Mobile Phones, Mobile Internet, and Employment in Uganda

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Abstract

We analyze the relation between mobile phone use – mobile Internet in particular – and employment, self-employment and job regularity in Uganda. We find no evidence of any positive impact of mobile Internet use on employment or job quality, suggesting that either respondents do not use mobile Internet for job search practices or as a job tool, or that these uses are ineffective. However, we find that the adoption and use of basic mobile phones are positively related to employment and job quality, and we argue that regulators should focus on promoting the affordability of basic phones and mobile airtime.

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1 Introduction

One of the most important trends of the last two decades has been the growing adoption of mobile phones worldwide. This phenomenon is considered an important vector of economic growth, especially in developing countries (Aker and Mbiti, 2010). It is now widely acknowledged that greater mobile phone penetration increases employment and supports entrepreneurship in many African countries such as Kenya (Moyi, 2019), and recent studies call for higher penetration of the most recent telecommunication technologies allowing the use of fast Internet on mobile phones, such as 4G and 5G networks (Commission et al., 2021).

Some countries such as Uganda have experienced a slower adoption of mobile phones than leading countries such as Kenya, and have therefore received less attention from the academic literature. The adoption of information and telecommunication technologies in Uganda is indeed still relatively low, as the mobile phone penetration rate is around 57% since 2016.[1] Mobile Internet subscriptions – which represent most of the use of the Internet in Uganda[2] – were also at a low rate of 8.6% at the end of 2016,[3] mostly among the urban population (Kasse et al., 2015). Moreover, there are important variations in penetration rates in the different regions of Uganda, resulting from different levels of coverage depending on the region. For 2G networks in 2017, 99% of the population is covered in Central and Eastern Uganda, while 4% of the population does not have access to 2G technology in Northern Uganda, the most rural region.[4] As a result, the main reason for not owning a phone was the absence of coverage for 11% of those leaving in rural areas, against 0.5% in urban areas.[5] This effect becomes stronger when considering more recent telecommunication technologies: only 65% of the population has access to 3G networks in Northern Uganda against 88% in Central Uganda, and when looking at 4G networks, the values are respectively 9% and 53%.

Uganda is thus among the countries where the adoption of information and telecommunication technologies (ICT) is the lowest in sub-Saharan Africa, and where the potential impacts of a greater adoption on employment could be especially strong. As Asongu and Odhiambo

[1] Number of mobile cellular subscriptions per 100 inhabitants in Uganda from 2000 to 2020, Statista.
[2] Mobile Internet Connectivity 2020 Sub-Saharan Africa Factsheet.
[3] Uganda now at 18 million on Internet, 3 million on Facebook; The Independent, March 1, 2021.
[4] GSMA Connected Society Uganda, 2018.
[5] National Information Technology Survey 2017/18 Report.

(2020) highlight, significant positive impacts on employment can be expected if mobile phones are adopted by a sufficient share of the population, and policy measures that increase mobile phone adoption and frequency of use may have far-reaching effects on employment and economic growth.[6] Indeed, 9.2% of the working population is unemployed in Uganda in 2016, with 61% of the workers being in a vulnerable situation characterized in particular by inadequate earnings.[7] It is thus essential to assess whether the greatest returns on investments by telecommunication operators reside in the roll-out of new technologies or in the widespread adoption and uses of basic mobile phones.

We analyze the relation between employment and mobile phone uses in Uganda. We use the Intermedia FII surveys on digital inclusion for 2015 and 2016, which provide us with individual-level data on a rich range of mobile phone uses – calling, sending and receiving text messages – and of mobile Internet – browsing and using social media – as well as on the employment status of respondents. We distinguish three categories of employment among respondents: having a job vs looking for a job; having a job that provides a regular source of income vs an irregular source of income; being employed vs being self-employed.

This article relates to a growing literature on ICT and employment in Uganda. Andjelkovic and Imaizumi (2012) review the effects of ICT for information exchange between entrepreneurs. Asongu and Odhiambo (2020) show how a high level of mobile penetration can be used to mitigate gender inequalities in Africa. In sub-Saharan Africa, Ebaidalla (2014) shows that mobile phones have a significant positive impact on employment, but for the years of their focus – 1995-2010 – there is no impact of the Internet on employment. We thus extend their analysis by considering data for the years 2015-2016, and by considering mobile Internet that has been increasingly used since 2010. Komunte (2015) focuses on Uganda and shows that mobile phones can promote entrepreneurship among women by supporting their emancipation.

We contribute to this literature by considering different statuses of employment among the whole Ugandan population, thus offering a better grasp on how mobile phones can be used for job-related practices such as looking for a job or as a job tool, or mobile phone uses among respondents

[6] For instance, the Ugandan government recently adopted a controversial increase in the cost of data for mobile Internet users (Uganda introduces 12% Internet data levy, critics say move will stifle online access, Reuters April 30, 2021.)

[7] Uganda National Household Survey 2016/17, last accessed December 22, 2021.

starting their own job. Our results support the fact that new mobile phone technologies do not have a strong positive impact on employment in Uganda, at least not in the short run. This absence of effects has important implications for policymakers. We argue that Ugandan network operators should focus in priority on facilitating the adoption of basic mobile handsets among the poorest, as well as on the affordability of mobile credit, rather than on the roll-out of last generation networks such as 4G and 5G.

The remaining of the article is organized as follows. Section 2 reviews the recent literature on mobile phones, the Internet, and employment in particular in Africa. We describe the telecommunication landscape in Uganda, as well as our data set in Section 3. Section 4 describes our methodology, and Section 5 provides the results of our analysis. Section 6 concludes.

2 Literature

The economic literature identifies three main mechanisms through which ICT can affect employment. We first consider how ICT can improve firm-worker matching, we then focus on the role of social networks in the job finding process, and we finally analyze firm productivity and self-employment. We describe for each dimension the mechanisms at play, and we provide evidence of these effects in the literature.

Firm-worker matching.

A first effect operates through job search practices on the Internet, which provides firms with an efficient way to advertise jobs and connect them with job seekers (Hjort and Tian, 2021). Hence, the Internet can reduce unemployment by speeding up the job-search process: individuals using the Internet to look for a job will find it quicker than with other mediums, and they may also find a job better fitted with their skills and wage demands. Kuhn and Mansour (2014) find indeed a positive effect of Internet job search on reducing unemployment duration in the U.S., and Bhuller et al. (2019) find a similar effect in Norway. This mechanism is potentially strong in markets with important search frictions such as Uganda (Bassi et al., 2017).

However, a high level of Internet penetration may be necessary for this effect to take place. Indeed, in a previous study Kuhn and Skuterud (2004) show that Internet job search is ineffective in reducing unemployment duration, probably because of the low level of adoption of the Internet in the U.S. job market at the time of the study, making online job-search practices inefficient. Whether the effect is at play in Uganda depends thus on Internet penetration, as well as on Internet use by firms and job seekers. For a more efficient job search to reduce unemployment duration, firms must be using the Internet as a job posting tool, and job seekers must be using the Internet for their job search process. We will show that web browsing on the Internet is not related to the different employment statuses considered in our analysis, suggesting that either respondents do not use the Internet for job-search practices, or that job search on mobile Internet is inefficient.

Stimulation of social networks

Social networks play an important role in the process of finding a job (Calvo-Armengol and Jackson, 2004; Magruder, 2010), especially as acquaintances are an important way through which information about job vacancies are disseminated among job seekers (Granovetter, 1973).

Kramarz and Skans (2014) analyze the role of networks and ties for the employment of job seekers who recently graduated, and show that social networks are important determinants of employment among the youth, in particular for job seekers with a low level of education, and in markets with few job postings.

Hence technologies enabling communications are expected to have a positive impact on employment through a better mobilization by job seekers of their remote acquaintances. For those who can expect support from their community, family and friends, communication technologies can help speed the job search process by improving the circulation of information (Cingano and Rosolia, 2012; Archambault, 2013). While for those without such a strong network, ICT can offer an interesting alternative to this support (Holzer, 1987). The Internet can indeed complement mobile phones in network mobilization. For instance, online social networks such as Facebook can be used to contact remote acquaintances without the need of having their phone numbers. We observe whether respondents use social networks on the Internet in our data set. We will show that online social networks do not significantly affect employment, but that they complement informal networks such as groups of financial support.

Enhanced productivity

Information and communication networks have a significant impact on the productivity of most economic activities by allowing better information for market participants. We identify three types of positive effects of information and communication technologies on firms and market efficiency.

First, for farming activities in rural areas, mobile phones can help to cope with weather hazards and market conditions (Ifeoma and Mthitwa, 2015; Lee and Bellemare, 2013; Krell et al., 2020). Better information on weather forecasts can help farmers to optimize their activities and reach a higher level of production.

Secondly, mobile phones can also help to smooth price dispersion in markets (Jensen, 2007). Better information about prices and demands can indeed allow producers to focus on markets with a high demand or a low offer, and sell their goods at a higher price by better responding to market characteristics (Andjelkovic and Imaizumi, 2012). In turn, such optimized market allocation allows producers to reach higher profits.

These first two effects can help ICT users to have a financially sustainable economic activity, and we thus expect mobile phone uses to have a positive impact on self-employment. However, these effects are unlikely to take place through the use of the Internet.

Nevertheless, the Internet also creates a new category of activities, as analyzed by Hjort and Poulsen (2019), who consider fast Internet and its impact on employment in Africa. They find positive effects of fast Internet on the average income, however with heterogeneous effects as less-educated workers see their revenue decreasing. Similarly, Avom et al. (2021) find that ICT have a positive impact on the creation of high-skilled jobs but a negative one on low-skilled jobs. As we focus on mobile Internet, which is in general not used for most work tasks, we do not expect to capture these last impacts of the Internet on high-skilled and low-skilled jobs.

3 Empirical Description

3.1 Telecommunications in Uganda

The overall rate of mobile phone subscriptions in Uganda in 2016 is 57.6%. For mobile Internet subscriptions, the rate was of 8.58% at the end of 2016.[8] These values are relatively low, especially compared with neighbouring countries such as Kenya, leading the way for new uses of information and communication technologies. These low penetrations are an important motivation for our focus on Uganda. Most of the literature has focused on Kenya and the success story of mobile financial services, with a risk that countries with a lower level of use of mobile phones are left behind in the economic analysis.

Figure 1 provides a map of the telecommunication network coverage for 2G, 3G, and 4G networks in Uganda.[9]

[8]Source: Statista, last accessed June 2, 2021.

[9]This map focuses on the latest data for the year 2019. Even though our data will be for the years 2015 and 2016, roll-outs of telecommunication networks take time, and the map is still informative of the level of development of telecommunication networks at the time of the survey.

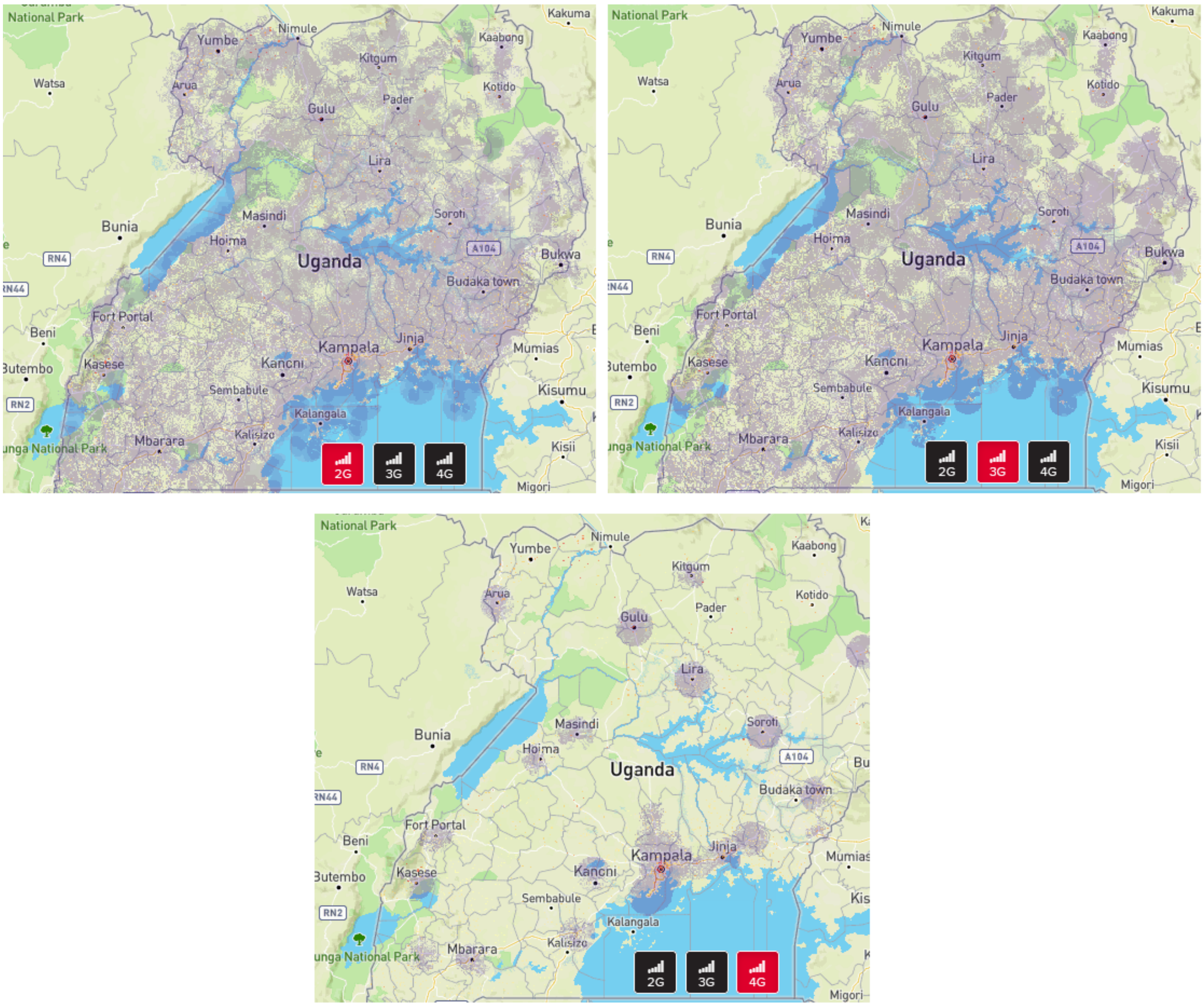

Figure 1: Network coverage in Uganda: 2G, 3G and 4G; source Open Signal, 2019.

Regarding 2G and 3G networks, almost the whole country benefits from access, apart from small isolated rural areas in the North-East part of the country. In contrast, 4G networks have a low level of roll-out, and mostly serve large cities. Rural areas thus typically do not have access to 4G networks. This limitation of geographical access to 4G translates into a low level of adoption of smartphones, which have a low utility compared with feature phones providing access to 2G and 3G. Most respondents using smartphones are thus concentrated in urban areas, where they can use 4G networks.

This important coverage by 2G networks – and 3G networks to a lesser extent – allows a wide adoption of mobile phone services, even those based on mobile Internet. In particular, we can show that even respondents in the poorest group use mobile social media such as Facebook or WhatsApp as much as the rest of the population.[10] Hence our analysis applies to the majority of the population and does not exclude the most vulnerable respondents.

3.2 Database

We use the Financial Inclusion Insights (FII) surveys for Uganda to conduct our empirical analysis. These surveys provide us with cross-sectional annual data for 2015 and 2016.

The FII surveys are designed to capture major mobile money trends in developing countries: banking, use of mobile money, relationships with financial institutions, use of non-bank financial instruments, etc. In addition to mobile money and other financial-related elements, they contain information about socio-demographic characteristics, and the ownership and use of mobile phones. In particular, we will consider mobile Internet uses such as social network or web browsing, as well as information on the type of mobile handset, and the frequency of basic mobile phone uses, which, to the best of our knowledge, are only provided by the FII surveys, and are absent from alternative data sets such as the Uganda National Household Survey.

The FII surveys have been conducted from 2013 to 2017. However, several important questions asked in the surveys have been changed over the years, and our focus is on the years 2015 and 2016 for which the questions we are interested in were asked. In particular, detailed questions about the uses of mobile Internet by respondents are the focus of this analysis.

Data from the FII surveys are representative of the national population in Uganda. Data are at the household levels, and households are chosen randomly based on the national census. We restrain our analysis to individuals that are employed or looking for a job, and we obtain a sample of 3.566 individuals.

An important characteristic of this data set concerns the structure of the job market. A vast majority of respondents have a job, and only 5.6% of the respondents are unemployed and looking for a job. However, when focusing on the nature of employment, a large share of respondents -

[10] However the poorest have fewer chances to own a feature and a smartphone. The result is available upon request.

38.2% - has an irregular source of income. This characteristic is one of the main motivations for our detailed analysis of mobile phone and mobile Internet use according to the different natures of employment. We detail in the next section how the different variables used in the analysis are constructed from the survey.

3.3 Explained variables

We are interested in three explained binary variables in our empirical analysis.

- *Being employed*: indicates whether the respondent has a job or is looking for one. In our sample, around 94 % of respondents have a job, taking part-time jobs and entrepreneurship into account.

- *Regular job*: indicates among employed respondents those who have a regular job, who account for roughly 66 % of respondents.

  With this variable, we want to look at the relationship between mobile phone use and the regularity of income. In particular, we will verify whether mobile phones are used by individuals with irregular incomes to find complementary sources of revenue.

- *Self-employed*: indicates among the employed respondents if they are self-employed. In our sample, this concerns around 35 % of respondents.

  Using this variable will help us to analyze how mobile phone and mobile Internet use affect entrepreneurship, as studied for instance by Andjelkovic and Imaizumi (2012) and Moyi (2019). Mobile Internet may be used by entrepreneurs to contact new customers through existing social networks for example.

3.4 Explanatory variables

3.4.1 Key variables: mobile phone use and ownership

We are interested in the effects of mobile phone ownership and uses. As certain uses, in particular for mobile Internet, require a specific handset such as a feature phone or a smartphone, we use a variable named *Mobile phone ownership* that takes value 0 if the respondent does not own a mobile phone, 1 if the respondent owns a basic mobile phone, 2 if the respondent owns a feature phone, and finally value 3 if the respondent owns a smartphone. In our sample, around 32 % of respondents do not own a mobile phone, roughly 21 % own a basic mobile phone, 40 % a feature phone and 7 % a smartphone. All types of phones cover basic functionalities such as text messaging and calling. However, basic mobile phones do not allow users to access social media or browse the Internet. Feature phones have some Internet capabilities but less than smartphones.

Besides mobile phone ownership, we consider four different types of mobile phone use, and we analyze their relation with the three explained variables described in section **3.3**. It is important to note that a respondent may borrow a mobile phone to perform some tasks. Our four variables related to mobile phone use therefore do not necessarily exclude respondents who do not own a mobile phone. We regroup these four variables under the name *Mobile phone use*.

Variables in *Mobile phone use* take the value 1 if the respondent has performed the task at least once in the week before the survey, and value 0 otherwise.

A limitation of these variables is that they allow only for an analysis of the weekly frequency of use, but not of a finer level (daily for example). Especially, we cannot distinguish between respondents who use their mobile phones several times a day from those who use them once a week. This limitation is due in part to the design of the survey, where the higher frequency of use is at the daily level. Moreover, we had to merge data at the weekly and daily level as this last group was composed of too few respondents, and considering separate groups would result in lower statistic robustness.

Nevertheless, frequency variables allow us to identify respondents who have regular use of mobile phones for basic operations from those who have a low frequency of use. Analyzing the economic behaviour of respondents in the latter group allows us to understand the relations between mobile phone use and economic activity.

Our four variables in *Mobile phone use* are the following:

1. *Last phone*: concerns basic uses of mobile phones (calls and text messages). In our sample, 83 % of respondents have used a phone for such activity in the week before the survey was taken.

2. *Last social media*: distinguishes respondents who have used social media such as Facebook or WhatsApp on their mobile phone from those who have not. In our sample, 9 % of respondents had used social media in the week before the survey.

3. *Last Internet*: this variable takes the value 1 when respondents have used a mobile phone for Internet browsing during the last week before the survey, which corresponds to around 9 % of the sample.

4. *Last smartphone use*: indicates whether a respondent has used a mobile phone to download music, videos, games or other mobile applications.

We want to analyze how the uses listed above are related to employment, the likelihood of having a job and job regularity. In the next section we describe the socio-demographic variables that we use to complement our analysis.

3.4.2 Other explanatory variables

We consider several socio-demographic variables to better understand the relations between mobile phone use and employment in Uganda. We have three groups of variables:

- *Group*: We use two variables to determine whether the respondent belongs to formal or informal social groups. *SACCO* is a binary variable that takes the value 1 if the respondent is a member of a Savings and Credit Cooperative Organization (SACCO). The variable *Number of informal groups* indicates the number of informal groups the respondent belongs to. Informal groups are defined here as informal group loan and savings schemes: investment groups or merry-go-round for example.

- *Financial situation*: We consider several variables to take respondents' financial situation into account. We use two binary variables to indicate whether a respondent has used a bank and/or a mobile money account to send money to (*Sending money*) or receive money from (*Receiving money*) friends, family or others. We also have a binary variable that indicates if the respondent has any savings (*Savings*). We also take into consideration whether part of a respondent's income comes from relatives with the binary variable *Income from social circle*.

- *Control variables*: We take also various individual or household-level characteristics into account: the age of the respondent (*Age*), gender (binary variable *Male*), whether the household is located in a rural or urban area (binary variable *Rural*) and number of members in the household (*Household size*). We also consider the education level with the variable *Education* that takes value 0 when the respondent has no formal education, value 1 when the respondent has only primary school education, value 2 when the respondent has stopped after secondary school and finally value 3 when the respondent has had higher education.

Descriptive statistics of all variables used in our empirical work can be found in table A1, appendix A.

4 Methodology

We want to analyze the relation between different uses of mobile phones (*Mobile phone use*) and:

- Having a job or not (*Being employed*)
- Having an irregular or a regular job (*Regular job*)
- Being self-employed (*Being self-employed*)

We also consider the type of mobile phone owned by respondents (if any) with the variable *Mobile phone ownership*.

We take several possible other factors into account in our empirical strategy: belonging to formal or informal social groups (*Groups*), sending, receiving, or saving money (*Financial situation*), and several individual or household characteristics (*Control variables*).

We thus have the following equations:

$$
\begin{aligned}
Y_{i,h} = \beta_0 &+ \Sigma_{j=1}^{j=4}\beta_{j,h}(\text{Mobile phone uses})_i \\
&+ \beta_{5,h}(\text{Mobile phone ownership})_i \\
&+ \Sigma_{j=6}^{j=7}\beta_{j,h}(\text{Group})_i \\
&+ \Sigma_{j=8}^{j=10}\beta_{j,h}(\text{Financial situation})_i \\
&+ \Sigma_{j=11}^{j=15}\beta_{j,h}(\text{Control variables})_i + \epsilon_{i,h}
\end{aligned} \tag{1}
$$

Where $h = 1, .., 3$ indexes the different explained variables:

- $Y_{i,1}$ = *Being employed;*
- $Y_{i,2}$ = *Regular job*;
- $Y_{i,3}$ = *Being self-employed.*

Our three dependent variables are binary, and we estimate three probit models using maximum likelihood estimation (MLE). We report the marginal effects in the estimations tables.

4.1 Instruments

There is a potential endogeneity issue if the variable *Mobile phone ownership* is correlated with hidden variables that also influence our explained variables. For example, mobile coverage could simultaneously affect the job market and the uses of mobile phones.

This potential endogeneity issue would bias our estimates if it were not taken into account. We thus specify a system of two equations. First, we have:

$$
\textit{Mobile phone ownership}_i = X_i\beta + \epsilon_1 \tag{2}
$$

where X_i is the set of control variables. Our main equations have the following form:

$$
Y_i = \textit{Mobile phone ownership}_i\, \delta + V_i\gamma + \epsilon_2 \tag{3}
$$

where V_i is a set of exogenous explanatory variables and δ is the parameter associated with the endogenous binary variable *Mobile phone ownership*. Equation 1 describes the specification of Equation 3 in more details.

For Equations 2 and 3, we assume that $(\epsilon_1, \epsilon_2)'$ is normally distributed with mean $(0, 0)'$ and standard error $(\sigma, \sigma)'$. We have the following covariance:

$$\Sigma = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix} \tag{4}$$

ρ is the parameter that indicates the value of the correlation between the unobserved variables. Following Knapp and Seaks (1998), we use a likelihood-ratio test of whether $\rho = 0$ as a Hausman endogeneity test. If $\rho = 0$ there is no potential issue of estimation bias due to endogeneity.

When $\rho \neq 0$, we use an Instrumental Variable approach to estimate a bivariate marginal effect probit model.

We use three instrumental variables:

- *Distance to nearest mobile money agent*
- *PPI cut-off*
- *Having electricity*

The first instrumental variable is the distance to the nearest mobile money agent. We use this instrument as a proxy for 2G mobile networks coverage, which is necessary for mobile money services to work. It can be reasonably expected that operators combine mobile network coverage with mobile money coverage. The majority of our sample (55.2%) is less than 1 km from a mobile money agent, which confirms that there is very broad mobile network coverage in Uganda.

Our second instrument is the variable *PPI cut-off* that takes the value 1 when the respondent is below a poverty line calculated using the Poverty Probability Index (PPI).[11] We use this variable as a proxy of wealth. 55.8% of our sample is estimated to be below the poverty line, while only 5.6% of respondents do not have a job. While at first glance, there is a risk of correlation between this instrument and employment – employed respondents having higher chances of being above the poverty threshold – we show in Table 2 that the correlation of employment with this second instrument is actually quite weak. Employed as well as unemployed respondents may live below the poverty line as we have defined it, since necessary conditions to be higher than the

[11] See the PPI website (last accessed July 6, 2021) for more details.

poverty threshold include for instance having a house with a roof or ground of certain materials, which are not directly related to employment.

Finally, we use the variable *Having electricity* as an instrument. As pointed out by Tadesse and Bahiigwa (2015), electric power is a good proxy for mobile phone ownership as mobile phones need to be charged regularly to function properly. Access to electric power is however quite low, as only 26.4% of our sample has one. There is again a low level of correlation between this instrument and employment, as a large share of employed respondents does not have electricity at home.

We thus specify Equation 2 as follows:

$$
\begin{aligned}
(\text{Mobile phone ownership})_i = \beta_0 &+ \Sigma_{j=1}^{j=4}\beta_j(\text{Mobile phone uses})_i \\
&+ \Sigma_{j=5}^{j=6}\beta_j(\text{Group})_i \\
&+ \Sigma_{j=7}^{j=9}\beta_j(\text{Financial situation})_i \\
&+ \Sigma_{j=10}^{j=14}\beta_j(\text{Control variables})_i \\
&+ \beta_{15}(\text{Distance to nearest mobile money agent})_i \\
&+ \beta_{16}(\text{PPI cut-off})_i \\
&+ \beta_{17}(\text{Having electricity})_i + \epsilon_i
\end{aligned} \tag{5}
$$

We insure that our three instrumental variables strongly influence mobile phone ownership while having limited effect on our explained variables by checking their respective correlations:

Table 1: Correlations table

	Mobile phone ownership	Being employed	Regular job	Being self-employed
Distance to nearest mobile money agent	-0.276	0.080	-0.236	-0.050
PPI cut-off	-0.371	0.076	0.323	-0.045
Having electricity	0.123	-0.091	0.058	-0.0001

All three of our instrumental variables have a higher correlation with the potentially endogeneous variable *Mobile phone ownership* than with our explained variables. We report in the following table the results of likelihood-ratio tests of whether $\rho = 0$ for all our regressions:

Table 2: Results - Likelihood-ratio tests of whether $\rho = 0$

	Full sample	Men	Women
Being employed	-0.147 (0.369)	-0.984^{***} (0.015)	0.160 (0.220)
Regular job	-0.514^{***} (0.105)	-0.610^{***} (0.164)	-0.575^{***} (0.121)
Being self-employed	-0.371^{*} (0.179)	-0.568 (0.376)	-0.402^{**} (0.174)
Note:	*p<0.1; **p<0.05; ***p<0.01		

We find that there is an endogeneity issue for male respondents regarding whether they have a job or not. We also find this for job regularity and for the full sample and female respondents only for being self-employed.

If ρ is significantly different from 0 we use the two-steps approach described above. Otherwise, we estimate only Equation 1 with a probit model.

4.2 Multicollinearity bias

Specifying our regression models with four variables of mobile phone uses simultaneously (*Last phone*, *Last social media*, *Last Internet* and *Last smartphone use*) could lead to a multicollinearity bias. For instance, respondents who use the Internet on their smartphones frequently also call and send messages more frequently than other respondents. We therefore verify for each of our regressions that no variance inflation factor (VIF) is greater than 5. This is the case for all displayed results afterward.[12] Moreover, even though the regressions in our analysis display all variables of use simultaneously, we also run them separately taking only one of the variables into account, and we find no significant difference in the results.[13]

5 Results and interpretation

We analyze in this section the relation between mobile phone use and employment. We first compare the uses between respondents who are employed and those looking for a job. Then we

[12]VIF statistics available upon request.

[13]The different regressions are not displayed in the article for readability, and are available upon request.

distinguish between those having a regular job and those working with irregularity. Finally we consider self-employment.

All results displayed in the following tables are marginal effects.

5.1 Mobile phone and employment

In the first set of regressions that we present in Table 3, we analyze the relation between the different uses of a mobile phone and in particular mobile Internet and being employed or looking for a job.

Table 3: Results - Being employed

Dependent variable: Being employed	Full sample	Men	Women
Mobile phone use			
Last phone	0.014 (0.009)	-0.089^{***} (0.020)	-0.0005 (0.015)
Last social media	0.008 (0.016)	-0.017 (0.038)	0.058^{***} (0.022)
Last Internet	-0.010 (0.015)	-0.009 (0.039)	-0.026^{*} (0.014)
Last smartphone use	-0.011 (0.013)	-0.007 (0.021)	-0.032^{***} (0.011)
Mobile phone ownership			
Basic mobile phone	-0.031^{**} (0.013)	0.312^{***} (0.051)	-0.067^{***} (0.023)
Feature phone	-0.009 (0.009)	0.309^{***} (0.052)	-0.004 (0.011)
Smartphone	-0.016 (0.016)	0.307^{***} (0.054)	-0.001 (0.021)
Group			
SACCO	0.018 (0.017)	-0.016 (0.038)	0.068^{***} (0.025)
Number of informal groups	0.274^{***} (0.097)	0.003 (0.011)	0.041^{***} (0.011)
Financial situation			
Sending money	0.019^{**} (0.008)	0.050^{***} (0.016)	0.012 (0.013)
Receiving money	0.021^{**} (0.008)	-0.020 (0.015)	-0.006 (0.016)
Savings	0.033^{***} (0.009)	0.051^{**} (0.021)	0.048^{***} (0.015)
Control variables	Yes	Yes	Yes
Dependent variable: Mobile phone ownership			
Instrument			
Distance to nearest mobile money agent		-0.017^{**} (0.009)	
PPI cut-off		-0.076^{***} (0.025)	
Having electricity		-0.008 (0.020)	
Observations	3566	1469	2097
Note:	*p<0.1; **p<0.05; ***p<0.01		

We find that employed men have higher chances to own a basic mobile phone, even though they have less frequent basic uses – calling and texting – than unemployed men. This result suggests that employment supports phone ownership, but that men have higher interests in the basic uses of mobile phones when they are unemployed. However, employed men have a higher tendency to send or receive money than the unemployed, and we can conclude that the greater frequency of basic uses among the unemployed is not related to practices of financial support. A simple explanation may be that employed respondents have less time for calling and texting than the unemployed, and therefore use them less frequently.

We find no evidence that mobile Internet can be used by unemployed respondents to look for a job. They have fewer chances of owning a feature phone or a smartphone than the employed, and they do not tend to use them more frequently. Contrary to basic mobile uses, mobile Internet uses are more costly[14] and unemployed respondents may not have the money to browse or use social media on their mobile phone.

Among women, we surprisingly find a significant negative relation between having a basic phone and being employed. This result contributes to recent studies by Ebaidalla (2014) and Metu et al. (2020) that show that increasing the rate of mobile subscription would reduce unemployment among the youngest. Our results also highlight the importance of basic mobile phones for unemployed women, but the granularity of our data does not allow us to conclude that mobile phones are used for job search practices. In particular, unemployed women may rely more heavily on networks of financial support than employed women. In this case, a mobile phone can be a useful tool to ask for financial support. Owning a feature phone or a smartphone has no significant effect on the likelihood of having a job.

Women respondents without a job tend to use smartphones and to browse the Internet more frequently than employed women. This may be explained by the low level of adoption of smartphones, which is limited to the wealthiest part of the population. Hence among this group, women may be unemployed because they can afford not to work, and are therefore less financially constrained than employed women without a smartphone. In this case, unemployed women owning a smartphone have more time, and can afford to use their smartphones more

[14] GSMA Connected Society Uganda, 2018.

frequently than those outside this group. We find however that employed women use social media on their mobile phones more frequently than the unemployed. This higher frequency of use may be explained by the greater tendency of employed women to belong to saving groups and informal groups, and thus to exchange frequently with the members of these groups.

Finally, there seems to be no significant benefit of mobile Internet uses compared with standard mobile phone use for job-seeking practices. We analyze in the next section whether mobile phone and in particular mobile Internet are used by those having an irregular job.

5.2 Mobile phone and job regularity

In the second set of regressions presented in Table 4, we analyze how job regularity is linked to the different uses of mobile phones and of mobile Internet.

Table 4: Results - Regular job

Dependent variable: Regular job	Full sample	Men	Women
Mobile phone use			
Last phone	-0.131^{***}	-0.225^{***}	-0.093^{**}
	(0.037)	(0.064)	(0.038)
Last social media	-0.028	-0.043	0.010
	(0.056)	(0.076)	(0.070)
Last Internet	0.006	0.001	0.021
	(0.064)	(0.081)	(0.084)
Last smartphone use	0.011	0.027	-0.024
	(0.036)	(0.048)	(0.047)
Mobile phone ownership			
Basic mobile phone	0.416^{***}	0.460^{***}	0.452^{***}
	(0.067)	(0.093)	(0.077)
Feature phone	0.408^{***}	0.474^{***}	0.402^{***}
	(0.060)	(0.080)	(0.074)
Smartphone	0.519^{***}	0.577^{***}	0.538^{***}
	(0.066)	(0.087)	(0.079)
Group	No	No	No
Financial situation			
Sending money	0.020	-0.017	0.064^{**}
	(0.023)	(0.034)	(0.029)
Receiving money	0.024	0.034	0.009
	(0.021)	(0.029)	(0.029)
Savings	0.128^{***}	0.143^{***}	0.087^{*}
	(0.035)	(0.042)	(0.052)
Control variables	Yes	Yes	Yes
Dependent variable: Mobile phone ownership			
Instrument			
Distance to nearest mobile money agent	-0.009	-0.018^{*}	0.001
	(0.008)	(0.010)	(0.010)
PPI cut-off	-0.141^{***}	-0.092^{***}	-0.190^{***}
	(0.020)	(0.026)	(0.025)
Having electricity	0.006	-0.028	0.041^{*}
	(0.020)	(0.024)	(0.025)
Observations	3365	1407	1958
Note:	*p<0.1; **p<0.05; ***p<0.01		

We find that respondents with a regular job have higher chances to own any type of mobile phone, even though they have less frequent basic uses – calling and texting – than those with an irregular job. This result suggests that job regularity supports phone ownership, but that those with irregular jobs have higher benefits from using mobile phones for calling and texting. This may be explained by the nature of the activities of those with irregular jobs. Mobile phones are useful to contact potential employers or potential clients, and are thus important tools for those with irregular jobs. This effect does not hold for mobile Internet uses – social media and web browsing – which may again be explained by the significantly higher costs of these uses compared with text-sending and calling.

Women who hold a regular job send money significantly more frequently than those with irregular jobs. There is no significance when considering male respondents or the whole sample. These results have interesting connections with the conclusions of Archambault et al. (2010) who show that in Mozambique, it is expected for women to actively seek and provide financial support, while it is less likely to be the case among men.

Regardless of gender, we do not find any significant effect of belonging to more informal groups or having a fraction of revenue coming from supportive relatives or friends on job stability. However, we find that those with a regular job have a higher tendency to save money, which is coherent with the fact that they may also have significantly higher revenues.

5.3 Mobile phone and self-employment

We now turn to mobile phone and mobile Internet use by respondents who are self-employed or own their businesses. This part of the population is mostly composed of rural respondents, relatively old and for a majority, women. Results are reported in Table 5.

Table 5: Results - Self-employed

Dependent variable: Being self-employed	Full sample	Men	Women
Mobile phone use			
Last phone	-0.113^{*} (0.061)	-0.051 (0.055)	-0.070 (0.060)
Last social media	-0.041 (0.053)	-0.034 (0.080)	-0.050 (0.088)
Last Internet	-0.069 (0.055)	-0.021 (0.078)	-0.148^{*} (0.087)
Last smartphone use	-0.015 (0.031)	-0.031 (0.044)	0.027 (0.042)
Mobile phone ownership			
Basic mobile phone	0.267^{***} (0.082)	0.091^{**} (0.044)	0.301^{***} (0.097)
Feature phone	0.267^{***} (0.082)	0.115^{***} (0.043)	0.262^{***} (0.097)
Smartphone	0.246^{***} (0.093)	0.124^{*} (0.074)	0.154 (0.104)
Group			
SACCO	-0.002 (0.032)	0.001 (0.045)	-0.006 (0.041)
Number of informal groups	0.041^{**} (0.016)	0.038^{**} (0.018)	0.044^{***} (0.020)
Financial situation	No	No	No
Control variables	Yes	Yes	Yes
Dependent variable: Mobile phone ownership			
Instrument			
Distance to nearest mobile money agent	-0.008 (0.007)		0.00007 (0.010)
PPI cut-off	-0.121^{***} (0.020)		-0.166^{***} (0.028)
Having electricity	0.011 (0.020)		0.045^{*} (0.024)
Observations	3365	1407	1958
Note:	*p<0.1; **p<0.05; ***p<0.01		

Overall, we find a similar result to previous sections, as regardless of gender, respondents who are self-employed have a higher tendency to own mobile phones and feature phones than other employed respondents. However, contrary to previous results where phone ownership was inversely correlated with the frequency of basic uses, we find here that the self-employed are not less likely to use their mobile phones than the rest of the population. Note that self-employment is usually associated with lower revenues than employment, and the self-employed are in general considered a financially fragile part of the population.[15] Hence the fact that those respondents have a higher probability to own mobile handsets of different types highlights the uses that the self-employed may make of the mobile phone for job-related activities, such as contacting clients or suppliers for instance. This result is in line with the analysis of Moyi (2019) who finds that, in the case of Kenya, access and uses of mobile phone technologies drive respondents' decision to become self-employed.

6 Conclusion

As there is an important potential impact of mobile Internet on employment, it is essential to evaluate the stage of adoption and uses of mobile Internet by the population. A better understanding of these uses may help policymakers to optimally target schemes of support for the adoption of different information and telecommunication technologies and reach a more efficient impact of such policies on employment. In this article, we find no evidence of a positive impact of mobile Internet uses on employment, job regularity, or self-employment in Uganda. This result echoes Kuhn and Skuterud (2004) who find no effect of Internet job search on unemployment duration. In line with their conclusions, our results suggest that either respondents do not use mobile Internet for job search – by responding to ads or by mobilizing a social network – or that job search practices on mobile Internet are ineffective. Alternatively, Asongu and Odhiambo (2020) highlight a minimum threshold for mobile phone penetration rates to have a significant impact on employment. In such a case, the absence of correlation between mobile Internet uses and employment could be explained by a low level of adoption of the Internet and the importance of alternative means of communication in Uganda. Positive effects of mobile Internet could then arise in the future, if a sufficient share of the population adopts and uses mobile Internet frequently enough.

[15] Uganda National Household Survey 2016/17, last accessed December 22, 2021.

Hence, we highlight the importance of basic phone uses such as calling and sending text messages, which play an important role in the everyday life of respondents, for professional activities, but also as a tool to ask and provide financial support. However, those most in need have fewer chances of owning a mobile phone than the rest of the population. Our study suggests therefore that policymakers should ensure in priority that basic mobile phones are made more accessible to the population, before focusing on the roll-out of recent networks such as 4G and 5G. 2G networks are available on almost the whole territory, and the next step is to make handsets – even basic ones – and airtime available too.

Several regulatory measures have recently been proposed to increase the affordability of basic mobile phones. On the one hand, regulators can increase basic phone adoption by lowering their price. A first step to reduce handsets prices may be to reduce taxes, which would go against the recent measure of the Ugandan government to impose a 10% tax on imported mobile handsets.[16] Such measure aims at raising the price of imported handsets to improve the competitiveness of domestic phones, but may eventually lower the incentives of Ugandans to purchase a mobile phone. On the contrary, a subsidy of basic mobile phones would increase adoption by the population with the lowest revenues. There is already a Universal Access Fund for ICTs in Uganda – the Rural Communications Development Fund[17] – which could implement such subsidy. Regulators could even directly give mobile handsets to those who do not own one, in the spirit of cash transfers for development (Hanlon et al., 2012; Van Hove and Dubus, 2019).

On the other hand, regulators can also increase the frequency of use of mobile phones by controlling directly the airtime price (Mathur et al., 2015; Hasbi and Dubus, 2020). Recent measures have been implemented in Uganda to tax Internet airtime resulting in a higher price and a lower affordability for mobile phone users.[18] This follows a regional trend as airtime taxes have also been implemented in Kenya,[19] and are under consideration in Nigeria.[20] We argue on the contrary that the widespread use of basic mobile phones requires the affordability of mobile airtime and that regulators should therefore focus on reducing their prices.

[16] Uganda to impose 10% tax on imported phones; ITWEB Africa, June 10, 2020.
[17] The Rural Communications Development Fund (RCDF) – Project Brief, last accessed, March 21, 2022.
[18] Uganda introduces 12% internet data levy, critics say move will stifle online access.
[19] Excise duty on airtime rings up gloom across EA region; The East African, July 15, 2021.
[20] Nigeria considering excise tax on telecoms airtime charges; Reuters, June 15, 2021.

Further research could analyze the role of social media on the Internet with mechanisms of international financial support. Our study does not capture this dimension, and focuses on domestic networks. Social media such as Facebook and WhatsApp are much cheaper than phone networks, and they may be used as a tool for remittances and emergency support.

References

Aker, J. C. and Mbiti, I. M. (2010), 'Mobile phones and economic development in africa', *Journal of economic Perspectives* **24**(3), 207–32.

Andjelkovic, M. and Imaizumi, S. (2012), 'Mobile entrepreneurship and employment', *Innovations: Technology, Governance, Globalization* **7**(4), 87–100.

Archambault, J. S. (2013), 'Cruising through uncertainty: Cell phones and the politics of display and disguise in inhambane, mozambique', *American Ethnologist* **40**(1), 88–101.

Archambault, J. S., Ngaméni, N. M. et al. (2010), 'La fièvre des téléphones portables: un chapitre de la "success story" mozambicaine?', *Politique africaine* (1), 83–105.

Asongu, S. A. and Odhiambo, N. M. (2020), 'Inequality and gender inclusion: Minimum ict policy thresholds for promoting female employment in sub-saharan africa', *Telecommunications Policy* **44**(4), 101900.

Avom, D., Dadegnon, A. K. and Igue, C. B. (2021), 'Does digitalization promote net job creation? empirical evidence from waemu countries', *Telecommunications Policy* p. 102215.

Bassi, V., Nansamba, A. and Liberia, B. (2017), 'Information frictions in the labor market: Evidence from a field experiment in uganda', *University College London. Processed* .

Bhuller, M., Kostol, A. and Vigtel, T. (2019), 'How broadband internet affects labor market matching', *Available at SSRN 3507360* .

Calvo-Armengol, A. and Jackson, M. O. (2004), 'The effects of social networks on employment and inequality', *American economic review* **94**(3), 426–454.

Cingano, F. and Rosolia, A. (2012), 'People i know: job search and social networks', *Journal of Labor Economics* **30**(2), 291–332.

Commission, A. U. et al. (2021), 'Digital transformation for youth employment and agenda 2063 in west africa'.

Ebaidalla, E. M. (2014), Effect of icts on youth unemployment in sub saharan africa: A panel data analysis, *in* 'African Economic Conference'.

Granovetter, M. S. (1973), 'The strength of weak ties', *American journal of sociology* **78**(6), 1360–1380.

Hanlon, J., Barrientos, A. and Hulme, D. (2012), *Just give money to the poor: The development revolution from the global South*, Kumarian Press.

Hasbi, M. and Dubus, A. (2020), 'Determinants of mobile broadband use in developing economies: Evidence from sub-saharan africa', *Telecommunications Policy* **44**(5), 101944.

Hjort, J. and Poulsen, J. (2019), 'The arrival of fast internet and employment in africa', *American Economic Review* **109**(3), 1032–79.

Hjort, J. and Tian, L. (2021), 'The economic impact of internet connectivity in developing countries'.

Holzer, H. J. (1987), 'Informal job search and black youth unemployment', *The American Economic Review* **77**(3), 446–452.

Ifeoma, O. D. and Mthitwa, H. T. (2015), An analysis of the impact of the use of mobile communication technologies by farmers in zimbabwe. a case study of esoko and ecofarmers platforms, *in* 'Proceedings of SIG GlobDev Pre-ECIS Workshop', SIG GlobDev Munster, Germany.

Jensen, R. (2007), 'The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector', *The quarterly journal of economics* **122**(3), 879–924.

Kasse, J. P., Munuulo, J. and Nagujja, S. (2015), 'Empowerment digital divide: Case of internet adoption in uganda's rural urban areas', *Advances in Social Sciences Research Journal* **2**(11), 77–84.

Knapp, L. G. and Seaks, T. G. (1998), 'A hausman test for a dummy variable in probit', *Applied Economics Letters* **5**(5), 321–323.
URL: *https://doi.org/10.1080/758524410*

Komunte, M. (2015), 'Usage of mobile technology in women entrepreneurs: A case study of uganda', *The African Journal of Information Systems* **7**(3), 3.

Kramarz, F. and Skans, O. N. (2014), 'When strong ties are strong: Networks and youth labour market entry', *Review of Economic Studies* **81**(3), 1164–1200.

Krell, N., Giroux, S., Guido, Z., Hannah, C., Lopus, S., Caylor, K. and Evans, T. (2020), 'Smallholder farmers' use of mobile phone services in central kenya', *Climate and Development* pp. 1–13.

Kuhn, P. and Mansour, H. (2014), 'Is internet job search still ineffective?', *The Economic Journal* **124**(581), 1213–1233.

Kuhn, P. and Skuterud, M. (2004), 'Internet job search and unemployment durations', *American Economic Review* **94**(1), 218–232.

Lee, K. H. and Bellemare, M. F. (2013), 'Look who's talking: the impacts of the intrahousehold allocation of mobile phones on agricultural prices', *The Journal of Development Studies* **49**(5), 624–640.

Magruder, J. R. (2010), 'Intergenerational networks, unemployment, and persistent inequality in south africa', *American Economic Journal: Applied Economics* **2**(1), 62–85.

Mathur, A., Schlotfeldt, B. and Chetty, M. (2015), A mixed-methods study of mobile users' data usage practices in south africa, *in* 'Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing', pp. 1209–1220.

Metu, A. G., Ajudua, E., Eboh, I., Ukeje, C. and Madichie, C. (2020), 'Ending youth unemployment in sub-saharan africa: Does ict development have any role?', *African Development Review* **32**, S20–S31.

Moyi, E. D. (2019), 'The effect of mobile technology on self-employment in kenya', *Journal of Global Entrepreneurship Research* **9**(1), 1–13.

Tadesse, G. and Bahiigwa, G. (2015), ‘Mobile phones and farmers’ marketing decisions in ethiopia’, *World Development* **68**, 296–307.
URL: *https://www.sciencedirect.com/science/article/pii/S0305750X14004082*

Van Hove, L. and Dubus, A. (2019), ‘M-pesa and financial inclusion in kenya: of paying comes saving?’, *Sustainability* **11**(3), 568.

A Descriptive statistics

Table A1: Descriptive statistics

Variables		Full sample (N = 3566)	Men (N = 1469)	Women (N= 2097)
Explained variables				
Being employed	Yes	94.4%	95.8%	93.4%
	No	5.6%	4.2%	6.6%
Regular job	Yes	56.1%	56.8%	55.7%
	No	38.3%	39.0%	37.7%
Being self-employed	Yes	61.2%	65.8%	58.0%
	No	33.1%	30.1%	35.3%
Mobile phone use				
Last phone	During the last week	82.6%	86.5%	79.8%
	Never or longer	17.4%	13.5%	20.2%
Last social media	During the last week	9.1%	12.4%	6.8%
	Never or longer	90.9%	87.6%	93.2%
Last Internet	During the last week	9.6%	12.8%	7.3%
	Never or longer	90.4%	81.2%	92.7%
Last smartphone use	During the last week	10.2%	12.8%	8.4%
	Never or longer	89.8%	87.1%	91.7%
Mobile phone ownership				
No mobile phone		31.8%	23.1%	37.9%
Basic mobile phone		20.6%	23.1%	18.8%
Feature phone		40.2%	43.6%	37.9%
Smartphone		7.4%	10.2%	5.4%
Group				
SACCO	Yes	8.4%	9.2%	7.9%
	No	91.6%	90.8%	92.1%
Number of informal groups	0	60.1%	65.5%	56.4%
	1	28.2%	24.4%	30.9%
	2	8.4%	7.0%	9.4%
	3	2.4%	2.5%	2.3%
	4	0.5%	0.4%	0.6%
	5	0.3%	0.3%	0.2%
	6 or more	0.1%	0.0%	0.1%
Financial situation				
Sending money	Yes	39.6%	46.3%	35.0%
	No	60.4%	53.7%	65.0%
Receiving money	Yes	47.4%	50.2%	45.5%
	No	52.6%	49.8%	54.5%
Savings	Yes	12.0%	17.0%	8.5%
	No	88.0%	83.0%	91.5%

Table A2: Descriptive statistics - continued

Variables		Full sample (N = 3566)	Men (N = 1469)	Women (N= 2097)
Control variables				
Age	15-25 years old	30.0%	26.7%	29.5%
	26-30 years old	18.9%	17.4%	19.9%
	31-35 years old	11.8%	12.2%	11.4%
	36-40 years old	10.6%	11.0 %	10.4%
	41-55 years old	15.2%	21.6%	18.7%
	Over 55 years old	13.5%	11.2%	10.1%
Rural	Yes	71.6%	75.6%	68.7%
	No	28.4%	24.4%	31.3%
Household size	1 member	16.8%	23.6%	12.1%
	2 members	13.3%	10.7%	15.1%
	3 members	15.3%	12.6%	17.1%
	4 members	15.3%	13.9%	16.4%
	5 members	15.8%	14.1%	17.1%
	6 or more members	23.5%	25.1%	12.3%
Education	No formal education	10.7%	6.7%	13.5%
	Primary school	51.3%	49.9%	52.2%
	Secondary school	32.6%	36.1%	30.0%
	Higher than secondary school	5.5%	7.2%	4.2%
Instruments				
Distance to nearest mobile money agent	0.5km or less	36.6%	32.3%	39.6%
	0.5km to 1 km	18.6%	18.1%	18.9%
	More than 1km to 5km	23.0%	26.1%	20.8%
	More than 5km to 10km	21.8%	23.5%	20.7%
	More than 10km to 15km	0.0%	0.0%	0.0%
	More than 15km	0.0%	0.0%	0.0%
PPI cut-off	Above poverty line	44.2%	45.2%	43.5%
	Below poverty line	55.8%	54.8%	56.5%
Having electricity	Yes	26.4%	25.5%	73.0%
	No	73.6%	74.5%	27.0%