Mobile phone access, Agriculture Productivity and Labour market transitions in Tanzania

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Abstract

Access to mobile phones has increased substantially over the last decade in Sub-Saharan Africa (SSA). Evidence suggests that increased use of mobile phones in the region has led to higher market prices received by producers for their cash crops, but so far there is limited knowledge on the labour market transition effects of mobile phone access (MPA). Using household and labour force data from Tanzania, we show that MPA substantially increases labour mobility. Specifically, the results indicate that MPA significantly reduces the intensity of work by household members on the farm and is instead associated with a transition to non-agriculture sectors and an increase in hired farm workers. Our results further show that MPA has heterogeneous labor market effects. Given the surge in mobile use in Tanzania, the results suggest that MPA stimulates agricultural developments which then improve marginal productivity of labour in the agriculture sector and, hence, induce a surge in non-agriculture employment opportunities.

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1 Introduction

Improving agricultural productivity is one of the prime goals for policymakers 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 agriculture technologies to smallholders, among others. On other hand, mobile phone access (MPA) has 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 have been proven to increase efficiencies within the agriculture sector (Aker, 2010; Aker and Mbiti, 2010; Klonner and Nolen, 2010). Further, the existing evidence has indicated that using mobile has allowed for sufficient market information by grain traders to engage in optimal arbitrage, and assuring symmetric information, hence reducing agricultural price distortions in Niger (Aker, 2010). Through innovative services and applications available in this platform, MPA can play a key role in enhancing productivity in the agricultural sector. This is particularly relevant for SSA, where production levels have historically been below the average compared to the rest of the world, yet the livelihood of more than 60 of households relies mainly on agriculture (FAO, 2019). The region has also experienced a considerable surge in MPA over the last two decades. For instance, by 2018, the use of mobile handsets in SSA was as high as 45 percent, while in Tanzania, as shown in Figure 1, it was almost 70 percent. The rate of smart phone use, which is key in the development of mobile phone applications, was estimated recently to be around 36 percent for SSA (GSMA, 2019). In this paper, we disentangle the effects of MPA on labour supply household decisions. The goal of this study, therefore, is to examine how the use of mobile handsets affects labor supply decisions within farm households in Tanzania. Specifically, using three waves (2008/09, 2010/11 and 2012/13) household balanced panel data from Tanzanian National Panel Survey (NPS), we estimate the effect of MPA on household labour supply. In addition, We provide the mechanisms through which the increased agriculture productivity,

induced by mobile phone use, leads to non-agriculture employment opportunities[1].

This study finds the following key results. First, we show that mobile phone ownership significantly reduces the proportion of time spent on agriculture 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, when they have MPA. We further indicate that the average number of days worked on the farm by hired workers increases by 30.5 percentage points in households with mobile handsets.

Secondly, we also show that MPA increases the likelihood of hiring more casual women on the intensive margin to work on the farm. In communities with intensive mobile networks, households hire more women to work on their farm, at about 1.72 more days (an increase of around 18 percent) compared to non-mobile phone households. This suggests that farm households may prefer hiring female to male farm casual workers and could indicate a role for bargaining power between the male and female counter part.

Thirdly, we find that households with MPA are more likely to experience a substantial move away from agriculture business to non-agriculture employment opportunities. Specifically, communities with high incidence of mobile handsets are associated with labour flows to the public sector (government employment) and non-agriculture private businesses (labour pulling hypothesis). It is also shown that labour reallocation in the private sector is significantly much higher (around 4 percentage point) than into public or other off-agriculture family business[2]. 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). We importantly indicate that economically active

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

[2]Other off-agriculture 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 not paid

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 aged between 45-65 years old.

We also identify the agricultural productivity shocks resulted from MPA as the possible transmission channels under which mobile ownership can cause labour re-allocations. We qualitatively explain the channels through which mobile handsets can affect farm productivity and lead to labour re-allocations among household members. The MPA reduces information and transaction costs, thereby improving networks that facilitate business linkages between input suppliers and farm households. This leads to increased farm productivity, and in turn, allows household members to reduce time spent (labour) on their farm plots. Moreover, owning mobile can improve marginal productivity of labour, as it is considered as an integral input of the factors of production. The development of ICT infrastructure is crucial in upgrading symmetric information among market agents. Hence, MPA may facilitates improving marginal productivity of labor among farm household (intensive margins of labour), after which, it will arouse the marginal household worker to move into non-farm sector. Overall, the findings suggest that as majority of household labour force are found in agriculture sector in most of developing countries, the MPA has been proven to plays crucial cross-sectoral spillovers. Specifically, we show that through the increase in agricultural productivity, the MPA can induce substantial labor reallocation into non-agricultural sector.

This study contributes to the existing literature in the following ways. By providing evidence of how mobile phone ownership increases agriculture productivity and non-agricultural employment opportunities, this paper is related to the extant studies on labour market structural transformation and agriculture productivity. This is similar to Emerick (2018) who 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 increases agricultural productivity in Brazil has 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 labor market reallocation through the labor supply and demand channel respectively. Muto (2012) finds that mobile phone ownership has labour market implications as it increases the probability of migration for work and the effect is larger for those in minority ethnics group in Uganda. 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 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.

By analysing the impact of mobile phone ownership on agriculture productivity, we add to what is known so far about the infrastructural development effects 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. The effect of mobile phone ownership in improving efficiency and production in the agricultural sector and its effects in reducing market prices differences has been extensively investigated (Mittal et al., 2010; Qiang et al., 2012; Aker and Fafchamps, 2014; Aker and Ksoll, 2016). A review of the potential impact of mobile phone diffusion in SSA is provided by Porter (2012) and the author further discusses the effects on livelihoods which include the role of MPA in job-searches and in micro enterprise development.

The rest of this paper is structured as follows. Section 2 provides the empirical 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 total annual farm output in monetary terms, log of number of days worked on the farm by household members, log of number of farm working days 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 the farm household was random, we could derive the average treatment effect (ATE) of mobile phone use ($_1$) by estimating using ordinary least square (OLS) as follows:

$$y_{hvrt} = \quad + \quad _1 D_{hvrt} + \quad _v + \quad _r + \quad _t + \quad _{r\ t} + \quad _{hvrt} \tag{1}$$

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

$$y_{hvrt} = \quad + \quad _2 D_{hvrt} + \quad _2 X_{hvrt} + \quad _2 W_{hvrt} + \quad _v + \quad _r + \quad _t + \quad _{r\ t} + \quad _{hvrt} \tag{2}$$

Where community/agriculture covariates W_{hvrt} include land gradients (slopes), land elevation (m), distance to main markets and main roads from households, household agriculture land areas (hectare), level of pesticides, fertilizer and hybrid seed use by agriculture 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 agriculture household members that are economically active to control for the work intensity 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 network (including intensity of Antenna and tower placements) across the regions in Tanzania.[3] Therefore, having non-random distributions of mobile phone networks induces extra biases when examining the effect of mobile phone use on the outcomes. To deal with such challenges, we instrument for MPA using the intensity of average mobile phones in the community (Z_{vrt}), and estimate the first stage as

$$D_{hvrt} = \ _0 + \ _1 Z_{vrt} + \ _2 \mathbf{M}_{hvrt} + \ _{vrt} \tag{3}$$

Where Z_{vrt} refers to the instrument, $\mathbf{M}_{hvrt}$ represents a set of covariates (overlapped with variables in equation 2) and $_{vrt}$ to account for other unobserved remaining variances of MPA. Using the intensity of average mobile phones within communities we are clearly able to explain exogenous variations in mobile phone networks in given communities by assuming that higher intensity of the mobile phones in community implies that the respective com-

[3]Note 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 of using mobile phones by those in the locality

munity has more network infrastructure, including network towers. From this point, we can intuitively assume that the variations in network towers in different communities does not have a direct effect of the outcomes, but instead the effect is possible only via MPA. This is possible because the villages with more tower placements have a higher likelihood of having more local households using mobile phones. Hence, using this identification strategy, we assume that by conditioning the household and community attributes, including distance to local economic centers, topographic conditions and regional fixed effects, the intensity of mobile phones in the community does not independently affect the outcomes. In this setting, it is noteworthy to mention that we proxy the community/village level by Primary Sampling Unity (PSU) from the dataset.

3 Data sources and sample statistics

To analyse the labor market allocation effects of the mobile phone use, we construct a household panel dataset using three rounds (2008/09, 2010/11 and 2012/13) from the Tanzanian NPS. The rounds are implemented by the Tanzanian National Bureau of Statistics (NBS), with support provided by the World Bank under the Living Standard Measurement Study-Integrated Surveys Agriculture (LSMS-ISA) program.[4] 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.[5] To get the total production, we combined household agriculture yield from the short and long rain seasons

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

[5]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 are usually early maturing. Crops of early maturing varieties like beans, maize and Irish potatoes are usually produced in the short rain season. Unlike the short rain farming period, in 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.

and summed up the market values from the six most produced and consumed food crops (Maize, Beans, Rice, Groundnut, Sorghum and Cassava) in Tanzania. All monetary values data are converted using 2011 USD prices, based on the GDP de ator and exchange rate in Tanzania. To complement the analysis, in some parts of the study, we also use some additional data from FAO dataset. Further, the NPS provides the number of days the household members worked on agriculture plots. Combining short and long rain season plot information, we compute the annual number of days the household members have worked on the agriculture in each agricultural season of surveyed year. We also derive the number of days and wages on hired women and men to work on agriculture plots. This information is relevant in this study, as it is utilized to analyse household labor use, both on and o -agriculture activities.

3.1 Demographic and Household attributes

In Table 1 and 2, we provide the descriptive statistics of the key variables used in this study. The variables are all derived from the NPS implemented by the NBS and all the results in this study are weighted. The study uses a balanced panel of 1618 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 socio-economic attributes and community (proxied by Enumeration Area) characteristics. The information of mobile phone ownership is given by the response to the question \Whether household member owns mobile phone". From this, we de ne a dummy variable (equal to one if there is at least one household member with 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 identi cation strategy in the previous section. An illustration of the distribution of rates of mobile phone by agriculture households and changes in mobile phone intensity over

the three waves from the dataset is provided in Figure 3 and Figure 4 respectively. Mobile phone ownership by agriculture households has been consistently increasing across the three waves. While in 2009 the rate of mobile phone ownership was around 31 percent, it had reached 64 percent by 2013. This implies that in ve years, agriculture household mobile phone ownership has doubled in Tanzania. We also present the mobile phone intensity within agriculture households across regions in Tanzania as reported in the lower panel of Figure 4. We observe high levels of mobile phone intensity across Tanzania in the rst wave which is followed by increases in agricultural productivity as proxied by agriculture 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 the households characteristics which provide further information on the household characteristics is provided below.

3.2 Household workforce allocation

Generally, in 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 agriculture activities and other domestic works (Lado, 1992; Punch, 2001). As provided in Table 2, agriculture is still the mainstay for rural for rural economic activities in Tanzania, as it accommodates approximately 80 percent of total household labour forces. The rest of rural household labour forces are absorbed by the private sector, non-agriculture family business and public sector, with an average of 10, 8 and 2 percent 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 percent 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 percent) are aged between 15-30 years old. The data also reveals

the number of days the household members work on their farm plots. We see that on average, the household members spent over 75 percent of the year (280 days in year) working on the farming plots. The data also reveals that more women are hired to work on the plots than men, with an average of 25 days against 23 days respectively. An important observation from Table 2 is that across the three round surveys, the share of household labour force in agriculture has declined by 10 percent level over the ve year period (2008-2013). On other hand, over the same period of time, the rural household labour force in the private sector and non-agriculture family business has increased by 6 percent 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-agriculture employment opportunities.

4 Results and discussions

The results from di erent regressions based on various household outcome measures are presented in Tables 3 - 7. 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 rst stage are reported in the Table 10.

4.1 Mobile phone ownership, agriculture productivity and agriculture labour

The results from the OLS regression in Table 3 show that ownership of a mobile phone has a statistically signi cant and positive e ect on the value of agriculture output, with an approximation of almost 40 percent increase compared to those without, and the e ect 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 xed e ects

and are con rmed by the IV results, which show that ownership of mobile phones increases agriculture value by over 70 percent compared to those without phones in male-headed households. The main di erence between the OLS and IV results is that the magnitude of the impact is much larger under the IV speci cation 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.

The study further indicates that there is a strong negative relation between mobile phone ownership and number of days worked on the farm plots by the household members. Specifically, the study nds that ownership of a mobile phone is associated with a decrease in number of days worked on the plot when the households have access on mobile handsets (see Table 4). We approximate that there is a reduction of around 22 percent in the number of days worked on the plot by household members compared to other households with no mobile phones. Given that households spend, on average, 280 days working on the farm plots, 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 speci cations. Instead, what we see is an increase in the number of agriculture workers hired and wages paid out by the households. In particular, as can be seen in column 3 of Table 5, households with mobile phone access hire workers for 30 percent more days than those without, spending upto 37 percent more on wages for their agriculture labourers (Table 7). This is an important nding and points to the existence of positive bene ts 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 bene ts of mobile phone ownership by a household are transmitted to the other households (spillover e ects) within the region which are hired to work on the agriculture.

A gender-bias is apparent in terms of the hired workers, with more female agriculture

workers being hired and this difference is statistically significant. As can be seen in columns 3 and 4 of Table 6, households with MPA hire 15 percent more men and 32 percent 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 MPA 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 labor 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 agriculture 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 8, 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 a 8 percent probability reduction that the household members are employed in the agriculture sector. Instead, there is a 1.2 percent probability that the household members are employed in the public sector, a 4.4 percent they are in the private sector and a 2.5 percent they move to other non-agriculture 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 a ect 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 e ects of a land augmenting shock. We observe three speci c e ects in our households associated to mobile phone ownership. These are: an increase in household labour availability, increase in hired agriculture workers and an increase in value of the agriculture yields. These e ects 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 labor away from agricultural sector has been shown to favour males than females (Klonner and Nolen, 2010; Muto, 2012). In this study, we focus on the age speci c labour reallocations as the farmer's age has been shown to have implications for productivity, generally following an inverse concave relation (Tauer, 1995). As such, given that farmers at di erent ages respond di erently to the productivity and e ciency 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 8, the economically active age group, which is just slightly over half the sample, transition out of agriculture and also out of non-agriculture 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 to 45 at 14 percent, while those between 15 and 29 have an increased probability of being in the private sector of 9 percent, and 4 percent probability for those between 45 and 65. The only statistically signi cant move into the public sector is observed for those aged 45 to 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 to 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.

Further understanding of the observed employment transitions can be found in the analysis of the associated e ects of mobile phone ownership on economic labour reallocation. Our results shown in Table 9 nd that a unit increase in average mobile phones in the enumeration area is associated with a reduction in work on the own agriculture by the households of up to 6 percent, and a move into non-agriculture employment. The results in columns 2, 3 and 4 show that there is an analogous increased probability of 4 percent that the household members are employed by others in non agriculture employment, a 2 percent increased probability they are self employed and a 1 percent 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-agriculture activities, mainly for those aged 15 to 30, and this may explain why they transition even away from non-agriculture family work, as was seen in Table 8. We observe that the non-agriculture 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 8, 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 o -agriculture work and the bene ts 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 the modalities through which MPA can induce increases in agricultural productivity (Aker and Mbiti, 2010; Aker and Fafchamps, 2014; Dillon and Barrett, 2014; Aker and Ksoll, 2016). In Figure 5, we report the density distributions of annual agriculture yield in Tanzania. The gure shows that farming households with MPA have higher farm yields compared to farm households with no MPA. The increased productivity can be as a result of either labour or capital augmentation and this has di erent 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 MPA a ects agriculture productivity is through the provision of better access to information, extension services, market and distributional networks, and crucially for rural households nancial access via mobile money services (Aker, 2010; Mittal et al., 2010; Qiang et al., 2012; Klapper and Singer, 2014). These factors lead to increased e ciency and agriculture productivity which then allows for the households to spend less time working on their plots. This may eventually enable agriculture households move out of the agricultural sector into o -agriculture employment opportunities which may provide higher wages or a more stable source of income for the households, as can be seen from Figure 6. Additionally, these agriculture productivity gains may also generate additional labour demand of locally produced non-tradeable goods, that could eventually move more labour into o -agriculture employment sector (Foster and Rosenzweig, 2007).

While its role in improving marginal productivity of labour is regarded as an integral part of agriculture input, MPA can also enter the agricultural production process. Telecommunication infrastructure development improves symmetric information among market agents,

as alluded above, and allows agriculture households to engage in optimal arbitrage (Aker, 2010). Using mobile phones can therefore enable farm households increase their 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 agriculture productivity is reached, in line with Foster and Rosenzweig (2007), complementarity in the relationships between the agricultural and non-agricultural goods will induce the marginal household worker to move into non-agriculture sector (local demand e ects). This labour reallocation to non-agriculture 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 agriculture workers. At the intensive margin, the agriculture 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 e ect on agriculture labour demand and o -agriculture employment. The hiring of additional workers as a result of mobile phone use is what we refer to in Figure 6 as spillover bene ts of mobile phone use by agriculture households.

6 Conclusions

While using mobile handsets has extensively expanded over the last decade in almost every SSA country, development of their applications has drastically increased and expanded far beyond the usual voice and text communications. Using mobile phones has now emerged as an essential new method through which agricultural productivity can be improved substantially in rural Africa, where millions of households are still heavily reliant on agriculture as the main source of livelihood. In this study, we explore the channels through which MPA a ects 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. Speci cally, based on three waves of agriculture household balanced panel (2008/09, 2010/11 and 2012/13) from NPS, this study examine how MPA a ects labour supply and reallocation through its impact on agriculture productivity in Tanzania. We include a re- ned set of xed e ects at di erent levels- region and year of survey- to lter out unobserved heterogeneity at those levels and together with set of household and village controls, we derive the impact of MPA on our outcome variables, as accurately as possible.

This study qualitatively hypothesizes the channels through which mobile handsets can a ect agriculture productivity and lead to labour reallocations among household members. First, mobile phone access reduces information and transaction costs, thereby improving networks that facilitate business linkages between input suppliers and agriculture households. This leads to increased agriculture productivity, and in turn, allows household members to reduce time spent (labour) on their agriculture plots (Emerick, 2018; Gollin et al., 2007, 2002). Additionally, these agriculture productivity gains also generate additional labour demand of locally produced non-tradables, that would eventually move additional labour away from the agricultural sector into o -agriculture 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, MPA facilitates increased marginal productivity of labor among agriculture household (intensive margins of labour), and this, at a speci c threshold, will arouse the marginal household worker to move into non-agriculture sector (labour pulling hypothesis). This labour reallocation to non-agriculture work eventually allows the household to earn relatively higher wages (Alvarez-Cuadrado and Poschke, 2011), hence enabling households to pay hired farm workers. This implies that at the intensive margin, the agricultural household will hire farm

workers as long as the marginal product of the hired worker is at least equal to their wages. Therefore, increased marginal productivity of farm labour, resulting from mobile phone use, will have a positive e ect on agricultural labour demand and o -agricultural employment. In this study, we estimate the labour productivity gains from labour reallocation based on these solid assumptions discussed.

The ndings from this study show that mobile phone ownership signi cantly increases agricultural productivity, and at same time, reduces the number of days spent on agriculture activities by household members. Further, the study indicates that the number of days worked on agriculture by hired workers increase, by around 8 more days when agriculture households have mobile phone access. Interestingly, but not surprising, we show that mobile phone access increases the likelihood of hiring more casual women on the intensive margin. We speci cally show that in communities with intensive mobile networks, agriculture households hire more women to work on agriculture, for about 1.72 more days (an increase of roughly 18 percent) 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 signi cantly more likely to absorb individuals aged between 45-65 years old. The decomposed analysis, however, indicates that o -agriculture family jobs are marginally and signi cantly less likely to absorb workers when public and private jobs options are still possible.

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List of Tables and Figures

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

Table 2: Average values of the key outcome variables

	Wave 1(2008/09)		Wave 2(2010/11)		Wave 3(2012/13)	
Variable	Mean	SD	Mean	SD	Mean	SD
Real Farm wages per hh in USD	81.01	136.65	65.13	116.42	77.37	188.75
Annual output values in USD	351.84	567.09	340.60	726.32	490.91	1802.21
Total # days worked by hired Women	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 USD prices, based on GDP de ator 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. Source: Authors calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 3: Mobile phone use and Value of farm output (USD)

	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	No	Yes	No
Region by survey year FE	No	Yes	No	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

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: 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 USD prices, based on GDP de ator and exchange rate in Tanzania. Source: Authors calculation 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 household members

	OLS results		IV results	
	(1)	(2)	(3)	(4)
Mobile phone use by farm household (1/0)	-0.221	-0.201	-0.215	-0.207
	(0.062)	(0.066)	(0.061)	(0.066)
Household Controls	Yes	Yes	Yes	Yes
Farm Controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	No	Yes	No
Region by survey year FE	No	Yes	No	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

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: 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 calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 5: 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	0.260	0.305	0.226
	(0.108)	(0.121)	(0.119)	(0.135)
Household Controls	Yes	Yes	Yes	Yes
Farm Controls	Yes	Yes	Yes	Yes
Survey year FE	Yes	No	Yes	No
Region by survey year FE	No	Yes	No	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

Robust standard errors in parenthesis; p < 0:1, p < 0:05, p < 0:01

Notes: 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 calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 6: Reduced form e ect of mobile phone use on hired farm workers in Tanzania

	OLS results		IV results	
	(1) Men	(2) Women	(3) Men	(4) 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	No	Yes	No
Region by survey year FE	No	Yes	No	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
Number of regions	26	26	26	26
R-Squared	0.362	0.400	0.276	0.350

Robust standard errors in parenthesis; p < 0:1, p < 0:05, p < 0:01

Notes: 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 calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 7: E ect 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	No	Yes	No
Region by survey year FE	No	Yes	No	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

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: 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 USD prices, based on GDP de ator and exchange rate in Tanzania. Source: Authors calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 8: Reduced form e ects of mobile phone use on employment probabilities in sub-sectors

	Farm employment	Non-farm employment		
	(1) Agriculture	(2) Public	(3) Private	(4) 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
Region by survey year FE	Yes	Yes	Yes	Yes
Mean value of outcome	0.814	0.018	0.077	0.092
Obervations	8193	8193	8193	8193
R-Squared	0.114	0.053	0.071	0.074

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: 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 di erent types of non-farm sectors, namely public, private and other family non-farm jobs. Source: Authors calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 9: Reduced form e ects of Average mobile on economic lebour 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
Region by survey year FE	Yes	Yes	Yes	Yes
Mean value of outcome	0.860	0.063	0.050	0.028
Obervations	5755	5755	5755	5755
R-Squared	0.099	0.072	0.042	0.102

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: 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 di erent types of non-farm employment, namely employed, self employed and family non-farm unpaid work. Source: Authors calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

Table 10: The rst 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	0.899
	(0.021)	(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

Robust standard errors in parenthesis; $p < 0:1$, $p < 0:05$, $p < 0:01$

Notes: Data is from the all three waves of the NPS. The table presents the rst 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 calculation based on Tanzanian NPS (2008/09, 2010/11 and 2012/13 waves)

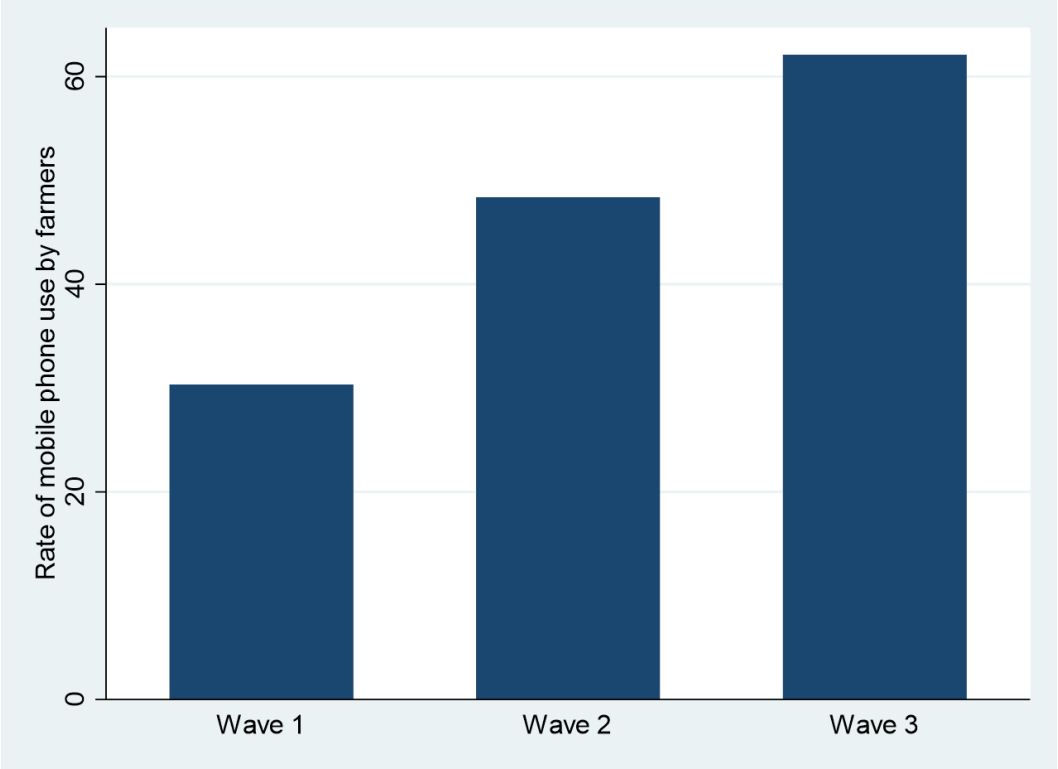
Figure 1: Mobile Cellular Telephone Subscriptions in Tanzania (2000 - 2017)

Notes: The gure shows trends in mobile cellular subscription rates per 100 inhabitants in Tanzania over the period 2000 to 2017. Source: Tanzania Communications Regulatory Authority.

Figure 2: Distribution of Enumeration Areas

Notes: The gure shows the distribution of enumeration areas from which survey data was collected in the all three waves.

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



Notes: Each bar represents the proportion of farm household with mobile handsets