Infrastructure Deficiencies and Adoption of Mobile Money in Sub-Saharan Africa*

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Abstract

We use survey data conducted in 11 countries in Sub-Saharan Africa in 2011 to analyze how the availability of physical infrastructure influences adoption of mobile phones and usage of mobile services. The availability of physical service infrastructure is approximated by data on nighttime light intensity in the areas in which survey respondents reside. After controlling for a number of individual and household characteristics including disposable income, we find that adoption of mobile phones is higher in areas with better physical infrastructure. However, in the group of mobile phone adopters, the use of mobile phones for mobile financial transactions is negatively influenced by the level of infrastructure. Mobile phone users who live in areas with poor infrastructure are more likely to rely on mobile phones to make financial transactions than individuals living in areas with better infrastructure. On the other hand, the use of mobile phones to access services such as email, skype, social media networks and Internet browsing is not dependent on the availability of physical infrastructure. Our results support the notion that mobile phones improve the livelihood of individuals residing in remote areas by providing them with access to financial services which are otherwise not available physically. Moreover, we find that all income groups equally benefit from mobile financial services.

Keywords: mobile money; M-Pesa; Sub-Saharan Africa; nighttime light data

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1 Introduction

The deployment of mobile telecommunications allows to overcome one of the main burdens to economic growth in low income countries, which is poor or non-existent fixed-line infrastructure and lack of Internet access. Access to mobile telecommunications can dramatically improve standard of living in those countries by saving wasted trips, providing information about prices or serving as a conduit to banking, health care and other services. Aker & Mbiti (2010) identify a few potential mechanisms through which mobile phones can provide economic benefits to consumers and producers in low income countries. First, mobile phones can increase market efficiency by improving access to information and reducing search costs. Second, better communication can improve management of supplies and increase productive efficiency of firms. Third, mobile phones facilitate services which are in general not available to low income households, such as mobile phone-based financial, agricultural, health, and educational services. In this paper, we focus on the third point and analyze how the availability of physical infrastructure influences the adoption of mobile phones and the use of mobile phone services such as mobile money.

As of 2014, mobile-cellular penetration in low income countries reached 90%, as compared with 121% in high income countries.[1] The main reasons for lack of access to financial services are deficient infrastructure, inaccessibility and financial illiteracy. Mobile phones can change this situation by enabling people to make use of financial services surpassing the problem of poor physical infrastructure. Mobile banking or m-money provides access to account balances and money transfers using mobile networks, which does not require the proximity of other physical infrastructure.[2] In this way, the expansion of mobile banking may have a significant impact on the economic growth and poverty reduction in the low income countries.

So far, there is a very short body of literature on the adoption of mobile financial services in low income countries.[3] This is largely due to shortage of individual-level data on the use of

[1] see www.itu.int At the same time, in low income countries only about 54% have an account, as compared to 94% in high income countries.www.worldbank.org

[2] For instance, one of the main South African banks, Standard Bank, as of 2012 operated about 10,000 so-called bank shops in townships with predominantly black population. These bank shops have a mobile phone banking capability allowing clients to do money transfers. They enable hawkers, who usually close shops in the evening when banks are already closed, to use the bank shops to deposit their money.

[3] The empirical literature focused on the adoption of mobile phones is already mature. For instance, Grzybowski (2015) analyzes adoption of mobile phones using panel data of South African households.

mobile banking in low income countries. Aggregate country-level data cannot fit the purpose because of short time span since the availability of mobile banking and low level of adoption in the majority of countries world-wide. Among few available studies, Mbiti & Weil (2011) use two waves of individual-level data in Kenya to analyze the use of M-Pesa. They find that use of M-Pesa lowers the propensity of people to use informal savings mechanisms but raises their probability of being banked. Gutierrez & Singh (2013) use data on 37,000 individuals from 35 countries to analyze factors which determine mobile banking usage. They construct a regulatory index and find that a supporting regulatory framework is associated with a higher use of mobile banking for the general population as well as for the unbanked. They conclude that regulators can foster the development of mobile banking services through the enactment of supporting regulation. In another paper, Economides & Jeziorski (2014) use mobile financial transactions among subscribers of a major mobile phone service provider in Tanzania during three months and to estimate price elasticities for different types of transactions. They find that demand for long-distance transfers is less elastic than for short-distance transfers, which suggests that mobile networks actively compete with antiquated cash transportation systems in addition to competing with each other. They use the demand estimates to provide measures of willingness to pay to avoid carrying cash in the pocket when traveling as well as keeping cash at home.

There is also short but growing literature on the impact of mobile phones on the wellbeing of people. For instance, Jensen (2007) uses data on fishermen in Indian state Kerala to shows that usage of mobile phones may improve market performance and increase welfare. In another paper, Aker (2008) analyzes how the phasing-in of mobile phone coverage between 2001 and 2006 affected grain prices in Niger. Klonner et al. (2010) analyse the effect of mobile phone coverage on rural labor market outcomes in South Africa. Using a qualitative approach Bourreau & Valletti (2015) asses the economic features of mobile payment in low income countries. They conclude that mobile money has the potential to drive financial inclusion to the poor at low cost.

Our paper contributes to this literature by analyzing how the availability of physical infrastructure influences adoption of mobile phones and mobile financial services. We estimate a number of logit models using a survey data of individuals from eleven Sub-Saharan African countries, which was conducted in 2011 by ICT Research Africa.[4] The survey data is comple-

[4]For information see http://www.researchictafrica.net

mented with the Defense Meteorological Satellite Program Open Linear Scanner (DMSP/OLS) nighttime light intensity data, which we use to approximate the availability of service infrastructure at the location of survey respondents. The use of nighttime light intensity data enables us to analyze how spatial differences in infrastructure development across Sub-Saharan Africa influence the adoption of mobile phones and use of mobile services by individuals.

After controlling for a number of individual and household characteristics including disposable income, we find that adoption of mobile phones is higher in areas with better physical infrastructure. However, the estimation results suggest that in the group of mobile phone adopters the use of mobile phones for financial transactions is negatively influenced by the level of infrastructure development. Individuals who live in areas with poor infrastructure are more likely to use mobile phones to make financial transactions than individuals living in areas with better infrastructure. On the other hand, in the group of mobile phone adopters, the use of mobile phones to access services such as email, skype, social media networks and Internet browsing, does not depend on the availability of physical infrastructure. Our results support the notion that mobile phones improve the livelihood of individuals who reside in remote areas by providing them with access to services which are otherwise not available physically. Moreover, we find that all income groups equally benefit from mobile financial services.

The remainder of the paper is organized as follows. In Section 2 we discuss the evolution of mobile phone industry in Sub-Saharan Africa. Section 3 discusses the data sets used in the paper. Section 4 introduces the econometric model and Section 5 presents the estimation results. Finally, Section 6 concludes.

2 Mobile Services in Sub-Saharan Africa

Due to poor fixed-line infrastructure, the Sub-Saharan Africa almost completely skipped the era of fixed-line services and embraced mobile phones for the use of both voice and Internet services. Before the deployment of mobile phone infrastructure, most individuals, and especially those living in remote areas, did not have access to telecommunications services at all. Figure 1 shows the total number of mobile and fixed-line subscribers in the eleven surveyed countries in years 2000-2014. The number of mobile phone subscriptions increased from 9.3 million in 2000 to 396.3 million in 2014. At the same time, the number of fixed-line connections stagnated,

growing from about 6.8 million in 2000 to 7.8 million in 2014.[5] This exponential growth in mobile phone adoptions can be attributed to the introduction of prepaid mobile services, due to which mobile phones became affordable to a broader group of consumers. In our survey data, 95% of individuals with access to mobile services declared using prepaid. Figure 2 shows changes in the number of mobile subscriptions per population in 11 countries included in the survey. There are substantial differences in the growth rate and the average number of SIM cards across these countries. In 2014, Botswana had the highest subscription rate with about 167 SIM cards per 100 inhabitants, followed by South Africa with (150 SIM cards), Ghana (115 SIM cards) and Namibia (114 cards). On the opposite end is Ethiopia with 32 SIM cards per 100 inhabitants.[6]

Many of mobile phone users in Sub-Saharan Africa live in remote ares without access to basic physical infrastructure and services. The evolution of the mobile networks coupled with advancement of mobile technologies has led to the emergence of various initiatives which rely on mobile phones to provide financial, health care, agricultural and other services. In 2008, a number of mobile phone operators in Sub-Saharan Africa started to deploy the 3G networks. This increased Africa's internet connectivity which was as low as zero in most of the countries. However, increased demand in mobile phone services and broadband Internet puts pressure on the current network capacity. To ease pressure on their networks most operators in Africa are now connected to the fiber optics cable and are migrating from the 3G to the 4G/LTE networks, which enable high speed Internet access. These technologies allow users to browse the Internet, engage in mobile commerce, receive and send emails and connect with friends on social media networks.

Mobile Money

Mobile phone services are defined as the use of mobile phones to remotely access services which are typically provided over the counter. In particular, we analyze the determinants of use of: (i) mobile money and (ii) mobile social and Internet activities.

The provision of financial services on the mobile phone, which is typically called mobile banking, enables consumers to use mobile phones to access bank accounts, transfer money,

[5] Own calculation from ITU mobile phone subscriptions data

[6] To increase coverage with mobile infrastructure some countries such as Botswana allowed for infrastructure sharing by mobile operators, which reduced cost of network development in remote areas.

make payments and perform other financial operations. A mobile phone can serve as a virtual bank card, a point of sale terminal, an automated teller machine (ATM), and an internet banking terminal which provides an immediate access to accounts and enables to make transfers remotely. The services may be provided by a particular financial institution as an addition to its existing electronic banking services, or independently by telecommunications providers. Alternatively, financial institution and telecommunications providers may establish a partnership to provide mobile banking (see Brown et al. (2003)).

The most common form of mobile banking in Sub-Saharan Africa is the M-Pesa. This is a mobile money transfer and micro-financing service, which was first launched in 2007 in Kenya by Vodafone for mobile operators Safaricom and Vodacom. It enables users to cash-in money using a mobile account (referred to as wallet) which is linked to a unique mobile phone number of a subscriber. It also allows accessing a wide range of services such as domestic and international money transactions, payments for bills, flights, hotels, and airtime top-up (see Morawczynski & Miscione (2008); Balasubramanian & Drake (2015)).

M-Pesa is most common in Eastern African countries such as Kenya, Uganda, Tanzania, Rwanda and Burundi but it is also increasingly popular in other African countries such as Cote d'lvore, Senegal, Madagascar, Mali, Niger, Botswana, Cameroon, South Africa and outside Africa in Jordan and Afghanistan. For instance, in Botswana mobile money is rolled out by two operators Orange Botswana (Orange Money) and Mascom Wireless (MyZaka) and enables VISA card payments and automated teller machine (ATM) cash-outs. A number of banks in Africa have also rolled out a similar service called e-wallet. E-wallet differs from M-Pesa in that it requires the sender to have a bank account while the receiver can only cash-out in ATMs using their mobile phone number and a pin.[7] Moreover, the increasing popularity of smart-phones in the last years allowed banks to launch mobile services which compliment over the counter and Internet banking services.

3 Data

We combine two data sets to analyze the impact of the availability infrastructure deficiencies on the use of mobile services. The first database includes a set of representative individual and

[7] See www.bocra.org.bw

household surveys which were conducted by ICT Research Africa in 2011 in the following eleven countries: Botswana, Cameroon, Ethiopia, Ghana, Kenya, Namibia, Nigeria, Rwanda, South Africa, Tanzania and Uganda. As a result of data sampling process, the respondents reside in 405 geographic districts in these countries. The survey data includes individual- and household-level information on fixed, mobile and Internet access and usage.[8] Table 1 shows the number of individuals surveyed in each country and the share of mobile phone users. In the total number of 13,814 survey respondents there are 8,292 individuals who declared having a mobile phone.[9]

The second database is Defense Meteorological Satellite Program Operational Line Scanner (DMSP/OLS) nighttime lights time series from the National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC).[10] We use information on nighttime light intensity for year 2011 in which the survey data was collected.[11]

These two databases were combined together as follows. First, Google Maps was used to generate coordinates for 405 districts in eleven countries in which survey respondents reside. Next, nighttime lights data was then extracted using these coordinates. Unfortunately, we information on nighttime light intensity is available for 275 areas out of 405, among which there are 91 rural and 174 urban areas. Nighttime light intensity is measured on a continuous scale between 1 and 63 pixel with a resolution of approximately 1 square kilometre. But the extracted data ranges between 0 and 63, where zero values imply background, which is replaced by missing values. Figure 3 shows the 2011 nighttime light intensity on the African continent. The lines on the map divide Africa into different countries using boarder line coordinates. The nighttime light intensity data was merged with survey data using location of survey respondents.

Table 4 shows the mean and standard deviation of light intensity across different countries in rural and urban areas. The urban areas are more lit in the night than rural areas as anticipated. There are significant differences in nighttime light intensity across countries.

We analyze individual's decision to adopt mobile phone and to use mobile services: (i)

[8]The survey was conducted in 12 African countries including Mozambique which was not provided to us. For details on the representativeness, sampling and data collection see http://www.researchictafrica.net.

[9]The initial sample size consists of 13,877 but 63 observations were dropped during data cleaning.

[10]The Defense Meteorological Satellite Program Operational Line Scanner (DMSP/OLS) was originally used to detect the global distribution of clouds and cloud top temperatures in the early 1970s. Since the establishment of a digital archive in 1992 by the NOAA/NGDC, these nighttime data have been widely exploited by the scientific community, for instance in economic applications to approximate the economic growth and development (see Ghosh et al. (2010), Henderson et al. (2011), Ma et al. (2012))

[11]For details on the data see http://www.ngdc.noaa.gov

mobile money, (ii) mobile transfers, (iii) mobile social and Internet activities. Table 2 shows the percentage of mobile phone owners which use each of these services. 'Mobile money' is defined as 0-1 variable based on answers to the following question: "Do you ever use your mobile phone to send or receive money (Mpesa, mobipay)?", while 'mobile transfer' is 0-1 variable constructed from answers to the following question: "Do you use mobile phone for sending or receiving money?". Overall, 18% of mobile phone adopters use mobile money with large differences across countries. Kenya has the highest share of mobile money users (81%) followed by Tanzania (46%) and Uganda (39%). The high level of adoption of mobile money in these countries can be attributed to the widespread of M-Pesa. The adoption of mobile money in the remaining countries is below 10% with the exception of Botswana (14%). The use of mobile transfers is a bit higher with an average of 21% and a similar pattern across countries.

'Mobile social' is defined in our study as 0-1 variables, which takes value of one when survey respondents confirmed using mobile phones for at least one of the following activities: (i) Browsing the Internet; (ii) Reading and writing emails; (iii) Facebook, Twitter, Mixit or other social networking; (iv) Skype / Voice over IP. On average 24% of survey respondents having a mobile phone use 'mobile social' services. The distribution is more even across countries with the highest share of users in Namibia (34%) followed by South Africa (31%) and Kenya (31%) and the lowest in Cameron (14%) and Ethiopia (12%).

Table 5 presents descriptive statistics for the dependent and explanatory variables used in the estimation. The explanatory variables can be divided into: (i) individual characteristics such as gender, marital status, age group, level of education and employment; (ii) household characteristics such as disposable income in US$ PPP, access to electricity, radio, TV, satellite TV, computer, bank account and fixed-line telephone. As one of the individual characteristics, we also use information on how many friends and family members of the respondent have mobile phones, which approximates network externalities in adoption of mobile phones and mobile services.

4 The Econometric Model

We estimate a standard model in which an individual decides whether to adopt a mobile phone or not. In addition, for the group of mobile phone adopters, we estimate three models in which

they decide whether to use 'mobile money', 'mobile transfers' and 'mobile social' services, which we defined in the previous section. Each of these decisions is 0-1 variable which is regressed on explanatory variables using logit model.

We assume that consumer i in geographic area m derives a linear utility from having a mobile phone or using a mobile service given by:

$$U_i = X_i\beta + I_{im}\gamma + \epsilon_{im} = V_i + \epsilon_i \tag{1}$$

where X_i denotes a vector of individual and household characteristics specified in the previous section, I_{im} is the availability of service infrastructure approximated by nighttime light intensity in the geographic area where the individual resides and ϵ_i is the error term which is assumed to be extreme value distributed. The probability that individual i decides to have a mobile phone, $y_{im} = 1$, is given by:

$$P_i(y_i = 1) = \frac{exp(V_i)}{1 + exp(V_i)} \tag{2}$$

and the probability of not having a mobile phone is denoted by $P_i(y_i = 0) = 1 - P_i(y_i = 1)$. The probability of using a particular mobile phone service can be written analogously.

Assuming that the decisions of all individuals in the sample $i = 1, 2, ..., N$ are independent, the cumulated log-likelihood function can be written as:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} y_i \log(P_i) \tag{3}$$

The vector of parameters which are estimated using maximum likelihood estimator is denoted by $\theta = (\beta, \gamma)$.

5 Estimation Results

Table 6 shows estimation results for eight logit regressions. First, we estimate two regressions for individual's decision to adopt a mobile phone. The first estimation is conducted using full survey data and the second for a sample restricted to individuals for whom nighttime light intensity data is available. Next, for the group of mobile phone users we estimate the decision to

use mobile services: 'mobile money', 'mobile transfers' and 'mobile social'. Again, we estimate these models using data for all mobile phone adopters and a sample restricted to mobile phone users for whom nighttime light intensity data is available. We use the same set of explanatory variables in all regressions.[12]

Our main variable of interest is the availability of physical infrastructure approximated by nighttime light intensity at the geographic location of survey respondents. We find that, after controlling for individual and household characteristics, the availability of infrastructure has a significant and positive impact on adoption of mobile phones. Thus, in more developed areas people benefit more from having a mobile phone. At the same time, the availability of infrastructure has a significant and negative impact on the usage of mobile money and mobile transfers in the group mobile phone adopters. At the same time, it has no impact on the use of mobile phones for social and Internet activities. Thus, mobile money can be considered as an alternative to physical infrastructure which benefits people who live in remote areas and may be excluded from access to financial services. This result confirms the role which mobile phones have for social inclusion and economic development in low income countries with poor physical infrastructure.

We find that the decision to adopt mobile phones and use mobile services is determined by a number of consumer characteristics. In particular, declared number of friends and family members which have mobile phones has a significant and positive impact on the probability of using a mobile phone. This effect can be attributed to network externalities. When the number of mobile phone users in the communications circle of an individual increases, the value of having a mobile phone also increases.[13] There is also a positive impact of the number of friends and family members using mobile phones on the probability of adopting mobile services considered.

Furthermore, we find that females are less likely to adopt mobile phones which may be due to social and cultural reasons. However, once females have a mobile phone they are more likely to use it for mobile money and mobile transfers but less likely for social and Internet activities. This result may suggest that women manage finances in the household. Married individuals are more likely to adopt mobile phones and use it for mobile money and transfers but less likely for

[12] As shown in Table 1, there are large differences in the use of mobile services between countries in the sample. We do not use country fixed effects in the estimation which explain large part of the variation but make many of the individual and household variables insignificant without having a clear economic interpretation.

[13] The previous literature also reported on the role of network externalities in the diffusion of mobile phones, see for example Birke & Swann (2010) and Grzybowski (2015).

social and Internet activities. Individuals in the age between 25 and 65 are more likely to adopt mobile phones. Interestingly, individuals aged between 15 and 35 are more likely to use mobile phones for finances and for social and Internet activities than the other age groups. Adoption of mobile phones and use of mobile services is higher for individuals with education and increases with the level of education. Moreover, adoption of mobile phones is higher among employed individuals. Usage of mobile phones for finances is also higher for employed individuals but at the same time employment reduces use of mobile phones for social and Internet activities.

Individuals with higher disposable income are more likely to adopt mobile phones but interestingly the level of income does not determine use of mobile money and transfers. At the same time higher income groups are more likely to use mobile phones for social and Internet activities. This result suggests that once consumers adopt a mobile phone, all income groups benefit equally from mobile money and transfer services. This emphasizes the role of mobile phones for social inclusion and economic development. Table 3 shows shares of users of mobile services by disposable income categories. It confirms that the adoption of mobile phones is determined by the level of income. But in the group of mobile phone adopters, the use of mobile money and transfer services is comparable for all income categories, while mobile social and Internet services are used more by better-off individuals.

Another result which indicates that households with limited access to infrastructure benefit from mobile financial services is that not having electricity at home negatively influences adoption of mobile phones but has a positive impact on the use of mobile money and transfers. Thus, people living in remote areas without basic infrastructure must rely on mobile phones for financial transactions. Moreover, the ownership of radio, TV and computer has overall a positive impact on adoption of mobile phones and mobile services. Thus, better equipped and wealthier households are more likely to adopt mobile phones and mobile services. Also, individuals with bank account are more likely to adopt mobile phones and mobile services. Finally, individuals from households with fixed-line connection are less likely to adopt mobile phones and use mobile money and mobile transfers. This suggests that mobile and fixed-line connections are substitutes and that fixed-line can be used as an alternative to financial transactions made on mobile phones.

6 Conclusions

The deployment of mobile telecommunications allows to overcome one of the main burdens to economic growth in low income countries, which are poor or non-existent physical infrastructure including fixed-line and Internet access. In particular, mobile phones provide access to services which are in general not available to low income households, such as financial, agricultural, health, and educational services. Besides the importance of mobile services in low income countries, the empirical literature which documents the benefits brought by mobile phones to consumers is very short due to lack of detailed data. In this paper, we contribute to this literature by analyzing the determinants of adoption of mobile phones and mobile financial services. For this purpose we combine two unique datasets. The first one is a survey data conducted among 13,814 individuals in 11 Sub-Saharan African countries in 2011, which includes answers to questions on access to mobile phones and use of mobile services including mobile money, transfers and social and Internet activities. The survey data is complemented with nighttime light intensity data, which we use to approximate the availability of service infrastructure at the location of survey respondents. The use of nighttime light intensity data enables us to analyze how spatial differences in infrastructure development across Sub-Saharan Africa influence the adoption of mobile phones and use of mobile services by individuals.

We estimate a number of logit regressions for 0-1 dependent variables. After controlling for a number of individual and household characteristics including disposable income, we find that adoption of mobile phones is higher in areas with better physical infrastructure. However, in the group of mobile phone adopters, the use of mobile phones for mobile money and transfers is negatively influenced by the level of infrastructure. On the other hand, the use of mobile phones to access services such as email, skype, social media networks and Internet browsing does not dependent on the availability of physical infrastructure. Thus, mobile money can be considered as an alternative to physical infrastructure which benefits people who live in remote areas and may be excluded from access to financial services. This result confirms the role which mobile phones have for social inclusion and economic development in low income countries with poor physical infrastructure. Our results support the notion that mobile phones improve the livelihood of individuals residing in remote areas by providing them with access to financial services which are otherwise not available physically. Moreover, we find that while individuals

with higher disposable income are more likely to adopt mobile phones, the level of income does not determine use of mobile money and transfers. At the same time higher income groups are more likely to use mobile phones for social and Internet activities. This result suggests that once consumers adopt a mobile phone, all income groups benefit equally from mobile money and transfer services. Even though our analysis is conducted for a number of low income countries in Sub-Saharan Africa, our finding on the use of mobile phones to overcome infrastructure deficiencies is more general. Also, in the high income countries, users of mobile phones are able to save time and money by having mobile access to financial and other services.

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7 Appendix

Figure 1: Mobile phone subscriptions in the Sub-Saharan African countries

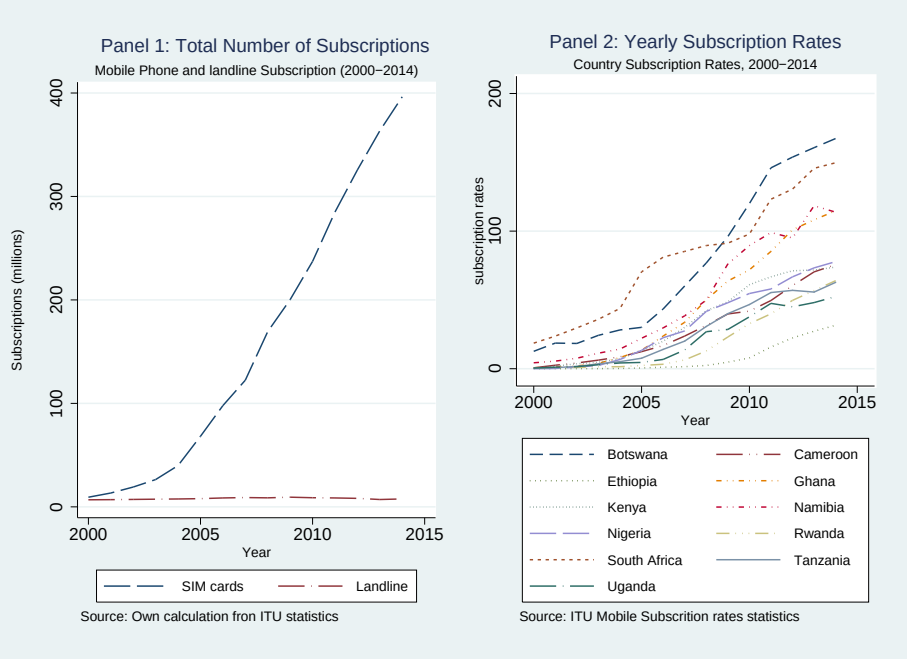

Table 1: Usage of mobile phones

Country	Full sample		Restricted sample		
	% mobile	obs.	% mobile	obs.	% of full
Botswana	84%	893	85%	824	92%
Cameroon	53%	1199	66%	839	70%
Ethiopia	36%	1608	45%	600	37%
Ghana	61%	1203	69%	809	67%
Kenya	70%	1239	72%	1162	94%
Namibia	66%	955	69%	746	78%
Nigeria	68%	1552	70%	1271	82%
Rwanda	32%	1200	54%	336	28%
South Africa	85%	1588	86%	1326	84%
Tanzania	47%	1177	56%	841	71%
Uganda	61%	1200	64%	912	76%
Total	60%	13814	69%	9666	70%

Restricted sample includes observations on individuals when nighttime light intensity data is available.

Table 2: Usage of mobile services (by mobile phone users)

Country	Full sample				Restricted sample			
	Social	Money	Transfer	Obs.	Social	Money	Transfer	Obs.
Botswana	28%	14%	17%	751	29%	14%	18%	701
Cameroon	14%	1%	5%	640	14%	1%	5%	552
Ethiopia	12%	0%	0%	580	17%	0%	1%	270
Ghana	17%	2%	2%	735	18%	2%	2%	562
Kenya	31%	81%	80%	871	32%	81%	80%	832
Namibia	34%	7%	9%	632	36%	7%	9%	513
Nigeria	26%	1%	6%	1058	26%	1%	6%	891
Rwanda	21%	9%	17%	386	29%	10%	22%	181
South Africa	32%	5%	8%	1349	34%	5%	9%	1141
Tanzania	19%	46%	48%	555	21%	50%	52%	471
Uganda	18%	39%	42%	735	18%	41%	44%	588
Total	24%	18%	21%	8292	26%	21%	23%	6702

For sample includes users of mobile phones. Restricted sample includes mobile phone users for whom nighttime light intensity data is available. Social is defined as usage of mobile social and Internet services. Money is defined as usage of mobile money and transfer as use of mobile phones for money transfer.

Table 3: Usage of mobile services (by income group)

Country	Full sample				Mobile phone users			
	Social	Money	Transfer	Obs.	Social	Money	Transfer	Obs.
no income	0%	1%	0%	1566	16%	14%	9%	44
income >0 and ≤ 20	6%	6%	7%	4753	13%	12%	13%	2335
income >20 and ≤ 100	17%	17%	18%	4926	23%	21%	24%	3704
income >100 and ≤ 300	28%	19%	21%	1863	34%	22%	25%	1546
income >300	46%	16%	20%	706	49%	17%	22%	663
Total	15%	12%	13%	13814	24%	18%	21%	8292

Statistics for all survey respondents vs. mobile phone users.

Table 4: Nighttime light intensity by country and type of area: rural vs. urban

Country	Rural		Urban	
	Mean(std)	No. of areas	Mean(std)	No. of areas
Botswana	21.0	8	45.1	8
	(20.8)		(13.2)	
Cameroon	11.8	4	38.7	19
	(10.4)		(25.6)	
Ethiopia	14.0	2	34.9	17
	(12.7)		(22.1)	
Ghana	15.1	9	32.1	19
	(19.5)		(24.2)	
Kenya	12.6	9	19.9	15
	(7.9)		(19.7)	
Namibia	15.0	14	36.0	23
	(14.0)		(22.5)	
Nigeria	20.0	20	34.9	29
	(23.0)		(23.2)	
Rwanda	7.0	1	7.3	4
	(0.0)		(1.3)	
South Africa	33.3	11	41.6	19
	(26.2)		(22.5)	
Tanzania	11.3	4	20.7	15
	(4.3)		(16.8)	
Uganda	11.8	9	23.3	6
	(5.1)		(18.8)	

Survey respondents reside in 405 districts in 11 countries. Nighttime light intensity data is available for 275 districts.

Figure 2: Nighttime light intensity

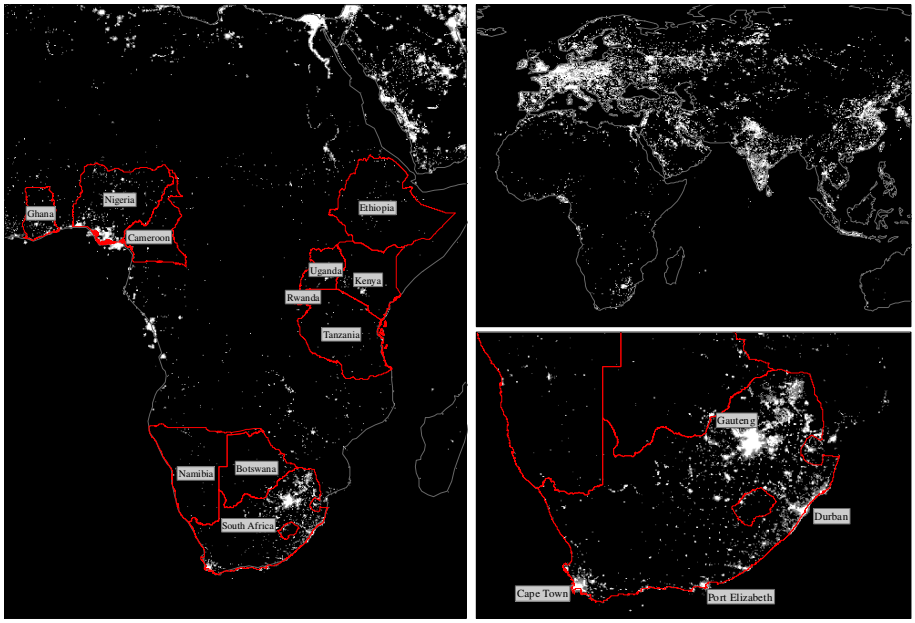

Table 5: Descriptive statistics

	N	Mean	Std	Min	Max
mobile_phone	13814	0.60	0.49	0	1
mobile_money	13814	0.12	0.32	0	1
mobile_transfer	13814	0.13	0..33	0	1
mobile_social	13814	0.15	0.35	0	1
mobile_friends	13814	3.13	2.01	0	5
female	13814	0.53	0.50	0	1
married	13814	0.46	0.50	0	1
age below 25	13814	0.33	0.47	0	1
age $>$ 25 and $\leq$ 35	13814	0.33	0.47	0	1
age $>$ 35 and $\leq$ 45	13814	0.16	0.36	0	1
age $>$ 45 and $\leq$ 55	13814	0.08	0.27	0	1
age $>$ 55 and $\leq$ 65	13814	0.06	0.23	0	1
primary	13814	0.32	0.47	0	1
secondary	13814	0.33	0.47	0	1
tertiary	13814	0.13	0.33	0	1
employed	13814	0.23	0.42	0	1
self_employed	13814	0.34	0.47	0	1
income $>$ 20 and $\leq$ 100	13814	0.34	0.48	0	1
income $>$ 100 and $\leq$ 300	13814	0.36	0.48	0	1
income $>$ 300 and $\leq$ 500	13814	0.13	0.34	0	1
income $>$ 500	13814	0.05	0.22	0	1
electricity	13814	0.62	0.49	0	1
radio	13814	0.66	0.47	0	1
tv	13814	0.49	0.50	0	1
satellite	13814	0.17	0.37	0	1
computer	13814	0.11	0.31	0	1
bank_account	13814	0.48	0.50	0	1
fixed_line	13814	0.07	0.25	0	1

Table 6: Estimation results

	Mobile phone		Mobile money		Mobile transfer		Mobile social	
	Est. I	Est. II	Est. I	Est. II	Est. I	Est. II	Est. I	Est. II
night light		0.01***		-0.01***		-0.01***		-0.00
		(0.001)		(0.001)		(0.001)		(0.001)
mobile friends	0.47***	0.46***	0.10***	0.08***	0.06***	0.04	0.09***	0.08***
	(0.014)	(0.017)	(0.024)	(0.026)	(0.022)	(0.024)	(0.024)	(0.027)
female	-0.12**	-0.09	0.24***	0.22***	0.18***	0.19***	-0.42***	-0.41***
	(0.053)	(0.065)	(0.062)	(0.066)	(0.058)	(0.063)	(0.062)	(0.067)
married	0.19***	0.21***	0.37***	0.38***	0.37***	0.38***	-0.15**	-0.18**
	(0.056)	(0.068)	(0.066)	(0.071)	(0.063)	(0.068)	(0.068)	(0.074)
age below 25	0.21	0.05	0.75***	0.89***	0.57**	0.63**	1.35***	1.51***
	(0.134)	(0.160)	(0.270)	(0.289)	(0.230)	(0.244)	(0.234)	(0.262)
age$>$ 25 and $\leq$ 35	0.59***	0.50***	0.64**	0.77***	0.43*	0.49**	0.77***	0.93***
	(0.135)	(0.161)	(0.268)	(0.287)	(0.229)	(0.243)	(0.234)	(0.262)
age$>$ 35 and $\leq$ 45	0.73***	0.62***	0.31	0.37	0.05	0.06	0.60**	0.72***
	(0.142)	(0.172)	(0.274)	(0.294)	(0.235)	(0.249)	(0.240)	(0.269)
age$>$ 45 and $\leq$ 55	0.57***	0.50***	0.14	0.13	-0.18	-0.27	0.05	0.20
	(0.154)	(0.185)	(0.288)	(0.310)	(0.250)	(0.267)	(0.257)	(0.285)
age$>$ 55 and $\leq$ 65	0.61***	0.57***	0.24	0.40	0.02	0.05	-0.45	-0.31
	(0.160)	(0.191)	(0.303)	(0.321)	(0.263)	(0.278)	(0.286)	(0.315)
primary	0.45***	0.45***	0.72***	0.62***	0.65***	0.69***	0.04	0.36
	(0.068)	(0.088)	(0.172)	(0.186)	(0.155)	(0.177)	(0.175)	(0.222)
secondary	1.15***	1.10***	0.93***	0.71***	0.84***	0.80***	0.53***	0.74***
	(0.079)	(0.097)	(0.171)	(0.184)	(0.154)	(0.176)	(0.168)	(0.214)
tertiary	1.67***	1.61***	1.54***	1.44***	1.38***	1.45***	1.28***	1.54***
	(0.142)	(0.160)	(0.179)	(0.193)	(0.163)	(0.184)	(0.175)	(0.220)
employed	0.40***	0.50***	0.46***	0.46***	0.43***	0.45***	-0.19**	-0.19**
	(0.082)	(0.095)	(0.083)	(0.088)	(0.079)	(0.084)	(0.081)	(0.088)
self-employed	0.03	0.22***	0.30***	0.32***	0.31***	0.36***	-0.43***	-0.39***
	(0.064)	(0.079)	(0.087)	(0.094)	(0.082)	(0.089)	(0.090)	(0.099)
income $>$ 20 and $\leq$ 100	3.49***	3.22***	-0.32	-0.04	0.34	0.39	0.37	0.32
	(0.172)	(0.186)	(0.461)	(0.503)	(0.540)	(0.546)	(0.464)	(0.473)
income $>$ 100 and $\leq$ 300	3.92***	3.61***	0.14	0.40	0.87	0.92*	0.78*	0.73
	(0.173)	(0.187)	(0.459)	(0.499)	(0.538)	(0.544)	(0.461)	(0.469)
income $>$ 300 and $\leq$ 500	3.89***	3.75***	0.08	0.33	0.78	0.82	1.10**	1.05**
	(0.186)	(0.204)	(0.461)	(0.502)	(0.540)	(0.546)	(0.463)	(0.472)
income $>$ 500	4.41***	4.15***	-0.27	0.02	0.58	0.66	1.34***	1.28***
	(0.251)	(0.280)	(0.470)	(0.511)	(0.546)	(0.552)	(0.467)	(0.477)
electricity	0.44***	0.32***	-0.77***	-0.76***	-0.65***	-0.66***	-0.17	-0.12
	(0.067)	(0.083)	(0.104)	(0.114)	(0.099)	(0.110)	(0.121)	(0.140)
radio	0.43***	0.42***	0.83***	0.78***	0.65***	0.57***	0.19**	0.20**
	(0.054)	(0.067)	(0.088)	(0.093)	(0.079)	(0.084)	(0.078)	(0.086)
TV	0.61***	0.58***	0.16	0.13	0.16*	0.18*	0.56***	0.58***
	(0.073)	(0.086)	(0.097)	(0.104)	(0.092)	(0.099)	(0.104)	(0.117)
satellite	0.22**	0.34***	-0.82***	-0.82***	-0.69***	-0.68***	0.10	0.11
	(0.099)	(0.110)	(0.088)	(0.093)	(0.082)	(0.086)	(0.074)	(0.080)
computer	0.31**	0.39***	0.44***	0.38***	0.45***	0.40***	1.25***	1.27***
	(0.134)	(0.145)	(0.089)	(0.094)	(0.084)	(0.089)	(0.078)	(0.084)
bank account	0.39***	0.27***	0.70***	0.72***	0.67***	0.70***	0.65***	0.73***
	(0.061)	(0.072)	(0.081)	(0.087)	(0.076)	(0.083)	(0.083)	(0.093)
fixed-line	-0.51***	-0.70***	-0.43***	-0.37***	-0.28**	-0.18	0.13	0.16
	(0.127)	(0.142)	(0.127)	(0.134)	(0.114)	(0.121)	(0.102)	(0.111)
constant	-6.67***	-6.42***	-4.52***	-4.29***	-4.50***	-4.08***	-4.54***	-4.97***
	(0.221)	(0.253)	(0.559)	(0.608)	(0.604)	(0.622)	(0.547)	(0.586)
Observations	13,814	9,666	8,292	6,702	8,292	6,702	8,292	6,702

Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$