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Mobile phone use, productivity and labour market in Tanzania

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Abstract: Access to mobile phone has increased substantially over the last decade in sub-Saharan Africa. The evidence suggests that increased use of mobile phones in the region has upgraded the market prices received by producers for their cash crops, but so far there is limited knowledge on labour market transitions effects of mobile phone access. In this study, we use farm household and individual labour force information, from LSMS-ISA Tanzania National Panel Survey, to examine the impact of mobile phone ownership on labour markets and farm productivity in the country. The study shows that successive increases in mobile phone use lead to movement of labour share from agriculture into non-farming sectors. The results also show that mobile phone access significantly reduces the intensity of work by household members on the farm and is instead associated with an increase in hired farm workers. Our results also show that mobile phone access has heterogeneous labour market effects, depending on the age of individuals. Given the important surge of information communication technology in sub-Saharan Africa, including Tanzania, the results suggest that using mobile phones to stimulate agricultural developments would improve marginal productivity of labour in the farming sector and induce a surge in off-farm employment opportunities.

Key words: mobile phone, farm productivity, market prices, Tanzania

JEL classification: Q12, O1, O33

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1 Introduction

Improving agriculture productivity is one of the main focus for policy makers and stakeholders in developing countries. Various strategies have been deployed to that effect, including improvement of road networks to increase market access as well as upgraded distribution of farm technologies to smallholders, among others. Mobile phones, furthermore, have emerged as an important new method in which agriculture productivity can be improved in developing countries. By reducing informational, search and transactions costs to farmers, mobile phones can increase efficiencies within the agriculture sector and lead to increased productivity (Aker 2010; Aker and Mbiti 2010; Klonner and Nolen 2010). This is more relevant specifically for SSA region, where agriculture productivity has historically been below the average compared to the rest of the world, but which has experienced a surge in mobile phone ownership. For example, in 1990, Africa accounted for only 13 per cent of the total global production value of maize, which is a staple food in most SSA countries. By 2016, this had increased marginally to 15 per cent of total world production (FAO 2019). In comparison, mobile phone ownership has been on the increase and by 2018, mobile phone penetration rates in sub-Saharan Africa (SSA) were as high as 45 per cent with projections that it would increase over 13 per cent by 2025. Through innovative services and applications available through this platform, mobile phones can play a key role in enhancing productivity in the agricultural sector, and smart phone adoption rates, which are currently at 36 per cent, have been projected to reach 66 per cent by 2025 (GSMA 2019). As noted by Aker (2010), the effects of mobile phone ownerships can have additional effects on households over and above increased agricultural productivity and in this paper, we disentangle the effects on labour supply household decisions.

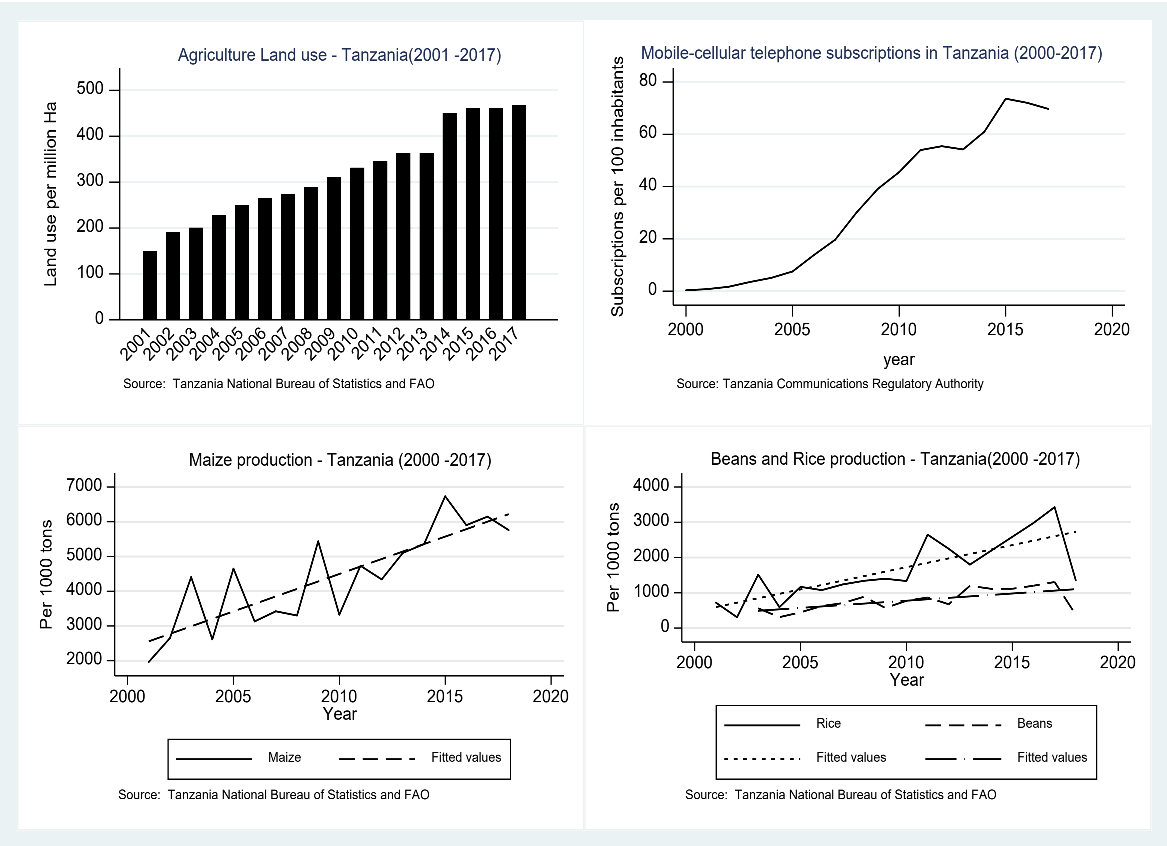
This paper estimates the impact of mobile phone access on households' labour market supply decisions in Tanzania. With up to 23.7 million unique mobile phone owners and a mobile penetration rate of 42 per cent, Tanzania has one of the highest mobile penetration rates in the East Africa Community (GSMA 2019). The distribution of mobile phones in the country is provided in Figure 1 and it shows that by end of 2018, rate of mobile phone subscription reached up to 75 of every 100 inhabitants. As shown further in Figure 1, this upward trend in mobile ownership coincides with an increase in agriculture land use and production, particularly for maize and rice, in Tanzania, and in this paper we test for association between the two. The channel under which mobile handsets affect agriculture productivity is through provision of better access to information, extension services, market and distributional networks, and crucially for rural households financial access through mobile money services (Aker 2010; Mittal et al. 2010; Qiang et al. 2012). The main goal of this study therefore is to provide additional evidence of the impact of mobile phone access by focusing on how the use of mobile handsets affects labour supply decisions within farm households in SSA and the resultant labour reallocation from its impact on farm productivity. Specifically, using farm household balanced panel data from the National Panel Survey (NPS), we estimate the effect of mobile phone ownership on household labour supply, and provide the mechanisms through which farm productivity induces non-farm employment opportunities.[1]

This study hypothesizes and tests two channels under which mobile handsets can affect farm productivity and leads to labour reallocations among household members. First, mobile phone access enables farm household to increase farm productivity through reduced information and transaction costs, thereby improving networks that facilitate business linkages between input

[1] In this study, the term off-farm and non-farm employment are used interchangeably.

suppliers and farm households. This increased farm productivity, in turn, allows to reduce time spent on farm plots by household members (labour) who would other- wise be important for food production needed by household for subsistence (Emerick 2018; Gollin et al. 2007, 2002). Additionally, these farm productivity gains can also generate additional labour demand of locally produced non-tradables, which would eventually move additional labour away from the agricultural sector into off-farm employment sector (Foster and Rosenzweig 2007). Secondly, using mobile phone can improve marginal productivity of labour, as it is considered as an integral input of the factors of production. The development of telecommunication infrastructure is crucial in upgrading symmetric information among market agents, since it allows for them to engage in optimal arbitrage (Aker 2010). Therefore, using mobile phone facilitates increased marginal productivity of labour among farm household (intensive margins of labour), and this, at a specific threshold, will induce the marginal household worker to move into non-farm sector (labour pulling hypothesis). This labour reallocation to non-farm work eventually allows the household to earn relatively higher wages (Alvarez-Cuadrado and Poschke 2011), and this would in turn enable households to pay relatively more hired farm workers. This implies that at the intensive margin, the farm household will hire farm workers as long as the marginal product of the hired worker is at least

Figure 1: Mobile phone ownership, land use and farm productivity in Tanzania



Note: the figure shows trends in agriculture land use and mobile cellular subscription rates in Tanzania over the period 2000–17 (top panel), and changes in maize, bean and rice production over the same period of time (bottom panel).

Source: Authors' computation based on data from FAO statistics, Tanzania National Bureau of Statistics, Tanzania Communication Regulatory Authority.

equal to their wages. Therefore, an increased marginal productivity of hired farm workers, resulting from mobile phone use, will have a positive effect on farm labour demand and off-farm employment. In this study, we estimate the labour productivity gains from reallocating workers based on these solid assumptions discussed.

In this paper, we apply two estimation strategies to identify the effect of mobile phone access on labour reallocation, taking into account possible endogeneity issues associated with mobile phone ownership. We first instrument the mobile phone ownership and analyse its effects on a vector of outcomes, namely, farm productivity, number of days worked on farm by household members, number of days worked on farm by hired workers and the wages paid to the hired farm workers. To do this, we use three rounds balanced panel data of the farm households merged with individual working placements together with mobile phone access dataset. We use intensity of average mobile phones within communities to explain exogenous variations in mobile phone networks in given communities. In this respect, we assume that higher intensity of the mobile phones in community would infer that the community has more network infrastructure, with possibly more effective tower placements and this would eventually increase the likelihood of local households to use mobile phones.[2] To set this identification strategy, we assume that by conditioning household and community attributes, the intensity of mobile phones in community does not independently affect the outcomes. To compliment this analysis, we also estimate ordinary least squares (OLS) together with bunch of fixed effects to derive the impact of mobile handsets use on farm productivity and employment. In addition to household and farm controls, we address the non-randomness of mobile phone access by controlling for survey year and region by year fixed effects and this allows us to estimate farm productivity and employment effects of mobile phone access using only within regional variations in mobile phone ownership.

The results from both estimations show that mobile ownership significantly increases agricultural productivity of the households and at same time reduces proportion of time spent on farm activities by household members. In particular, we find that household members are estimated to be 20 percentage points less likely to work on the farm but instead move to other jobs out of the agricultural sector, when they have access to mobile phones. Further, the study indicates that the number of days worked on the farm by hired workers changes to around 30.5 percentage increase for those with mobile handset access. The findings are the same in both OLS and instrumental variable models. We further find that mobile phone access increases the likelihood of hiring more casual women on intensive margin. In communities with intensive mobile networks, farm households hire more casual women to work on their farm, at about 1.72 more days (an increase of approximately 18 per cent) than non-mobile phone users. From both analyses, we find that hired casual male workers increase insignificantly in the presence of mobile phone use, and this suggests that household may prefer hiring female rather than male farm casual workers.

Having shown that households with mobile phone access reduce the number of days worked on the farm by household members and at same time have reduced probability of being farm households, we now turn to examining which non-farm agricultural sectors are more likely to grow in a wake of farm productivity shocks through mobile phone access. Focusing on farm households, we find that households with mobile phone access are more likely to experience a substantial shift away from farm business to non-farm employment opportunities. Specifically, higher intensity of mobile phones in the communities is associated with household labour flows to public (government employment), private (mostly NGOs and other non-government institutions) and other off-farm family jobs (labour pulling hypothesis). The labour reallocation to the private sector is relatively and significantly much higher (around 4 percentage points) than into public or other

[2] In this study, we proxy the community/village level by primary sampling unity (PSU).

off-farm family business.[3] The results are in line with recent evidence showing that most of labour that leaves agriculture is absorbed by higher locally productive sectors of manufacturing and service (McMillan and Harttgen 2014). Finally and importantly, we show that economically active household individuals of less than 45 years are more likely to move into private sector jobs, while the public sector is significantly more likely to absorb individuals between 45-65 years old. The decomposed analysis also indicates that the off-farm family job is marginally and significantly less likely to absorb workers when public and private jobs options are still possible.

This study contributes to the existing literature in the following manners. First, by analysing the impact of mobile phone ownership on farm productivity, it adds to what is known so far about infrastructural development of Mobile Application for Agriculture and Rural Development (m-ARD) in developing countries, the aim of which is to provide effective and easy market information, increasing access to extension services and market linkage facilities. In addition, the effect of mobile phone ownership in improving efficiency and production in the agricultural sector and its effects in reducing market prices differences have been extensively investigated (Mittal et al. 2010; Qiang et al. 2012; Aker and Fafchamps 2014; Aker and Ksoll 2016). In this paper, we provide evidence of how mobile phone ownership in- creases agriculture productivity and non-agricultural employment opportunities. This paper is also related to the extant studies that discuss labour market structural transformation and agriculture productivity. Emerick (2018) investigates the effect of an exogenous agricultural productivity shock on labour market reallocation in rural India. Bustos et al. (2016) finds that adoption of new agriculture technologies which increase agricultural productivity in Brazil had heterogeneous effects on labour market reallocation based on the factor bias of the technological change (i.e. whether it was labour or land augmenting). Ngai and Pissarides (2007) and Gollin et al. (2013) show how increased agriculture productivity leads to labour market reallocation through the labour supply and demand channel respectively. The closest precedent study to our work is Klonner and Nolen (2010) who studied the labour market effects of mobile coverage expansion in rural South Africa and find that it increases women wages while agricultural employment decreases, especially for men. Unlike to their study, our work highlights age groups differences in labour reallocation for various employment sectors: the agriculture sector, other family non-agricultural business, public and private sectors. The rest of this paper is structured as follows. Section 2 provides the estimation strategy of the paper. The data and descriptive statistics are set out in section 3 while the results are presented in section 4. The mechanism and transmission channels are discussed in 5 and section 6 concludes.

2 Estimation and identification strategy

To understand the effect of mobile phone use on productivity and how this translates into household labour allocation, let y_{hvrt} be the vector of outcomes (including the log of output in monetary terms, log of number of days worked on farm by household members, log of number of days worked on farm by hired workers and the log of wages paid to hired farm workers expressed in monetary term) for household (individual) h, in community v of region r at time period t. The D_{hvrt} is an indicator variable for whether a household has access to mobile phone or not by time t. If mobile phone use by farm household was random, we could derive the average treatment effect (ATE) of mobile phone use (a_1) by estimating the ordinary least square (OLS) as follows

[3] Other off-farm family businesses include any other type of household individual activities besides agriculture, such as selling in small family shops. Note that most of these family jobs are unpaid.

$$y_{hvrt} = a + a_1 D_{hvrt} + \varphi_v + \delta_r + \lambda_t + \gamma_{r\ t} + E_{hvrt} \quad (1)$$

Where φ_v and δ_r are community and regional fixed effects to account for unobserved cross community and regional time invariant differences, λ_t being survey year fixed effects included to control for temporal variations during the household survey period, γ_{r*t} is used to absorb common shocks within a particular region in given year of survey, and finally E_{hvrt} being an idiosyncratic error term. However, since the mobile phone access is not random, its use may be growing and enormously induced by unobserved factors, hence, making the $\hat{a}_{1OLS}$ upward biased. To deal with such unobserved attributes that could influence the growth use of mobile phone by farm households, we first introduce a vector of community covariates W_{vrt} and household (individual) characteristics X_{hvrt} and estimate equation (2)

$$y_{hvrt} = a + a_2 D_{hvrt} + \eta_2 X_{hvrt} + \theta_2 W_{hvrt} + \varphi_v + \delta_r + \lambda_t + \gamma_{r\ t} + E_{hvrt} \quad (2)$$

With community/farm covariates W_{hvrt} which include land gradients (slopes), land elevation (m), distance to main markets and main roads from households, household farmland areas (hectare), level of pesticides, fertilizer and hybrid seed use by farm household. The household (individual) attributes include the gender, age and education of household head, proxying for household decisions in economic activity (Dillon and Barrett 2014). In addition, we have also included the share of farm household members that are economically active to identify possible work locations across age group categories within households.

However, even though we have these controls in our model as shown in the previous equation, there might be some other confounding trends in households and communities as well as other unobserved political factors that could affect the distribution of mobile phone networks (including intensity of antenna and tower placements) across the regions in Tanzania.[4] Therefore, having non-random distributions of mobile phone networks induces extra biases when examining the effect of mobile phone use on farm productivity. To deal with such challenges, we instrument for mobile phone access using the intensity of average mobile phones in the community (Z_{vrt}), and estimate the first stage as

$$D_{hvrt} = \pi_0 + \pi_1 Z_{vrt} + \pi_2 \mathbf{M}_{hvrt} + \tau_{vrt} \quad (3)$$

Where Z_{vrt} being the instrument, $\mathbf{M}_{hvrt}$ represents a set of covariates (overlapped with variables in equation 2) and τ_{vrt} to account for other unobserved remaining variances of mobile phone access. Setting this identification strategy, we assume that by conditioning the household and community attributes, including distance to local economic centres, topographic conditions and regional fixed effects, the intensity of mobile phones in the community does not independently affect the outcomes.

3 Data sources and sample statistics

[4] Noting that the growth of mobile phone use can be endogenously explained by the number of towers in a given areas. The flatter slopes of the local topography would favour intensive network coverage, hence increasing the likelihood for farm households to use mobile phones.

To analyse the labour market allocation effects of the mobile phone use, we construct a household panel dataset using three rounds (2008/09, 2010/11, 2012/13) from Tanzanian NPS. The rounds are implemented by the Tanzanian National Bureau of Statistics (NBS), with supports provided by the World Bank under the Living Standard Measurement Study-Integrated Surveys Agriculture (LSMS-ISA) program.[5] The NPS uses stratified multi-stage cluster sampling method to derive a nationally representative sample. The survey provides sufficient and qualitatively good information on household seasonal yields.[6] To get the total production, we combined household farm yield from short and long rain seasons and summed up the market values from the six most produced and consumed food crops (maize, beans, rice, groundnut, sorghum, cassava) in Tanzania. All monetary values data are converted using 2011 USD prices, based on GDP deflator and exchange rate in Tanzania. To complement the analysis, in some parts of the study we also use some additional data from the FAO dataset. Further, the NPS provides number of days the household members worked on farm plots. Combining short and long rain season plot information, we compute the annual number of days the household members have worked on the farm in each agricultural season of surveyed year. We also derive the number of days and wages on hired women and men to work on farm plots. This information is relevant in this study, as it is utilized to analyse household labour use, both on and off-farm activities.

3. Demographic and household attributes

In Table A.1 in the appendix and Table 1, we provide the descriptive statistics of the key variables used in this study. The variables are all derived from the three NPS implemented by the NBS and all the results in this study are weighted. The study uses a balanced panel of 1,618 households from all 26 regions of Tanzania across a designed 294 enumeration areas (EA) as shown in Figure 2. In this study, we also use data on mobile phone ownership, household socioeconomic attributes and community (proxied by EA) characteristics. The information of mobile phone ownership is given by the response on the question 'Whether household member owns mobile phone'. From this, we define a dummy variable (equal to one if there is at least one household member with a mobile phone, or zero otherwise) at household level. Furthermore, the same question allows us to compute the number of households with mobile phones and the number of mobile handsets in household, and this was useful for setting up the identification strategy in subsequent sections.

An illustration of the distribution of rates of mobile phone by farm households and changes in mobile phone intensity over three waves from dataset are provided in Figure 3 and Figure 4 respectively. The mobile phone ownership by farm households has been consistently increasing across the three waves. While in 2009 the rate of mobile phone ownership was around 31 per cent, it reached 64 per cent in 2013. This implies that in five years, the farm household mobile phone ownership has doubled in Tanzania.

Figure 2: Distribution of enumeration areas

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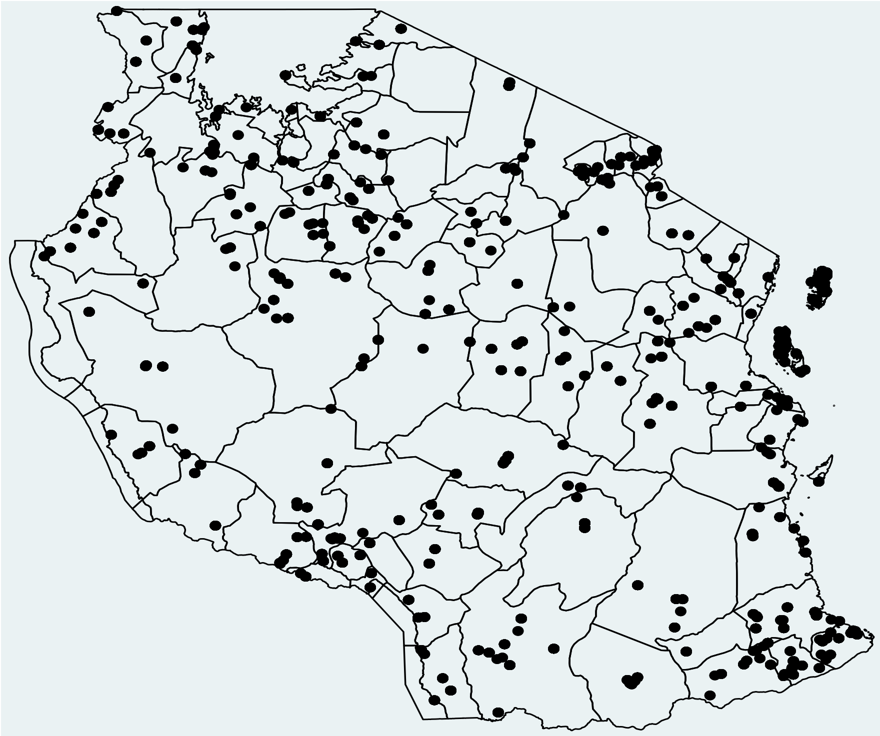
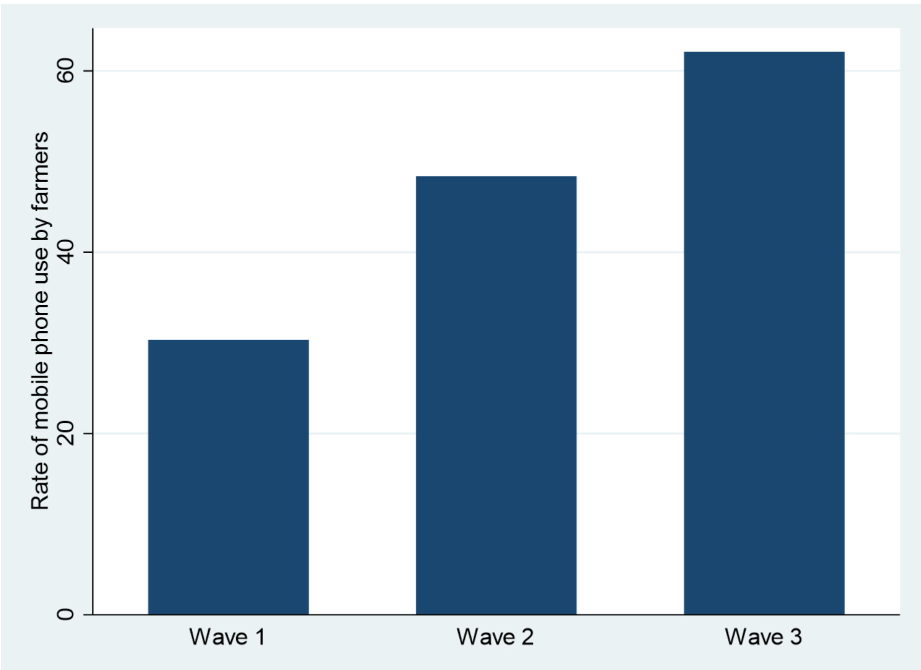
[5] The Living Standard Measurement Study-Integrated Surveys Agriculture (LSMS-ISA), through an ongoing initiative within the Development Research Group of the World Bank, promote and support the governments in SSA to generate nationally representative household panel data with more emphasis on agriculture and rural development. Much information can be accessed here: http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA

[6] In Tanzania, there are two main agricultural seasons: short (October-December) and long (February-May) rain seasons. In the short rain season, the farmers grow crops that usually take short time to mature. The crops of early maturing varieties (such as beans, maize, potatoes) are usually produced in the short rain season. Unlike the short rain farming period, in the long rain season farmers expand their crop production choices by including crops like sorghum and cassava which can usually withstand the droughts and even grow better in dry areas.



Source: Authors' calculations using TNPS (2008/09, 2010/11 and 2012/13 waves).

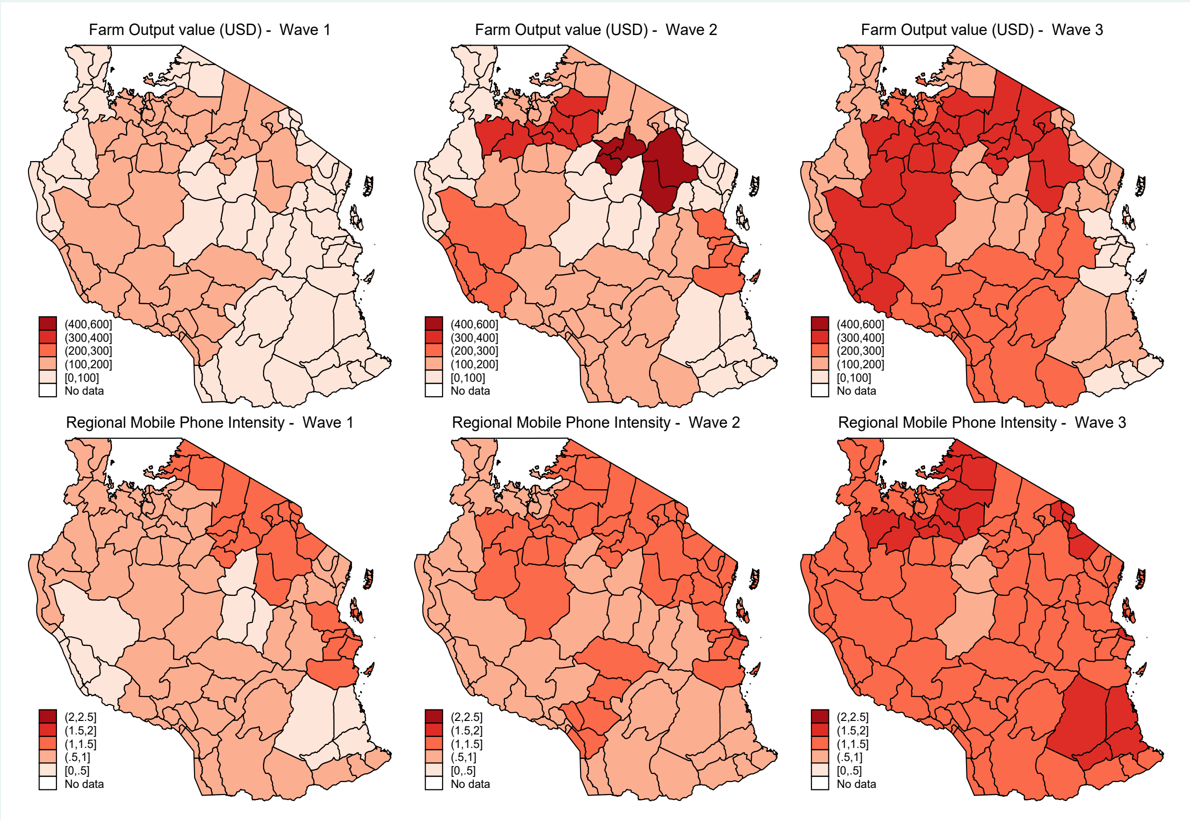
Figure 3: Distribution of mobile phone use by farmers across waves



Source: Authors' calculations using TNPS (2008/09, 2010/11 and 2012/13 waves).

We also present the mobile phone intensity within farm households across regions in Tanzania as reported in the lower part of Figure 4. We can observe the high levels of mobile phone intensity across Tanzania in the first wave which is followed by increases in agricultural productivity as proxied by farm output values in successive waves. This points to an underlying mechanism at play between the two variables which may explain the observed changes. A description of households' characteristics which provide further information on the household characteristics is provided below.

Figure 4: Mobile phone intensity and farm output value across waves



Notes: the figure shows regional level changes in farm output value and mobile phone intensity over the three waves. The top panel indicates farm output value (USD) which is the annual total farm yield value. The regional mobile phone intensity is presented in the bottom panel. The data includes all regions within Tanzania, with exception of Lake Victoria.

Source: Authors' calculations using TNPS (2008/09, 2010/11 and 2012/13 waves).

3.2 Household workforce allocation

Generally in the SSA region, labour allocated to farming activities plays an important role in rural household livelihood. The divisions of labour in rural households is usually along gender lines, with women involved substantially in farm activities and other domestic works (Lado 1992; Punch 2001). As provided in Table 1, agriculture is still the mainstay for rural economic activities in Tanzania, as it accommodates approximately 80 per cent of total household labour forces. The rest of rural household labour forces are absorbed by the private sector, off-farm family businesses and the public sector, with an average of 10, 8, and 2 per cent respectively. Further, as can be observed in the reported data, the share of economically active household members (between 15–65 years old) is roughly 52 per cent of total household members. The data in addition indicates that, in Tanzanian rural community, the majority of household members are youth and there are large number of dependent members. Disaggregation of the economically active members reveals that on average, the majority (55 per cent) are aged between 15–30 years old. The data also reveals the number of days the household members work on their farm. We see that on average, the household members spent over 75 per cent of the year (280 days in year) working on the farm. The data also reveals that more women are hired to work on farm than men, with an average of 25 days against 23 days respectively. An important observation from Table 1 is that across the three round surveys, the share of household labour force in agriculture has declined by 10 per cent level over the five year period (2008–13). On other hand, over the same time period, the rural household labour force in private sector and off-farm family business has increased by 6 per cent for each respectively. This is therefore a descriptive indication that there is a systematic relocation of household labour force from agricultural economic activity to non-farm employment opportunities.

Table 1: Average values of the key outcome variables

Variable	Wave 1 (2008/09)		Wave 2 (2010/11)		Wave 3 (2012/13)	
	Mean	SD	Mean	SD	Mean	SD
Real farm wages per HH in US$	81.01	136.65	65.13	116.42	77.37	188.75
Annual output values in US$	351.84	567.09	340.60	726.32	490.91	1802.21
Total # days worked by hired men	24.80	34.04	20.69	33.44	28.01	42.79
Total # days worked by hired men	23.35	35.08	27.58	44.84	28.51	46.63
Total number of days worked on plots	303.47	370.64	250.49	232.42	281.15	272.15
Share of economically active [15-65]	0.53	0.21	0.52	0.20	0.54	0.214
Share of economically active [15-30]	0.27	0.20	0.27	0.19	0.27	0.19
Share of economically active [30-45]	0.13	0.16	0.13	0.15	0.13	0.16
Share of economically active [45-65]	0.13	0.17	0.12	0.16	0.14	0.18
HH members work in agriculture	0.84	0.34	0.814	0.39	0.74	0.44
HH members work in public sector	0.02	0.141	0.016	0.125	0.02	0.14
HH members work in private sector	0.06	0.24	0.07	0.26	0.12	0.32
HH members work in family business	0.06	0.24	0.09	0.29	0.12	0.32
Number of households	1618		1618		1618	
Number of villages (EA)	294		294		294	
Number of regions	26		26		26	

Note: The table indicates the mean and standard deviation of farming households in each of the three waves of the NPS, pooled across all enumeration areas. All monetary values data are converted using 2011 US$ prices, based on GDP deflator and exchange rate in Tanzania. The observations for real wages and annual output are at household level, while the share of economically active and sectors of work are at the individual level. Sampling weights were applied. HH=household head. Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

4 Results and discussions

The results from different regressions based on various household outcome measures are presented in Tables 2–5. Linear regression estimates (OLS) are presented in columns 1 and 2, while columns 3 and 4 provide results from the IV approach. Columns 1 and 3 provide estimates for all the sampled households while columns 2 and 4 are restricted to male-headed households to ascertain whether gender has a role to play in the process. The results from the first stage are reported in the Table A.2 in appendix.

4.1 Mobile phone ownership, farm productivity and farm labour

The results from the OLS regression in Table 2 show that ownership of a mobile phone has a statistically significant and positive effect on the value of farm output, with an approximation of almost 40 per cent increase compared to those without, and the effect is higher in male-headed households. This is in line with expectations based on current literature on mobile phones and agricultural productivity (Aker and Mbiti 2010; Aker and Ksoll 2016; Klonner and Nolen 2010). These results are robust to inclusion of various fixed effects and are confirmed by the IV results, which show that ownership of mobile phones increases farm value by over 70 per cent compared to those without phones in male-headed households. The main difference between the OLS and IV results is that the magnitude of the impact is much larger under the IV specification and could be resulting from endogeneity within the OLS model, though the size of the standard errors suggests that the IV results are less precise.

Table 2: Mobile phone use and value of farm output (US$)

	OLS results		IV results	
	(1)	(2)	(3)	(4)
Mobile phone use by farm household (1/0)	0.377	0.390	0.522	0.731
	(0.054)***	(0.060)***	(0.203)**	(0.230)***
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Fstat	69.22	49.31	67.35	46.49
Mean value of outcome	149.61	169.43	149.61	169.43
Number of households	1618	1618	1618	1618
Number of Enumeration Areas	294	294	294	294
Number of regions	26	26	26	26
R-squared	0.357	0.349	0.241	0.208

Notes: robust standard errors in parenthesis; $p < 0.1$, $p < 0.05$, $p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The value of the farm output is the dependant variable and is based on the market values of annual farm yield from both short and long rain seasons. All monetary values data are converted using 2011 US$ prices, based on GDP deflator and exchange rate inTanzania.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

The study further indicates that there is a strong negative relation between mobile phone ownership and number of days worked on the farm by the household members. Specifically, the study finds that ownership of a mobile phone is associated with a decrease in number of days worked on the farm when the households have access on mobile handsets (see Table 3).

We approximate that there is a reduction of around 22 per cent in the number of days worked on the farm by household members compared to other households with no mobile phones. Given that households spend, on average, 280 days working on the farm, this translates to a reduction of around 60 days spent on the farm. This reduction is slightly less for male-headed households and the results are similar for both OLS and IV specifications. Instead, what we see is an increase in the number of farm workers hired and wages paid out by the households.

Table 3: Mobile phone use and number of days worked on farm by household members

	OLS results		IV results	
	(1)	(2)	(3)	(4)
Mobile phone use by farm household (1/0)	-0.221 (0.062)***	-0.201 (0.066)***	-0.215 (0.061)***	-0.207 (0.066)***
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	240.17	254.80	240.17	254.80
Number of Households	1618	1618	1618	1618
Number of enumeration areas	294	294	294	294
Number of regions	26	26	26	26
R-squared	0.398	0.395	0.238	0.222

Notes: Robust standard errors in parenthesis; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependent variable is total number of days worked on the farm by household members and was computed by summing up all days worked in short and long rain reasons.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

Table 4: Mobile phone use and number of days worked on farm by hired workers

	OLS results		IV results	
	(1)	(2)	(3)	(4)
Mobile phone use by farm household (1/0)	0.341 (0.108)***	0.260 (0.121)**	0.305 (0.119)**	0.226 (0.135)*
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	35.25	38.34	35.25	38.34
Number of households	622	493	622	493
Number of enumeration areas	294	294	294	294
Number of regions	26	26	26	26
R-squared	0.408	0.421	0.374	0.377

Notes: Robust standard errors in parenthesis; $p < 0.1$, $p < 0.05$, $p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependent variable is the number of days worked on the farm by hired workers and was computed by summing up all days worked in short and long rain reasons from hired workers.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

Table 5: Reduced form effect of mobile phone use on hired farm workers in Tanzania

	OLS results		IV results	
	(1)	(2)	(3)	(4)
	Men	Women	Men	Women
Mobile phone use by farm household (1/0)	0.195	0.354	0.147	0.322
	(0.145)	(0.102)***	(0.163)	(0.130)**
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	23.21	24.93	23.21	24.93
Number of households	622	493	622	493
Number of enumeration areas	294	294	294	294

Notes: Robust standard errors in parenthesis; $* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependant variable is number of hired workers and refers to the number of workers employed to work on farm and was computed by summing up all days worked in short and long rain reasons.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

Table 6: Effect of mobile phone use on wages paid to the hired farm workers

	OLS results		IV results	
	(1)	(2)	(3)	(4)
Mobile phone use by farm household (1/0)	0.383	0.317	0.366	0.287
	(0.087)	(0.097)	(0.092)	(0.104)
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	76.45	84.96	76.45	84.96
Number of households	622	493	622	493
Number of enumeration areas	294	294	294	294
Number of regions	26	26	26	26
R-squared	0.610	0.624	0.588	0.585

Notes: Robust standard errors in parenthesis; $p < 0.1$, $p < 0.05$, $p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependant variable is the wages paid to the hired farm workers was computed by summing up all farm wages paid to workers from short and long rain reasons. All monetary values data are converted using 2011 US$ prices, based on GDP deflator and exchange rate in Tanzania.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

In particular, as can be seen in column 3 of Table 4, households with mobile phone access hire workers for 30 per cent more days than those without, spending up to 37 per cent more on wages for their farm labourers (Table 6). This is an important finding and points to the existence of positive benefits within the region to other households over and above those that accrue to the mobile phone owning household. By being able to hire more workers and pay higher wages, the benefits of mobile phone ownership by a household are transmitted to the other households (spillover effects) within the region which are hired to work on the farm.

A gender bias is apparent in terms of the farm workers, with more female farm workers being hired and this difference is statistically significant. As can be seen in columns 3 and 4 of Table 5, households with mobile phone ownership hire 15 per cent more men and 32 per cent more women than households with no mobile phones. Similar results are obtained under the OLS specification. The coefficient for hired male workers is not significantly different from zero, but a statistically significant result obtains for hired female workers suggesting that the main difference between households with mobile phones and those without is the extra female workers hired by the former. This is in line with expectations because as previously noted, the agricultural sector is dominated by women in African countries and can be explained by the labour pull channel as discussed in Emerick (2018). Our findings are also in line with those of Klonner and Nolen (2010).

4.2 Mobile phone ownership and labour reallocation

The decrease in time spent on working at farm plot by household members as a result of mobile phone access raises the question of where the households reallocate their efforts. Is there a sectoral shift away from agriculture in households with mobile phones? Looking at the extensive margins of labour, as shown in column 1 of Table 7, we see that households are less likely to be employed in the agriculture sector when they have access to mobile phones. They instead reallocate into the public, private and other non-agriculture family jobs. The results show that an additional increase of mobile phone within an enumeration area is associated with an 8 per cent probability reduction that the household members are employed in the agriculture sector. Instead, there is a 1.2 per cent probability that the household members are employed in the public sector, a 4.4 per cent they are in the private sector and a 2.5 per cent they move to other non-farm family activities. The results are statistically significant and are in line with the findings from study conducted in India by Emerick (2018) that an agriculture productivity shock led to reallocation away from the agriculture sector. This is also interesting as it points to the channels through which mobile phone access can affect agricultural productivity. According to Bustos et al. (2016), a technological productivity shock that is labour augmenting leads to reallocation away from the sector as opposed to the effects of a land augmenting shock. We observe three specific effects in our households associated to mobile phone ownership. These are: an increase in household labour availability, increase in hired farm workers and an increase in value of the farm yields. These effects culminate in the reallocation of labour away from the agricultural sector into other sectors which may eventually provide more stable livelihoods for the households.

The reallocation of labour away from agricultural sector has been shown to favour males than females (Klonner and Nolen 2010; Muto 2012). In this study, we focus more on the age-specific labour reallocations because farmers' age has been shown to have implications for productivity, generally following an inverse concave relation (Tauer 1995). As such, given that farmers at different ages respond differently to the productivity and efficiency gains of mobile phone ownership, we expect to see variations in the impact of mobile phones based on age groups of economically active household members.

As can be seen in Table 7, the economically active age group, which is just slightly over half the sample, transition out of agriculture and also out of non-farm family businesses into public or private sector. The biggest move is into the private sector, not surprisingly, given scanty employment opportunities in formal public sector. In terms of point estimates, the probability of being employed in the private sector is the highest for those aged 30–45 years at 14 per cent, while those between 15 and 29 have an increased probability of being in the private sector of 9 per cent, and per cent probability for those between 45–65. The only statistically significant move into the public sector is observed for those aged 45–65 and we speculate that this may be resulted from a combination of previous work experience and more opportunities from established networks. Of note in our results is that the economically active group also move away from other family jobs, particularly for those aged 30–45. A tentative explanation is that those who move into the other family jobs are usually the dependants, those younger than 15 or older than 65, indicating that these activities might be low or non-paying jobs.

Table 7: Reduced form effects of mobile phone use on employment probabilities in sub-sectors

	Farm employment	Non-farm employment		
	(1)	(2)	(3)	(4)
	Agriculture	Public	Private	Other family jobs
Average # of mobile phone /PSU	-0.081	0.012	0.044	0.025
	(0.012)	(0.004)	(0.008)	(0.005)
Share of active members [15-30]	-0.059	0.012	0.086	-0.039
	(0.038)	(0.010)	(0.026)	(0.023)
Share of active members [30-45]	-0.104	0.015	0.141	-0.051
	(0.049)	(0.015)	(0.036)	(0.027)
Share of active members [45-65]	-0.056	0.027	0.038	-0.009
	(0.039)	(0.010)	(0.029)	(0.021)
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	0.814	0.018	0.077	0.092
Observations	8193	8193	8193	8193
R-squared	0.114	0.053	0.071	0.074

Notes: Robust standard errors in parenthesis; $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01. Data is from the all three waves of the NPS. The dependent variable in column 1 is an indicator variable for whether the individual works in the farming sector. For column 2 to 4, the dependent variables are indicators of the different types of non-farm sectors, namely public, private and other family non-farm jobs.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

Further understanding of the observed employment transitions can be found in the analysis of the associated effects of mobile phone ownership on economic labour reallocation. Our results shown in Table 8 find that a unit increase in average mobile phones in the enumeration area is associated with a reduction in work on the own farm by the households of up to 6 per cent, and a move into non-farm employment. The results in columns 2, 3 and 4 show that there is an analogous increased probability of 4 per cent that the household members are employed by others in non-farm employment, a 2 per cent increased probability they are self-employed and a 1 per cent increased probability the household member is involved in unpaid work. In the economically active share of the households, they also reduce work on unpaid non-farming activities, mainly for those aged 15 to 30, and this may explain why they transition even away from non-farm family work, as was seen in Table 7.

Table 8: Reduced form effects of average mobile on economic labour reallocation

	Farm employment	Non-farm employment		
	(1)	(2)	(3)	(4)
	Work on own-farm	Employed	Self-employed	Unpaid work
Average # of mobile phone /PSU	-0.062	0.036	0.021	0.005
	(0.011)***	(0.007)	(0.007)	(0.005)
Share of active members [15-30]	-0.059	0.079	0.024	-0.044
	(0.039)	(0.028)	(0.021)	(0.018)
Share of active members [30-45]	-0.087	0.076	0.043	-0.033
	(0.059)	(0.041)	(0.035)	(0.022)
Share of active members [45-65]	-0.071	0.087	0.002	-0.018
	(0.054)	(0.032)	(0.029)	(0.017)
Household controls	Yes	Yes	Yes	Yes
Farm controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes
Mean value of outcome	0.860	0.063	0.050	0.028
Observations	5755	5755	5755	5755
R-squared	0.099	0.072	0.042	0.102

Notes: Robust standard errors in parenthesis; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data is from the all three waves of the NPS. The dependent variable in column 1 is an indicator variable for where the individual works on their own farm or not. For column 2 to 4, the dependent variables are indicators of different types of non-farm employment, namely employed, self-employed and family non- farm unpaid work.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

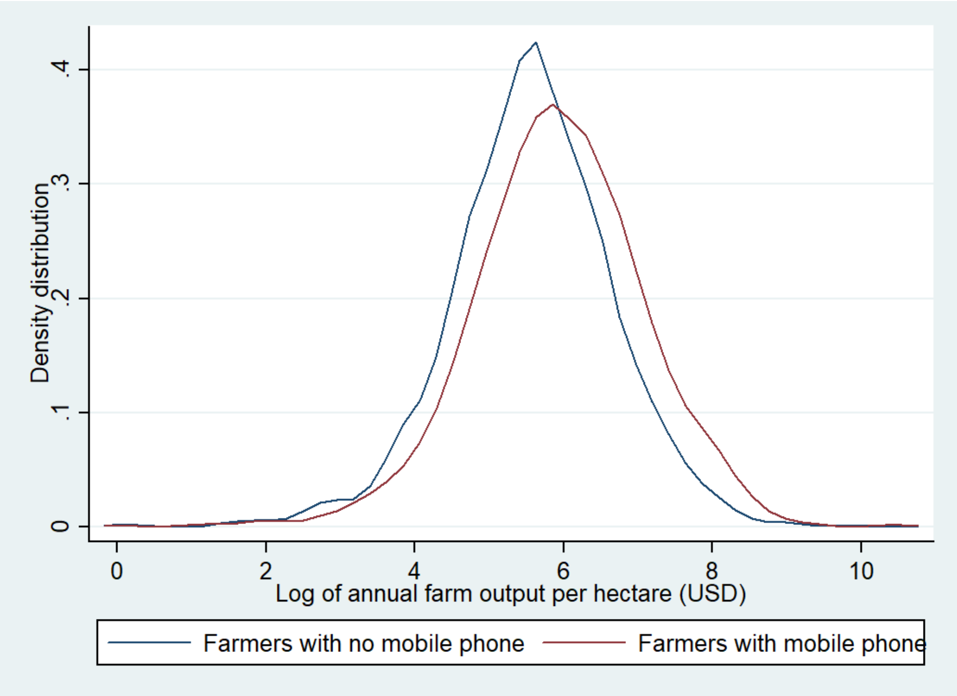
We observe that the non-farm work transition is mainly into the employment by others type, implying that mobile phone productivity is not necessarily leading to increased levels of entrepreneurship in the economy but that the individuals rather look for employed work, which is usually a more stable source of income. In line with the results from Table 7, we see a positive shift into unpaid work overall for given increase in mobile phones in the community, but the economically active group reallocates from this type of activity. It would be interesting to explore why households, dependants mainly, move into unpaid off-farm work and the benefits that accrue to the households as a result but that is beyond the scope of this paper.

5 Mechanism and transmission channels

In this section, we provide the mechanism and transmission channels through which mobile phone access leads to labour reallocation. A vast literature exists on modalities under which mobile phone access can induce increase in agricultural productivity (Aker and Mbiti 2010; Aker and Fafchamps 2014; Dillon and Barrett, 2014; Aker and Ksoll, 2016). In Figure 5 and Figure 6, we report the density distributions of annual farm yield and maize productivity in Tanzania. The figures show that farm households with mobile phone access have higher farm yield compared to farm households with no mobile phone access. The increased productivity can be as a result of either labour or capital augmentation and this has different implications for labour reallocation. We focus on increased agricultural productivity which is labour augmenting, i.e. leading to increased marginal productivity of labour. This is in line with previous works such as Emerick (2018) and Kirchberger

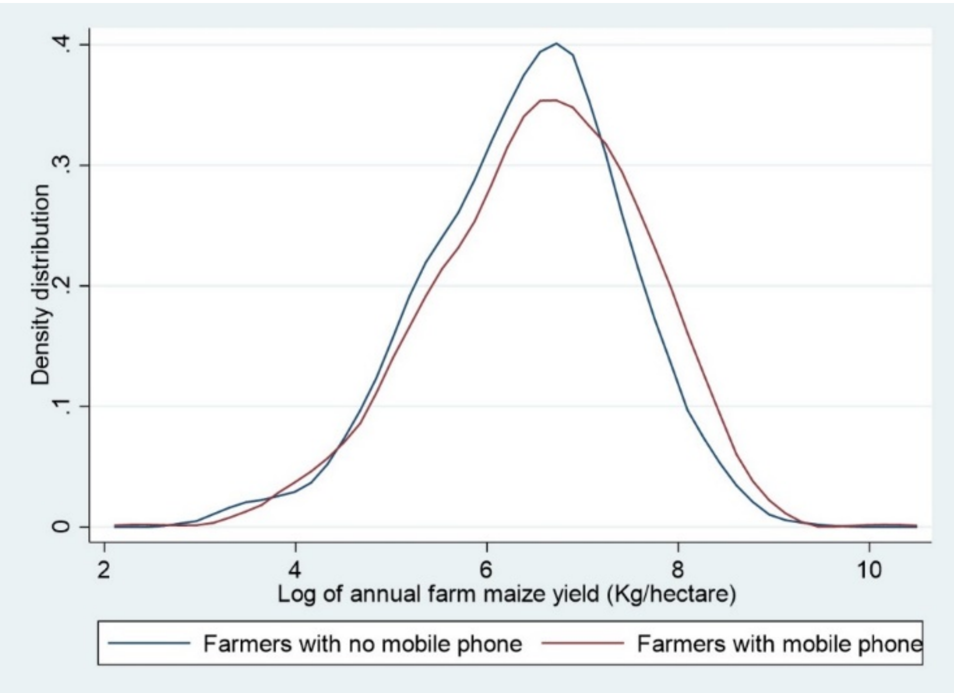
(2017). The channel through which mobile phone access affects agriculture productivity is through the provision of better access to information, extension services, market and distributional networks, and crucially for rural households financial access via mobile money services (Aker 2010; Mittal et al. 2010; Qiang et al., 2012).

Figure 5: Density distribution of annual farm yield and mobile phone use



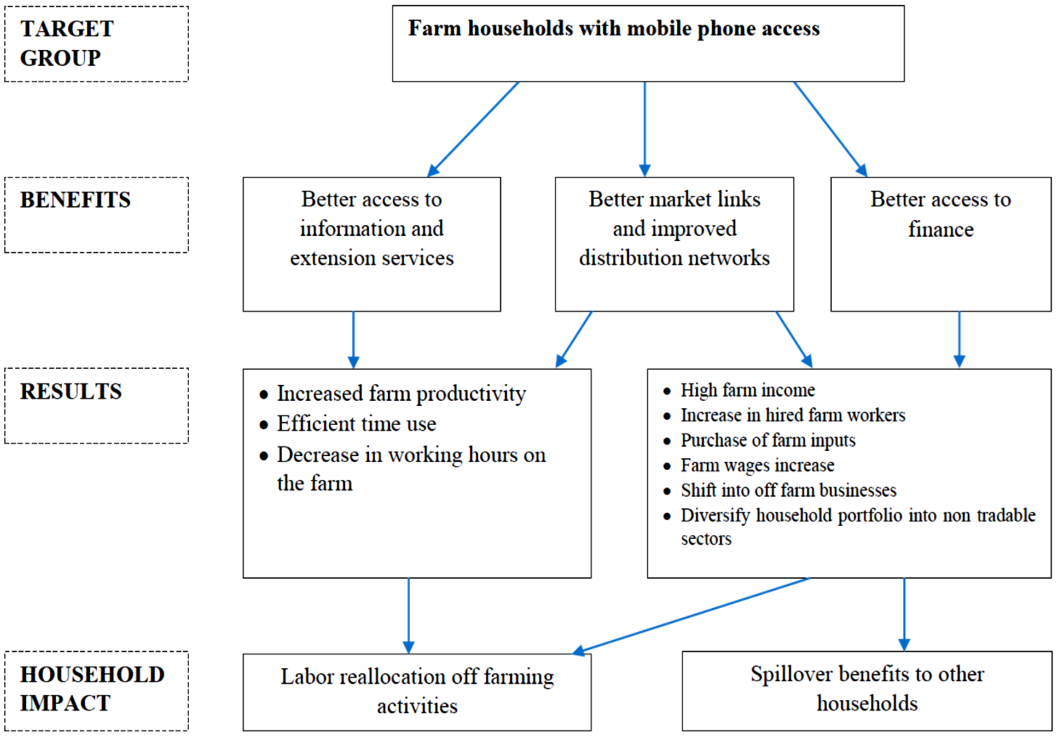
Source: Authors' calculations using TNPS (2008/09, 2010/11 and 2012/13 waves).

Figure 6: Density distribution of annual maize farm yield and mobile phone use



Source: Authors' calculations using TNPS (2008/09, 2010/11 and 2012/13 waves).

Figure 7: Theory of change: channels of mobile phone ownership to household labour decisions



Source: Authors' illustration.

Table 9: Mobile phone technology use and maize farm productivity (Kg/ha)

	(1)	(2)	(3)	(4)
Mobile phone use	0.217	0.174	0.235	0.241
	(0.089)	(0.093)	(0.120)	(0.127)
Mobile phone and radio		0.151	0.151	0.151
		(0.078)	(0.078)	(0.078)
Phone x distance to market			-0.023	-0.022
			(0.032)	(0.031)
Phone x distance to road				-0.005
				(0.033)
Village FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes
Number of households	1618	1618	1618	1618
R-squared	0.522	0.524	0.524	0.524

Notes: Robust standard errors in parenthesis; $p < 0.1$, $p < 0.05$, $p < 0.01$. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependent variable is the maize productivity expressed in kilograms per hectare.
Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

These factors lead to increased efficiency and agriculture productivity which then allows for the households to spend less time working on their plots. This might eventually allow farm households able to move out of agricultural sector into off-farm employment opportunities which may provide higher wages or a more stable source of income for the households, as can be explained more from Figure 7. Additionally, these farm productivity gains may also generate additional labour demand of locally produced non-tradeable goods, that could eventually move more labour into off-farm employment sector (Foster and Rosenzweig 2007).

In Tables 9 and 10, we estimate the effects of mobile phone access to maize farm productivity (Kg/ha) and agricultural technology adoption, respectively. The results reaffirm that access to mobile phone increase agricultural productivity and in the same time, using mobile handsets increases the probability of adopting agricultural technologies (e.g., hybrid seeds, fertilizers and pesticides use). By interacting mobile phone ownership with distance to main road and commercial market centres, we find negative and insignificant estimate. This indicates that the remote areas, where access to mobile network is limited, tend to reduce the probability of farmers to access markets inputs and output information, leading therefore to low farm yield levels.

Table 10: Mobile phone use and farm technology adoption (hybrid seeds, fertilizer, pesticides)

	(1)	(2)	(3)	(4)	(5)	(6)
Mobile phone use	0.059	0.043	0.030	0.025	0.207	0.182
	(0.020)	(0.020)	(0.010)	(0.010)	(0.081)	(0.082)
Mobile phone and radio		0.064		0.023		0.150
		(0.017)		(0.009)		(0.074)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
MP	0.280	0.280	0.131	0.131	0.081	0.081
Number of households	1618	1618	1618	1618	1618	1618
R-Squared	0.347	0.351	0.529	0.529	0.555	0.557

Notess: Robust standard errors in parenthesis; $*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$. Data is from the all three waves of the NPS. Mobile phone use refers to ownership of at least one mobile phone in the household. The dependent variable in column 1 and 2 is an indicator variable of adoption by the farming household of hybrid seeds, dependent variable in column 3 and 4 is an indicator variable of adoption by the farming household of fertilizer, dependent variable in column 5 and 6 is an indicator variable of adoption by the farming household of pesticides.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

While its role of improving marginal productivity of labour is regarded as an integral part of farm input, Mobile phone access can also be seen as entering agricultural production process. Telecommunication infrastructure development improves symmetric information among market agents, as alluded above, and allows farm households to engage in optimal arbitrage (Aker 2010). Using mobile phone can therefore facilitate farm households to in- crease marginal productivity of labour (labour intensive margins) as they are able to increase their output for each added unit of labour. When a certain threshold level of productivity is reached on the farm, in line with Foster and Rosenzweig (2007), complementarity in relationships between the agricultural and non-agricultural goods will induce the marginal household worker to move into non-farm sector (local demand effects). This labour reallocation to non-farm work would eventually allow the household to earn relatively higher wages (Alvarez-Cuadrado and Poschke 2011), and this would in return enable household to pay for more relatively cheaper hired farm workers. At the intensive margin, the farm household will hire additional workers as long as the marginal product of each hired worker is at least equal to wages. Therefore, increasing marginal productivity of hired workers, resulting from mobile phone use, will have a positive effect on farm labour demand and off-farm employment. The hiring of additional workers as a result of mobile phone use is what we refer to in Figure 7 as spill over benefits of mobile phone use by farm households.

6 Conclusions

While using mobile handsets has extensively expanded over the last decade in almost every SSA country, the developments of their applications have drastically increased uses of phones to expand far beyond the usual voice and text communications. Using mobile phones have now emerged as an essential new method through which agricultural productivity can be improved substantially in rural Africa, where millions of farm households are still heavily reliant on agriculture as main source of livelihood. In this study, we explore the channels under which mobile phone access affects household labour market supply decisions. We further provide evidence of its impact, by showing how short-term increase in mobile phone penetration reduces agricultural labour share and induces a considerable increase of non-agricultural employment opportunities. Specifically, based on three waves of farm household balanced panel (2008/09, 2010/11 and 2012/13) from NPS, this study uses two estimation strategies (a fixed effect and IV methods) to examine how using mobile handset affects labour supply and reallocation through its impact on farm productivity in Tanzania.

The findings from this study show that mobile phone ownership significantly increases agricultural productivity, and at same time, reduces the number of days spent on farm activities by household members. Further, the study indicates that the number of days worked on farm by hired workers increase, by around eight more days when farm households have mobile phone access. Interestingly, but not surprising, we show that mobile phone access increases the likelihood of hiring more casual women on intensive margin. We specifically show that the communities with intensive mobile networks, farm households hire more women to work on farm, for about 1.72 more days (an increase of roughly 18 per cent) compared to other regions with less intensive mobile networks. Finally but importantly, we show that, in light of increased mobile phone penetration within a community, economically active household members of less than 45 years are more likely to move in private sector jobs, while the public sector is significantly more likely to absorb individuals aged between 45-65 years old. The decomposed analysis, however, indicates that off-farm family jobs are marginally and significantly less likely to absorb workers when public and private jobs options are still possible.

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Appendix

Table A.1: Descriptive statistics of demographics and farm households from NPS

Variable	Mean	Std. Dev.	Min.	Max.
Household attributes:				
Household head is male (1/0)	0.802	0.399	0	1
Household size	6.996	5.07	1	55
Age of household head	51.01	14.80	19	107
HH head never went to school	0.274	0.446	0	1
HH received farm credit	0.022	0.148	0	1
dummy for tv users	0.066	0.248	0	1
dummy for radio users	0.617	0.486	0	1
dummy for mobile users	0.528	0.499	0	1
Demographic and farm attributes:				
Level of pesticide use	0.103	0.304	0	1
Level of fertilizer use	0.118	0.323	0	1
Use of improved seeds	0.318	0.466	0	1
land Area per farm household (hectare)	1.621	1.557	0.081	9
Distance to main road	2.153	3.067	0	41
Distance to main market	6.242	4.894	0	20
Annual produce of rice (kg/hh)	607.507	681.417	20	3000
Annual produce of maize (kg/hh)	645.667	647.481	20	3000
Annual produce of beans (kg/hh)	112.593	117.552	5	600
Annual produce of nuts (kg/hh)	220.687	248.924	7	1080
Annual produce of cassava (kg/hh)	416.845	462.690	5	2560
Annual produce of Sorghum (kg/hh)	325.516	351.161	10	1800

Note: The table shows descriptive statistics of farming households from all three waves of the NPS, pooled across all enumeration areas. The observations are at farm household level. Sampling weights were applied. The annual produce of the agriculture product is measured immediately after each farming season in Tanzania. HH=household head.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).

Table A.2: The first stage of the mobile phone use in Tanzania

	(1)	(2)
	Mobile phone use (1/0)	# of mobile phones in household
Average # of mobile phone per PSU	0.245 (0.021)***	0.899 (0.053)***
Survey year FE	Yes	Yes
Region by year FE	Yes	Yes
Fstat	34.540	44.040
Mean value of outcome	0.494	0.669
Number of enumeration areas	294	294
Number of regions	26	26
Number of households	1618	1618
R-squared	0.229	0.404

Notes: Robust standard errors in parenthesis; $p < 0.1$, $p < 0.05$, $p < 0.01$. Data is from the all three waves of the NPS. The table presents the first stage results from the IV. The dependent variable for column 1 is whether the household has a phone or not, while the dependent variable for column 2 is the number of mobile phones in the household. Survey weights are applied.

Source: Authors' calculations based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves).