, capital, and sales are expressed in thousand Nairas; labour in number of workers; and formal as the share of formal firms in the industry. FIRE indicates financial, insurance, and real estate services.

$$Y_{iht} = \alpha + \beta mobile_{ht} + \gamma X_{it} + \zeta Z_{ht} + \sigma_h + \tau_t + \psi_j + \epsilon_{iht} \tag{1}$$

where Y_{it} is a placeholder for the outcomes of interest at the NFE (i) level, belonging to household h (sales per worker, and sectoral transition for structural change; firm labour and firm entry for inclusion); $mobile_{ht}$ is the percentage of 3G coverage in the household's LGA, weighted by mobile phones per capita at the household level (β is therefore the main coefficient of interest). X_{it} is a vector of time-varying controls at the firm level, such as owner's age, sex and education; Z_{ht} is a second vector of controls, this time at the household h level, which includes number of household members, agricultural activities, distance from markets, towns, and main roads. As mentioned in Section 3.1.3, the vector Z also includes the number of conflicts in the household district. In order to account for the higher conflict number in more populated LGAs, the variable is added as a per capita measure. Finally, household (σ_h), time (τ_t) and industry[12] (ψ_j) fixed effects are added to capture household and industry unobserved heterogeneity, along with time-related fixed effects. In all estimations, the standard errors are clustered at the enumerator area level (equivalent to the size of a village in rural areas).

Nevertheless, the estimation of Equation (1) is likely to be biased by endogeneity, as the roll-out of 3G mobile internet is not likely to be 'as good as random'. Endogeneity issues

[12]Industries are grouped according to the ISIC major groups, as per Table 2.

can have several causes, including measurement errors, omitted variable bias (for example, the presence of unobserved, time-varying geographical or societal features that may influence both 3G adoption and structural change/inclusion) and reverse causality (households with NFEs have higher income and may attract more mobile operators). Moreover, Equation (1) will be correctly identified only in the absence of pre-trends in both structural change and inclusion. In order to causally estimate the effect of mobile internet adoption on structural change and inclusiveness, the analysis resorts to two different identification strategies; the first is based on an instrumental variable approach, the second on an event study design. Both approaches are described below.

3.3.1 Instrumental Variable: lightning strikes

The first part of the identification strategy consists of an Instrumental Variable (IV) approach, implemented using a Two-Stage Least Squares (2SLS) estimation. The instrument exploits the geographical variation in lightning strikes across subnational areas, based on the evidence that the mobile phone infrastructure (mainly the cell towers responsible for 3G signal emission, installed by mobile operators) is affected by frequent storms, as cloud-to-ground lightning strikes cause power surges making cell tower maintenance more costly (Manacorda and Tesei, 2020). While this instrumental variable approach has been previously used in empirical settings studying the effect of fast mobile internet on social phenomena, such as citizens' political mobilisation (Manacorda and Tesei, 2020) or trust in government (Guriev et al., 2021), a growing body of literature has employed the variation in lightning strikes to break the endogeneity between mobile internet diffusion and economic outcomes (Andersen et al., 2012; Mensah, 2021; Caldarola et al., 2022).

The core argument is well described by Andersen et al. (2012), who use US data to demonstrate that lightning strikes can influence growth and productivity via their impact on the diffusion of IT technologies, due to the fact that the power surges caused by cloud-to-ground strikes disrupt the functioning of sensitive electronic equipment used to diffuse mobile signals. The implementation of the 2SLS approach used in this paper follows the one suggested by Guriev et al. (2021): an instrument based on a strikes per capita measure at the LGA level is constructed (details of the variable construction are described in Section 3.1.3). The rationale behind using a per capita measure of lightning strikes is that this will reflect the mobile operators' decision criterion when installing a mobile cell tower: the higher costs due to frequent power surges, which may discourage the operator from installing a mobile cell tower in an area highly exposed to storms, are moderated by a larger market (proxied by higher population density) which may offset the additional maintenance costs of the cell towers in areas with higher strike density. Moreover, Guriev et al. (2021) use a time-invariant measure of strikes per capita, constructed as the average strike density per capita throughout the available series. This choice, also adopted here, is based on evidence that lightning strikes follow a stationary process, so the instrument will capture the intrinsic exposure of geographical areas to strikes, on the grounds of which the mobile operators make the decision whether or not to build a cell tower. In order to reflect the increasing mobile internet roll-out, the time-invariant measure is interacted with a linear time trend.

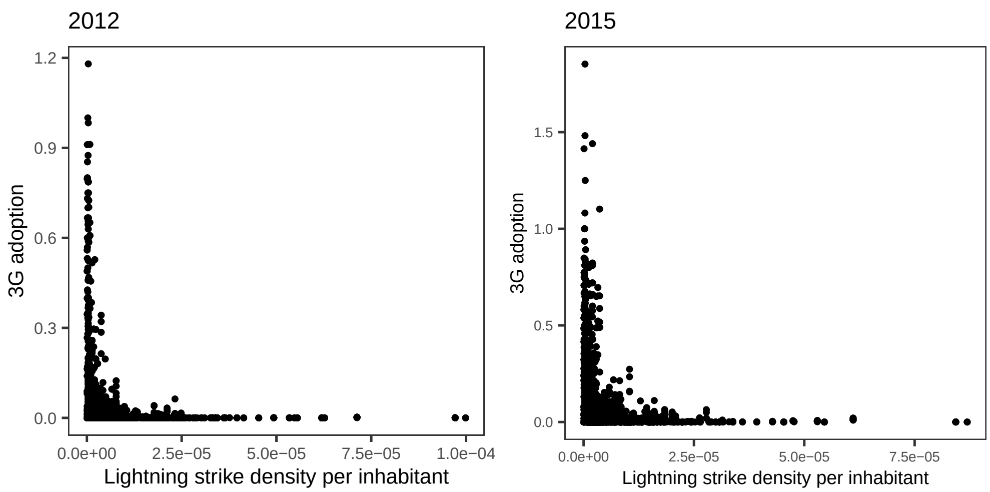

Figure 8: Relevance restriction: correlation between lightning strikes per capita in Nigerian LGAs (x axis) and the adoption of 3G mobile internet services by Nigerian households. Year 2010 is excluded due to the absence of mobile internet coverage. Source: GSMA and WGLC data.

The relevance of the instrument – lightning strikes per capita in Nigerian Local Government Areas – with respect to mobile internet adoption is shown clearly by Figure 8, which reveals a neat, negative, and hyperbolic correlation between the two variables. It is interesting to note that the pattern is consistent over time, as the areas with the highest number of lightning strikes per capita show the smallest (in some cases null) rate of 3G adoption both in 2012 (left panel in Figure 8) and in 2015 (right panel). The particular shape of this relationship suggests implicitly that an over identified first stage could be used in the 2SLS estimation to increase its precision, using the square of the *strikes* variable, as shown by Equation (2):

$$mobile_{ht} = \gamma_0 + \gamma_1 strikes_l \times t + \gamma_2 (strikes_l \times t)^2 + \gamma_3 X_{it} + \gamma_4 Z_{ht} + \sigma_i + \tau_t + \psi_j + u_{ht} \quad (2)$$

where $strikes_l$ is the measure of lightning strike density in the LGA, interacted with a linear time trend t. The second stage estimation is defined by Equation (3):

$$Y_{iht} = \theta_1 \widehat{mobile}_{ht} + \theta_2 X_{it} + \theta_3 Z_{ht} + \sigma_h + \tau_t + \psi_j + \epsilon_{iht} \tag{3}$$

where the coefficient θ_1 can be interpreted as a continuous, Locally Averaged Treatment Effect (LATE, Angrist (2004)) of mobile internet adoption on the outcomes of interest related to structural change (NFE performance, and household sector transition) and inclusion in terms of entrepreneurial and working opportunities (NFE ownership and labour).

A possible concern is that lightning strikes may directly affect the performance of non-farming enterprises by disrupting access, quality and cost of electricity. The study tests this, using self-reported household information on the constraints to starting and operating a business, included in the LSMS data. Each household was asked to report the three major constraints to starting and operating a business, and this analysis focuses on whether access to, the quality of, or the cost of electricity represent an obstacle to starting or operating a business in areas with higher exposure to lightning strikes. First, Table 3 shows that living in areas with frequent lightning does not affect firm entry on the basis of electricity-related hurdles: although areas where NFE owners are located experience lower average lightning density, the difference is very small with respect to the full variable range. Moreover, this does not affect electricity access, quality, or cost; in fact, electricity seems to be a more pressing constraint for NFE owners as compared to non-owners. Secondly, Table 4 shows the percentage of households indicating electricity access, cost, and quality as obstacles to running household businesses, by different levels of lightning strike density. Again, there is no clear association between the frequency of strikes, and electricity-related obstacles to running a business. Finally, Figure 9 plots the relationship between lightning density and total NFE operating costs.[13] It shows that there is no positive correlation: higher lightning density does not seem to be related to higher costs for NFE, on average. If anything, the correlation between lightning density and average firm costs by household is negative. This descriptive evidence is consistent with the argument and evidence proposed by Andersen et al. (2012), that lightning strikes affect the economy only via their effect on the diffusion of ICT technologies, and not directly.

3.3.2 Event study

The 2SLS estimation with fixed effects presented above works only under the assumption that there are no pre-trends before the treatment (that is, that the outcomes of interest did not show the same trend before and after adopting mobile internet) and no anticipation (meaning that individuals could not have anticipated the arrival of the new mobile internet technology,

[13] Costs include (in the last month before each interview): salaries and wages, purchase of goods, transport, insurance, rent, interest on loans, raw materials, and other costs.

Table 3: Electricity constraints in Nigerian households

Variable	No NFE	Has NFE	Difference	T stat.
Lightning density (mean)	0.0025	0.0023	2e-04	4.08***
Lightning density (sd)	0.0017	0.0018	-1e-04	-
Electricity cost (mean)	0.0227	0.065	-0.0423	-7.501***
Electricity cost (sd)	0.0227	0.065	-0.0423	-
Electricity quality (mean)	0.0312	0.0839	-0.0527	-8.01***
Electricity quality (sd)	0.1739	0.3983	-0.2244	-
Electricity access (mean)	0.0244	0.068	-0.0437	-7.443***
Electricity access (sd)	0.0244	0.068	-0.0437	-
Households (N)	3443	5233	-	-

Note: The table compares the extent to which electricity (access, cost, and quality) represents a constraint on starting or operating a business for Nigerian households, comparing the share of households that identify these as one of the three obstacles across NFE-owning and non-owning households. The t-stat column is the result of an t-student inference test on the statistical significance of the difference between the two groups. Source: LSMS Nigeria and WGLC.

Table 4: Electricity constraints by lightning strike density exposure

Lightning quintile	N	Lightning density (mean)	Electricity cost (mean)	Electricity quality (mean)	Electricity access (mean)
1^{st}	1783	7e-04	0.0333	0.0972	0.0365
2^{nd}	1804	0.0012	0.0197	0.0685	0.042
3^{rd}	1762	0.002	0.0908	0.07	0.0876
4^{th}	1783	0.003	0.0561	0.0417	0.0451
5^{th}	1776	0.0051	0.0542	0.057	0.0611

Note: The table compares the share of households indicating electricity (cost, quality, and access) as a major constraint to operating or starting a business in Nigeria, comparing households by the lightning strike density of the LGAs in which they leave (divided by quintiles of the lightning strike distribution). Source: LSMS Nigeria and WGLC.

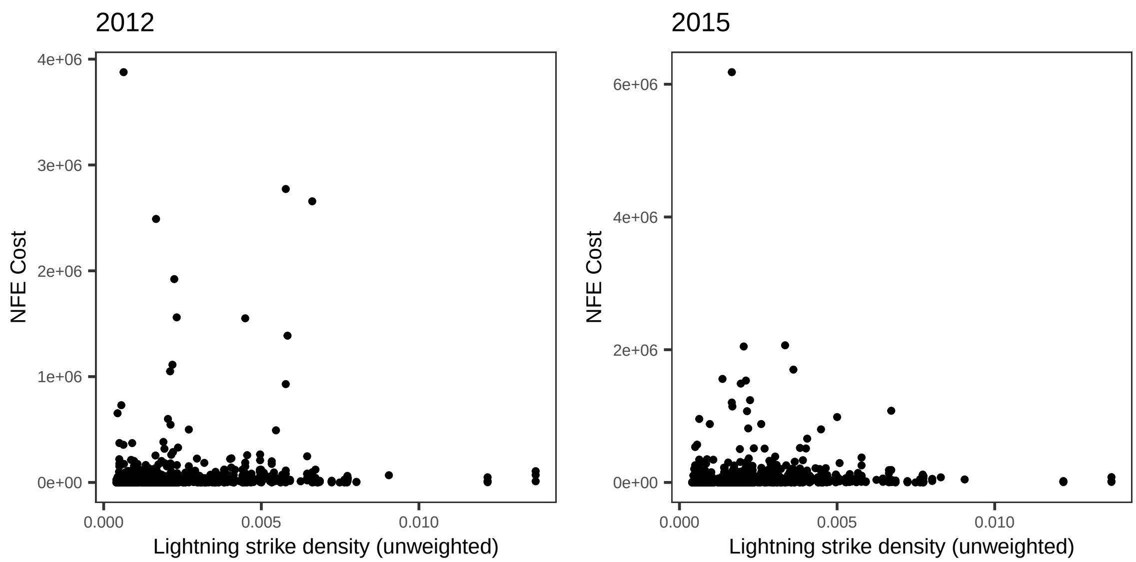

Figure 9: Exclusion restriction: correlation between lightning strike density (X axis) and operating costs of non-farming enterprises (Y axis). Source: LSMS Nigeria and WGLC.

for instance taking decisions on how to operate their enterprises from the perspective of imminent access to the new technology, thus affecting the outcome variables of interest before treatment. In order to make sure that the 'non-parallel trends' and 'no anticipation' assumptions hold, the analysis also implements an event study design, which particularly recommended in cases where an experimental setting is absent (Clarke and Tapia-Schythe, 2021). This approach requires the definition of a dichotomous treatment (or event) through a set of variables measuring whether a household has or has not been 'treated' in all time periods. This is implemented by adding lags and leads to Equation (1) to measure the time distance from mobile internet adoption:

$$Y_{iht} = \sum_{\tau=-2}^{2} \phi_\tau treated_{ih} + \phi_2 X_{it} + \phi_3 Z_{ht} + \sigma_i + \tau_t + \psi_j + \epsilon_{iht} \tag{4}$$

where the variable *treated* is a dichotomous variable that is activated only for the time periods τ in which a household h adopts mobile internet, and in subsequent time periods. Given that the dataset covers only three time periods, the event design disposes of a maximum of two lags (periods before treatment) and two leads (periods after treatment). To define the dichotomous variable, the following arbitrary threshold is adopted: a household is 'treated' by adoption of mobile internet when $mobile > 0.2$. In practice, this means that a household is treated if, for instance, it is located in an area fully covered by 3G internet access and 20 per cent of households in the area have a mobile phone; or, when a household has one phone per member of working age, and is located in an area where at least 20 per cent of the population in the LGA have access to 3G internet.[14] As a robustness check, event study regressions are also run for different treatment thresholds (0.15, 0.2, 0.3, and 0.4). The main advantage of this approach is that, although it requires the use of a categorical treatment variable, it makes it possible to check for parallel trends (in the absence of which the causal interpretation of the parameters cannot be claimed) and to observe the persistence of the treatment effect over time. The baseline period is $\tau = -1$ – the year before the treatment. For the 'no parallel trends' and 'no anticipation' assumptions to hold, it is required that the coefficient of the event variable before the baseline period is not significant. The event study results will be presented along with the 2SLS results in the next section.

4 Results

4.1 Structural change

Table 5 reports results of estimating Equation 1 using both OLS and 2SLS. The 2SLS estimation results (columns 3 and 4) show that mobile internet adoption leads to an increase in sales per worker for the average NFE. Comparison with the OLS results (columns 1 and 2) suggests that these estimations suffer from a downward bias (consistent with similar studies, such as Manacorda and Tesei (2020); Mensah (2021); Caldarola et al. (2022)). Column 5 in Table 5 displays the results of the first stage of the 2SLS estimation in column 4, indicating that the instrument enters significantly with a negative sign in its base form, and with a positive sign when squared. The exclusion of both instruments has a Kleibergen-Paap rk Wald F statistic of 27.56, safely above the $F > 10$ criterion suggested by Stock and Yogo (2005) to test against weak instruments. The Sargan-Hansen test yields a p-value above 0.05, indicating that the null hypothesis of valid over identifying restrictions cannot be rejected.

The quantification exercise at the bottom of Table 5 gives a clearer idea of the size of the effect of mobile internet adoption on NFE performance, showing that a change from the 25^{th} to the 75^{th} percentile along the mobile internet adoption distribution increases a firm's sales per worker by 3.6 per cent. The positive effect of 3G adoption on NFE performance is corroborated by the results of the event study estimation (Figure 10), which show a statistically significant positive effect of mobile adoption on sales per worker after two time periods from adoption, and not before. The statistically insignificant coefficient before the treatment confirms that there are no parallel trends. The robustness checks in Figure A1 also

[14] It can be expected that households living in areas with good mobile internet coverage will have an incentive to purchase mobile phones to access the mobile internet service.

Table 5: OLS and 2SLS results: Log sales per worker

VARIABLES	(1) OLS FE log(sales PW)	(2) OLS FE log(sales PW)	(3) 2SLS log(sales PW)	(4) 2SLS log(sales PW)	(5) First stage Dig. adop.
3G adoption	0.260	0.189	1.947**	2.071**	
	(0.224)	(0.213)	(0.804)	(0.860)	
Owner is female		-0.827***		-0.822***	-0.00304
		(0.0443)		(0.0449)	(0.00221)
Age		0.00408***		0.00411***	-4.48e-05
		(0.00147)		(0.00147)	(8.93e-05)
N. members		0.00779		0.0257	-0.00953***
		(0.0192)		(0.0221)	(0.00267)
Female head		0.0799		0.0660	0.0130
		(0.110)		(0.110)	(0.0134)
Agriculture		-0.0534		-0.0466	-0.00617
		(0.0811)		(0.0808)	(0.00556)
Owner can read		0.0582		0.0651	-0.00516
		(0.0546)		(0.0546)	(0.00317)
Owner attended school		0.0538		0.0455	0.00329
		(0.0675)		(0.0681)	(0.00380)
Dist. from main road		0.000717		-0.00244	0.00118***
		(0.00340)		(0.00369)	(0.000262)
Dist. from town		-0.00426		-0.00339	-0.000467*
		(0.00288)		(0.00293)	(0.000255)
Dist. from market		-0.00290		-0.00129	-0.000149
		(0.00429)		(0.00465)	(0.000315)
Dist. from capital		0.00132		0.00216	-0.000385
		(0.00467)		(0.00496)	(0.000284)
Conflict PC		-72.36		1,352	-556.3*
		(4,280)		(3,942)	(325.0)
Lightning PC					-6.379***
					(0.973)
Lightning PC^2					17.24***
					(4.607)
Constant	8.806***	9.213***			0.249***
	(0.00858)	(0.357)			(0.0440)
Observations	11,258	10,989	11,220	10,989	10,989
R-squared	0.588	0.635			0.680
Household FE	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Mean DV	8.810	8.810	8.810	8.810	
Quantification			3.131	3.616	
Sargan (p value)			0.412	0.275	
Fstat					27.56

Note: The dependent variable measures the log of sales per worker of NFEs. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. The F-stat in column 5 reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution, after unlogging the dependent variable. Clustered standard errors in parenthesis: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

support the ‘no anticipation’ and ‘no parallel trends’ assumptions, and indicate that the effect of 3G adoption on NFE performance remains stable for both lower and higher treatment thresholds.

It is worth mentioning that column 5 in Table 5 shows only two positive coefficients among the control variables; the ones on the gender (female) and age of the NFE owner. The coefficient on gender (female) is strongly significant and negative, with a large point estimate,[15] indicating the presence of gender-based inequality structures, with female-owned NFEs showing systematically lower sales per worker. This result is consistent with the findings of Nagler and Naudé (2017), who identify as a possible cause the presence of time constraints for women, who are more often also involved in household duties.

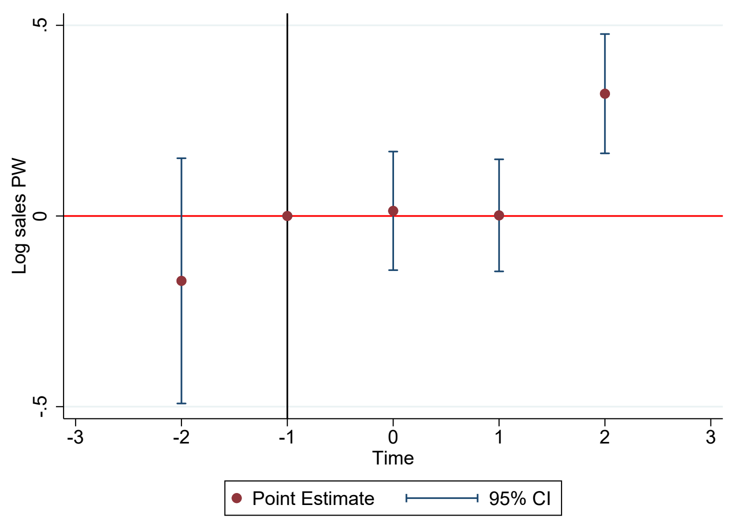

Figure 10: Event study: sales per worker. The event study design uses the first year in which a household hits 0.2 of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. The coefficients reported in the figure come from a model based on Equation (4), at the NFE level, including household, industry, and year fixed effects, incorporating the following controls: owner’s gender (female); owner’s age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

This paper examines various mechanisms that could possibly lead to a positive impact of internet adoption on NFE sales per worker. It investigates whether internet adoption has an effect on access to credit, capital,[16] costs,[17] sales, or labour demand. Table 6 shows that

[15] Although the coefficient is omitted in the following table (7), the coefficient on gender (female) remains significant and negative.

[16] Capital quantifies the current value of physical capital stock, including all tools, equipment, buildings, land, vehicles, inputs, supplies, and merchandise (goods for sale).

[17] Costs include (in the last month before each interview): salaries and wages, purchase of goods, transport,

Table 6: 2SLS results: mechanisms

VARIABLES	(1) 2SLS Credit	(2) 2SLS Capital	(3) 2SLS CapitalPW	(4) 2SLS Costs	(5) 2SLS CostsPW	(6) 2SLS Sales	(7) 2SLS Labour	(8) First stage Dig. Adop.
3G Adoption	0.0421	-0.152	0.414	0.131	0.471	1.540**	-2.614*	
	(0.138)	(1.098)	(1.136)	(1.825)	(1.742)	(0.645)	(1.562)	
Lightning PC								-6.379***
								(0.973)
Lightning PC^2								17.24***
								(4.607)
Constant								0.249***
								(0.0440)
Observations	10,983	10,989	10,989	10,989	10,989	10,989	10,989	10,989
R-squared								0.680
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Mean DV	0.0424	10.17	9.330	7.902	7.139	9.671	2.649	
Quantification						1.910	-0.483	
Sargan (p value)	0.757	0.161	0.159	0.538	0.464	0.345	0.0846	
Fstat								27.56

Note: The dependent variables measure: the amount of credit received by the NFE (in thousand Nairas); the amount of capital stock owned by the NFE (in thousand Nairas), and its per-worker equivalent; the amount of costs sustained by the NFE in the last month (in thousand Nairas), and its per-worker equivalent; the amount of sales made the NFE in the last month (in thousand Nairas); and the number of labourers hired by the NFE. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution. Clustered standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1

mobile internet adoption does not have a statistically significant impact on capital, costs, nor credit (columns 1 to 5 in Table 6, corroborated by Figure A2). Instead, internet adoption has a direct significant negative impact on the number of employees, and a significant positive impact on sales. The poor effect of internet adoption on credit is probably due to the limited adoption of mobile money in Nigeria: in 2014 only 2.3 per cent of the Nigerian population had access to a mobile money account. This is much lower than in other African countries, like Kenya, where in the same year 58 per cent of the population had access to mobile money (Demirgüç-Kunt et al., 2018).

We next focus on different industries. Results indicate that the positive effect of internet adoption on sales per worker is statistically significant only in trade activities (Table 7, column 9). These results are consistent with Houngbonon et al. (2022), who suggest that the concentration of benefits in trade services could be due to lower operating costs in the sector. An additional reason could be that mobile internet technologies are more suitable for retail

insurance, rent, interest on loans, raw materials, and other costs.

and wholesale activities, due to the higher relevance of person-to-person interactions, when compared for instance to the manufacturing industry. However, it is also notable that, due to the small number of NFEs in some of the industries, the IV does not perform equally well for all of them. Concentration of effects in services is confirmed by the event study design presented in Figure A3, which indicates that in the aggregate and FIRE services there is also a positive effect of mobile internet adoption on NFE performance, measured as sales per worker. However, as the FIRE sector is also the smallest sector in the sample, these results should be interpreted cautiously.

We next examine whether internet access has an impact on structural change also through the change in the composition of industries. Table 8 illustrates the results for the probability that a household h enters industry j in $t+1$, conditional on not being active in that industry in the previous time period t. We find that households with higher mobile adoption are less likely to enter the manufacturing industry, suggesting that they may be induced to specialise in industries – such as trade – where there are higher benefits from accessing internet. If new working opportunities stemming from the diffusion of mobile internet are more likely to arise in service activities, this could fuel the process of tertiarisation of the informal sector. Due to the availability of only two time periods for the transition of households, imposed by the way in which transition has been defined, it has not been possible to conduct an event study in this case. Moreover, the definition of household transition imposes to have a balanced panel structure, which explains the lower number of observations – corresponding to households which own at least one NFE both in 2012 and 2015.

Table 7: 2SLS results: (log) sales per worker, by sectors

	(1) Manuf.	(2) 1 stage	(3) Constr.	(4) 1 stage	(5) Transp.	(6) 1 stage	(7) Serv.	(8) 1 stage	(9) Trade	(10) 1 stage	(11) Hosp.	(12) 1 stage	(13) FIRE	(14) 1 stage
3G adoption	1.588		0.978		2.099		1.657		1.840*		8.446		-4.480	
	(2.168)		(5.526)		(2.697)		(1.009)		(1.034)		(7.544)		(5.215)	
Lightning density PC		-5.744***		-8.030**		-9.756***		-6.567***		-6.818***		-6.067*		-12.08**
		(1.647)		(3.681)		(3.251)		(1.097)		(1.158)		(3.531)		(5.944)
Lightning density PC^2		15.04***		22.86**		36.73*		17.63***		18.17***		32.72		25.88
		(5.373)		(11.11)		(20.82)		(5.218)		(5.257)		(22.67)		(17.42)
Constant		0.238***		1.034*		0.172		0.271***		0.289***		1.148		-0.380
		(0.0659)		(0.569)		(0.171)		(0.0573)		(0.0515)		(1.336)		(1.270)
Observations	1,849	1,849	250	250	425	425	7,452	7,452	5,856	5,856	388	388	122	122
R-squared		0.647		0.707		0.738		0.701		0.694		0.841		0.825
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean DV	8.334		9.051		9.390		8.876		8.950		8.397		9.608	
Quantification	2.031		0.865		3.734		2.213		2.762		2428		-0.516	
Sargan (p value)	0.979		0.615		0.716		0.249		0.296		0.470		0.217	
Fstat		6.561		2.700		5.424		23.46		22.45		1.987		

Note: The dependent variables measures the log of sales per worker of NFEs. Odd numbered columns indicate the sectoral sub-sample used in the 2SLS estimation, followed by their respective first-stage regression. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution. Clustered standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1

Table 8: 2SLS results: household transition

Transition to	(1) 2SLS Services	(2) 2SLS Manuf.	(3) 2SLS FIRE	(4) First stage 3G Adoption
3G Adoption	0.122	-0.540*	0.0179	
	(0.249)	(0.297)	(0.106)	
Lightning PC				-6.856***
				(1.203)
Lightning PC^2				19.18***
				(6.241)
Constant	-0.0946**	0.0328	0.0151	0.246***
	(0.0371)	(0.0418)	(0.0135)	(0.0478)
Observations	4,761	4,761	4,761	4,761
R-squared				0.641
Number of HH	1,590	1,590	1,590	
Controls	YES	YES	YES	YES
Household FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Fstat				25.16

Note: The dependent variables measure the household transition toward services, manufacturing, and FIRE services. A household transitions towards a sector if they start an NFE in that sector in $t+1$, conditional on not being active in the same sector in t. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: ratio of female members (female); members' mean age; number of household members; female-headed household; household is active in agriculture; percentage of household members in working age who can read;percentage of household members in working age who have ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution. Clustered standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1

4.2 Inclusion

Results for sales and number of employees (columns 6 and 7 in Table 6) are useful to discuss if the structural changes induced by access to mobile internet are also inclusive. These indicate that the increase in NFE sales per worker is likely to be driven by the simultaneous effect of higher sales (for instance, allowing NFEs to reach a larger market) and lower labour requirements (a possible substitution effect of mobile internet rather than complementary to labour). Both results are confirmed by the event study approach (Figure 11), which indicates that these effects are more likely to occur after two time periods following mobile 3G internet adoption.

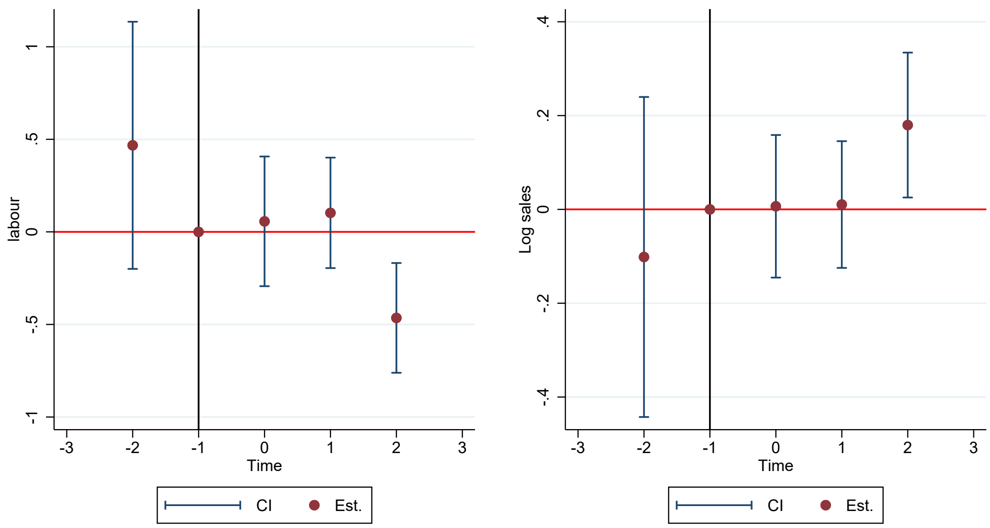

Figure 11: Event study: labour and sales. The event study design uses the first year in which a household hits 0.2 of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. The outcome variable used in the event study specification is indicated on the vertical axis. The coefficients reported in the figure come from a model based on Equation 4, including household, industry, and year fixed effects. The model uses NFEs as units of observation, and incorporates the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

In order to provide more detail on the labour substitution effect, the study examines whether NFEs reduced the number of employees sourced from the household or whether they hired

Table 9: 2SLS results: household and non-household labour in NFEs

VARIABLES	(1) 2SLS Household labour	(2) 2SLS Non-household labour
3G Adoption	-6.338***	1.911*
	(2.010)	(1.014)
Observations	10,986	10,986
Controls	YES	YES
Household FE	YES	YES
Sector FE	YES	YES
Year FE	YES	YES
Mean DV	2.404	0.246

Note: The dependent variables measure the number of NFE workers from within (column 1) and from outside (column 2) the household. All estimations are run using a 2SLS estimator. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: owner's gender (female) and age; number of household members; female-headed household; household is active in agriculture; owner can read; owner has ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution.Clustered standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1

labour. Table 9 indicates that there is a difference between within-household and external labour: the former decreases and the latter grows, indicating that, after adopting mobile internet, NFEs are more likely to free up household labour, in favour of employees from outside the household. One possible explanation is that, after adopting the new technology, firms retain only those household members who are most skilled, and seek more skilled employees outside. If it is the case that skilled labour is sought outside the household, the adoption of mobile internet may lead to labour market inequalities, favouring highly skilled workers over unskilled ones, but the data includes no information on the skills of the workers employed by the NFEs with which to test this. Another possible explanation is that household members find a more remunerative job outside the household; Bahia et al. (2020) show that internet adoption increases labour market participation of waged workers, while Strazzeri (2021) documents an increase in migration.

An attempt is made to test the former hypothesis by estimating the effect of mobile internet adoption on the share of household members employed outside the household. Columns 1 and 2 in Table 10 indicate that mobile internet adoption by the household has a positive effect on the share of household members employed outside the household, irrespective of whether the household has (column 2), or does not have (column 1), a non-farming enterprise. The effect of the adoption of mobile internet is also positive if we consider any type of employment for households that do not run a non-farming enterprise (column 3), but not for NFE-owning households. Results suggest that the diffusion of mobile internet has been successful in reducing unemployment overall, but there is no increase in total employment for households that own an NFE; one possible explanation for the non-significant effect of 3G adoption in column 4 is that households that own an NFE are more likely to be in full employment already before adopting fast mobile internet. These results therefore suggest that while households are able to free household labour from their NFEs as a result of adopting the new technology, the excess labour can indeed be absorbed outside the household, although this will not lead to an increase in the share of employed working age individuals. This finding partly confirms the presence of a labour-substitution effect: within NFEs, household labour is substituted both by the new technology, and by external labour. Within households, what is observed is more of a reallocation effect – the household labour that is pushed outside NFEs is re-absorbed outside the household.

These results suggest that, although mobile internet may increase the number of employees in a location, as also suggested in the literature, this is likely to come from the entry of new firms, or creation of employment in the formal sector, rather than from an increase in labour in existing firms in the informal sector.

The study then tests whether mobile internet leads to the entry of new firms into the informal sector. Table 11 (columns 1 and 2) shows that mobile internet adoption does not predict NFE ownership at the household level (or new entry of households that did not own an NFE in the previous year (Table 11, columns 4 and 5). This result suggests that, within the informal sector, only incumbent firms reap the benefits of mobile internet roll-out, increasing their sales. At the same time, the adoption of mobile internet does not prevent the exit of households from the NFE market (columns 6 and 7), suggesting that incumbents who benefit from mobile internet adoption increase their market shares in the informal sector. The insignificant effect of mobile internet adoption on firm entry contrasts with the evidence presented by Houngbonon et al. (2022) who document increased firm entry resulting from the diffusion of land line internet: however their focus is on formal firms.

Finally, an event study is conducted to explain NFE ownership, as entry is based on only two time periods. Figure 12 shows that mobile internet adoption has no positive effect on NFE ownership, and is even negative in the first year after treatment; in subsequent years, however, the effect becomes positive and weakly significant (90 per cent confidence interval),

Table 10: 2SLS results: labour within and outside the household

Employment share	(1) 2SLS Outside hh	(2) 2SLS Outside hh (NFE)	(3) 2SLS Overall	(4) 2SLS Overall (NFE)	(5) First stage Dig. Adop.	(6) First stage Dig. Adop.
3G Adoption	0.209**	0.185*	0.415*	0.113		
	(0.107)	(0.110)	(0.249)	(0.295)		
Agriculture	-0.0190**	-0.00520	0.133***	0.0963***		
	(0.00825)	(0.0125)	(0.0194)	(0.0307)		
NFE	-0.0308***		0.152***			
	(0.00643)		(0.0148)			
Lightning PC					-3.666***	-6.782***
					(0.258)	(0.464)
Lightning PC^2					5.911***	18.80***
					(1.079)	(1.978)
Constant					0.190***	0.257***
					(0.0211)	(0.0372)
Observations	12,617	6,644	12,617	6,644	12,617	6,644
R-squared					0.617	0.661
Controls	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Sargan (p value)	0.26	0.07	0.16	0.39		
Fstat					217.1	139.5

Note: The dependent variables measure, respectively: the ratio of household members employed outside the the household over the total number of household members, across all households (column 1) and only in NFE-owning households (column 2); the ratio of household members employed both inside and outside the the household over the total number of household members, across all households (column 3) and only in NFE-owning households (column 4). All estimations are run using 2SLS. Column 5 reports the first stage results for models 1 and 3; column 6 reports the first stage results for models 2 and 4. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: ratio of female household members (female); household members' mean age; number of household members; female-headed household; household is active in agriculture; percentage of household members in working age who can read; percentage of household members in working age who have ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution. Clustered standard errors in parenthesis: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: 2SLS and OLS results: NFE ownership. entry, and exit

VARIABLES	(1) OLS FE NFE	(2) 2SLS NFE	(3) First stage Dig. Ado.	(4) OLS FE Entry	(5) 2SLS Entry	(6) OLS FE Exit	(7) 2SLS Exit	(8) First stage Dig. Ado.
3G Adoption	-0.0114	0.141		0.0775	-0.206	-0.126	-0.373	
	(0.0489)	(0.198)		(0.0912)	(0.362)	(0.0824)	(0.464)	
Lightning PC			-3.650***					-3.544***
			(0.548)					(0.980)
Lightning PC^2			5.909***					5.191***
			(1.331)					(1.451)
Constant	0.625***		0.189***	0.199*		0.0839		0.250***
	(0.0844)		(0.0241)	(0.110)		(0.101)		(0.0402)
Observations	13,297	13,297	13,297	8,912	8,912	8,912	8,912	8,912
R-squared	0.690		0.620	0.452		0.457		0.839
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Sargan (p value)		0.28			0.68		0.50	
Fstat			29.69					6.537

Note: The dependent variables measure, respectively: whether households own an NFE (columns 1-2); whether households start an NFE at time $t+1$, conditional on not having an NFE at time t (columns 4-5); whether households leave the market at time $t+1$, conditional on having an NFE at time t (columns 6-7). All estimations are run using a 2SLS estimator. 3G adoption measures the percentage of 3G coverage in the household's LGA, weighted by the number of mobile phones per capita available in each household. All regressions include the following controls: ratio of female household members (female); household members' mean age; number of household members; female-headed household; household is active in agriculture; percentage of household members in working age can read; percentage of household members in working age who have ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. The F-stat reports the results of the Kleibergen-Paap rk Wald F statistic. Mean DV is the average value of the dependent variable in the estimation sample. The quantification reports the estimated change in the mean of the dependent variable resulting from a shift in the variable of interest (3G) from the 25th to the 75th percentile of its distribution. Clustered standard errors in parenthesis: *** p<0.01, ** p<0.05, * p<0.1

indicating that households may take some time to find the resources or develop the skills needed to enter the NFE sector, or they may decide to exit and take advantage of better paid opportunities. The fact that the internet has no effect on costs (6) may also help explain why entry is not made easier by the adoption of mobile internet.

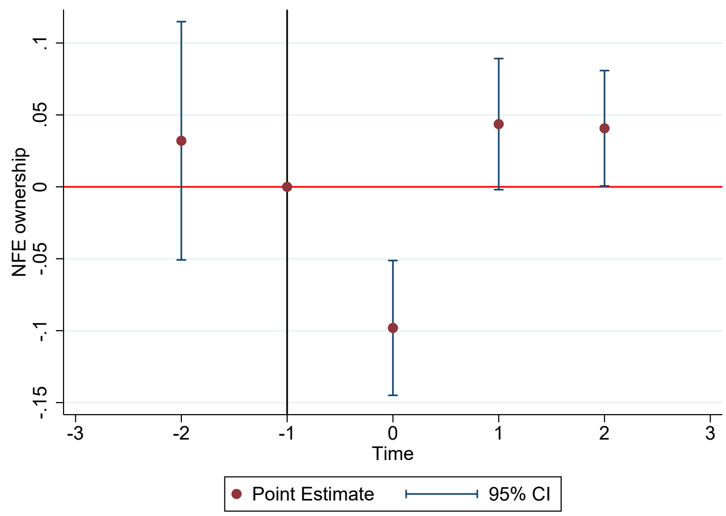

Figure 12: Event study: NFE ownership. The event study design uses the first year in which a household hits 0.2 of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. The outcome variable used in the event study specification measures whether households own an NFE. The coefficients reported in the figure come from a model based on Equation 4, including household, and year fixed effects. The model uses households as units of observation, and incorporates the following controls: percentage of female household members; mean age in the household; number of household members; female-headed household; household is active in agriculture; percentage of household members in working age who can read; percentage of household members in working age who have ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

5 Conclusions

This paper has attempted to establish a linkage between mobile internet adoption, structural change – measured in terms of NFE performance and sectoral dynamics – and inclusion – measured by the creation of labour and entrepreneurial opportunities. The analysis builds on the Inclusive Structural Change framework (Ciarli et al., 2021b) and aims to identify the trade-offs and synergies that exist between innovation, structural change and inclusion in a context dominated by informal firms, in this case Nigeria.

First, the findings suggest that the adoption of a rapidly diffusing and ground-breaking technology, such as mobile internet, has a strong effect on the performance of Nigerian NFEs, and on their trajectory of structural change. Basing the analysis on a double identification strategy (IV approach exploiting geographical variation in lightning strikes, and an event study), the study finds that 3G adoption is associated with higher sales per worker, on average. However, benefits are likely to be concentrated in low-productivity services, particularly trade activities, with households moving away from manufacturing. Overall, the uptake of mobile internet is found to sustain structural change by increasing firm performance, and by fuelling the process of tertiarisation of the economy, supporting the extant literature on internet access and productivity in SSA (Hjort and Poulsen, 2019; Hjort and Tian, 2021).

The results on the effect of the internet on inclusive or exclusive structural change (Saha and Ciarli, 2018; Ciarli et al., 2021b) require a deeper discussion. This paper investigated whether internet-driven structural change has translated into better/reduced working and entrepreneurial opportunities. With respect to the former, the findings indicate that the improved NFE performance is also a result of lower labour requirements by firms. We then investigated what happens to the labour shed by internet-adopting NFEs, finding that NFEs tend to free up household labour, and to retain (or increase) external labour, possibly because adopting firms will require new and higher levels of skills that are not available within the household. The study also examined what happens to excess household labour in NFEs by investigating the effect of mobile internet adoption on working opportunities outside household NFEs: results indicate that, overall, working opportunities outside the household increase for all households, whether or not they own an NFE. For NFE-owning households, however, mobile adoption does not increase the total employment rate (including labour employed within and outside the household), indicating that the household labour shed by NFEs does not negatively affect the employment rate in NFE owning households, who benefit from the creation of jobs outside the household. Household labour freed by the NFEs is therefore only displaced, from within the household to external activities. Coupled with the findings that, for households that do not own an NFE, total employment rates increase, and that NFEs hire more labour outside the household, it can be concluded that the overall effect of mobile internet adoption on labour outcomes has been positive in Nigeria.

Regarding the effect of mobile internet adoption on the creation of new entrepreneurial opportunities, the results portray a different scenario. In fact, mobile internet does not appear to encourage the entry of new firms, indicating that digitalisation in the informal sector may lead to concentration rather than creation of opportunities, as suggested by Altenburg et al. (2021). This finding can be explained by two results concerning the drivers of the increase in NFE performance. First, mobile adoption has a positive effect on sales, suggesting that the benefits are concentrated mainly in incumbent firms, which increase their market share.

Second, mobile internet adoption does not affect the costs of operating an NFE: if costs are not reduced, barriers to entry will persist, thwarting entrepreneurship and new entries to the market, which are pivotal to making structural change an inclusive process. However, it cannot be ruled out that adopting households refrain from entering the market, given the availability of new job opportunities either in the formal or in the informal sector, but in any case outside the household (Bahia et al., 2020, 2021; Houngbonon et al., 2022). Moreover, as the effect of mobile internet on firm-performance is concentrated in services, households owning NFEs in other sectors are not likely to reap any benefits, and will therefore be excluded by the process of structural transformation.

In summary, the analysis conducted in this paper has shown that the adoption of 3G mobile internet does indeed have the potential to transform the economy and propel inclusive structural change in Nigeria, especially in terms of the creation of working opportunities. However, some challenges for inclusion persist if the benefits are only to be reaped by existing firms in the trade sector. Policies will play a fundamental role in unlocking the potential brought by the rapid (although late) diffusion of mobile internet in Nigeria and SSA, by making sure that workers displaced by household firms are occupied in sectors that are compatible with their skills, in such a way as to enable the absorption of both skilled and unskilled labour. In fact, mobile internet has been shown to have a positive effect on the creation of new jobs, both inside and outside the household, and policies will be crucial to the alignment f incentives in a way that 'oils' the mechanisms of labour creation, reallocation, and upgrading described above. The inclusiveness of the transformation brought about by mobile internet will also depend on whether entry barriers are actively removed, as technological change will not reduce the cost of entry for new firms, but more likely will lead to concentration. The removal of such constraints will be essential if we are to tap into the potential of new entrants and to foster a virtuous and inclusive process of structural change.

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A Appendix

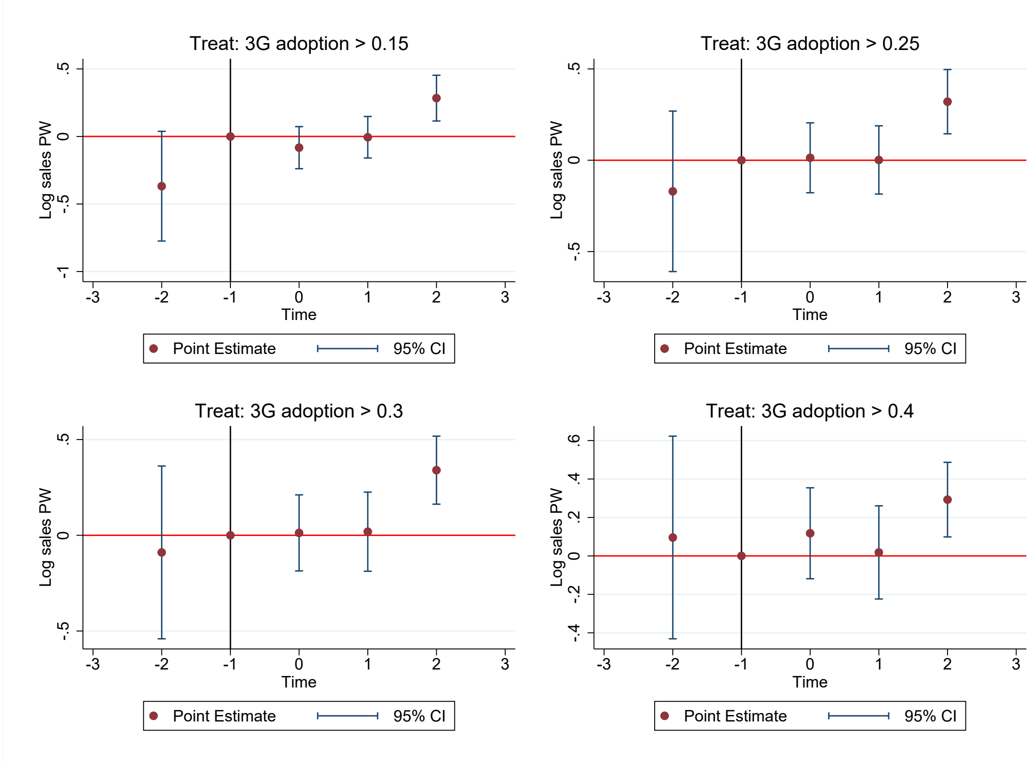

Figure A1: Event study: robustness checks. Each event study design uses the first year in which a household hits a different threshold of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. Thresholds are indicated on the top of each graph. The outcome variable used in the event study specification is the log of the NFE sales per worker. The coefficients reported in the figure come from a model based on Equation (4), including household, industry, and year fixed effects. The model uses NFEs as units of observation, and incorporates the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

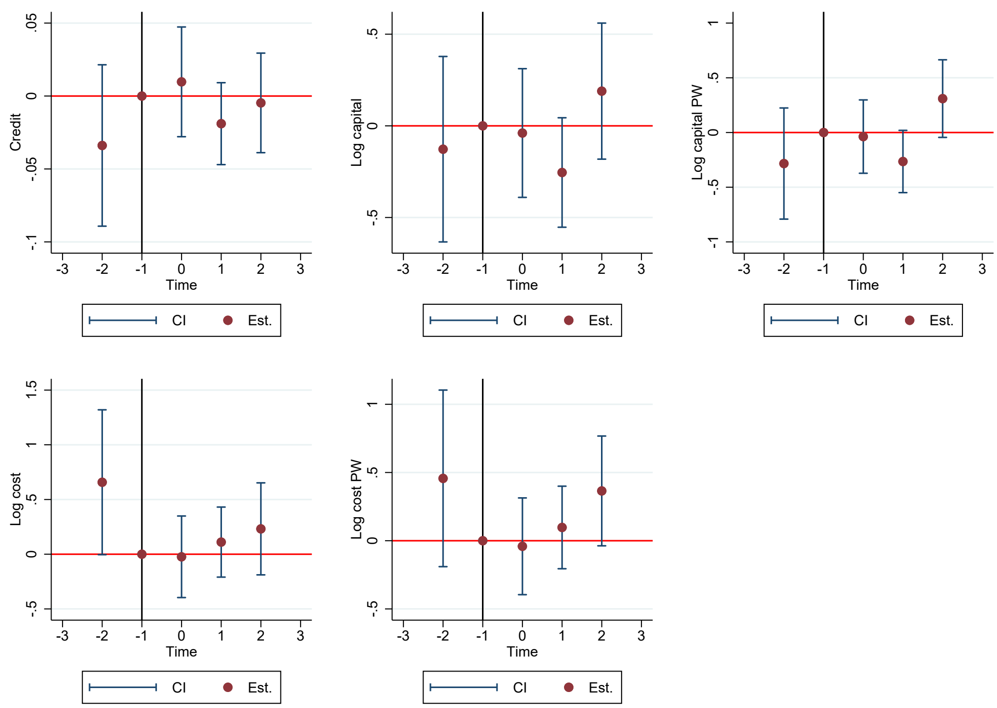

Figure A2: Event study: mechanisms. The event study design uses the first year in which a household hits 0.2 of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. The outcome variable used in the event study specification is indicated on the vertical axis. The coefficients reported in the figure come from a model based on Equation (4), including household, industry, and year fixed effects. The model uses NFEs as units of observation, and incorporates the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

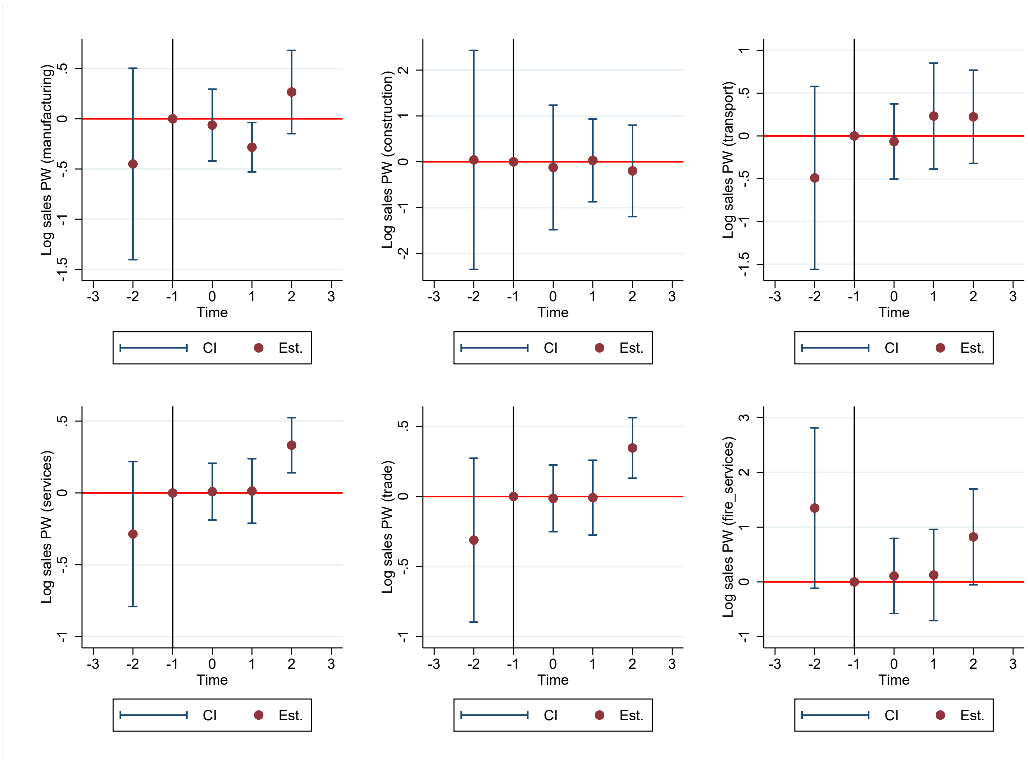

Figure A3: Event study: sales per worker, by sector. The event study design uses the first year in which a household hits 0.2 of 3G mobile internet adoption as treatment, corresponding to time 0 in the horizontal axis. The outcome variable and the industry-level sample used in the event study specification are indicated on the vertical axis. The coefficients reported in the figure come from a model based on Equation (4), including household, industry, and year fixed effects. The model uses NFEs as units of observation, and incorporates the following controls: owner's gender (female); owner's age; number of household members; female-headed household; household is active in agriculture; owner can read; owner ever attended school; distance of the enumerator area from main road, town, market, and capital city (in km); number of conflicts per capita in the LGA. Standard errors are clustered at the enumerator area level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.