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Mobile internet, skills and structural transformation in Rwanda

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ABSTRACT

This paper examines the relationship between mobile internet, employment and structural transformation in Rwanda. Thanks to its ability to enable access to a wide range of ICT technologies, internet coverage has the potential to affect the dynamics and the composition of employment significantly. To demonstrate this, we have combined GSMA network coverage maps with individual-level information from national population censuses and labour force surveys, creating a district-level dataset of Rwanda that covers the 2002 to 2019 period. Our results show that an increase in mobile internet coverage affects the labour market in two ways. First, by increasing employment opportunities. Second, by contributing to changes in the composition of the labour market. Education, migration and shifts in demand are all instrumental in explaining our findings.

1. Introduction

The diffusion of fast internet and complementary technologies has potentially disruptive effects on both the scale and composition of employment. Existing evidence from advanced countries shows that the high complementarity between digital technologies and skills is leading to polarisation in the labour market (see, among others, Autor et al. 2003, Goos et al. 2014, Autor 2015, Buera et al. 2021). In developing economies, technological change has been viewed as either fuelling a catching-up process (see, among the others, Fagerberg and Verspagen 2021 and the literature reviewed by Vivarelli 2021) or as a factor leading to de-industrialisation (for its effect in combination with globalisation, see Rodrik 2016). There is, however, little evidence on how Information and Communication Technology (ICT) applications made available through internet access can impact on the labour markets. This in spite of the fact that ICT is one of the most transformative technologies, spreading rapidly across the developing world.

Over the past two decades, in fact, developing countries have experienced a substantial boost in the diffusion of broadband connectivity. In sub-Saharan Africa (SSA), 30 per cent of the population had access to the internet by 2021, and mobile phone subscriptions stood at over 90 per cent: in both cases, the figures have more than doubled since 2010.[1] In a context in which hard infrastructure, such as fixed telephone lines and cables, is rarely available, mobile phones are the most common means by which Africans access the internet (Manacorda and Tesei, 2020).

In this paper, we look at the expansion of the mobile internet network in Rwanda and analyse its implications in terms of structural transformation, focusing on changes in the labour market.

The case of Rwanda is particularly interesting for the purposes of this study. The role of the ICT sector is deeply embedded in national development strategies. The country's industrial policy, grounded in its Vision 2020 strategy (MINICOM, 2011),[2] aims to diversify the economy and explicitly promote the transition towards a knowledge-based society in which science and technology, education and the acquisition of ICT skills are actively encouraged. Since its inception in 2015, the Government's Smart Rwanda Master Plan has highlighted the objective of digitally transforming seven key sectors, namely governance, education, health, finance, women and youth empowerment,

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[1] World Bank, ''WorldBankDevelopmentIndicators'', accessed 8 November 2021.

[2] While the Vision 2020 national development strategy has been replaced by the more recent Vision 2050 strategy in December 2020 (Ministry of Finance and Economic Planning, Republic of Rwanda, 2020), throughout the study we will refer to policies that were in place over the period under consideration (between 2012 and 2019), in order to capture the synergy between Rwanda's policies and the contemporary developments of technical and structural change in the country.

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trade and industry, and agriculture. This is combined with a strategy to ensure universal access to broadband connectivity. This package of policies led to the fact that by 2018, 4G mobile coverage had already reached over 96 per cent of Rwanda, with 47.7 per cent of the total population able to access the internet.[3]

The diffusion of mobile internet and its ICT applications can be assimilated to a General Purpose Technology (GPT) (for a review, see Bresnahan, 2010). This makes it difficult to evaluate its impact because of a time lag between the adoption of the technology and its effects, and due to existing complementarities across different technologies. This notwithstanding, the aggregate evidence reported by Niebel (2018) is somewhat reassuring in that the positive link between ICT and GDP growth is also confirmed for developing countries. The main novelty of this work has to do with investigating the sources of this transformation in a more granular way, in the context of a developing country that has implemented a policy framework that aims at promoting complementarities between ICT adoption and sectoral specialisation. In doing so, we contribute to the literature on GPTs by assessing the impact of one such technology on a country's structural transformation at the early stages of economic development. In contrast, the extant empirical literature on GPTs has focused mostly on mature economies. Moreover, from a theoretical perspective, our work contributes to the literature that has studied the consequences of the diffusion of GPTs on labour markets (Autor et al., 2003; Buera et al., 2021; Autor, 2022). This is done by assessing their heterogeneous labour-enhancing potential across different occupational skill levels and economic sectors.

We measure the effect of the diffusion of a highly relevant GPT in the context of Rwanda, as the rapid rollout of the internet has the potential to trigger changes in the process of structural transformation in the labour market. However, these changes are difficult to assess *a priori*. On the one hand, the exponential growth of ICT-related activities, such as mobile internet, and the drastic cost reduction of transmitting information have dramatically expanded the value of services in Africa (Fagerberg and Verspagen, 2021). On the other hand, the expansion of services at low levels of GDP per capita (Owusu et al., 2021), coupled with stagnant industrialisation (Rodrik, 2016), makes the question of whether mobile internet can play a positive role in economic development all but trivial. Understanding the mechanisms at work between mobile internet, employment, and structural transformation is, therefore, an empirical question that we aim to explore in the context of Rwanda.

In our analysis, we link the rollout of mobile internet in Rwanda to a number of outcomes related to changes in the size and composition of employment in the country. This includes a shift towards more highly skilled occupations and/or higher value-added activities across sectors. The analysis is based on the collection and harmonisation of data from two main sources. The first is the Global System for Mobile Communications Association (GSMA), which provides information on the coverage of different mobile technologies (2G, 3G, and 4G) over time and across locations within the country. The second is individual-level data from population censuses and labour force surveys. The harmonisation of these two sources allows us to obtain consistent indicators of labour market participation covering a sufficiently long time span, which ranges from a baseline year with no internet coverage (2002) to the most recent year (2019). In the study, we use districts, the second administrative level in Rwanda, as the unit of analysis.

Our analysis exploits the staggered – across districts and time – rollout of the 3G network and employs an econometric specification with district and time fixed effects that link changes in the coverage of mobile internet to changes in employment in each district over time. Given that the decision on where and when to introduce mobile technologies is unlikely to be "as good as random", we base our analysis on an instrumental variable approach that – following existing literature (Manacorda and Tesei, 2020; Guriev et al., 2021) – exploits the geographic variation in the incidence of lightning strikes as a factor influencing the distribution of the mobile network within the country. While the instrumental variable approach that we use provides us with a theoretically grounded and statistically strong source of exogenous variation, the lack of an experimental setting suggests some notes of caution about the interpretation of our findings.

Our results show that improvements in the coverage of 3G mobile internet technologies affect the composition of the labour market in two distinct ways: (1) through an increase in the share of employed individuals, among whom are both skilled and unskilled workers, with the former increasing at a faster rate, given their relatively small initial size; (2) through a sectoral shift of employment towards services and, within the service sector, to some high value-added and skill-intensive industries. Results are robust to a battery of additional tests, including changes in the specification and the adoption of an event study approach. To rationalise some of these findings, we run additional analyses showing that improvements in mobile internet coverage are also related to (1) an increase in the number of years of schooling in the younger population; and (2) a larger supply of workers in treated locations due to increasing shares of migrants. We also find evidence of demand-side mechanisms at play. Using administrative data on Rwandan formal firms (in all sectors), we show evidence of agglomeration of more productive ones in locations with higher 3G coverage.

The remainder of the paper is structured as follows: Section 2 presents the theoretical framework of the study linking GPTs to structural transformation, along with the related empirical literature on the impact of internet diffusion in SSA; Section 3 introduces all the data used in the analysis; Section 4 discusses the empirical specification and the identification strategy based on a 2SLS estimator; Section 5 reports the main results and a set of robustness checks. Section 6 discusses the main results and concludes.

2. Theoretical framework and related literature

2.1. General purpose technologies and structural transformation

Mobile internet represents the first opportunity to connect to the internet for many Africans. The diffusion of mobile internet, together with other ICTs and digital applications that it enables, can be considered a General Purpose Technology (GPT) (see, among the others, Basu and Fernald, 2007; Cardona et al., 2013). While there are several possible definitions of GPT, they all agree on three basic ingredients: widespread diffusion, the continuous improvement of the technology and the tendency to foster innovation in the sectors of adoption (for two in depth reviews, refer to Jovanovic and Rousseau, 2005; Bresnahan, 2010).

As argued by Kaplinsky and Kraemer-Mbula (2022) all these features of GPTs are well incorporated in mobile technologies. Mobile phones do not depend on a centralised grid; they are cheap, can be shared by more than one user, and, focusing on a distinguishing feature of GPTs, they have an impact across a large number of different economic activities, including farming (on this last application see, for instance, Mehrabi et al. 2021). Finally, mobile phones have allowed easier access to mobile internet, which has become progressively faster and cheaper: the progressive development of different generations of mobile internet technologies – from 2G to 5G – is a very good example of the continuous improvement of GPTs.

While some challenges in the identification of a GPT and measurement of its effect are general in nature, for instance the time lag before the effects become apparent (see, among the others, Brynjolfsson, 1993; Jovanovic and Rousseau, 2005), some might be more pronounced in the case of developing countries. The latter have often experienced delayed diffusion and adoption of GPTs due to a

[3] Ministry of ICT and Innovation (MINICT), "Digital Transformation Directorate General: Mandate"accessed 22 March 2022.

mismatch between the socio-institutional framework and the conditions required for their diffusion (Perez, 1986). Given the existence of complementarities with other technologies, in the context of a typical developing country, the relevance of the effect of the GPT might be dwarfed (Zanello et al., 2016). The lack of complementary investments and capabilities at the firm and governmental level may lead to small or even negative returns for adopters, limiting innovation (Cirera and Maloney, 2017) and catching up to the technological frontier (Verspagen, 1991).

Another crucial feature of GPTs is their linkage with structural transformation, defined as the reallocation of production factors from low- to high-productivity activities. Technological change plays a significant role in driving the process of structural transformation, allowing the emergence of new and more productive sectors (Saviotti and Pyka, 2004). However, while the emergence of new industries may lead to employment opportunities, new technologies may make some existing occupations redundant – a process defined by Schumpeter (1934) as "creative destruction". Moreover, technological adoption by firms may favour workers with higher skills, with technology replacing the low-skilled, leading to skill-biased structural change (Autor et al., 2003; Akerman et al., 2015; Buera et al., 2021).

The sectoral reallocation of labour following the diffusion and adoption of a GPT will depend heavily on the nature of the inputs required by the new technology, which characterise the type of industry emerging within the new technological paradigm (Perez, 1985). Under this perspective, workers not equipped with the necessary skills to be employed in emerging industries may find themselves unable to find new employment opportunities, if their skills are made redundant by the unfolding of technological change.

Given their disruptive nature, GPTs and mobile internet have the potential to transform labour markets in different ways, which are difficult to assess *a priori* (Ciarli et al., 2021). The wide range of innovations enabled by internet connectivity is likely to have contrasting effects on employment dynamics: studies anticipating the overall impact on the labour market are far from unanimous. On the one hand, process innovation is typically supposed to be associated with labour-saving effects. On the other hand, the positive effect of product innovation on employment appears to be less in dispute.[4]

It has been argued that the current wave of technological change, characterised by the diffusion of ICT technologies, can represent a window of opportunity for African countries to leapfrog towards modern services (Fagerberg et al., 2021; Kaplinsky and Kraemer-Mbula, 2022). Nonetheless, the literature looking at the impact of the diffusion of GPTs on structural transformation and employment in African contexts is scant. This is the first gap addressed by the empirical analysis conducted in this paper.

As we aim at establishing whether the diffusion of digital technologies, such as mobile internet, will deliver a virtuous structural transformation, it is crucial to assess whether it will lead to employment creation, who will benefit from it, and in which sectors of the economy. Our study contributes to the literature that links the diffusion of GPTs to labour markets. We do this by assessing the consequences of introducing mobile internet for the local labour markets in Rwanda, and the related heterogeneity across occupational skill levels and industries. This is motivated by the fact that, based on previous evidence and theory (Autor et al., 2003; Buera et al., 2021), we can expect a certain degree of skill-bias in the process of structural change triggered by the diffusion of digital technologies, which may lead to favour certain types of occupations and/or sectors.

2.2. Mobile internet and structural transformation in sub-Saharan Africa

In sub-Saharan Africa, the shift from subsistence and informal activities to high-productivity occupations has been relatively slow, with labour moving directly from agriculture to low-productivity services (McMillan et al., 2017; Baccini et al., 2022). This process has been accompanied by a contraction of technologically dynamic and high-productivity sectors, such as manufacturing (Rodrik, 2016). Causes are numerous: among others, lack of adequate policy (Mkandawire, 2014), human capital deficits (Stiglitz et al., 2013), insufficient infrastructures (Oqubay and Ohno, 2019), globalisation and labour-saving technical change (McMillan et al., 2014; Rodrik, 2016). At the same time, the exponential growth of ICT-related activities has dramatically expanded the value of services (Hsieh and Rossi-Hansberg, 2019; Fagerberg and Verspagen, 2021), putting into question the historical argument that an expansion of the service sector hampers long-run economic growth. The continuous rise of Africa's service sector could offer new development opportunities, if supported by technical progress (De Vries et al., 2015; Newfarmer et al., 2018).

Internet connectivity can be the engine of both labour-augmenting and labour-saving technological change. Greater connectivity affects labour-biased productivity directly, and can support human capital accumulation by increasing training opportunities (both on the job and in educational settings). The evidence summarised by Hjort and Tian (2021) shows that improved access to the internet supports increases in firms' productivity (India), workers' wages (Brazil) or both (China).[5] Mobile technologies can, however, be biased towards skilled workers (including those performing non-routine tasks), who can benefit disproportionately from better connectivity. This has the potential to increase labour market inequality. However, evidence on this is more nuanced. Bahia et al. (2021) find that, in Tanzania, it is mainly the better educated workers who take advantage of improvements in mobile connectivity. Hjort and Poulsen (2019), on the other hand, show that the arrival of fast internet in Africa has benefited both poorly and more highly educated workers. However, the latter have gained the most. This is possibly related to a demand side effect: fast internet coverage seems to promote both the entry and the performance of more productive and technologically intensive firms. Moreover, internet expansion unlocks the potential for firms to benefit from internet-enabled services, such as mobile money and e-commerce (Hjort and Tian, 2021). Mobile money, which requires internet connectivity for its underpinning infrastructure, has been found to stimulate demand both by increasing consumption and supply and by fostering enterprise development (for a review of the evidence, see Suri et al. 2021). On the other hand, electronic commerce allows firms to expand into new markets at a relatively low cost. Furthermore, evidence from African countries shows that the arrival of fast internet has promoted firms' export, with associated benefits for local employment (Hjort and Poulsen, 2019).

It must be noted that, in most African countries, most of the population does not have access to the landline network, making mobile phones the primary source of access to internet. Despite this, the majority of studies on fast internet access focus on landline internet (Hjort and Poulsen, 2019; Hjort and Tian, 2021). When mobile internet is studied, the focus of the analysis are households and their economic activities (e.g. Bahia et al., 2020, 2021), rather than labour markets. By examining the impact of mobile internet diffusion on the employment and sectoral composition of Rwandan districts, this study aims to tackle this gap in the empirical literature on the economic consequences of the diffusion of fast internet in Africa.

Overall, we aim to add to the debate around the impact of mobile internet on the structural transformation in developing countries. After

[4] Evidence on the linkage between innovation and employment is also available for a sample of sub-Saharan countries (Avenyo et al., 2019).

[5] There is evidence on the capacity of mobile internet diffusion to increase employment opportunities. For instance, a recent paper by Bahia et al. (2020) on Nigeria reports significant employment uptake following the rollout of mobile internet at the sub-national level.

having framed mobile internet as a GPT, and having reviewed the existing literature on the impacts of mobile internet in sub-Saharan African economies, in the following sections we will investigate the links between mobile internet, employment, and structural transformation in the context of a developing country – Rwanda – that extensively promotes mobile internet through policy. More specifically, looking at local labour markets, we will test whether mobile internet coverage leads to (i) overall job creation, (ii) the creation of skilled and unskilled jobs, and (iii) a reallocation of labour towards modern sectors.

3. Data

For our empirical analysis, we combine information on mobile coverage with individual-level data on the working-age population for all the second-level administrative divisions (districts) of Rwanda. Following changes in administrative divisions, since 2006 there have been 30 districts in Rwanda. According to the data from the latest available population census,[6] the size of the districts is fairly balanced in terms of population, with a range of 300 to 500 thousand people, the latter living in Gasabo, one of the three districts (along with Kicukiro and Nyanrungenge) of the Kigali province. Economic activity is not evenly distributed across districts, though. About 23% of the establishments that were active according to the 2017 census is located in the districts that are part of Kigali's administration. This percentage goes up to over 38% when considering only firms in high-value added services, including financial, business and professional activities.[7] Also, more than 56% of the FDI projects, and again the vast majority of which are in high-value added activities, are hosted by the Kigali province.[8]

3.1. Mobile internet

Data on mobile internet coverage are sourced from the GSMA in partnership with Collins Bartholomew. The original data consists of a raster of 1 km × 1 km cells, with a layer of information for each technology (2G, 3G, 4G). While 2G (GSM) supports voice calls and messaging, the main technologies of interest in our study are 3G and 4G, which support mobile broadband internet services. In each layer, cells take the value of 1 if the area is covered by a mobile signal, and 0 otherwise. To identify the share of the population with access to mobile internet at the district level, this information is combined with a population density grid, available at the same resolution and obtained from NASA's Socioeconomic Data and Applications Center.[9] In every district, the share of the population with access to mobile internet is given by the sum of the population living in cells covered by mobile internet divided by the total population.[10]

Mobile internet technologies were introduced in Rwanda at the end of the 2000s. According to the GSMA data, before 2009 only the 2G technology was available. After 2009, 3G internet technologies started to be introduced in a staggered manner across districts and over time (see Fig. 1). In contrast, the diffusion of the 4G network has been sudden. Developed in partnership with the South Korean firm, KT, the rollout of the network began in 2015, reaching almost universal coverage within a couple of years. However, the number of subscriptions to the 4G network is still lagging behind those of other technologies.[11]

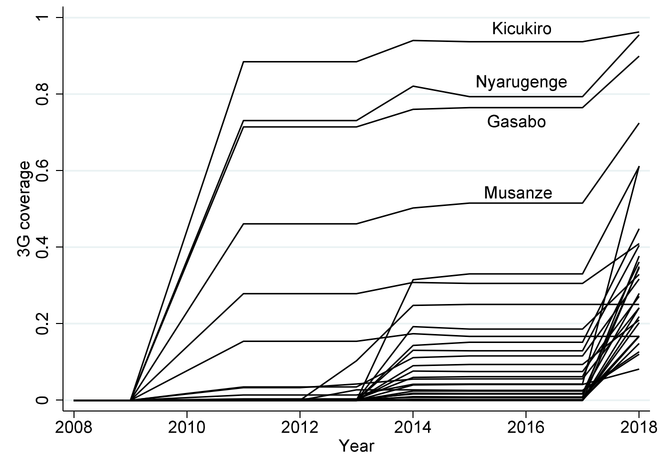

Fig. 1. District-level mobile internet 3G coverage diffusion (2008–18). *Source:* GSMA data. Lines represent the mobile internet 3G coverage diffusion in each district.

3.2. Individual-level data

To build our indicators of labour-market participation, we combine the two most recent waves (2002 and 2012) of the Rwanda National Population and Housing Census[12] (from IPUMS International) with three waves (2017, 2018 and 2019) of the nationally representative Rwanda Labour Force Survey (RLFS)[13] (from the National Institute of Statistics of Rwanda). We aggregate the individual-level information to obtain a district-level[14] panel dataset on a sample restricted to the working-age population (which we define as covering individuals aged 15 to 64 years old).

[6] The 2012 Population and Housing Census, available at the following link: https://www.statistics.gov.rw/datasource/42

[7] The data come from the 2017 Establishment Census, which is available at the following link: https://www.statistics.gov.rw/datasource/establishment-census-2017

[8] This information refers to the distribution of greenfield data considering the period 2003–2020. Data are sourced from fDiMarkets.

[9] Centre for International Earth Science Information Network CIESIN Columbia University (2018), ''Populationdynamics'', accessed 25 February 2022.

[10] The data cover only up to 2018, and we assume no major changes in the following year. Results remain robust when dropping 2019.

[11] A recent report of the Rwanda Utilities Regulatory Authority (RURA) shows that currently only 1.2 per cent of the total number of mobile broadband subscriptions use 4G technologies (see Rwanda Utilities Regulatory Authority, 2021: Table 13).

[12] The third (2002) and fourth (2012) waves of the Rwanda National Population and Housing Census include demographic and socio-economic information about the total population of the country. The national territory is divided into enumeration areas (EAs), each the size of a village, typically including 150–200 households; for each EA, households are listed and 10 per cent of randomly selected households in the EA are interviewed. In the third wave, 843,392 individuals were interviewed and in 2012 interviewees totalled 1,038,369.

[13] The RLFS has been implemented in 2017, 2018 and 2019 to monitor the trend in employment and labour underutilisation at the national, province and district level (National Institute of Statistics of Rwanda, 2018). Samples in each year are constructed using a two-stage sampling procedure: during the first stage, a stratified sample of enumerator areas from the latest population census is drawn with probabilities proportional to size. During the second stage, a fixed number of households is selected with equal probability within each sample EA. Finally, all qualifying household members in the sample households are selected for survey interviewing: 77,719 (2017), 76,670 (2018) and 81,778 (2019).

[14] The district, the second administrative division of Rwanda (ADM2), is the lower level of geographic disaggregation at which we can combine the information of the censuses and the RLFS. Other administrative units are the province (ADM1) and the sector (ADM3). In 2006, Rwanda implemented a reform of its administrative boundaries: 12 provinces were replaced with 5 larger provinces and the number of districts dropped from 106 to 30. In our dataset, districts and provinces in 2002 have been collapsed in such a way as to reflect the administrative boundaries introduced by the 2006 reform.

Note that, following changes that occurred in the international labour statistics standard, which narrowed the definition of employment to those working for pay or profit,[15] throughout the sample we consider subsistence farmers as not being in employment.

Despite differences in scope, the combination of these two data sources is made possible by the presence of a wide range of comparable and geographically detailed demographic and socio-economic information. Both data sources provide individual and household sampling weights which allow creating representative figures at the district level. Based on this information, we compute indicators related to (i) occupations, (ii) industries and (iii) education.

Occupations: As we are keen to capture the dynamics of skilled occupations over time, we adopt the ISCO division of occupations into skill levels (ISCO-2008) (International Labour Office, 2012). Our data include a 3-digit ISCO 88 code for each employed individual in 2002 and a 4-digit ISCO 08 occupation for all individuals in subsequent years. Unfortunately, the break between the two classifications means that a one-to-one harmonisation exercise cannot be performed between classifications. However, ISCO major occupation groups (at the 1-digit level of the ISCO classification) have remained unchanged; this allows grouping based on skilled and unskilled occupations, according to the ISCO skill groups, to be created. Skilled occupations consist of skill levels 3 (professionals) and 4 (managers, technicians and associate professionals); unskilled workers are those belonging to skill levels 2 (clerical support, services and sale, skilled agricultural, craft and related trades, plant and machine operators) and 1 (elementary occupations).[16]

Table 1 shows the average, across districts, of the labour shares in each ISCO major occupation group between 2002 and 2019. The most striking figures are those related to elementary occupations, increasing from 2 per cent to 24 per cent between 2002 and 2019, and skilled agricultural workers, decreasing from 37 per cent in 2002 to 3 per cent in 2012. Rather than reflecting an abrupt shift in Rwanda's employment structure, this change is likely to be due to a reclassification of many agricultural occupations in the census (2002 and 2012) from skilled to elementary occupations (2017–19). Nevertheless, as these two groups both belong to the unskilled occupations group, the reclassification of agricultural occupations is not a major concern for our analysis.

It is worth noting that, while major occupational groups have remained unchanged, the more disaggregated occupations attributed to each group have changed. For instance, agricultural managers used to be considered as part of the Managers ISCO 88 major group (skill group 4) but have been moved to Skilled agricultural workers (skill group 2) under the new ISCO 08 classification.[17] As a result, jobs that used to be considered skilled under ISCO 88 are now considered unskilled under ISCO 08. Despite this, skilled occupations still exhibit a slow but steady upward trend both on average across districts (Fig. 2), with significant concentration in the urban districts, such as the capital, Kigali.

The correlation between the share of people employed in skilled occupations and the rise of the country's mobile internet coverage is given in Fig. 3. The figure incorporates information on education and shows that areas with higher internet coverage are those in which highly skilled workers, in terms of both the content of their occupation and their level of education, are employed.

Table 1
Share of occupations, average across districts (selected years, 2002–19).
Source: Authors' elaboration on national census and RLFS data.

Occupation	Skill level	2002	2012	2017	2018	2019
Crafts	Unskilled	1.4	3.2	3.27	3.63	3.59
Elementary	Unskilled	1.96	2.83	25.43	25.3	24.48
Services	Unskilled	1.51	5.07	7.7	8.3	8.5
Clerks	Unskilled	0.29	0.2	0.33	0.33	0.35
Machinery	Unskilled	0.34	0.96	0.97	1.11	1.14
Agriculture	Unskilled	37	39.48	2.76	3.3	3.08
Technicians	Skilled	0.28	0.63	0.56	0.49	0.56
Managers	Skilled	0.08	0.21	0.49	0.46	0.48
Professionals	Skilled	0.68	1.45	2.45	2.64	2.22
Not in employment[a]		56.45	45.97	56.05	54.44	55.61

[a]Not in employment refers to those individuals not currently working and to those working in subsistence farming.

Industries: Both the Rwanda population census and the labour force survey provide information on industries of employment, following the International Standard Industrial Classification (ISIC), revision 3.1. We create variables measuring the employment share of each of the ISIC major sectors and industries. Table B.1 in the Appendix shows the labour shares across industries (ISIC major groups) over the time span under analysis (2002–19) averaged across districts. The descriptive evidence on employment by industry (Fig. 4) indicates that, while employment in agriculture decreases, services expand over time. Growth in the tertiary sector has been driven mainly by the growth of trade activities, but with a rising trend in skilled services too, such as finance and health (Table B.1). Employment in manufacturing also increased, although its share remains relatively small.

Education: Education-related questions in the census and in the labour force surveys are not harmonised. We have selected two questions from the census which present the same formulation in the RLFS. The first is the level of education. Although the question is framed identically in the two questionnaires, the way in which responses are classified does not match. Therefore, we have harmonised answers into a categorical variable, including: (i) no education, (ii) primary (which in the census covers less than primary and primary respondents), (iii) secondary (which in the labour force survey includes lower secondary and upper secondary degree) and (iv) tertiary (which is identical in the two questionnaires). The second variable measures the number of years of education. This information has been collected directly only in the census; for the labour force survey, years of schooling have been elicited using the 2019 wave, which is the only one in which they were reported as a continuous variable. Hence, average years for each educational level are computed for 2019, and then attributed to individuals in 2017 and 2018 based on their educational level.[18] For the entire period covered (2002–19), the enrolment age in elementary school is set at six years old. It should be noticed, however, that the so-called basic education, granted for free in Rwandan public schools for nine years (i.e. elementary and lower secondary education-up to grade 9), was extended to grade 12 in 2012. This resulted in a higher enrolment in upper secondary classes, with a jump from 21 per cent in 2011 to 30 per cent in 2017 (Neumann et al., 2012). The need to collapse upper and lower secondary education for all the years in the categorical response prevents the study from capturing this shift. Average years of education have increased between 2002 and 2019 across districts (see Fig. A.1 in the Appendix). Furthermore, if we compare the share of people with tertiary education and the increase

[15] See the 19th International Conference of Labour Statisticians (International Labour Organization, 2013). The Rwanda National Institute of Statistics has integrated these changes and, since 2017, the definition of employment no longer includes subsistence workers, leading to a consistent drop in the share of agricultural employment. For a discussion on some practical implications of this change in definition, see also Gaddis et al. (2020).

[16] We exclude armed forces and subsistence agricultural producers from the sample. The former only appear in 2019; the latter have been considered unemployed since 2017, creating an inconsistency in the longitudinal dimension of the dataset.

[17] For the full list of inclusions and exclusions of disaggregated occupations between ISCO 88 and ISCO 08, see CEDEFOP (2014)

[18] For example, if a respondent declares that they have achieved the primary diploma in 2017, we compute the number of years of education they have received by averaging out the years of education of a person with a primary diploma in 2019. As the education system has not undergone any changes over these three years, we consider this assumption to be realistic. Note also that we consider only individuals who have completed the education level.

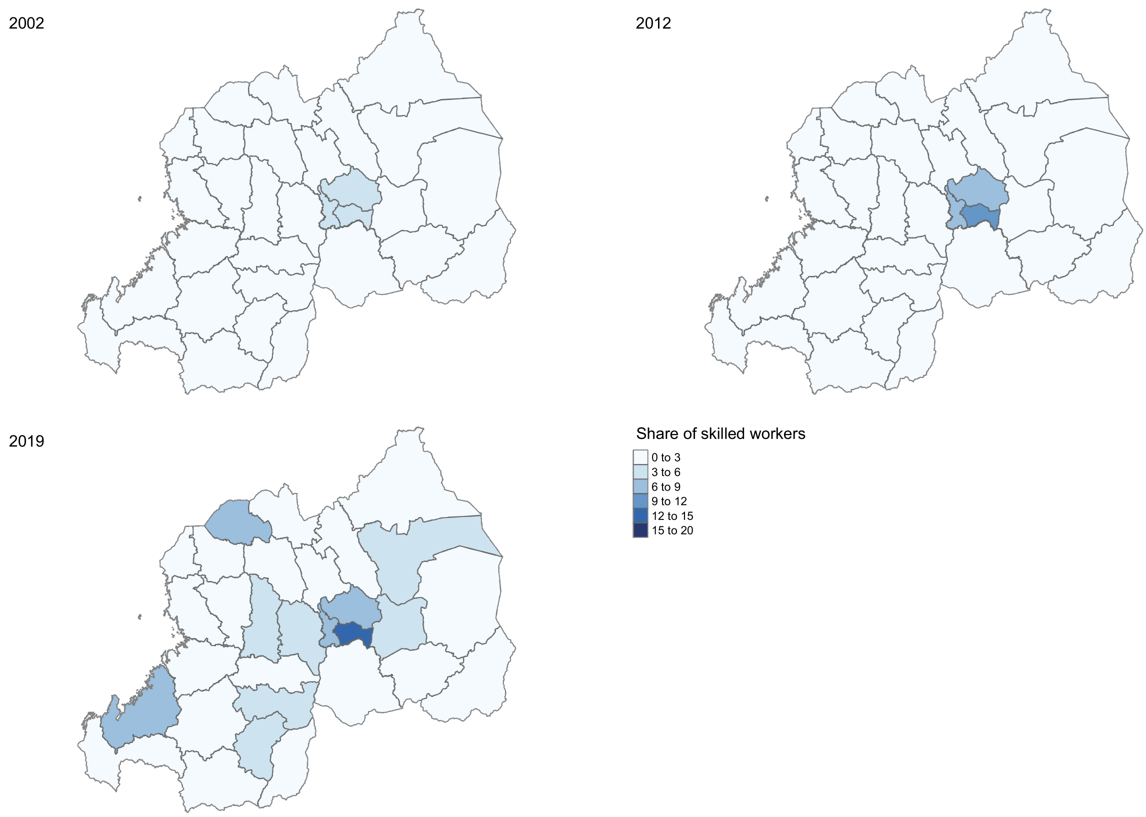

Fig. 2. Percentage of skilled workers at district level (2002, 2012, 2019).
Source: Authors' elaboration on national census and RLFS data.

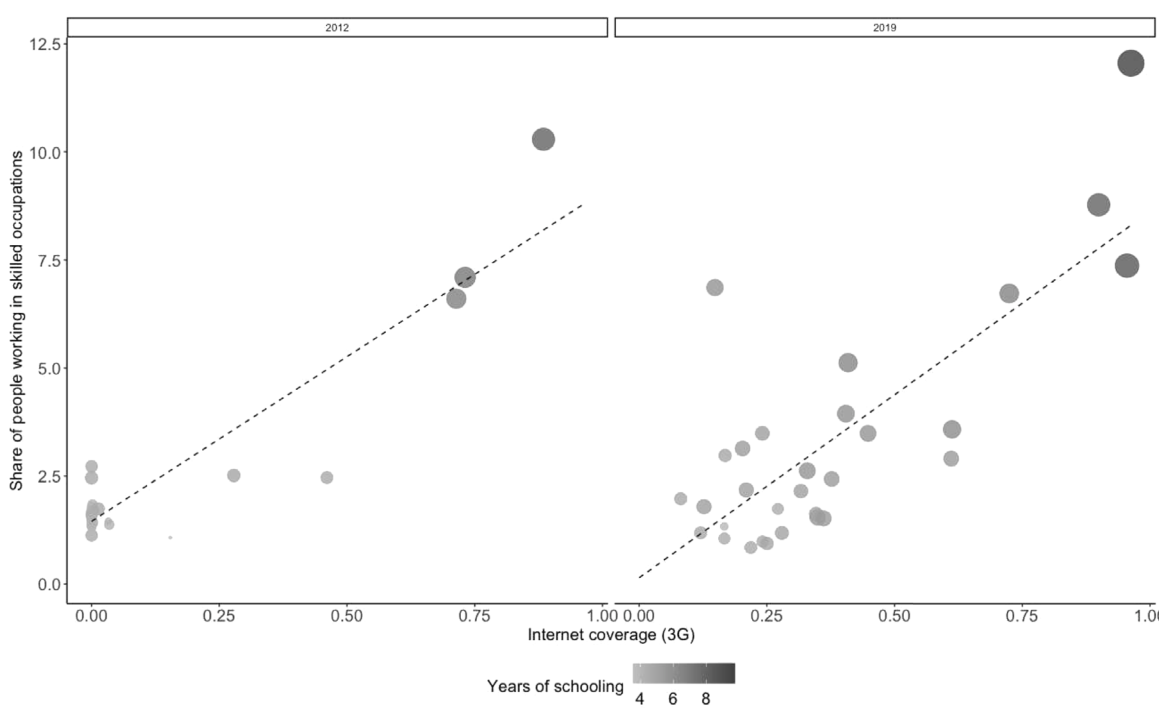

Fig. 3. Share of people working in skilled occupations and mobile internet 3G coverage (2012 and 2019). The colour of the dots indicates the average schooling years of the working age population in each district, from low (light) to high (dark).
Source: Authors' elaboration on national census and RLFS data.

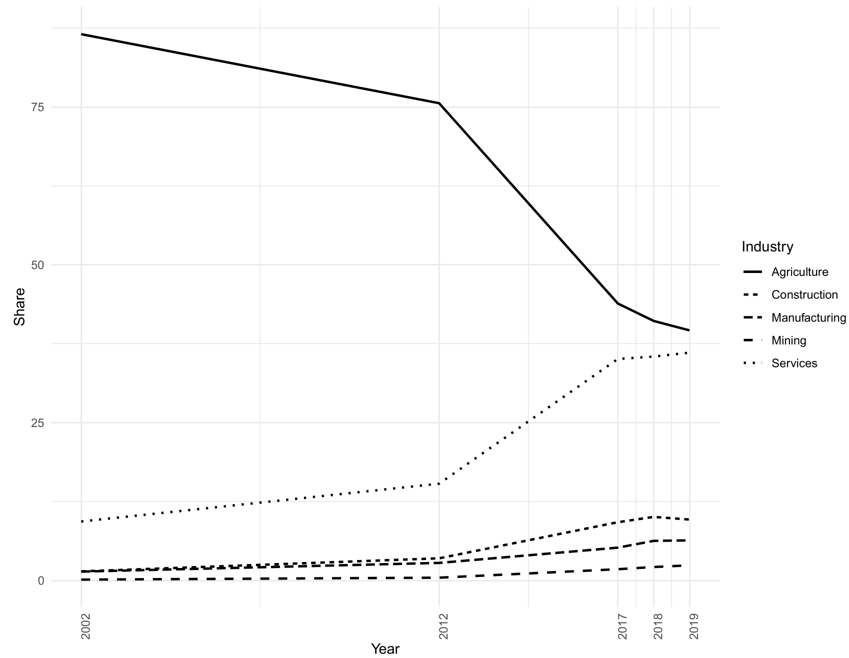

Fig. 4. Shares on the y-axis indicate the percentage of the working-age population in employment by industry. In each year, shares sum to 100.
Source: Authors' elaboration on national census and RLFS data.

in mobile internet diffusion at the district level in the time window 2012–19 (Fig. 3), we observe a positive correlation.

Additional variables: We use the RLFS data to cross-check the information available on mobile internet coverage. Specifically, we use questions asking respondents about (a) the presence of mobile phones (Fig. A.2 in the Appendix) and (b) internet connections at home (Fig. A.3 in the Appendix). In both cases, we find a correlation with the mobile internet data and the self-reported data from the RLFS, with the jump being driven by urban districts.[19]

4. Empirical specification

In our empirical analysis, we are interested in understanding how changes in the spatial and temporal variation of mobile phone coverage are correlated to changes in the composition of the labour force in Rwanda. Our empirical specification follows the existing literature (Manacorda and Tesei, 2020; Guriev et al., 2021) and links the rollout of mobile internet coverage to the outcomes of interest, as follows:

$$Y_{it} = \beta 3G_{it} + \gamma X'_{it} + \theta_i + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} is one of the variables defining the labour market in district i at time t.

We will present results on the basis of three different sets of outcomes. First, the size of employment, using the share of persons in employment in the working-age population. Second, the distribution of workers by skill level. This analysis is based on the information drawn from the occupations classified as discussed in Section 3.2. Third, the distribution of workers across sectors. This classification mimics the pattern of structural transformation of the country, by looking at whether increases in coverage of the mobile network correlate with shifts of workers from less to more modern activities across sectors.

Following the discussion in Section 3, our variable of interest is $3G_{it}$, which measures the share of a district's i population covered by the 3G signal in any given year t. In our baseline specification, we use 3G expansion, as this technology was the first to allow users to browse and create online content. The expansion of 4G technology was sudden and quickly reached almost universal coverage in the country while still being the least widely adopted by users: these characteristics do not allow enough variation in the data to exploit. In contrast, the timing of the introduction of the 3G technologies is ideal to be combined with labour force data. While the technology was formally introduced in the early 2000s, the rollout covered only a few districts before 2012, and even those had minimal coverage (see Fig. 1). After 2012, coverage expanded to other districts, but still not uniformly.

X'_{it} is a vector of district-specific controls. These include characteristics drawn from the survey data, i.e. the average age of the population and the percentage of the female population on the total. We also add variables that account for some of the geographic features of the district.[20]

Finally, in all regressions we include a coefficient measuring the share of a district's population covered by the 2G network. This is added to ensure that our coefficient correctly identifies the contribution of the upgrade to 3G coverage, and not merely the expansion of the network. If a location is covered by the 3G network, it is in fact also covered by 2G. Hence, controlling for 2G should isolate the net contribution of the 3G technologies (a similar strategy is adopted by Bahia et al. 2021).

We include district (θ_i) and wave (δ_t) fixed effects. This reduces our identification to one that explores the changes over time in the outcomes of interest within each district which are (conditionally) correlated with the corresponding changes in the rollout of the mobile broadband network. All the regressions are weighted using the districts' total population. Standard errors are clustered by district, which is the level of the treatment.

[19] We define an urban district as a district where at least 60 per cent of the population lives in urban areas. In the years analysed, these are Gasabo, Nyarugenge and Kicukiro.

[20] These variables include the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the variables are measured at the district level and were made available by Alesina et al. (2021). As most of these variables are time invariant, we have interacted them with a time trend as done by Manacorda and Tesei (2020).

The estimation sample consists of a balanced panel covering the 30 Rwandan districts over the 5 waves of the combined censuses and national labour force surveys. Summary statistics of the variables of interest are reported in Table B.2 in Appendix.

Identification strategy: Eq. (1) will be correctly identified under some restrictive conditions, i.e. that the rollout of the broadband network is not influenced by existing pre-trends, so that the treatment is "as good as random", at least after conditioning for district fixed effects and time-varying controls. These assumptions can arguably be questioned under different circumstances. Not only can initial conditions influence the decision to prioritise investments in connectivity, but the same could be said for some (omitted) variables that we cannot precisely account for in our analysis. In what follows, we try to address both of these issues while being aware that – absent an experimental setting – causal interpretation of the findings could be hard to achieve in our case.

In order to deal with endogeneity, we employ an instrumental variable (IV) approach based on a two-stage least squares estimator (2SLS). To do this, we use an instrument previously adopted in other papers that consider the rollout of the mobile network in contexts which, similar to ours, exploit sub-national level information (Guriev et al., 2021; Manacorda and Tesei, 2020; Mensah, 2021). The instrument exploits differential intensities in lightning strikes across districts to explain differences in the coverage of the mobile network. The rationale for the use of such an instrument is that mobile phone infrastructure is affected by frequent electrostatic discharges caused by storms (Manacorda and Tesei, 2020). Hence, the more frequently an area is affected by lightning strikes, the more costly it becomes to construct such infrastructure (Guriev et al., 2021). With respect to the exclusion restriction – i.e. that lightning strikes do not affect our outcomes of interest directly – (Andersen et al., 2012) provide evidence that the effect of lightning strikes on aggregate economic outcomes only occurs through its effect on investments in ICT technologies. They show that the density of lightning strikes is a time-stationary process, which has started showing a negative correlation with labour productivity growth of US states only after the 1990s due to the effect of power spikes and dips caused by cloud-to-ground strikes on ICT user cost.

To build our instrument, we use lightning strike density data provided by the World Wide Lightning Location Network (WWLLN) Global Lightning Climatology and Timeseries. The raw data come in a raster of 5-arcminute cells (around 8 km ×8 km at Rwanda's latitude), with a unique layer measuring the number of daily strikes per square kilometre. The measure is taken every month and it is currently available for the period between 2010 and 2020. To capture a district's exposure to lightning strikes, we have averaged the lightning strike density over the period covered by the data in each cell[21] and aggregated cell values by district, taking their mean. The resulting measure of daily lightning strikes per square km in every district is then converted into daily lightning strikes per inhabitant[22] by multiplying the measure by each district's area and dividing it by its population. The resulting time-invariant measure of daily lightning strikes per capita at the district level is then interacted with a time trend, following Guriev et al. (2021).

[21] Although the definition of the instrument adopted is the best in terms of first-stage statistics, our results remain unaffected by changes in the construction of the instrument. In particular, we have experimented with (a) using initial values of lightning instead of their average over the period and (b) removing the population from the denominator.

[22] As the size of the variable is small, to give a better interpretation of the coefficient of the first-stage regression we have computed it for 1,000 inhabitants.

5. Results

In this section, we discuss the findings of our empirical analysis. Each regression relates one of the labour market outcomes to the expansion of broadband internet coverage within each district over time. The unit of observation is the district, which is also the level at which standard errors are clustered. We organise the discussion of the main results into three different sets of outcomes: employment, occupations and sectors.

Employment: Table 2 reports a first set of results linking mobile internet coverage to jobs, measured as the share of employment among the working-age population. Column 1 provides the unconditional ordinary least squares (OLS) estimates, while column 2 introduces district and year-fixed effects, along with all the controls. In both cases, the coefficient of 3G coverage is positive and statistically significant, indicating a positive correlation with employment. The coefficient of the 2G coverage does not correlate significantly with the outcome, meaning that, if anything, the relationship between broadband internet and employment has mainly to do with the introduction of technologies that allow the internet to be accessed from mobile phones. Columns 3 and 4 report the first and the second stage of the IV estimate, respectively. The coefficient of the first stage regression (column 3) displays a negative coefficient that is highly statistically significant. This proves the validity of the instrument showing that those districts that are more likely to be affected by frequent lightning strikes have lower mobile network coverage. The F-statistic reported at the end of column 4 is well above 10, which further confirms the strength of the instrument adopted. The coefficient of interest in column 4 remains positive and is highly statistically significant.

Compared to the OLS estimation, the coefficient of the 2SLS estimation is larger. The size and the direction of the bias are similar to (if not smaller than) the results reported by Manacorda and Tesei (2020). There are a few possible reasons to expect a downward bias of the OLS coefficient. In addition to the possibility of a measurement error, which will bias the OLS coefficient to zero, and the presence of omitted variables, one explanation is that the districts most strongly influenced by the instrument are those with higher potential for employment, i.e. those starting from a position of lower employment levels. As such, the economic interpretation of the coefficient is relevant. A move from the sample's 25th percentile of the distribution of mobile internet coverage to its 75th percentile is associated with an 11 percentage point increase in the share of employment, which is a 23.3 per cent increase from the sample average.

Occupations: The first two columns of Table 3 report findings covering the relationship between 3G mobile internet coverage and variables measuring the skill content of occupations. We find that the spread of mobile internet is positively related to a growth in both skilled and unskilled types of occupations. Although the size of the coefficients is higher for the unskilled, the quantification exercise shows that mobile internet matters relatively more for highly skilled employment, a finding that is consistent with related evidence from African countries (Hjort and Poulsen, 2019). A move from the 25th to the 75th percentile of the distribution of mobile coverage does, in fact, contribute to raising skilled employment by about 75 per cent, compared to 20 per cent for the unskilled.

Sectors: Next, we check whether the rollout of mobile internet matters for the process of structural transformation occurring across sectors at the district level. Over the past 20 years, Rwanda has experienced a process of structural transformation that is common among African countries, i.e. one that sees a reduction in agricultural employment in tandem with the growth of available jobs in the service sector, rather than in manufacturing (see Rodrik 2016, Baccini et al. 2022). An interesting aspect of Rwanda's structural transformation is the focus on some of the service industries with higher potential in terms of jobs and value-added generation (Newfarmer et al., 2018). This includes the tourism industry, as well as financial and business services activities.

Table 2
OLS and 2SLS results, employment.

	Dependent variable:			
	Employment			
	OLS	OLS	2SLS (1S)	2SLS (2S)
	(1)	(2)	(3)	(4)
3G	0.0632**	0.0475*		0.341***
	(0.0251)	(0.0265)		(0.0712)
2G		0.00247		−0.109
		(0.117)		(0.113)
Age		−0.0135		−0.0112
		(0.00848)		(0.0103)
Female		0.248		−0.456
		(0.249)		(0.274)
Malaria ×t		4.28e−06		−0.00899
		(0.00557)		(0.00550)
Ruggedness ×t		−0.000106***		−0.000132***
		(3.23e−05)		(4.21e−05)
Agricultural suitability ×t		−0.0259		−0.0112
		(0.0207)		(0.0283)
Distance to coast ×t		0.0393		−0.0567
		(0.0909)		(0.0857)
Distance to railway ×t		−0.0608***		−0.0453*
		(0.0202)		(0.0252)
Distance to border ×t		0.00132		−0.00639
		(0.00496)		(0.00526)
Lightning strikes (1,000 pop.) ×t			−4.030***	
			(1.155)	
Constant	0.450***	1.019	−11.71	
	(0.00595)	(1.789)	(7.430)	
Observations	150	150	150	150
R-squared	0.062	0.684	0.863	
District FE	NO	YES	YES	YES
Year FE	NO	YES	YES	YES
District controls	NO	YES	YES	YES
Mean DV	0.463	0.463		0.463
Quantification	0.0200	0.0150		0.108
F-stat				15.81

Note: The dependent variable measures the share of employed individuals among the working-age population. 3G and 2G measures the percentage of the population covered by the respective mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted using a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

The latter are also specifically targeted by the country's industrial policy provisions. Understanding whether this process can be linked in some way to the rollout of mobile internet coverage would therefore be of relevance. Results of this exercise, reported in columns 3 to 5 of Table 3, show that this does indeed seem to be the case. Districts that improved their internet connectivity are also experiencing an increase in services-related employment. Expecting heterogeneity across services, we checked for specific patterns at the industry level. Results are plotted in Fig. 5. While a positive coefficient is generally found for most industries within the services sector, those that are statistically different from zero include highly skilled activities, such as finance and health, and low-skilled ones, such as private services to households.

5.1. Robustness checks

Alternative specifications: We first check the robustness of our results to alternative specifications. First, we run our analysis introducing province-specific time trends. There are five provinces in Rwanda, which were established in 2006. The introduction of such additional fixed effects, as shown in Table B.3 in the Appendix, does not affect our estimates. Second, in order to deal with pre-trends more effectively, we run an exercise in which interaction terms between time trends and initial values of the outcome variables are included as additional regressors. This should help to alleviate the concern that districts with, for instance, high initial levels of skilled or agricultural employment

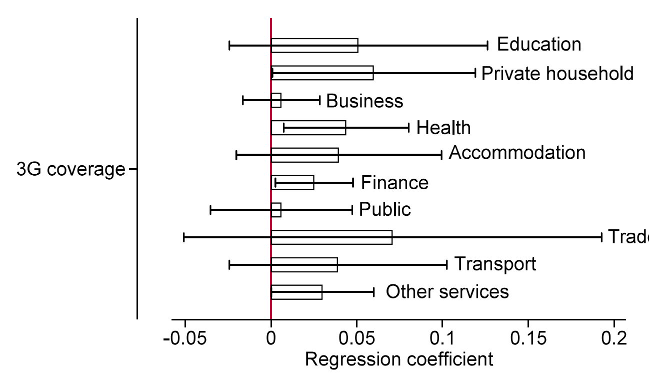

Fig. 5. The graph reports the coefficient of the variable 3G as estimated from different regressions using the employment share of each service-related industry in the district's total employment as dependent variables. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of the female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator.

Table 3
2SLS results, by type of occupation and sector of employment.

	Dependent variable:				
	Skilled (1)	Unskilled (2)	Agriculture (3)	Manuf. (4)	Tertiary (5)
3G	0.0654*** (0.0207)	0.276*** (0.0741)	0.0957 (0.196)	0.0408 (0.0521)	0.259** (0.125)
Observations	150	150	150	150	150
District FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
District controls	YES	YES	YES	YES	YES
Mean DV	0.0274	0.436	0.585	0.0442	0.285
Quantification	0.0207	0.0873	0.0303	0.0129	0.0820
F-stat	15.81	15.81	15.81	15.81	15.81

Note: The dependent variables measure, respectively, the share of skilled workers among the working-age population (skilled); the share of unskilled workers among the working-age population (unskilled); and the share of agricultural, manufacturing, and services (tertiary) in the district's total employment. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

prior to the rollout of the 3G network, may experience different trajectories. Results, reported in Table B.4 in the Appendix, show that initial values interacted with time dummies do not alter either the size or the direction of the initial findings.

4G coverage: As discussed in Section 4, a potential issue of concern for our analysis is that most of our results are driven (or strengthened) by the introduction of 4G technology, which mainly occurred during the second half of the 2010s. The policy leading to the almost universal rollout of 4G coverage, and the lack of individual-level data for the years during which this happened, pose a potential threat to our identification strategy. To understand whether the introduction of the latest mobile internet technology affects our results, we have replicated our analysis adding 4G coverage as an additional control. If the effects are explained by differential coverage of 4G, we should observe our coefficient of interest (3G coverage) weakening or losing statistical power. Nevertheless, as shown in Table B.5 in the Appendix, we find that the 3G coefficient explains all of the changes in labour market participation and composition, whereas the 4G coefficient is generally not statistically significant (an exception being the specification on the manufacturing sector, for which the 4G variable reports a negative and weakly significant coefficient).

Event study approach: As a final exercise, we take advantage of the panel structure of our data, which allows us to follow all the districts over different time periods, and of the staggered introduction of the treatment to estimate our relationships using an event study approach. Event studies are particularly useful when treatment is not randomised, but outcomes and trajectories before and after treatment, as well as across treated and control units, can be compared. For the purposes of this exercise we define the treatment as a binary variable, i.e. a dummy taking the value of 1 once a district achieves a certain coverage and 0 otherwise. More specifically, we use a value of 11 per cent coverage as a threshold. This value seems the most appropriate, given that it is both the overall sample median as well as the sample mean in 2012 (the first year in which we can observe 3G coverage in our districts).[23]

[23] Results remain robust to alternative definitions of this threshold, including 20 per cent and 50 per cent.

We estimate the event study based on Eq. (1), i.e. conditioning on the observables and district and year fixed effects and replacing the treatment with a number of lags and leads (a maximum of three on both terms), measuring the distance between each observation and the time at which a district was treated. Fig. 6 provides a summary of the results. First, and importantly for identification purposes, on a visual inspection there is no evidence of pre-trends potentially affecting the estimation results. Second, the direction of the result is in line with those reported in the previous section. Third, most of the results show that the impact of granting access to mobile technologies is likely to improve over time, which is an important addition to our initial findings, offering some evidence on the dynamic impacts of mobile technologies.

Alternative individual data: We verify whether the relations estimated so far can be replicated using alternative sources of information on individuals' participation to the labour market. For these purposes, we use information from Rwanda's Demographic and Health Surveys (DHS). DHS collects nationally representative data on several socio-economic variables at both the household and individual levels. Relevant to this exercise is the fact that DHS surveys also include a module on employment, which records information about the employment status of each individual aged 15–49, as well as their main occupation. Based on occupational data we can identify whether an individual performs a skilled or an unskilled activity,[24] and if they are employed in the agricultural sector or in modern activities.[25]

There are four waves of DHS currently available for Rwanda, run in 2005, 2010, 2014 and 2019. Together, they cover about 61 thousand individuals, equally distributed across districts and over time.[26] As the DHS is representative at the regional level (and within each region, at the urban/rural level), we do not aggregate the data at the district level, but treat them at the individual level adjusting our regressions using sample weights. We run regressions in which a given outcome, measured at the individual level, changes in response to changes in the 3G coverage in the district in which individuals are interviewed. All regressions include the 2G coefficient, as well as individual specific controls (their age and gender), district and year fixed effects. Results are summarised in Table B.6 in the Appendix, and are in line with our main results. They confirm that there is a positive relation between mobile internet coverage and employment. They also show that individuals are more likely to be employed in more skilled occupations and in non-agricultural activities following the rollout of the mobile internet.

5.2. Mechanisms and extensions

In this section, we intend to extend our results by exploring some of the potential mechanisms at play in the relationship between mobile internet and changes in employment composition. We look more closely into three specific dimensions. The first is related to education levels of the working-age population. The second looks at migration. Finally, we investigate possible demand-side factors, i.e. whether and how internet coverage has affected firms' characteristics.

Education: In Table 4, we replicate our results using indicators of educational attainments as outcome variables to understand whether

[24] Following International Labour Office (2012) and Hjort and Poulsen (2019) an individual is classified as skilled if employed in one of the following occupations: clerical, skilled manual, sales, services and professional. Unskilled occupations are unskilled manual, domestic and (formal and informal) agriculture.

[25] Unfortunately, DHS do not include industry level information on employment, hence, following existing evidence workers in agricultural related occupations are assigned to the agricultural sector, while all the others to other industries (Diao et al., 2017).

[26] By design, DHS targets women as the main respondent. As such, our sample includes about 69% of women. The proper application of sampling weights, which we apply in our analysis following the DHS recommendations, takes this unbalance into account.

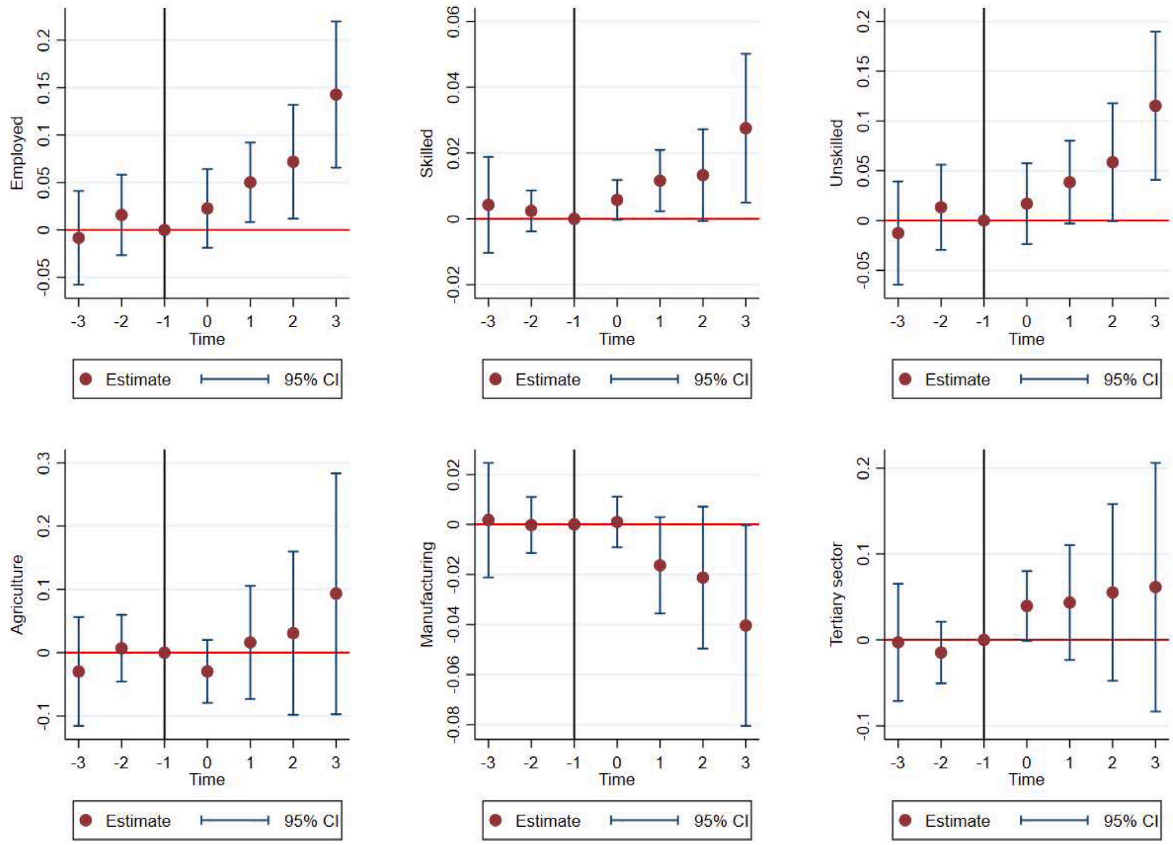

Fig. 6. The event study design uses the first year in which a district hits 11 per cent coverage of its population by the 3G network as treatment, corresponding to time 0 in the horizontal axis. The coefficients reported in the figure come from a model based on Eq. (1), including district and year fixed effects, incorporating the following district-specific controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. Standard errors are clustered at the district level. Regression coefficients are reported together with their 95 per cent confidence interval (CI). The graphs have been created using the STATA command `eventdd`.

the introduction of new technologies might have affected the educational choices of individuals. For this analysis, we have modified our sample in such a way as to consider only the cohort of individuals that were in their school age (i.e. 5 to 25 years of age) at the time of the survey. This is done to avoid pooling both sets of new entrants to the labour market: on the one hand, the youngsters, whose educational choices might be directly affected by the current availability of internet connectivity; on the other hand, incumbents, whose levels of education are not affected by recent changes in mobile technologies. Results show that the diffusion of mobile internet has a positive effect on educational attainment: in fact, the former runs in parallel with a reduction in the share of pupils with primary or no education (column 1), and with a corresponding increase in the share of those with secondary or tertiary education (columns 2 and 3). More generally, an increase in mobile internet leads to an overall increase in the number of years of education, as reported in column 4.

Migration: Changes in the distribution of economic activity are considered an important pull factor for internal migration in developing countries. Provided that improved mobile internet access generates differential gains across districts, one could expect a larger inflow of migrants into treated locations in comparison to other areas. Descriptive evidence seems to support this hypothesis (Fig. A.4). Districts with higher levels of internet coverage are also those with a higher share of migrants.

We can test this hypothesis more formally by replicating our main specification using a different set of outcomes related to migration. Information on migration can be obtained from the data by using a question that asks individuals about their previous place of residence and the timing of their move to their current district. Note that this question was not available in the 2017 and 2018 editions of the RLFS: those two waves are therefore excluded from this exercise.

We combine the information on migration with the employment status of workers to generate a variable that measures the share of employed migrants among the working-age population. Results of the 2SLS estimation using this variable as the dependent variable are reported in Table 5. As we can distinguish the origin of each individual, a migrant is defined according to whether they have relocated from a different district (column 1) or a different province (column 2) to the place that they are residing at the time of the interview. Results show that higher levels of mobile internet coverage make a location more attractive to migrant workers. Also, the specific definition of migrant applied to the variable does not make a significant difference to the results. In further analysis, we also find that this effect seems to be driven by migrants being employed in skilled occupations and in modern sectors (both manufacturing and services). These additional results are reported in Table B.7 in the Appendix, and are based on a more restrictive definition of migration, i.e. individuals coming from a different province.[27]

[27] Note that while the effect is positive on migrants ending up in both skilled and unskilled employment: a simple quantification based on evaluating a shift from the 25th to the 75th percentile of the 3G coverage distribution shows that the estimated improvement on skilled migrant employment is 128% higher than the actual average for skilled professions, as compared to 48% for unskilled ones.

Table 4
2SLS results, by education.

	Education:			
	Primary/no (1)	Secondary (2)	Tertiary (3)	Years (4)
3G	−0.457***	0.373***	0.0838***	0.0150***
	(0.0845)	(0.0821)	(0.0218)	(0.00519)
Observations	150	150	150	150
District FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
District controls	YES	YES	YES	YES
Mean DV	0.856	0.134	0.00985	0.0299
Quantification	−0.145	0.118	0.0265	0.00476
F-stat	15.81	15.81	15.81	15.81

Note: The dependent variables measure, respectively, the population share of individuals with tertiary, secondary and primary (or no) education, and the number of years of education. The sample of individuals used for this exercise is restricted to those in the cohort aged 5–25 years old. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of the female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5
2SLS results, migrant workers.

	Migrants from:	
	Other districts (1)	Other provinces (2)
3G	0.264**	0.190**
	(0.109)	(0.0836)
Observations	90	90
R-squared	0.618	0.659
District FE	YES	YES
Year FE	YES	YES
District controls	YES	YES
Mean DV	0.161	0.113
Quantification	0.0836	0.0602
F-stat	10.66	10.66

Note: The dependent variables measure, respectively, the share of migrant workers relocated from other districts (column 1) or from other provinces (column 2) of Rwanda. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Demand-side mechanisms: We use firm level data to investigate potential demand-side mechanisms that might corroborate the relationships that have been so far identified by looking at the supply-side only. More specifically, we are interested in understanding whether firms took advantage from the rollout of broadband internet across the country and over time.

Table 6
OLS results, firm productivity.

	Productivity:	
	TFP (1)	LP (2)
3G	0.364**	1.763**
	(0.163)	(0.761)
Constant	1.540**	15.70***
	(0.588)	(1.094)
Observations	4,670	18,549
R-squared	0.951	0.678
Firm FE	YES	YES
Year FE	YES	YES

Note: The dependent variables measure, respectively, total factor productivity (column 1) and labour productivity (column 2) of Rwandan firms, using Rwandan CIT-PAYE data. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the 2G mobile coverage, in addition to firm and year fixed effects. Standard errors are clustered at the district level *** p<0.01, ** p<0.05, * p<0.1.

For these purposes, we use information on firms registered in the following two national tax databases: (1) the Corporate Income Tax (CIT) database, recording revenues, expenditures and other financial indicators; and (2) the Pay As You Earn (PAYE) database, which includes information on employment. These databases can be matched using anonymised firm identifiers.[28] Data are available for the period 2008–2016, and cover all sectors of the economy. For the purposes of this exercise we only use information on those firms for which we can correctly match CIT and PAYE data. This results in a sample of about 10,400 unique firms and 40 thousand observations. For these firms we calculate two indicators of productivity. First, a simple indicator of labour productivity, which we can measure as the log of total sales (from CIT) over the number of employees (from PAYE). Next, we also estimate Total Factor Productivity (TFP), though this is only possible for a smaller number of firms. We do this applying the approach by Levinsohn and Petrin (2003) that uses the costs of materials as a proxy for unobservable productivity shocks to correct for simultaneity bias. We also address potential collinearity in the first stage due to simultaneity bias in the labour coefficient by adopting the correction suggested by Ackerberg et al. (2015). We use total sales as a measure of output, the stock of assets at the beginning of period to measure capital, the wage bill for employment and the cost of goods sold to measure intermediate inputs.[29] Table B.8 in the Appendix reports production function coefficients at the industry level.

Table 6 reports the results of a regression in which the outcome of interest, that is a firm's TFP (column 1) or labour productivity (2),[30] is explained by the indicator of district level coverage of the 3G network. All regressions include the 2G coverage (as before) as well as firm and year fixed effects. By including firm fixed effects we can identify within-firm changes in productivity that correlate with changes in mobile internet coverage. Standard errors are clustered at the district level.

Results show that there is a positive relation between mobile internet coverage and firm productivity: this is suggestive of demand side mechanisms at play, including more employment opportunities, possibly with higher skill content.

[28] Data are confidential, and they were obtained by the Rwanda Revenue Authority.

[29] Productivity is estimated using the `prodest` command in STATA (Rovigatti and Mollisi, 2018).

[30] The estimation samples for TFP and labour productivity are different, the latter being larger. Estimates based on TFP (labour productivity) are based on 1,322 (4,046) unique firms observed in the period 2010–2016 (2008–2016). Trade services is the most represented industry in both samples, accounting for 58% and 33% of the total, respectively.

6. Discussion and conclusions

The findings of this study contribute to an assessment of the contribution of mobile internet provision to the process of structural transformation in Rwanda. We find that an increase in the coverage of mobile internet has a positive impact on employment, and that the increase in jobs is observed in both skilled and unskilled occupations. This is in line with the evidence reviewed in Section 2.2, confirming that the diffusion of disruptive technologies such as mobile internet has led to a net positive effect on employment size across Rwandan districts. However, this positive effect may hide heterogeneity in terms of both the type of jobs (skilled and unskilled) and the sectoral distribution of employment. In fact, the quantification exercise (Table 3) shows that mobile internet is relatively more important for creating highly skilled occupations, likely due to their initial lower shares. This finding indicates that, in the long run, the diffusion of mobile internet may lead to skill-biased technological change. This may also lead to a potential disequilibrium in the labour market, in the absence of the skills required by the increased availability of highly skilled jobs (Behuria and Goodfellow, 2019).

Next, we show that districts that improved their internet connectivity are also those experiencing increased employment in services, especially in high-value-added activities, such as finance and health. The findings on the sectoral reallocation of the Rwandan labour force following the diffusion of mobile internet resonate with the sectoral imbalances generated by GPT-led structural change. Having noted that the trajectory of structural transformation depends heavily on the nature of the inputs required by the new technology (Perez, 1986), we observe an asymmetric growth of services with respect to agriculture and manufacturing, which remain unaffected. This last finding confirms the theoretical prediction that economies transform along the complementarities between industries and technologies, which in this case are more appropriate for the service sector.

Overall, these results contribute to the debate on the impact of GPTs on labour markets by assessing both the labour-generating effect of mobile internet, and its heterogeneity across skills and sectors of the economy. In particular, our findings support some cautious optimism around the diffusion of ICTs in developing countries like Rwanda, since jobs have been growing consequent to the introduction of mobile internet, with skilled jobs growing faster than unskilled ones. However, we cannot rule out the possibility that some low-skilled occupations have been entirely replaced by the diffusion of mobile internet, followed by the adoption of interlinked ICTs.

The evidence on the sectoral reallocation of labour towards services is also informative for the debate on the tertiarisation of African economies and the role that technological change can play. Through its development strategies, Rwanda has actively pursued the goal of transforming into a knowledge-based economy – a commitment that was renewed in the recent Vision 2050 national development strategy (Ministry of Finance and Economic Planning, Republic of Rwanda, 2020). With the target of granting universal access to the internet by 2050, the Rwandan government aims to capitalise on this technology by investing in connectivity. Our results provide some empirical support to the effectiveness of this strategy. The direction of structural change that we find to be associated with the rapid diffusion of mobile internet is indeed pushing towards more skilled occupations and high-value added activities within the services. Ensuring the availability of skills suitable for the rapidly growing skilled occupations will be paramount to avoid bottlenecks in the growth of Rwandan domestic labour markets. However, we also show significant internet-driven employment growth rates in low-productivity services. This might indicate that low-productivity services are likely to keep providing a large share of the new employment opportunities in the future.

In trying to rationalise some of the findings recalled above, we also show that supply-side factors are activated by mobile internet coverage by means of (a) a higher intake of education by the cohorts currently of school age and (b) an increase in the share of migrant workers. On the demand side, we show that firms take advantage of higher 3G coverage by raising their productivity.

Our results can also be informative from policy-makers perspectives in countries at early stages of structural transformation. Low- and middle-income countries may build on tertiarisation to leapfrog their productive structure towards knowledge-intensive industries (Fagerberg et al., 2021; Kaplinsky and Kraemer-Mbula, 2022). To reap the benefits of technological diffusion, it will be necessary that pre-existing barriers, such as the lack of appropriate skills, do not hamper access to ICTs. In this respect, the Rwandan government has already put in place policies to guarantee access to ICT literacy and skills in both past and current national development strategies (MINICOM, 2011; Ministry of Finance and Economic Planning, Republic of Rwanda, 2020), training its current and future workforce. While Rwanda – a small landlocked country – has reached universal mobile broadband coverage in 2020 (also thanks to targeted, intentional policies steering the roll-out of mobile internet), the situation in larger sub-Saharan countries may be different, with mobile internet coverage concentrated in urban districts. The persistence of the digital divide represents an obstacle to the diffusion of ICTs and their opportunities, reinforcing pre-existing inequality structures between regions/subnational areas and increasing within-country inequalities. Policy mechanisms should be in place to deliver outcomes that the market alone may not be able to provide. The Rwandan case shows that digital literacy programmes can exert a crucial role in levelling the playing field.

Nevertheless, the tertiarisation of the economy presents at least two challenges. The first is the exclusion of manufacturing workers and entrepreneurs, who may need to be better equipped with the necessary skills to take advantage of emerging opportunities in services. Reskilling and retraining policies can help the seamless transition of manufacturing and agricultural workers into the service sector. The growth of low-productivity services poses the second challenge. While these services are often labour-intensive, providing a source of income for African households (Behuria and Goodfellow, 2019), they may reinforce the trend of labour reallocation towards below-average productivity industries, reinforcing the process of growth-reducing structural change described by McMillan et al. (2014). Once more, industrial policy can play a pivotal role in incentivising investments in those sectors that, at the same time, ensure high levels of productivity while also creating opportunities to absorb labour from below-average productivity industries.

Last, we would like to conclude highlighting a few limitations in this contribution that we hope to address in future research. First, although very granular, the analysis we propose cannot provide more detailed explanations of what happens in the field once fast mobile internet connectivity comes in. For instance, existing evidence shows that mobile technologies help consumers discover the quality of products in nearby markets, which fosters upgrading (Jensen and Miller, 2018). Anecdotal evidence from Rwanda seems consistent with this evidence. For instance, e-Soko[31] – an electronic platform that gives farmers, consumers, and traders up-to-date market price information by short message services – is widely used in the country, as it allows farmers to market their agricultural products better and to get premium prices. This is to say that complementing quantitative evidence with qualitative information from fieldwork would provide a better picture of the transformative role of mobile internet in Rwanda. Second, and related, the evidence we provide is biased towards the consequences on modern sectors and, most likely, urban areas. This hinders the potential first-order impact on (subsistence) agriculture. Existing research on the impact of technological change on agriculture does, in fact, suggest that it has the potential to kick off structural transformation by improving

[31] http://www.esoko.gov.rw/ (last accessed: May 25, 2022)

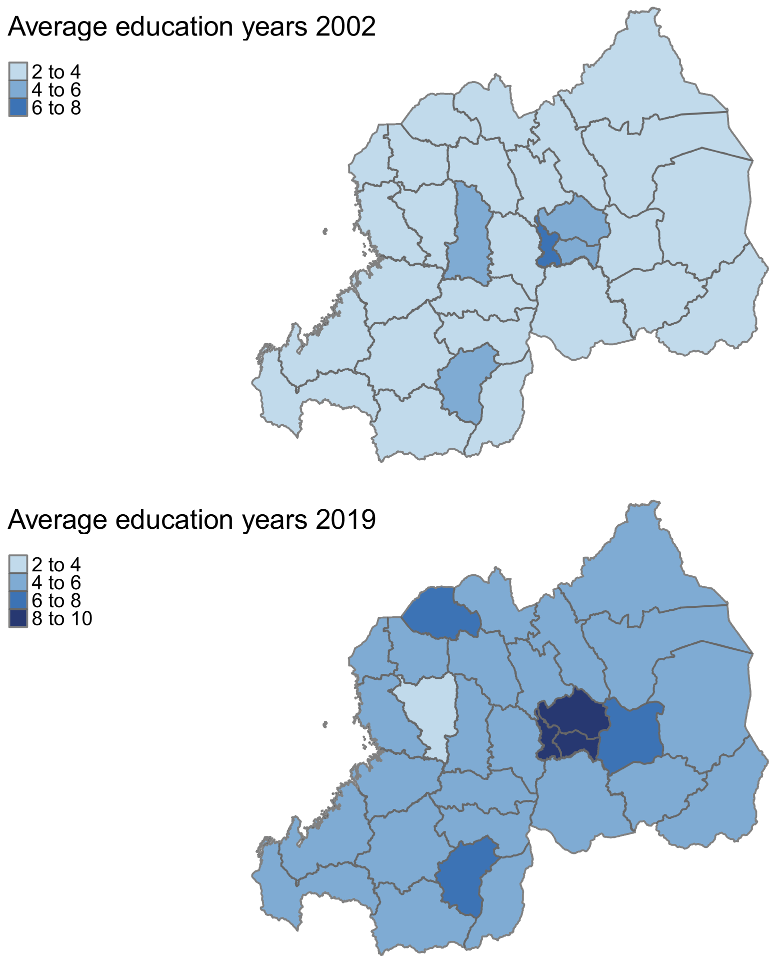

Fig. A.1. Geographical distribution of the average number of years of education (2002 and 2019).
Source: Authors' elaboration on RLFS data

productivity in agriculture, freeing up resources for the modern sectors (Bustos et al., 2016). We can expect similar effects in response to fast internet provision.[32] Further research looking at cases of internet-driven applications and innovations happening across individuals and firms, also from a qualitative perspective, could represent a promising avenue to investigate the way in which GPTs transform economies also at the micro-level.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bernardo Caldarola, Marco Grazzi, Martna Occelli, Marco Sanflippo report financial support was provided by International Labour Organization.

Data availability

The authors do not have permission to share the mobile internet data. The code can be shared upon request

[32] As shown by Gupta et al. (2020), reductions in information frictions brought in by increased mobile connectivity promoted the adoption of high-yielding varieties of seeds and other complementary inputs.

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Appendix A. Figures

See Figs. A.1–A.4.

Appendix B. Tables

See Tables B.1–B.8.

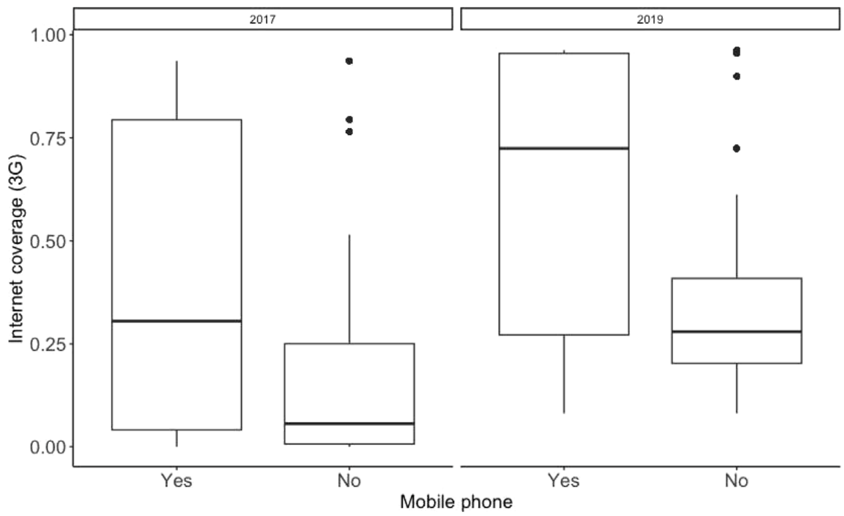

Fig. A.2. Mobile phone ownership in relation to the increase in 3G coverage (2017 and 2019).

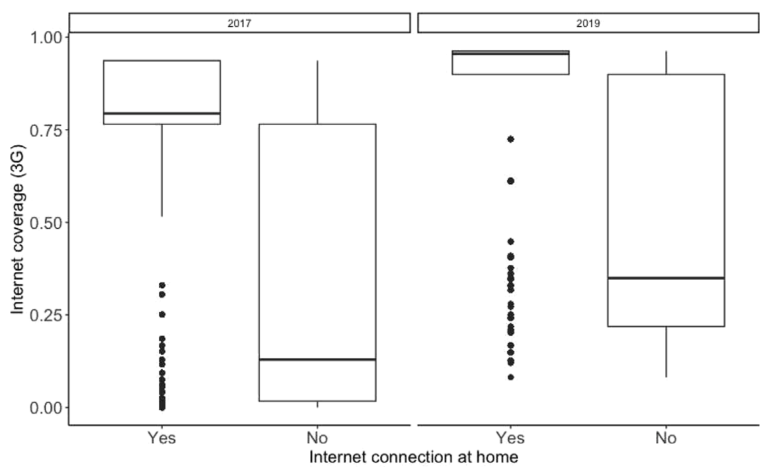

Fig. A.3. Having an internet connection at home in relation to the increase in 3G coverage (2017 and 2019).

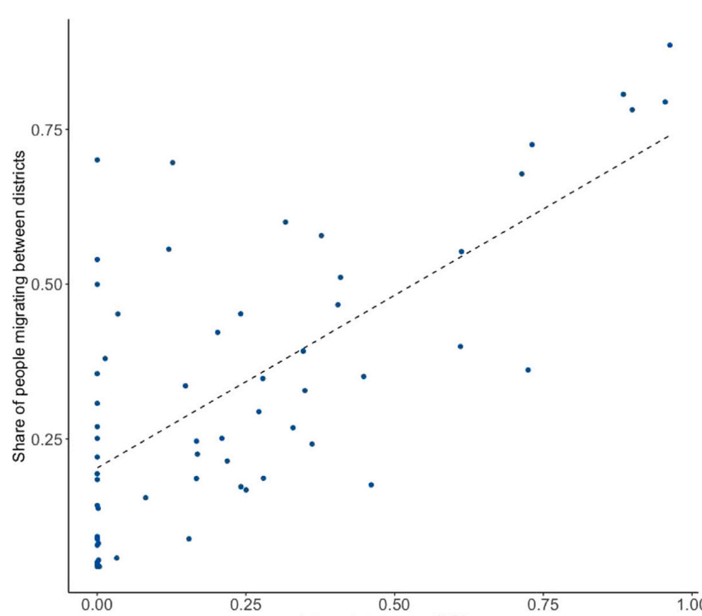

Fig. A.4. The graph reports the share of people migrating between districts and the increase in fast internet coverage (3G).
Source: Authors' elaboration on national census and RLFS data.

Table B.1
Share of industries, average across districts.
Source: Authors' elaboration on national census and RLFS data.

Industry	2002	2012	2017	2018	2019
Manufacturing	1.4	2.77	5.2	6.32	6.39
Private work in households	2.72	2.99	6.74	6.89	6.65
Education	1.33	1.8	3.83	3.35	3.84
Construction	1.47	3.42	9.24	10.05	9.66
Accommodation	0.25	0.84	1.19	2.03	2.73
Trade	3.32	5.15	14.73	14.14	13.99
Other services	0.79	1.15	2.18	2.56	2.63
Public	0.78	0.99	1.9	1.63	1.29
Business	0.31	1.1	0.62	0.7	0.67
Transport	1.23	2.09	3.97	4.21	5.08
Agriculture	85.53	75.95	45.89	43.22	41.93
Utilities	0.1	0.21	0.54	0.38	0.44
Finance	0.09	0.32	0.59	0.71	0.87
Health	0.51	0.76	1.51	1.45	1.29
Mining	0.16	0.46	1.87	2.37	2.52

Table B.2
Descriptive statistics.

Statistic	N	Mean	St. Dev.	Min	Max
Occupations					
Skilled	150	0.027	0.024	0.004	0.131
Unskilled	150	0.436	0.064	0.276	0.619
Employed	150	0.463	0.067	0.290	0.636
Industries					
Agriculture	150	0.585	0.258	0.048	0.970
Manufacturing	150	0.044	0.028	0.003	0.170
Tertiary sector	150	0.285	0.199	0.024	0.783
Education					
Primary or less	150	0.812	0.151	0.369	0.995
Secondary	150	0.154	0.112	0.005	0.386
Tertiary	150	0.034	0.050	0.000	0.260
Years of education	150	5.032	1.300	2.910	9.731
Demographic					
Age	150	32.072	1.366	27.780	34.748
Female	150	0.531	0.022	0.448	0.578
Migration (district)	90	0.272	0.198	0.032	0.798
Migration (province)	90	0.191	0.167	0.012	0.612
Internet					
2G	150	0.773	0.386	0.000	1.000
3G	150	0.203	0.263	0.000	0.963
4G	150	0.497	0.416	0.000	1.000
Geographic					
Malaria stability	150	0.528	0.668	0.000	2.338
Terrain ruggedness	150	223.686	68.723	107.334	382.963
Agricultural suitability	150	0.495	0.123	0.308	0.827
Distance from coast	150	1,076.845	43.879	979.015	1,149.148
Distance from railway	150	234.493	28.792	165.686	281.594
Distance from capital	150	58.820	30.770	6.447	139.695

Table B.3
Robustness, province-specific time trends.

	Dependent variable:					
	Employed (1)	Skilled (2)	Unskilled (3)	Agriculture (4)	Manuf. (5)	Tertiary (6)
3G	0.448**	0.0795**	0.369**	0.0243	0.0714	0.488***
	(0.179)	(0.0365)	(0.175)	(0.234)	(0.0777)	(0.171)
Observations	150	150	150	150	150	150
District FE	YES	YES	YES	YES	YES	YES
Province trends	YES	YES	YES	YES	YES	YES
District controls	YES	YES	YES	YES	YES	YES

(*continued on next page*)

Table B.3 (*continued*).

	Dependent variable:					
	Employed (1)	Skilled (2)	Unskilled (3)	Agriculture (4)	Manuf. (5)	Tertiary (6)
Mean DV	0.463	0.0274	0.436	0.585	0.0442	0.285
Quantification	0.142	0.0252	0.117	0.00769	0.0226	0.155
F-stat	5.369	5.369	5.369	5.369	5.369	5.369

Note: The dependent variables measure, respectively, the share of skilled workers among the working-age population (skilled); the share of unskilled workers among the working-age population (unskilled) and the share of agricultural, manufacturing and services in the district's total employment. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.4
Robustness, initial conditions.

	Dependent variable:					
	Employed (1)	Skilled (2)	Unskilled (3)	Agriculture (4)	Manuf. (5)	Tertiary (6)
3G	0.337***	0.0620*	0.300***	−0.336	0.137*	0.653***
	(0.0713)	(0.0316)	(0.0865)	(0.227)	(0.0799)	(0.195)
Observations	150	150	150	150	150	150
District FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
District controls	YES	YES	YES	YES	YES	YES
Initial DV	YES	YES	YES	YES	YES	YES
Mean DV	0.463	0.0274	0.436	0.585	0.0442	0.285
Quantification	0.00784	0.000175	0.00654	−0.0218	0.00116	0.0317
F-stat	16.57	8.774	11.37	8.386	11.79	7.533

Note: The dependent variables measure, respectively, the share of skilled workers among the working-age population (skilled); the share of unskilled workers among the working-age population (unskilled) and the share of agricultural, manufacturing and services in the district's total employment. 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of a district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. In addition, all regressions include initial values of the dependent variable, interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.5
Robustness, accounting for 4G coverage.

	Dependent variable:					
	Employed (1)	Skilled (2)	Unskilled (3)	Agriculture (4)	Manuf. (5)	Tertiary (6)
3G	0.278***	0.0691***	0.209**	0.0214	0.0882	0.362*
	(0.0932)	(0.0242)	(0.0964)	(0.288)	(0.0661)	(0.178)
4G	0.156	−0.00910	0.166	0.183	−0.117*	−0.253
	(0.131)	(0.0241)	(0.138)	(0.326)	(0.0659)	(0.196)
Observations	150	150	150	150	150	150
District FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
District controls	YES	YES	YES	YES	YES	YES
Mean DV	0.463	0.0274	0.436	0.585	0.0442	0.285
Quantification	0.0879	0.0219	0.0660	0.00676	0.0279	0.115
F-stat	13.13	13.13	13.13	13.13	13.13	13.13

Note: The dependent variables measure, respectively, the share of skilled workers among the working-age population (skilled); the share of unskilled workers among the working-age population (unskilled) and the share of agricultural, manufacturing and services in the district's total employment. 3G and 4G measure the percentage of the population covered by the respective mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. In addition, all regressions include initial values of the dependent variable, interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.6
OLS results, individual DHS data.

	Dependent variable:				
	Employed (1)	Skilled (2)	Unskilled (3)	Agriculture (4)	No Agriculture (5)
3G	0.0501*	0.115***	−0.0511	−0.104***	0.156***
	(0.0295)	(0.0321)	(0.0350)	(0.0393)	(0.0416)
2G	−0.0242	−0.0605**	0.0427	0.0519	−0.0746*
	(0.0395)	(0.0287)	(0.0496)	(0.0566)	(0.0415)
Female	0.00765	−0.0801***	0.0882***	0.146***	−0.138***
	(0.00599)	(0.00369)	(0.00649)	(0.00640)	(0.00476)
Age	0.00939***	0.00202***	0.00753***	0.0111***	−0.00164***
	(0.000201)	(0.000170)	(0.000239)	(0.000214)	(0.000197)
Constant	0.451***	0.0951***	0.343***	0.129**	0.319***
	(0.0363)	(0.0263)	(0.0461)	(0.0522)	(0.0389)
Observations	61,065	61,105	61,105	61,105	61,105
R-squared	0.127	0.107	0.136	0.235	0.180
District FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Mean DV	0.808	0.147	0.658	0.558	0.249

Note: The dependent variables are dummies measuring, respectively, if an individual is employed (column 1), if he/she is employed in a skilled or an unskilled occupation (columns 2–3), if he/she is employed in or outside the agricultural sector (columns 4–5). 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include individual specific controls (their age and gender) as well as a variable measuring the 2G mobile technology coverage of the district's total population. All regressions are adjusted for the complex sample design of DHS using the approach recommended by the data provider (for more details, see the following link). Mean DV is the average value of the dependent variable in the estimation sample. Standard errors are computed after adjusting regressions for their sampling design. *** p<0.01, ** p<0.05, * p<0.1.

Table B.7
2SLS results, migrant workers by occupation and industry.

	Share of migrant workers:				
	Skilled (1)	Unskilled (2)	Agriculture (3)	Manufacturing (4)	Tertiary (5)
3G	0.0371**	0.155*	0.0760	0.0237*	0.0903***
	(0.0168)	(0.0824)	(0.0900)	(0.0135)	(0.0316)
Observations	90	90	90	90	90
R-squared	0.504	0.627	0.584	−0.034	0.730
District FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
District controls	YES	YES	YES	YES	YES
Mean DV	0.00908	0.103	0.0582	0.00434	0.0388
Quantification	0.0117	0.0491	0.0241	0.00751	0.0286
F-stat	10.66	10.66	10.66	10.66	10.66

Note: The dependent variables measure, respectively, the share of migrant workers relocated from other provinces in skilled (column 1) and unskilled (column 2) occupations, and in agriculture, manufacturing and tertiary sectors (columns 3 to 5). 3G measures the percentage of the population covered by the mobile technology in each district. All regressions include the following controls: the 2G mobile technology coverage of the district's total population; the average age of the district's population; the share of female population in the district's total population; the stability of malaria; terrain's ruggedness; the suitability of the terrain for agricultural use; the distance (in km) to the nearest coast; the distance (in km) to the closest colonial railway; the distance (in km) to the nearest border. All the geographic variables are interacted with a time trend. All regressions are estimated using a 2SLS estimator. 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. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.8
Production function coefficients.

Sector	Labour	Capital	Materials
Agriculture, forestry and fishing	0.1226	0.0336	0.8085
Mining and quarrying	0.3511	−0.1564	0.8169
Manufacturing	0.1691	0.0338	0.7223
Electricity, gas and air conditioning supply	0.0065	0.2676	0.4716
Water supply; sewerage, waste management	0.1609	0.005	0.684
Construction	0.246	0.0029	0.5292
Wholesale and retail trade; repair of motor vehicles	0.0808	−0.0095	0.8627
Transportation and storage	0.4445	0.1327	0.3315
Accommodation and food service activities	0.3331	−0.0269	0.694
Information and communication	0.2502	0.0265	0.6372

(*continued on next page*)

Table B.8 (*continued*).

Sector	Labour	Capital	Materials
Financial and insurance activities	−0.08	0.0064	0.9529
Real estate activities	−0.1753	0.2195	0.6612
Professional, scientific and technical activities	0.178	0.0733	0.617
Administrative and support service activities	0.148	−5e−04	0.8361
Education	0.6176	0.0239	0.1754
Human health and social work activities	0.5411	0.0706	0.1795
Arts, entertainment and recreation	0.3231	0.1506	0.2562
Other service activities	0.1705	−0.0439	0.785

Note: The table reports coefficients of the production function estimated for each industry (ISIC rev. 4 "sections" following the methodology described in Section 5.2.

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