Mobile phones and financial inclusion in Sub-Saharan Africa*

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Abstract

Sub-Saharan Africa leapfrogged technology, leaving out fixed-line telecommunication. This affects also banking and remittances. Especially, for the rural population mobile money became essential for financial inclusion. We estimate the usage determinants of mobile money and how spatial infrastructure differences impact on its adoption. Our results are based on a cross-section from a geocoded survey conducted in eight countries in 2017. We find that individuals ...

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

JEL Classification: O16, O17, O33, O18, L14, L96

*All errors are ours.

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1 Introduction

Mobile phones are arguably the most ubiquitous modern technology with about 62% (4.78 billion) of the world's population owning a mobile phone in 2018. In some developing countries more people have access to a mobile phone than to clean water, bank account or even electricity. Mobile communications offers a major opportunity to advance economic growth in developing countries. A number of studies have identified potential mechanisms through which mobile phones can stimulate inclusive economic growth, reduce poverty and inequality (see Aker & Mbiti (2010); Andrianaivo & Kpodar (2012)). Other than increasing market efficiency, mobile phones can serve as a channel for provision of services which are in general not available to people at the bottom of the pyramid, such as mobile-based financial, Internet, health and agricultural services (see (Aker & Mbiti, 2010; Mothobi & Grzybowski, 2017)). Moreover, new mobile services such as mobile money have broaden access to financial services by allowing users to send, receive and save money via a mobile phone wallet (see Mbiti & Weil (2015); Jack et al. (2013); Jack & Suri (2011)). Existing studies focused on investigating the effect of mobile money on financial inclusion with particular focus on Kenya (see for instance Hughes & Lonie (2007); Jack & Suri (2011)). In this paper, we contribute to this literature by studying the flow of money between people living in more developed and remote areas. We use access to infrastructure to approximate the level of economic development and provide evidence that mobile money enables transfers between poor and richer areas in the country, thus reducing income inequality on geographic level.

The African banking sector remains underdeveloped. A recent survey conducted by Research ICT Africa in 2017 in eight African countries, found that 71% of people living in these countries do not have a bank account.[1] The main reasons for lack of access to financial services are deficit infrastructure, inaccessibility and financial illiteracy. Mobile phones can change this situation by enabling the excluded to make use of mobile-based financial services, which does not require the proximity of other physical infrastructure or a bank account (see Hughes & Lonie (2007)). Thus, mobile technology overcomes the problem of poor infrastructure and expensive traditional banking model consisting of a network of branches.

In this paper, we estimate the determinants of using mobile phones for financial remit-

[1] Demirguc-Kunt et al. (2018) find that between 2014 and 2017, the share of adults who have an account with a financial institution or through mobile rose globally from 62% to 69%. The study further shows that in developing countries, the proportion of people with either a bank account or mobile money wallet rose from 54% to 63%.

tances based on individual survey conducted in eight Sub-Saharan African countries in 2017. In particular, we analyze how spatial differences in infrastructure impact the adoption of mobile money and the flow of remittances between geographic areas. The survey data contains exact geo-coordinates of respondents, which allow us to complement it with variables approximating infrastructure and economic development on geographic level. We use a number of proxies for economic development. First, we use nighttime light intensity data to approximate level of economic development of geographic areas in the broader sense. Second, we use a measure of distance from the household to a tarred or paved road to approximate the cost of transportation and development on a more detailed level. Lastly, we use a measure of distance from households to banking facilities (ATM and Bank) to measure availability and access of traditional banking facilities

Our results from a standard probit model suggests that individuals who live in areas with better infrastructure are more likely to own a mobile phone than those who live in areas with relatively poor infrastructure. Among mobile phone users, we find that the likelihood of smartphone ownership is high among relatively wealthier individuals and those residing in areas with better infrastructure. Our results suggests that females are less likely to own a mobile phone and a smartphone as compared to their male counterparts. The results from a two stage Heckman probit model suggest that individual who live in localities with poor infrastructure are more likely to use mobile money services for transactions than those who live in areas with better infrastructure. We also find that mobile money wallets serve as a compliment amongst those who have access to traditional banking services but as a substitute to those who are excluded by the traditional banking facilities. Moreover, we find that individuals who resides in households that are further away from cities transact larger amounts of cash via a mobile money wallet as compared to those who live within or near cities. Our findings also suggest that the use of mobile money wallets as a storage of wealth depends on infrastructure. Individuals who reside in households that are further away from cities store larger amounts of cash on their mobile money wallets than those who live near cities. However, our results also indicate that the amount of money transacted through mobile money are determined by individual characteristics. Wealthier individuals send and receive larger amounts of cash via their mobile money wallets than the relatively poorer individuals.

The remainder of the paper is organized as follows. Section 2 reviews related infrastructure. Section 3 discusses the evolution of mobile money services in Sub Saharan Africa. In Section

4, we discuss the data set used in the paper. Section 5 introduces the econometric model and Section 6 presents the estimation results. Finally, Section 7 concludes.

2 Literature Review

So far there is a short but growing body of literature on the adoption and use of mobile services in low income countries.[2] Among these studies, Mbiti & Weil (2011) use two waves of individual level data on financial access to analyze the use and economic impact of M-Pesa in Kenya. They find that an increased use of M-Pesa lowers the propensity of people to use informal savings mechanism but raises the probability of being banked. While their results suggest that M-Pesa improves individual welfare by promoting banking and increasing money transfers, they find little evidence that people use M-Pesa accounts to store wealth. Jack et al. (2013) use two waves of about 3,000 households in Kenya to study transactional networks and whether M-Pesa users make different kinds of transactions. They conclude that households which include M-Pesa users exhibit more remittance activity than those which do not. They also find that households that use M-Pesa are more likely to remit for routine support, credit and insurance purposes. They conclude that mobile money allow households to spread risk more efficiently through deeper financial integration and expanded informal networks. Murendo et al. (2018) assess the effects of social network on mobile money adoption among rural households in Uganda. They find that mobile money is positively influenced by the size of social networks. In another paper, Munyegera & Matsumoto (2016) use data on 846 rural households to analyze adoption of mobile money, remittances and household welfare in Uganda. They find a positive and significant effect of mobile money access on household welfare. Similar to Jack et al. (2013), they conclude that households that use mobile money are more likely to receive remittances than non-user households. They also find that the total value of remittances received by households that use mobile money is significantly higher than of non-user households.

There are some studies on mobile money that could apply a randomized controlled trial (RCT) to estimate causal effects. Randomized access is either given for mobile money directly at the community level (Batista & Vicente (2013) and Batista & Vicente (2018)) or with small-scale entrepreneurs (Aggarwal et al. (2020) or by the mobile money agents (Wieser et al. (2019)).

Other studies focuses on how regulatory framework affects mobile money usage. Gutierrez

[2]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.

& Singh (2013) use data on 37,000 individuals from 35 countries to analyze determinants of mobile banking usage, with a particular focus on the regulatory framework. They conclude that a supporting regulatory framework is associated with higher usage of mobile banking in the whole population and among the unbanked. **?** adopt a mix of quantitative and qualitative research methods to analyze the development and diffusion of mobile money innovations across and within countries. They find that supportive regulatory framework played a key role in guiding innovations and accelerating mobile money diffusion in Kenya.

Another stream of research is focused on the impact of mobile phones on the wellbeing of people. Using a micro-level survey data, Jensen (2007) shows that the adoption of mobile phones by fisherman and wholesalers in Kerala led to a reduction in price dispersion. He also finds that the use of mobile phones led to complete elimination of waste and near adherence to the Law of One Price, which increased both consumer and producer welfare. Aker & Mbiti (2010) analyze how the introduction of mobile phone between 2001 and 2006 affected grain prices in Niger. Klonner et al. (2010) analyze the effect of mobile phone coverage on rural labor market in South Africa. Using a qualitative approach Bourreau & Valletti (2015) assess the economic features of mobile payment systems in low income countries. They conclude that mobile money has the potential to drive financial inclusion of poor households at low cost.

The effect of infrastructure on economic outcomes in developing countries focused mainly on India. The infrastructure of interest is very manifold and covers besides (mobile) internet networks, electrification, water supply, and transportation infrastructure, as well as the very basic paved roads. For India, Duflo & Pande (2007) show the positive effect of irrigation dams on agricultural production and how these can reduce rural poverty. Rud (2012) looked at increased manufacturing output by electricity through the channel of electric pumpsets where groundwater was used as an instrument. Electrification in rural areas was analyzed by Dinkelman (2011) for South Africa as well. She shows that electrification increases female employment. Similar effects are found by Grogan & Sadanand (2013) for Nicaragua. Aggarwal (2018) applies exogenous in the variation in the timing and placement of paved roads in rural India. She finds that paved roads lead to lower prices, higher market integration and higher use of agricultural technologies. The literature on infrastructure usually exploits geographic characteristics. For instance Duflo & Pande (2007) apply river gradient and whether districts are located downstream a river. Land gradient is used in Dinkelman (2011) as an instrument to account for the cost to connect households to the electric net. Finally, Donaldson (2018) investigates the effect of railroads in colonial India. He finds that the railroads decreased trade costs and hence increased interregional and international trade and also increased real income levels.

The body of literature that analyze how availability of infrastructure influences adoption of mobile phone and mobile money services is scarce. Mothobi & Grzybowski (2017) combine a micro-level survey data conducted in 2011 for 11 African countries with night-time light intensity to assess the effect of infrastructure on adoption of mobile phones and mobile money services. They find a positive and significant relationship between adoption of mobile phones and availability of infrastructure. Their results also shows that individuals who live in areas with poor infrastructure are more likely to use mobile phone for financial transactions. They conclude that mobile phones improve the livelihood of individuals residing in remote areas.

Our paper contributes to the literature by analyzing the effect of infrastructure on adoption of mobile phone and mobile money for financial remittances. We use a number of proxies for economic development. First, we use nighttime light intensity data to approximate level of economic development of geographic areas in the broader sense. Second, we use a measure of distance from the household to a tarred or paved road to approximate the cost of transportation and development on a more detailed level. Lastly, we use a measure of distance from households to banking facilities (ATM and Bank) to measure availability and access of traditional banking facilities. We analyze how availability of infrastructure influences the uptake of mobile phone and mobile money, as well remittance activities and the use of mobile money wallets as a store of wealth.

3 Mobile money in Sub-Saharan Africa

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, make payments and perform other financial operations. A mobile phone can serve as virtual bank card, point of sale terminal, automated teller machine (ATM), and Internet banking terminal which provides an immediate access to accounts and money transfers. These services may be provided by a particular financial institution as an addition to its existing electronic banking services or independently by mobile telecommunications operators. Alternatively, financial institution and mobile operator may establish partnership to provide mobile banking together (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.[3]

A number of banks in Africa 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.[4] Moreover, increasing popularity of smart-phones in the last years allowed banks to launch mobile services which compliment over the counter and Internet banking services.

According to the GSMA as of 2017, there were 348.3 million registered mobile money accounts in Sub-Saharan Africa. Of these accounts, 123.8 million were active for a 90-day period. In total there were about 1.5 billion transactions worth $23.3 billion.

4 Data

For the purpose of this study, we construct a unique dataset which consisting of different databases. The first database includes a set of representative individual and household surveys which were conducted in 2017 by Research ICT Africa in the following nine African countries: Ghana, Kenya, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania and Uganda.[5] Table 1 shows the number of individuals surveyed in each country and the share of mobile phone users. In the total number of 12,778 survey respondents there are 8,970 individuals who declared having a mobile phone. Within the group of respondents that own a mobile phone, 4,538 use mobile phone to send, receive or save money using their mobile money wallets. The

[3] For instance, in Botswana mobile money is rolled out by two operators Orange Botswana (Orange Money) and Mascom Wireless (MyZaka), which enable VISA card payments and ATM cash-outs.

[4] See www.bocra.org.bw

[5] The survey was conducted in 10 African countries including Lesotho. Lesotho survey was cconducted a year earlier to pilot the 2017 wave and is not included in this analysis. For details on the representativeness, sampling and data collection see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/765.

survey was conducted using electronic android tablets and an external GPS device, which was used to capture exact household coordinates. The geographic coordinates were used to merge with the other databases, which include proxy measures for the availability and proximity of infrastructure.

The second database are Nighttime Lights (NTL) stemming from the Visible Infrared Imaging Radiometer Suite (VIIRS) from the *Suomi* satellite provided by the Earth Observations Group (EOG), Payne Institute for Public Policy. We apply the yearly cloud-free averaged data from 2016. Though, traditionally in the economic literature the Defense Meteorological Satellite Program (DMSP) was applied (starting with Henderson et al. (2011)), the VIIRS data has huge advantages. First, the DMSP 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. However, night light data for scientific research was only a byproduct and not the main purpose. This is different for the VIIRS Second, the DMSP was stopped by 2013. So, for more recent data access the VIIRS is the only source. Nevertheless, third, the VIIRS data is more precise in the light intensity as well as in the base area. We exploit light averages at 15 arc-second geographic grids ($\approx 465m \times 465m$ at the equator, or $\approx 465m \times 385m$ at 35 degrees of latitude). Outliers, such as lights from aurora, fires, boats, and other temporal lights were filter out by EOG. Finally, background (non-lights) are set to zero.

The third database comes from OpenStreetMap (OSM). OSM is a collaborative afford to set up a free database for geographic data. Besides the use of satellite images, users can add information. We downloaded the data from Geofabrik's free download server in December 2019. This database provides infrastructure data on the (geo) location of cities and towns, of banks and ATMs, of railway and bus stations and stops, and of major roads. From the location distances to the survey households are calculated. Cities contain the countries capital and ofen have more than 100,000 inhabitants. Towns are smaller and have between 10,000 and 100,000 inhabitants. Cities and towns are defined by the national, state, or provincial government. Major roads contain motorways / freeways, trunks, and national, regional, and local roads.

The fourth database includes information on the ruggedness of the terrain. The data is provided by Nathan Nunn and Diego Puga. An advantage is the 30 arc-seconds grid-cell-level on which the Terrain Ruggedness Index (TRI) and the slope is given. The concept of the TRI comes originally from Riley et al. (1999) and depends on differences in the elevation of neighboring grid-cells. It is measured in millimeters. The slope refers to the average uphill slope and is measured in thousands of a percentage point. The TRI was already used in the economic literature as an instrumental variable (e.g. Kolko (2012) and Klonner & Nolen (2010)).

The fifth database on the cell tower location was downloaded from OpenCelliD.[6] Besides the exact geo-location of each cell, the date of creation and the kind of technology (GSM (2G), UMTS (3G) and LTE (4G)) can be observed. We use only antennas which were constructed before 2017 to make sure that individuals in our surveys could use these antennas. We calculate the minimum distance for each household to the closest antenna for each technology.

4.1 Statistics

According to the survey data, there are some differences in the adoption of mobile phones and smartphones across countries in the sample. For instance, as shown in Table 1, the highest penetration of mobile phones was in Kenya (88%) and the lowest in Uganda (57%) and Ghana (58%). The highest penetration of smarpthones was in Spouth Africa (44%) and the lowest in Rwanda (11%).

Table 1: Adoption of mobile phones and smartphones

Country	Mobile phone	Smartphone	Obs
Ghana	65%	17%	1,808
Kenya	88%	34%	1,217
Mozambique	58%	17%	1,200
Nigeria	78%	26%	1,200
Rwanda	55%	11%	1,217
Senegal	81%	22%	1,233
South Africa	86%	44%	1,815
Tanzania	66%	20%	1,200
Uganda	57%	13%	1,864
Total	70%	23%	12,778

Source: Research ICT Africa After Access Survey, 2017

The use of mobile money usage also varies across countries and is higher in East Africa, as shown in Table 2. Kenya has the highest share of mobile money users (84%) followed by Tanzania (55%) and Ghana has the lowest share of only 3%. Mobile money usage still remains low in South Africa, which can be attributed to well developed financial sector with 57% of

[6] https://www.opencellid.org/downloads.php

South Africans declaring that they have a bank account.

Table 2: Use of mobile money and bank account

Country	Mobile money	Bank account	Obs
Ghana	3%	44%	1,808
Kenya	84%	43%	1,217
Mozambique	24%		1,200
Nigeria	54%	32%	1,200
Rwanda	34%	35%	1,217
Senegal	33%	11%	1,233
South Africa	8%		1,815
Tanzania	55%		1,200
Uganda	48%	3%	1,864
Total	34%		12,778

Source: Research ICT Africa After Access Survey, 2017

When comparing use of mobile money between two waves of the survey conducted in 2011 and 2017, Ghana had the highest increase from 2% in 2011 to 54% in 2017. A substantial increase in the use of mobile money was also observed in Rwanda, from 9% in 2011 to 34% in 2017. This increase in adoption in these countries can be attributed to the development of inter-operable mobile money payment systems, which give users the ability to make transfers between accounts held with different mobile money providers and other financial institutions.

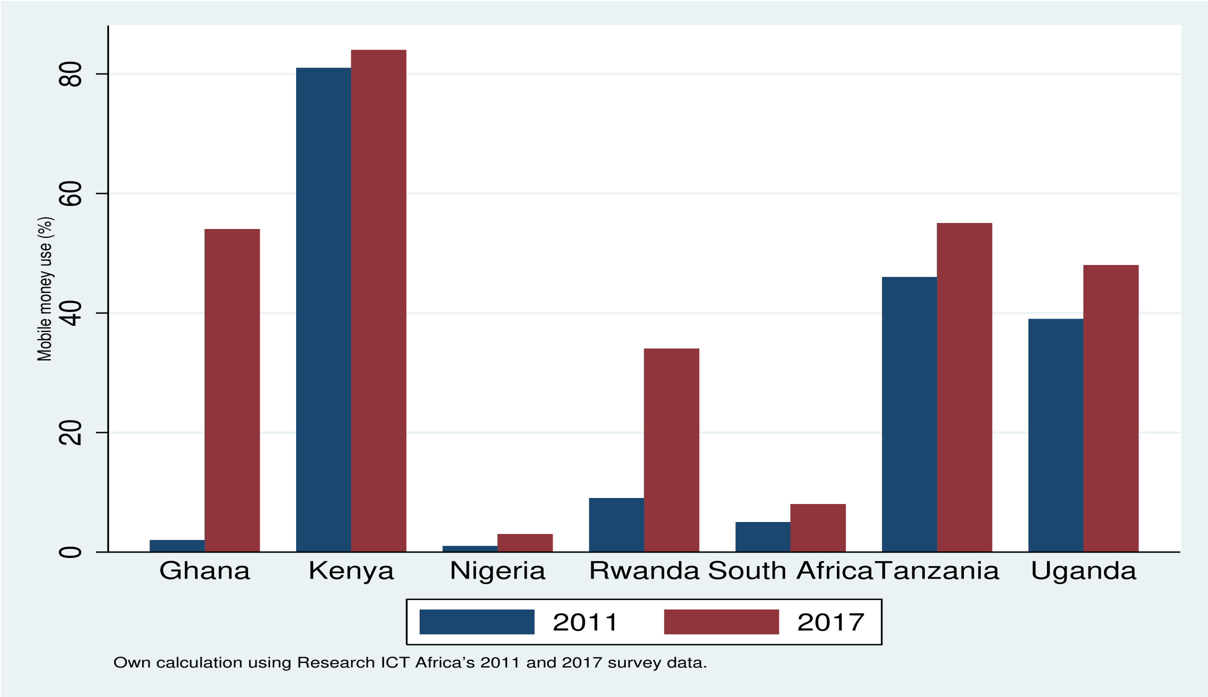

Figure 1: Evolution of mobile money use between 2011 and 2017.

Tables 3, 4 and 5 show respectively the summary statistics for the value of money sent, received and saved in the mobile wallets. On average, a mobile money user received about US$ 81.52 and sent US$ 53.89. There are substantial differences in the average value of transactions across countries. South Africa has the highest average value of sent transactions (US$ 67.47), followed by Nigeria (US$ 49.8) and Ghana (US$ 39.6). The lowest average value of money sent is in Uganda (US$ 11.8), Mozambique (US$ 13.3) and Tanzania (US$ 13.4). Similarly, the average value of received transactions is in South African (US$ 95.6), followed by Nigeria (US$ 75.6) and Ghana (US$ 56.7) and the lowest in Uganda (US$ 17.5), Mozambique (US$ 17.8) and Tanzania (US$ 17.8). The average amount of money saved in mobile money wallets is the highest in Nigeria (US$ 122.9) and South Africa (US$ 45.9), and the lowest in Uganda (US$ 13.9) and Rwanda (US$ 14.7).

Table 6 presents the descriptive statistics for the variables which we use 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,

Table 3: Amount of mobile money sent by individuals (US$)

Country	Obs	Mean	Std	Min	Max
Ghana	548	39.55	78.42	0.22	1149.42
Kenya	683	22.27	39.77	0.24	483.51
Mozambique	294	13.26	21.17	0.31	157.28 8
Nigeria	45	49.83	72.05	0.32	412.04
Rwanda	245	15.86	27.57	0.001	240.52
Senegal	377	26.78	53.29	0.68	858.97
South Africa	237	67.47	106.43	1.50	1350.33
Tanzania	483	13.40	18.79	0.45	224.33
Uganda	430	11.78	24.57	0.28	276.91
Total	3299	53.89	644.08	0.001	28965.52

Source: Research ICT Africa After Access Survey, 2017

which approximates network externalities in adoption of mobile phones and mobile services.

Table 6: Online services

Variable	N	Mean	Std	Min	Max
mobile phone	9 613	0.71	0.45	0	1
female	9 613	0.54	0.49	0	1
urban	9 613	0.60	0.48	0	1
age > 25 and < 35	9 506	0.29	0.45	0	1
age > 35 and < 45	9 506	0.20	0.39	0	1
age > 45 and < 55	9 506	0.12	0.32	0	1
age > 55 and < 65	9 506	0.08	0.27	0	1
age > 65	9 506	0.06	0.25	0	1
single	9 596	0.39	0.49	0	1
widowed	9 596	0.09	0.28	0	1
divorced	9 596	0.03	0.17	0	1
years of schooling	9597	8.49	5.42	0	60
student	9 596	0.12	0.32	0	1
unemployed	9 596	0.56	0.49	0	1
retired/Inactive	9 596	0.13	0.34	0	1
telephone	9 600	0.02	0.14	0	1
refrigerator	9600	0.33	0.47	0	1
radio	9 600	0.62	0.48	0	1
television	9 600	0.55	0.49	0	1
Internet	6 923	0.40	0.49	0	1
ln(income)	8 735	4.12	1.51	-6.03	11.09
ln(capita)	9 613	7.51	.093	6.24	8.92

Source: Research ICT Africa After Access Survey, 2017

Table 4: Amount of mobile money received by individuals (US$)

Country	Obs	Mean	Std	Min	Max
Ghana	611	56.67	112.26	0.22	1333.33
Kenya	681	28.39	50.50	0.29	580.21
Mozambique	295	17.81	25.07	0.31	157.28
Nigeria	41	75.64	118.42	0.32	654.04
Rwanda	247	20.86	32.54	0.002	240.52
Senegal	376	35.07	66.81	0.005	1030.77
South Africa	230	95.60	141.62	0.15	1350.34
Tanzania	499	17.77	27.12	0.45	269.19
Uganda	459	17.48	37.74	0.005	553.82
Total	3390	81.52	1063.26	0.002	45977.01

Source: Research ICT Africa After Access Survey, 2017

Table 7 shows the average light intensity at locations of individuals in the sample, for whom such information was available.

5 The Model

5.1 Theoretical framework

Each user i decides on the volume of money, indexed by j to transact on a mobile money wallet. Transfers are characterised by remittances and payments. Each transfer j has a recepient r. The value of amount transfered is conditional on the amout of money stored s on the wallet at the time of transaction. Users are not allowed to borrow from the mobile money wallet and transactions can only be effected if $s > 0$. The amount of money stored in the wallet is a function of cash received c_i by indivdual i as well as user current account balance b_t^i and remittances r conditional on b_t^i and mobile phone ownership m_i. Formally, the amount of cash transacted over mobile money wallet is given by

$$r_i|b_t^i m_i = s_i(received, b_t^i, r_i, m_i), s_i >= 0, b_t^i >= 0, \tag{1}$$

and the saving function is formally given by

$$s_i(received, b_t^i, r_i, m_i) = received_i|m_i + b_t^i|m_i - r_i|b_t^i, m_i), \tag{2}$$

Table 5: Amount of mobile money saved by individuals (US$)

Country	Obs	Mean	Std	Min	Max
Ghana	543	34.08	97.67	0.22	1379.31
Kenya	610	25.69	38.38	0.01	290.11
Mozambique	277	23.21	37.28	0.01	235.92
Nigeria	35	122.89	313.32	0	1635.11
Rwanda	224	14.75	21.66	0.001	120.26
Senegal	273	36.08	62.05	0.02	429.48
South Africa	140	45.92	144.47	0.07	1500.37
Tanzania	325	25.17	47.24	0	448.66
Uganda	409	13.92	30.09	0	276.91
Total	2797	123.02	2608.268.26	0.002	114942.5

Source: Research ICT Africa After Access Survey, 2017

Table 7: Light intensity

Country	Mean	Std	Min	Max	Obs
Ghana	4.81	8.74	0	63.43	1804
Kenya	7.79	11.55	0	44.49	1217
Mozambique	8.35	11.40	0	52.79	1220
Nigeria	6.41	6.39	0	26.56	1200
Rwanda	1.61	3.45	0	28.07	1217
Senegal	6.54	9.54	0	62.87	1233
South Africa	13.34	13.98	0	80.23	1796
Tanzania	4.74	6.49	0	28.85	1200
Uganda	1.15	2.61	0	14.69	1856

Source: Research ICT Africa After Access Survey, 2017 & nighttime lights data from NOAA/NGDC.

The utility of executing a transaction over a mobile wallet is given by

$$u_i = v_i + \beta x_i + \alpha s_i + \epsilon_i, \tag{3}$$

where v_i is the baseline utility of the effecting a transaction over a mobile money wallet, x_i is individual characteristics, s_i is geographical development and ϵ_i represents idiosyncratic shocks to the utility of effecting a transaction over mobile money wallet. In particular, ϵ_i alters users's avearge preferences for transfers and rationalises the fact that users do not make the same transactions even if balance and geographical characteristics are the same.

5.1.1 The Cash flow model

The consumer is aware of the distance to the receipient d_m and forms belives about the receiver current account balance in relation to his current account. For transfers between family members, the consumer is able to correctly estimate his status in relation to the receiver. However, if a transfer is a payment for a service, the sender is likely to correctly assume whether the balance of the receiver is large or small. The mode of transportation is also dependent on the direction, i.e whether the transaction originate from developed areas to areas with poor physical infrastructure or vice versa. Both the recepient and sender are assumed to be aware of direction of the transaction. If the transaction originates from areas with poor infrastructure or within a locality the receiver forms a belive that its a payment. If the transaction originates from areas with better infrastructure to areas with poor infrastructure the receiver is assumed to correctly estimate that the transaction is a remmittance and also correctly estimate whether the balance of the sender is large or small in relation to his/her account. Formally, the transportation model is given by

$$u_i = v_i + \beta d_m + \alpha z_i + \gamma t_i + \omega o_i + \lambda c_i + \eta s_i + \epsilon_i, \tag{4}$$

where d_m is the distance to the receiver m, z_i is the speed of mode of transport used for transaction, t_i is the type of transanction: remittance or payment, o_i is the direction of the transaction and s_i is the location characteristics.

5.1.2 The saving model

The model of storage/saving is similar to the transaction model. Each consumer i decides on whether to use mobile money as a storage of wealth or outside option such as store money between mattress, move with the money in their pocket or deposit on their bank account. The amount stored on the money wallet is characterised by availability of infrastructure and the difference between money received and amount transferred. The utility derived from using mobile money as a store of wealth is formally given by

$$u_i^s = v_i^s + \beta^s x_i + \alpha^s s_i + \gamma^s b_i + \epsilon_i^s, b_i >= 0, \tag{5}$$

where the superscript s distinguishes the parameters of the saving model from the parameters of the transactional model and b_i^s is the current account balance.

5.2 Empirical model

We now introduce the empirical model of money transfers and savings. We estimate a reduced-form equation for the individual's decision to transfer, receive and save money via mobile banking. When estimating the model we need to account for the sample selection problem.

In our sample, there are some individuals who do not have mobile phones and hence cannot use mobile money and make remittances. We take this into account by estimating Heckman's sample selection model in two stages (see Heckman (1979)). In the first stage, we estimate a sample selection equation by means of probit model:

$$Pr((z_i = 1|W_i) = \Phi(W_i\alpha) \tag{6}$$

where Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The vector of estimated parameters is denoted by α. Using latent variable model specification we can write equation (6) as:

$$z_i^* = W_i\alpha + \epsilon_i \tag{7}$$

where $z_i^* > 0$ for individuals having mobile phones and ϵ_i is standard normally distributed error term. The use of mobile money for transfers and savings is denoted by equation:

$$y_i = X_i\beta + u_i. \tag{8}$$

In the second stage, the modified usage equation is estimated for the sample of individuals with mobile phones $z_i^* > 0$:

$$y_i = \beta X_i + \sigma_u\hat{\lambda}(W_i\alpha) + e_i. \tag{9}$$

In equation (9), we use the fact that the error term u_i can be decomposed into the sum of two terms, $u_i = \sigma_u\hat{\lambda}(W_i\alpha) + e_i$, where by construction e_i is mean zero conditional on X_i. The hazard function (inverse Mills ratio), denoted by $\hat{\lambda}(W_i\alpha)$, is computed using the first-stage probit estimates as follows:

$$\hat{\lambda}(W_i\alpha) = \frac{\phi(W_i\alpha)}{\Phi(W_i\alpha)}. \tag{10}$$

Heckman's selection model also needs to satisfy the exclusion restrictions. We need at least one variable which determines the adoption of mobile phones and is included in Z_i, but which does not impact usage of mobile money and is not correlated with the error term e_i in the usage equation (9).

6 The Results

6.1 Mobile phone Adoption

The results in Panel A of Table 8 show that availability of infrastructure, as approximated by nighttime light intensity, at geographical location of respondents have a positive and significant impact on mobile phone adoption. Using household spatial differences, measured by distance from major road and distance from financial service infrastructure (Automated Teller Machine (ATM) and Bank), we find that individual decision to adopt a mobile phone is determined by how far is the repsondent household from developments. Individuals who reside in households that are near ATM or closer to tarred road/major road are more likely to own a mobile phone that those who live in households that are relatively far from developments. At the same time, we find that decision to adopt a mobile phone is determined by a number of consumer characteristics. In particular, wealth have a positive effect on the adoption of mobile phone. Individuals who declared that they leave in household with electricity, financially included (own a bank account/credit card) and employed are more likely to adopt a mobile phone. Furthermore, our results suggests that married individuals are more likely to have a mobile phone while females are less likely to have a mobile phone as compared to their male counterparts. The results on Panel B of Table 8 show that the availability of infrastructure have a positive and significant impact on the adoption of smartphones. We find that individuals who live in areas with better infrastructure are more likely to adopt a smartphone than those who live in remote areas. Furthermore, individuals who reside in households that are near banking facilities (ATM or Bank) are more likely to own a smartphone than those who live in households that are distant from these facilities. Similarly, individuals how resides in households that are near tarred roads are more likely to be smartphone users than those who resides in households that are far from the paved roads or major roads. Consistently, results in results Panel A of Table 8, the results also indicate that wealtheir individuals who live in households that have electricity and those that are financially included are more likely to own a smartphone than the relativey poor individuals. We find that the likelihood of smartphone adoption decreases with an increase in age. We also find a significant gender gap in the adoption of smartphone. Females are less likely to own a smartphone as compared to males.

6.2 Mobile money use

Table 10 presents estimation results of Heckman's sample selection model, which we use to correct for sample selection bias in the adoption of mobile money. The results indicate that availability of infrastructure have a negative and significant effect on adoption of mobile money. Thus, the use of mobile money is high among individuals who live in areas with poor infrastructure. At the same time, we find a positive and significant impact of household distance from paved or tarred road on adoption of mobile phone. Thus, individuals who live in households that are further away from tarred or paved roads are more likely to depend on mobile money to do financial transactions. Interestingly, the results suggets that mobile money serves as a compliment to the traditional banking facilities for those who are financially included and a susbstitute for those who are excluded. Individuals who resides in households that are near banking facilities and those who have a bank account are more likely to have a mobile money wallet than those who do not have a bank account and those who live in households that are further from banking facilities. The results also indicate that individuals who reside in larger households are more likely to have a mobile money as compared to those who live in relatively small sized households. Married individuals are less likely to a have mobile money account while females are more likely to own a mobile money account. We also find that individuals who own properties are less likely to use mobile money for financial transactions.

6.3 Remittances

The results in Table 11 indicate that the bulk of mobile money transactions occurs in areas with better infrastructure. More specifically, we find that availability of infrastructure has a positive and significant impact on the value of transactions received and sent. The results in panel A Table 11 show that in comparison to individuals who live in areas with relatively poor infrastructure those who live in areas with better infrastructure transfer or send larger amounts of cash via a mobile money wallet. Consistently, with findings in Table 10 we find that individuals who live in households that are near banking facilities (ATM and bank) send or transafer larger amounts of money through mobile money wallets as compared to those who live in households that are further away from banking facilities and those that do not have a bank account. A further evidence that mobile money serves as a compliment to banking facilities for those who have a bank account and can access banking facilities and a substutute to traditional banking services for those who do not have access to banking facilities or live further away from banking facilities. On the other hand, our results suggests that individuals who live in households that are further away from cities transfer/send larger volumes of cash via a mobile money wallet in comparison to those who live in households that are near cities or within a city. Panel B Table 11 also indicate that individuals who live in areas with better infrastructure receive larger amounts of cash via a mobile money wallet as compared to those who live in areas with relatively poor infrastructure. Our results show that the distance from the city have a positive and significant impact on the amount of cash transfered via a mobile money wallet. As the distance from the city increases individials who have a mobile money account receive larger volume of cash or receive large amounts of remmittances through a mobile money wallet. The finding in Panel A and B Table 11 shows that transaction activities in the mobile money platform increases with distance from the city. Suggesting that people who live in rural areas transact more on mobile money platforms than those who live in the city. However, transactional activities via a mobile money wallet are determined by individual characteristics. Relatively wealthier individuals and those who are financially included, employed are more likely to transact larger amounts of cash via a mobile money platform as compared to the poor.

Results in Panel C Tabe 11 show that individuals who live further away from cities store larger amounts of cash on their mobile money wallet than those who live near or within cities. The amount of money stored within a mobile money wallet, however, are determined by both individual characteristics and location characteristics. We find that availability of infrastructure has a positive and significant effect on the amount of cash stored on the mobile money wallet. Individuals who live in areas with better infastructure are likely to store large amounts of cash on their mobile wallet as compared to those who live in areas with poor infrastructure. However, individuals who resides in households that are further away from banking facilities store larger amounts of cash on their mobile money wallet as compared to those who have access and live near banking facilities. Our findings also suggest that individuals who have a bank account store larger amounts of cash on their wallets than those who do not have bank accounts. A further suggestion that indeed mobile money is a compliment to the traditional banking services for those who have access to traditional banking facilities and services.

7 Conclusion

In this paper, we estimate the determinants of using mobile phones for financial remittances based on individual survey conducted in eight Sub-Saharan African countries in 2017 and Heckman's sample selection model. In particular, we analyze how spatial differences in infrastructure impact the adoption of mobile money and the flow of remittances between geographic areas. The survey data contains exact geo-coordinates of respondents, which allow us to complement it with variables approximating infrastructure and economic development on geographic level. We use a number of proxies for economic development. First, we use nighttime light intensity data to approximate level of economic development of geographic areas in the broader sense. Second, we use a measure of distance from the household to a tarred or paved road and to the city to approximate the cost of transportation and development on a more detailed level. Lastly, we use a measure of distance from households to banking facilities (ATM or bank) to approximate the availability and access of banking facitities. First, we estimate a standard probit model which analyses the determinats of mobile phone adoption. Secondly, we use a Hechprobit model to estimate determinats of smartphone and mobile money adoption, Thirdly, we use a heckman model to estimate determinats of mobile money transactions, with specific focus on transfers, remmittances and savings.

Our results suggests that individuals who live in areas with better infrastructure, approximated by nighttime light intesnsity are more likely to adopt a mobile phone than those who reside in areas with relatively poor infratsructure. We find a sugnificant gender gai in mobile phone and smartphone ownership in faviour of males. An outcome which might be attributed to income differentials between males and females and in some cases cultural issues. This results, however, might have significant implications. First, they imply that women lack the necessary devices required to access and use the Internet. Secondly, bacause women are less likely to own smartphone, which are common devices used in Africa to access the Internet, women participation in the digital economy is likely to be limited and therefore mostly to be left behind and in turn widening the gender gap. We also find that availability of infrastructure has a negative and significant impact on mobile money adoption. That is individuals who live in areas with better infrastructure are less likely to have a mobile money wallet as compared to those who live in areas with relatively poor infrastructure. A finding which suggests that indeed mobile phones have the potential to provide services that could not be provided to residents of rural areas mainly due to high costs of setting phyisical branches in those areas and in some cases due to lack of electricity and roads networks. Our findings also suggests that mobile money acts as a substitute to individuals who do not have access to banking facilities but a compliment to those who have access and live near banking facilities.

We also find that individuals who live in households that are further away from cities transact larger amounts of cash via a mobile wallet than those who live within or near cities. However, the amount of money transfered, received or saved via mobile money wallet are determined by both individual and household characteristics. Individuals who live in areas with better infrastructure transact and save larger amounts of mobile on their mobile money than those who live in areas with relatively poor infrastructure. Most importantly, the results suggests that individuals who live in rural areas are more likely to use mobile money as a store of wealth as compared to those who live in rural areas. Individuals who resides in households that are further away from banking facilities store larger amounts of cash on their mobile money wallet as compared to those who have access and live near banking facilities. Our findings also suggest that individuals who have a bank account store larger amounts of cash on their wallets than those who do not have bank accounts. A further suggestion that indeed mobile money is a compliment to the traditional banking services for those who have access to traditional banking facilities and services.

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8 Appendix

Table 8: Estimation results

	(1)	(2)	(3)
VARIABLES	phone	smartphone	mobile_money
ln_lights_inp	0.0592***	0.150***	-0.211***
	(0.0183)	(0.0215)	(0.0246)
ln_city	0.00379	0.00278	-0.0463***
	(0.0144)	(0.0167)	(0.0117)
ln_atm	-0.0398***	-0.0414***	-0.0907***
	(0.0113)	(0.0128)	(0.0163)
ln_major_road	-0.0183**	-0.0122	0.0574***
	(0.00859)	(0.0113)	(0.0122)
married	0.179***	-0.0668*	-0.00140
	(0.0295)	(0.0354)	(0.0434)
respondent_gender	-0.245***	-0.0596*	0.118***
	(0.0273)	(0.0321)	(0.0391)
2.age_cat	0.316***	-0.378***	-0.0839
	(0.0369)	(0.0423)	(0.0540)
3.age_cat	0.236***	-0.770***	-0.0824
	(0.0423)	(0.0516)	(0.0614)
4.age_cat	0.141***	-1.017***	-0.259***
	(0.0498)	(0.0646)	(0.0727)
5.age_cat	0.0991*	-1.166***	-0.257***
	(0.0555)	(0.0756)	(0.0854)
6.age_cat	-0.316***	-1.491***	-0.423***
	(0.0555)	(0.102)	(0.113)
2.income_cat_ppp	0.322***	0.0590	0.132***
	(0.0315)	(0.0372)	(0.0438)
3.income_cat_ppp	0.504***	0.488***	0.124*
	(0.0593)	(0.0519)	(0.0635)
4.income_cat_ppp	0.210**	0.962***	0.0968
	(0.0905)	(0.0739)	(0.0924)
HHsize	-0.0118**	0.00824	-0.0732***
	(0.00509)	(0.00666)	(0.00750)
employed	0.290***	0.235***	0.441***
	(0.0467)	(0.0387)	(0.0534)
credit	0.525***	0.373***	0.306***
	(0.0639)	(0.0452)	(0.0601)
ownership_house	-0.0127	0.00346	-0.0999**
	(0.0326)	(0.0367)	(0.0457)
bank	0.599***	0.554***	
	(0.0468)	(0.0433)	
electricity	0.519***	0.472***	
	(0.0337)	(0.0441)	
ln_bank			-0.105***
			(0.0159)
Constant	0.264	-0.857***	2.945***
	(0.172)	(0.207)	(0.215)
Observations	12,714	8,938	5,460

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

Table 9: Remittances estimation results

	(1)	(2)	(3)
VARIABLES	send	receive	save
ln_lights_inp	0.156***	0.138***	0.213***
	(0.0248)	(0.0249)	(0.0545)
ln_city	0.115***	0.129***	0.0732***
	(0.0121)	(0.0121)	(0.0257)
ln_atm	0.0517***	0.0359**	0.115***
	(0.0150)	(0.0153)	(0.0329)
ln_bank	-0.0143	-0.0214	-0.0710**
	(0.0156)	(0.0158)	(0.0347)
ln_major_road	-0.0158	-0.0103	-0.111***
	(0.0122)	(0.0123)	(0.0272)
married	0.154***	0.0263	-0.0818
	(0.0419)	(0.0419)	(0.0916)
respondent_gender	-0.0496	-0.00644	-0.105
	(0.0380)	(0.0381)	(0.0831)
2.age_cat	0.159***	0.110**	0.211*
	(0.0502)	(0.0504)	(0.110)
3.age_cat	0.391***	0.308***	0.404***
	(0.0587)	(0.0592)	(0.129)
4.age_cat	0.423***	0.366***	0.461***
	(0.0747)	(0.0746)	(0.164)
5.age_cat	0.520***	0.470***	0.494**
	(0.0931)	(0.0913)	(0.207)
6.age_cat	0.317**	0.514***	0.446
	(0.156)	(0.135)	(0.312)
2.income_cat_ppp	0.397***	0.403***	0.650***
	(0.0432)	(0.0432)	(0.0948)
3.income_cat_ppp	0.821***	0.735***	1.221***
	(0.0610)	(0.0622)	(0.134)
4.income_cat_ppp	1.286***	1.364***	2.429***
	(0.0859)	(0.0890)	(0.189)
HHsize	-0.00340	0.00831	0.00904
	(0.00835)	(0.00837)	(0.0187)
employed	0.242***	0.127***	0.111
	(0.0443)	(0.0458)	(0.0976)
credit	0.184***	0.249***	0.308***
	(0.0495)	(0.0512)	(0.107)
ownership_house	-0.00733	-0.0423	-0.0527
	(0.0446)	(0.0449)	(0.0981)
Constant	1.433***	1.986***	1.095**
	(0.208)	(0.211)	(0.464)
Observations	3,668	3,857	3,110
R-squared	0.210	0.182	0.126

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

Table 10: Mobile money Heckman estimation results

	(1)	(2)
VARIABLES	mobile money	mobile phone
ln_lights_inp	-0.194***	0.178***
	(0.0202)	(0.0235)
ln_atm	-0.104***	0.0137
	(0.0136)	(0.0137)
ln_major_road	0.0605***	-0.0407***
	(0.0106)	(0.0102)
ln_city	-0.0298***	0.0259
	(0.0106)	(0.0161)
married	-0.0975***	0.200***
	(0.0376)	(0.0353)
respondent_gender	0.206***	-0.331***
	(0.0338)	(0.0327)
2.age_cat	-0.214***	0.368***
	(0.0478)	(0.0450)
3.age_cat	-0.190***	0.321***
	(0.0539)	(0.0509)
4.age_cat	-0.283***	0.191***
	(0.0623)	(0.0596)
5.age_cat	-0.274***	0.181***
	(0.0730)	(0.0687)
6.age_cat	0.00181	-0.345***
	(0.0797)	(0.0721)
2.income_cat_ppp	-0.102***	0.418***
	(0.0386)	(0.0383)
3.income_cat_ppp	-0.148**	0.672***
	(0.0591)	(0.0750)
4.income_cat_ppp	-0.118	0.359***
	(0.0868)	(0.114)
HHsize	-0.0491***	0.00950
	(0.00621)	(0.00617)
ownership_house	-0.134***	0.0389
	(0.0404)	(0.0397)
employed	0.332***	0.325***
	(0.0517)	(0.0581)
p_computer		0.488***
		(0.0937)
credit	0.0303	0.800***
	(0.0634)	(0.0935)
bank	0.148***	0.577***
	(0.0500)	(0.0584)
electricity		0.483***
		(0.0382)
Constant	2.498***	-0.828***
	(0.169)	(0.204)
Observations	8,479	8,479

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

Table 11: Remittances Heckman estimation results

VARIABLES	(1) receive	(2) mobile phone	(3) send	(4) mobile phone	(5) savings	(6) mobile phone
ln_lights_inp	0.142***	0.157***	0.133***	0.143***	0.234***	0.152***
	(0.0232)	(0.0300)	(0.0234)	(0.0294)	(0.0512)	(0.0315)
ln_atm	0.0373***	0.0215	0.0207	0.0161	0.0834***	0.0122
	(0.0143)	(0.0177)	(0.0145)	(0.0176)	(0.0319)	(0.0187)
ln_major_road	-0.0124	-0.0184	-0.00732	-0.0130	-0.111***	-0.00487
	(0.0123)	(0.0139)	(0.0123)	(0.0136)	(0.0273)	(0.0147)
ln_city	0.108***	-0.0249	0.124***	-0.0200	0.0658**	-0.0363
	(0.0122)	(0.0211)	(0.0122)	(0.0209)	(0.0259)	(0.0223)
married	0.159***	0.0471	0.0295	0.00397	-0.0761	0.0284
	(0.0418)	(0.0485)	(0.0418)	(0.0475)	(0.0915)	(0.0505)
gender	-0.0394	-0.0109	0.00467	0.0321	-0.0881	0.0451
	(0.0378)	(0.0433)	(0.0381)	(0.0425)	(0.0832)	(0.0454)
2.age_cat	0.144***	0.0239	0.0986*	0.0145	0.188*	0.0215
	(0.0500)	(0.0598)	(0.0504)	(0.0589)	(0.110)	(0.0626)
3.age_cat	0.371***	0.0402	0.293***	0.0282	0.375***	0.0467
	(0.0586)	(0.0678)	(0.0591)	(0.0668)	(0.129)	(0.0710)
4.age_cat	0.400***	-0.158*	0.350***	-0.151*	0.439***	-0.137
	(0.0745)	(0.0807)	(0.0745)	(0.0790)	(0.164)	(0.0844)
5.age_cat	0.475***	-0.287***	0.441***	-0.225**	0.452**	-0.281***
	(0.0932)	(0.0962)	(0.0914)	(0.0930)	(0.207)	(0.101)
6.age_cat	0.263*	-0.769***	0.477***	-0.527***	0.390	-0.571***
	(0.156)	(0.128)	(0.135)	(0.115)	(0.313)	(0.127)
2.income_cat	0.405***	0.335***	0.410***	0.289***	0.658***	0.346***
	(0.0433)	(0.0511)	(0.0433)	(0.0500)	(0.0953)	(0.0536)
3.income_cat	0.820***	0.443***	0.734***	0.384***	1.221***	0.378***
	(0.0608)	(0.0744)	(0.0621)	(0.0736)	(0.134)	(0.0781)
4.income_cat	1.261***	0.494***	1.344***	0.434***	2.404***	0.430***
	(0.0858)	(0.108)	(0.0890)	(0.108)	(0.189)	(0.114)
HHsize	-0.00490	-0.0103	0.00618	-0.0128	0.00658	-0.0153*
	(0.00855)	(0.00822)	(0.00858)	(0.00810)	(0.0195)	(0.00873)
ownership_house	-0.0164	-0.0225	-0.0531	-0.0122	-0.0801	-0.0446
	(0.0443)	(0.0504)	(0.0447)	(0.0498)	(0.0975)	(0.0528)
employed	0.233***	0.303***	0.125***	0.268***	0.105	0.295***
	(0.0451)	(0.0625)	(0.0466)	(0.0629)	(0.100)	(0.0658)
p_computer		0.304***		0.300***		0.311***
		(0.0853)		(0.0855)		(0.0888)
credit	0.0964*	0.413***	0.188***	0.429***	0.221*	0.483***
	(0.0546)	(0.0954)	(0.0567)	(0.0961)	(0.118)	(0.0984)
bank	0.207***	0.497***	0.149***	0.466***	0.206**	0.472***
	(0.0468)	(0.0659)	(0.0479)	(0.0654)	(0.103)	(0.0685)
Constant	1.411***	-0.472*	1.902***	-0.299	0.0954**	-0.336
	(0.184)	(0.286)	(0.186)	(0.280)	(0.0464)	(0.299)
Observations	5,497	5,497	5,686	5,686	4,939	4,939

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