Mobile phones and financial inclusion in Sub-Saharan Africa*

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Abstract

In this paper, we use a survey data of 12,735 individuals from nine Sub-Saharan African countries conducted in 2017. We use geo-location of respondents to combine the survey data with information on the proximity of mobile network towers and banking facilities. We estimate a two-stage model, where in the first stage consumers decide to adopt a feature phone or a smartphone, and in the second stage they decide whether to use mobile money services. We find that individuals who live within 2km radius from GSM, UMTS and LTE towers are more likely to adopt both a feature phone and a smartphone, with a greater impact on the latter. In counterfactual simulations, we consider that the whole population lives within 2km from towers of any of these networks and find that the adoption of smartphones would increase by 12-32% depending on a country. We also find that overall there is less mobile money usage in areas which are less developed economically, while a greater distance to banking facilities increases the incentives to use mobile money. Furthermore, individuals who live in less developed areas are less likely to send money, but this is not the case with respect to receiving money. Thus, mobile money services enable transfers from richer to poorer areas, which contributes to reduction in income inequality.

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

JEL Classification: O12; O16; O18; O33; L86; L96

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[*] All errors are ours.

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1 Introduction

Mobile communications offers a major opportunity to advance economic growth in developing countries by: providing information about prices; improving management of supplies; increasing productive efficiency of firms; reducing transportation costs and other means (see Aker & Mbiti (2010)). Mobile phones can also serve as a channel for provision of services which are in general not available to poor people living in remote areas without infrastructure, such as mobile-based financial, educational, health and agricultural services. Moreover, according to a survey data conducted by Research ICT Africa in nine Sub-Saharan African countries in 2017, 95% of Internet connections were made using smartphones, while only 7.7% of households own a computer. Since smartphones are much cheaper than computers and their quality constantly increases, they have the potential to reduce digital divide within and between African countries.

In this paper, we focus on the role of investment in mobile infrastructure for broadening access to Internet and financial services in nine Sub-Saharan African countries. The banking sector in Sub-Saharan Africa remains underdeveloped. Based on the mentioned survey by Research ICT Africa, which we use in this paper, as of 2017 only 29% of people in nine Sub-Saharan African countries had bank account. This number is much below the average for developing countries worldwide.[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 people who are excluded from access to financial services to use them in the form of mobile wallet through which they can transfer, receive and save money. In this way, they can overcome the problem of poor infrastructure and expensive traditional banking model, which relies a network of branches at physical locations. Mobile phones can also contribute to reduction in inequality when there is a transfer of money from richer to less developed areas.

The literature which studies the effect of mobile money on financial inclusion focused mainly on Kenya, where M-Pesa became very successful (see Hughes & Lonie (2007); Jack & Suri (2014)). The literature on the adoption of mobile phones on the other hand does not consider the type phone and differences in adoption on detailed geographic level. In this paper, we contribute to this literature by analyzing how investments in mobile network coverage and proximity of banking facilities impacts the adoption of mobile phones and use of mobile money services. We

[1] Demirguc-Kunt et al. (2018) find that in 2017 the global share of adults who have an account with a financial institution or through a mobile money provider was 69% (up from 51% in 2011). In high-income countries 94% of adults have an account, while in developing economies 63% do.

use a rich survey data of 12,735 individuals conducted in 2017 in nine Sub-Saharan African countries: Ghana, Kenya, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania and Uganda. We use geo-location of respondents to combine the survey data with information on the proximity of mobile networks and banking facilities. We approximate access to physical infrastructure and the level of economic development using a number of variables. First, we use nighttime light intensity data from the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership satellite to approximate the level of economic development at the location of survey respondents. Second, we compute distance from the household location to mobile towers of GSM, UMTS and LTE networks. The GSM networks are used for making voice calls and sending SMS messages, while UMTS and LTE networks are used for both voice and data services. The handsets used by subscribers must be compatible with UMTS and LTE technologies to use data services. We also use variables such as distance to the nearest bank branch, automated teller machine (ATM), main road and town, which we obtained from Open Street Map (OSM).

We estimate a number of different two-stage models. In the first stage, individuals decide to adopt a mobile phone, where we distinguish between a feature phone which cannot access Internet and a smartphone. In the second stage, depending on adopted handset, they decide whether to use mobile money services. We analyze how these decisions are impacted by the proximity of towers for different mobile networks and by distance to ATMs and banking facilities. We use our model to simulate how investments in coverage of mobile networks impact the adoption of feature phones and smartphones, and use of mobile money services. We also estimate how the proximity of physical infrastructure and banking facilities impact the decision to send or receive money.

We find that network coverage has a significant impact on the decisions to adopt a mobile phone. In particular, individuals who live within 2km radius from GSM, UMTS and LTE towers are more likely to adopt both a feature phone and a smartphone, where there is a greater impact on the adoption of smartphones. The coverage by these different networks is highly correlated, where approximately 66% of individuals in our sample live within 2km from GSM tower, 64% from UMTS tower and 21% from LTE tower. We estimate different model specifications including coverage by one or more networks with comparable results. In counterfactual simulations, we consider that the whole population lives within 2km from any of these networks. We find that in such scenario the adoption of smartphones would increase by 12-32% depending on a country. The adoption of feature phones would decline for most countries when network coverage expands. The share of population without cellphones would decline by 8-18% depending on a country. Our results emphasize the role of investments in network coverage for increasing penetration of smartphones in African countries and for reduction of digital divide.

Overall, individuals who live in less developed economically areas, i.e., without nighttime light at all, are less likely to use mobile services. Next, we find that smartphone users who live within 10km from a bank branch are less likely to use mobile money services, but this is not the case for users of feature phones. Furthermore, users of any type of handset who live within 25km from an ATM are also less likely to use mobile money services. Thus, while overall there is less mobile money usage in areas which are less developed economically, a greater distance to financial facilities increases the incentives to use mobile money services. We also find that individuals who live in less developed areas are less likely to send money, but this is not the case with respect to receiving money. Thus, mobile money services enable transfers from richer to poorer areas and contribute to reduction in income inequality.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 discusses the development of mobile money services in Sub-Saharan Africa. In Section 4, we discuss the data sets used in our analysis. Section 5 introduces the econometric model and Section 6 presents the estimation results. Finally, Section 7 concludes.

2 Literature Review

There is a growing body of literature on the adoption and use of mobile services in low income countries.[2] Among these studies, many focus on M-Pesa in Kenya, which was the first and most prominent mobile money service in Sub-Saharan Africa. Mbiti & Weil (2015) analyze the use and economic impact of M-Pesa in Kenya using two waves of individual-level data on financial access. They find that M-Pesa has a positive impact on individual welfare by promoting banking and increasing money transfers. Jack & Suri (2014) use two waves of about 3,000 households in Kenya to study transactional networks and conclude that in households with M-Pesa users there is more remittance activity than in those without. They also find that households which use M-Pesa are more likely to remit for routine support, credit and insurance purposes. They

[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. Aker & Mbiti (2010) investigate the increase in mobile coverage and usage in Africa.

conclude that mobile money allows 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 adoption 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, remittance activity and household welfare in Uganda. They find a positive and significant effect of mobile money access on household welfare. Similar to Jack & Suri (2014), 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 for non-user households.

In another paper, Gutierrez & Singh (2013) use data on 37,000 individuals from 35 countries to analyze determinants of mobile banking usage. They conclude that a supporting regulatory framework is associated with higher usage of mobile banking in the whole population and among the unbanked. Lashitew et al. (2019) 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. Also 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. Finally, 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.

Most of the papers discussed above rely on surveys of individuals or households. There are also recent studies which apply a randomized controlled trial (RCT) to estimate causal effects of mobile money. Randomized access to mobile money is either given directly to individuals (Batista & Vicente (2013) and Batista & Vicente (2018)) or to small-scale entrepreneurs (Aggarwal et al., 2020). Batista & Vicente (2013) run the experiment of a set of individual dissemination activities, including the explanation of the services and functionalities as well as hands-on experiences with trial money in rural Mozambique. They find that remittances increased within rural households in experimental locations. In a follow-up study, Batista & Vicente (2018) show the economic effects of their experiment. They see the potential of mobile money (as a tool) to improve economic welfare of rural households as they are less affected by negative shocks in terms of consumption and lower vulnerability, e.g. severe flood and hunger episodes. Furthermore, households seem to shift away from investments in agriculture to investment in migration. Aggarwal et al. (2020) run their RCT on access to mobile money among micro-entrepreneurs in urban Malawi, where usage of mobile money was still modest. Treated individuals received assistance and basic training for their mobile money account opening. The treatment increased the usage extensively, in large part due to savings, rather than due to lower cost of interpersonal transfers. Wieser et al. (2019) randomized access to mobile money by the rollout of mobile money agents. They analyze effect of access to mobile money agents for poor households in rural northern Uganda. They conclude that the agent rollout increased non-farm self-employment rates. Moreover, mobile money has the potential to increase food security in more remote areas probably due to increased peer-to-peer transfers and cost savings for remittance transactions.

Another stream of literature studies the impact of mobile phones on the wellbeing of people. For example, Jensen (2007) uses a micro-level survey data to show 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. In a related paper, Aker & Mbiti (2010) study how the introduction of mobile phone between 2001 and 2006 affected grain prices in Niger. These papers emphasize the importance of rolling out mobile network infrastructure for improving economic efficiency of markets.

There is also a large body of related literature on the effect of infrastructure on economic outcomes in developing countries, which focused mainly on India. The infrastructure of interest is very manifold and covers besides mobile networks, electrification, water supply, transportation infrastructure as well as the very basic paved roads. Duflo & Pande (2007) show the positive effect of irrigation dams on agricultural production and how these can reduce rural poverty in India. Rud (2012) looked at increased manufacturing output by electricity through the channel of electric pump sets. Electrification in rural areas was also analyzed by Dinkelman (2011) for South Africa. She shows that electrification increases female employment. Similar effects are found by Grogan & Sadanand (2013) for Nicaragua. Aggarwal (2018) studies the development of paved roads in rural India and finds that paved roads lead to lower prices, higher market integration and higher use of agricultural technologies. The literature on infrastructure usually exploits variation in 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, as well as increased real income levels.

The body of literature that analyze how availability of infrastructure influences adoption of mobile phone and use of mobile money services is scarce. Mothobi & Grzybowski (2017) combine a micro-level survey data conducted in 2011 for eleven African countries with nighttime light intensity information to assess the effect of infrastructure on adoption of mobile phones and mobile money services. They find 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 studying the effect of infrastructure on the adoption of mobile phones and on the use of mobile money based on a survey conducted in nine Sub-Saharan African countries which includes information on geo-location of respondents. Most of the other studies which use survey data focus on a single country. First, we combine this data with nighttime light intensity information which we use to approximate the level of economic development of geographic areas. Second, we use distance from the household to mobile network towers to estimate the impact of coverage on the adoption of smartphones. Third, we use distance from the household to banking facilities such as bank branch and ATM to estimate how the proximity to physical infrastructure impacts the use of mobile money services.

3 Mobile Money in Sub-Saharan Africa

Mobile banking are financial services which enable consumers to access bank account, transfer money, make payments and perform other financial operations on their mobile phones. A mobile phone can also serve as virtual bank card, point of sale terminal or an ATM. These services may be provided by a bank or other financial institutions in addition to other banking services, or independently by mobile network operators (MNO). A financial institution and an MNO may also establish a partnership to provide mobile banking (see Brown et al. (2003)).

Mobile money services, on the other hand, are linked to a unique mobile phone number and are provided entirely on the mobile networks. They enable users to cash-in money using a mobile account called mobile wallet. Subscribers can use mobile wallet for a range of financial services including domestic and international money transfers, payments of bills, airtime top-up and others. The transactions are settled through the network of agents, which is established by an MNO.

The most common mobile money service in Sub-Saharan Africa is M-Pesa, which was first launched in Kenya in 2007 by Safaricom and Vodacom. Today, M-Pesa is the most popular mobile money service in East African countries including Uganda, Tanzania, Rwanda and Burundi and has been increasingly used in other African countries such as Cote d'lvore, Senegal, Madagascar, Mali, Niger, Botswana, Cameroon, South Africa as well as outside Africa in Jordan and Afghanistan.

As of 2008 in Kenya, there were about 2.7 million registered active mobile money users and more than 3,000 M-Pesa agents.[3] In 2019, the number of active mobile money accounts increased to 54.8 million and the agent network grew to about 222,000. The success of mobile money in Kenya can be attributed to 'laissez-faire' regulatory approach and a large network of mobile money agents across the country. In 2014, however, the Central Bank of Kenya introduced regulation of mobile money services which includes capital, inter-operability, governance, reporting and other obligations.[4]

The regulatory approach in other East African countries was similar to Kenya. In Tanzania for instance, mobile money services were launched in 2008 by Vodacom as M-Pesa and by Zantel as Z-Pesa. The Bank of Tanzania also initially took a 'laissez-faire' regulatory approach. In 2015, the Bank introduced regulation of inter-operability between mobile services and mandated non-exclusivity, which allows agents to work for many MNOs. The objective of this regulation was to mitigate the first mover advantage and market dominance by M-Pesa. Eventually, the number of agents working for six mobile money operators reached about 398,000.[5] Inter-operability between mobile money services is also the main regulatory focus in other African countries.

[3] Source:https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2012/03/What-makes-a-successful-mobile-money-implementation.pdf

[4] ibidem

[5] https://pathwayscommission.bsg.ox.ac.uk/sites/default/files/2019-11/Tanzania%20-%20creating%20a%20diverse%20mobile%20money%20market.pdf

In contrast to the majority of the East African countries, which allowed MNOs to innovate and launch mobile money services, in Nigeria these services were launched by the banks. As argued by the Central Bank of Nigeria, the objective was to control their rollout and avoid money laundering. As a result of this, the adoption of mobile money in Nigeria was much slower and eventually in September 2019, licences were also granted to MNOs. Mozambique also differs from other countries in that the regulator requested MNOs to provide mobile money services in a partnership with the banks. In South Africa on the other hand, mobile money services are less popular due to competition from existing financial institutions, which provide hybrid mobile banking services. For example, in 2017 the mobile network operator MTN stopped mobile money services which were launched earlier this year.

A number of banks in Africa rolled out a similar service called e-wallet. The difference to M-Pesa in that e-wallet requires the sender to have a bank account and the receiver can only cash-out money at ATMs using their mobile phone number and a pin.[6] Moreover, increasing popularity of smartphones in the last years allowed banks to launch mobile services which complement their over the counter and Internet banking services.

4 Data

We combine a few different data sets in this analysis. The first data 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.[7] Table 1 shows the number of individuals surveyed in each country and the share of mobile phone users. There are 8,970 individuals who declared having a mobile phone among 12,778 survey respondents in total. Furthermore, 4,538 individuals used a mobile wallet to send, receive or save money. The survey was conducted using electronic Android tablets and an external GPS device, which was used to capture the exact coordinates of the household. We use the geographic coordinates to merge the survey with the other data sets including information on 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

[6] See www.bocra.org.bw

[7] There was also a pilot survey conducted a year earlier in Lesotho, which is not included in our analysis. For details on the representativeness, sampling and data collection see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/765.

Group (EOG), Payne Institute for Public Policy. We apply the yearly cloud-free averaged data from 2016. In the earlier economic literature, initiated by Henderson et al. (2011), the Defense Meteorological Satellite Program (DMSP) was used, but the VIIRS data has better quality for the purpose of our study. 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, the nighttime light data was not created for scientific research as the main purpose, which is different for the VIIRS data. Second, the DMSP was stopped by 2013. So, for more recent data access the VIIRS is the only source. 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 light from aurora, fires, boats, and other temporal lights were filtered out by EOG.

The third database comes from OpenStreetMap (OSM), which is a collaborative effort 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, banks and ATMs, railway stations and bus stops, and of major roads. We used these geo-location information to calculate distances to the surveyed households. Cities have often more than 100,000 inhabitants including capital cities. 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 on the cell tower location was downloaded from OpenCelliD.[8] Beside the exact geo-location of each cell, the date of creation and the kind of technology can be observed: GSM (2G), UMTS (3G) and LTE (4G). We use only the antennas which were constructed before 2017 to make sure that individuals in our survey could use these antennas. For each household we calculate distance to the closest antenna of each technology.

4.1 Statistics

Table 1 shows penetration of mobile phones, usage of banking services and nighttime light data. The overall number of interviewed individuals in our sample is 12,735, with some differences

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

Table 1: Adoption of mobile phones, smartphones, mobile money and bank accounts

	Phone		Infrastructure	Financial			
Country	Phone Basic	Smartphone	Dark	Mobile Money	Bank	Card	N
Ghana	52.2%	25.8%	23.9%	51.6%	30.6%	8.03%	1196
Kenya	54.7%	33.6%	50.1%	80.5%	42.2%	19.9%	1216
Mozambique	41.4%	17.0%	41.0%	23.9%	24.4%	20.6%	1220
Nigeria	48.8%	16.5%	45.7%	2.49%	38.2%	31.0%	1804
Rwanda	43.9%	10.7%	69.2%	33.9%	32.7%	8.96%	1217
Senegal	59.0%	22.1%	34.6%	32.8%	10.6%	4.7%	1233
South Africa	41.6%	43.9%	22.4%	7.58%	57.2%	33.2%	1794
Tanzania	45.4%	20.3%	51.6%	55.4%	17.4%	10.6%	1200
Uganda	43.7%	13.2%	75.2%	47.8%	2.7%	6.79%	1855
Total	47.4%	22.8%	46.4%	34.8%	28.9%	17.0%	12735

across countries ranging from 1,196 in Ghana to 1,855 in Uganda. Mobile phone was owned by 70.2% of individuals in the sample, where 47.4% own a feature phone and 22.8% own a smartphone. In our sample, 34.8% use mobile money, 28.9% have a bank account and 17.0% have a credit card. Using mobile money, owning a bank account and owning a credit card are not mutually exclusive.

There are substantial difference in usage of mobile phones and smartphones across countries. For instance, the highest penetration of mobile phones was in Kenya (88.3%) and the lowest in Rwanda (54.6%). In South Africa, 85.5% of population had a mobile phone, among whom 43.9% are smartphone users. The lowest smartphone penetration was in Rwanda at 10.7% among 54.6% of mobile phone users. With respect to usage of mobile money, Kenya is at the top (80.5%) followed by Tanzania (55.4%). More economically developed countries, Nigeria and South Africa, have the lowest share of mobile money users, respectively 2.5% and 7.6%. As discussed earlier, this may be due to relatively high penetration of bank accounts in South Africa (57.2%). In Nigeria on the other hand, very low usage can be attributed to regulation due to which initially only banks were allowed to provide mobile money services.

Based on the NTL satellite data, 46.4% of individuals in our sample live in places which are not light at night. There is substantial variation in economic development approximated by nighttime light data. The countries with the less illuminated places are Uganda and Rwanda, where 75.2% and 69.2% of people in our sample live in 'dark' areas. On the other side are South Africa and Ghana, where only 22.4% and 23.9% of the respondents live in 'dark' places.

Figure 1 compares the use of mobile money in 2017 with the earlier survey conducted by

Research ICT Africa in 2011.[9] Kenya had a substantial penetration already in 2011 which increased further. In South Africa and Nigeria, a very low penetration of mobile money remained almost unchanged. In Tanzania and Uganda, the use of mobile money doubled from a relatively high level of nearly 25% in 2011 to about 48-55% in 2017. A substantial increase in the use of mobile money was also observed in Rwanda from 3.5% to 33.9%. The highest increase is observed in Ghana from 1.5% to 51.6%. A large increase in adoption in these countries can be attributed to the development of inter-operable mobile money payment systems, which make it possible for users to transfer money between accounts held with different MNOs and other financial institutions.

Figure 1: Evolution of mobile money usage between 2011 and 2017 by country. Source: Research ICT Africa

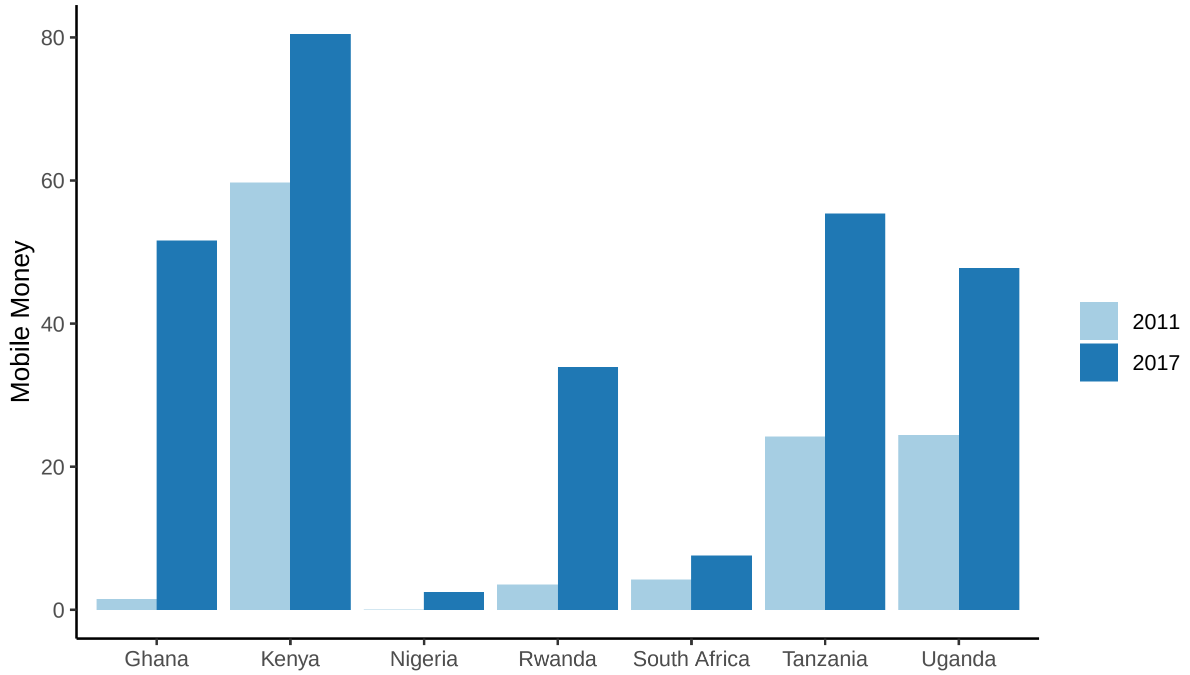


Table 2 compares the control variables which we use in our estimation across handset types, between 'dark' and 'lighted' locations, and between users and non-users of mobile money. The explanatory variables include individual characteristics such as gender, marital status, age group, level of education and employment status, as well as household characteristics such as number of people in the household, house ownership, disposable income in US$ PPP, access to lap-

[9] We do not use this data from 2011 in our empirical analysis because it lacks precise geo-location information of households and there are some differences in the range of questions asked. Additionally, the countries do not match exactly. In particular, Mozambique and Senegal are not shown in this figure.

Table 2: Comparison across individuals across adoption of phone type, infrastructure, and mobile money

Variable	Phone Types			Dark		Mobile Money	
	No Phone	Basic Phone	Smartphone	No	Yes	No	Yes
Female	0.55	0.51	0.48	0.53	0.53	0.56	0.48
Married	0.41	0.56	0.43	0.45	0.55	0.48	0.53
HHsize	4.54	4.11	3.79	4.01	4.23	4.30	3.75
None	0.15	0.14	0.02	0.10	0.24	0.23	0.05
Employed	0.13	0.17	0.37	0.24	0.12	0.13	0.29
Self-employed	0.22	0.35	0.20	0.25	0.34	0.27	0.32
Housework	0.12	0.16	0.07	0.14	0.21	0.20	0.12
Student	0.18	0.07	0.19	0.14	0.10	0.13	0.11
Retired	0.12	0.06	0.03	0.06	0.05	0.08	0.02
Internet	0.03	0.03	0.16	0.07	0.03	0.04	0.08
Laptop/comp	0.08	0.06	0.29	0.16	0.03	0.07	0.15
Own house	0.73	0.65	0.53	0.54	0.78	0.70	0.55
Car	0.13	0.06	0.25	0.14	0.04	0.10	0.09
Motorbike	0.07	0.08	0.10	0.08	0.08	0.08	0.09
TV	0.69	0.55	0.85	0.75	0.27	0.48	0.61
Fixed-line	0.03	0.02	0.08	0.05	0.01	0.03	0.04
Electricity	0.88	0.77	0.97	0.91	0.54	0.69	0.83
Age <25	0.31	0.22	0.33	0.29	0.29	0.30	0.27
Age >25 and <35	0.21	0.29	0.36	0.30	0.27	0.24	0.35
Age >35 and <45	0.17	0.21	0.17	0.18	0.18	0.17	0.21
Age >45 and <55	0.14	0.12	0.08	0.10	0.11	0.11	0.09
Age >55 and <65	0.10	0.09	0.05	0.08	0.07	0.09	0.05
Age >65	0.06	0.06	0.02	0.05	0.08	0.09	0.02
Income-Category 1	0.73	0.74	0.50	0.64	0.84	0.78	0.64
Income-Category 2	0.22	0.23	0.36	0.28	0.14	0.18	0.30
Income-Category 3	0.05	0.03	0.10	0.06	0.01	0.03	0.05
Income-Category 4	0.00	0.00	0.04	0.02	0.01	0.01	0.02

top/computer, car, motorbike and bank account. The statistics shows that women tend to use mobile money a bit less, married people a bit more. People in younger age groups tend to use mobile money more, as well as people in higher income groups. Furthermore, mobile money is used more by smaller households. Employed and self-employed people tend to use mobile money more, while students and retired people less.

Table 3 shows that there are large differences in average distance to infrastructure by individuals from different countries in our sample. We consider the following types of infrastructure. The general infrastructure is approximated by nighttime light data (lights-viirs), as well as distance in kilometres to major road (road) and to towns/cities (city-town). Banking infrastructure is approximated by distance to an ATM (atm), bank branch (bank) and the minimum distance to either of them (finance). Transport infrastructure is approximated by distance to railway station (railway) and bus stop (bus) and the minimum distance to either of them (transport). Finally, coverage by mobile infrastructure is approximated by distance to antennas from different networks such as GSM, UMTS and LTE.

Table 4 presents the summary statistics for the adoption of smartphones in proximity to

Table 3: Average distance to infrastructure across countries

	Ghana	Kenya	Mzbq	Nigeria	Rwanda	Senegal	S. Africa	Tanzania	Uganda	Total
Infrastructure										
lights-viirs	5.95	7.61	8.29	4.53	1.39	6.13	12.91	4.37	0.97	5.82
road	0.92	1.27	1.37	0.78	0.70	0.43	0.84	0.70	0.95	0.88
town	7.06	10.45	16.05	20.35	6.53	8.83	12.20	23.25	13.76	13.47
city	54.16	25.17	58.48	34.15	26.41	29.21	47.82	57.28	34.98	40.48
city-town	5.64	6.12	9.26	12.18	5.36	3.55	11.08	16.53	8.03	8.87
Finance										
bank	18.24	6.80	23.11	57.42	14.53	14.79	18.67	19.79	17.38	22.59
atm	40.42	33.76	40.06	103.77	18.69	38.12	26.13	24.46	39.81	42.85
finance	18.03	6.59	19.59	56.82	13.86	14.03	15.72	17.89	16.89	21.33
Transport										
railway	148.00	28.52	68.14	53.11		42.89	13.56	61.95	56.80	56.22
bus	13.40	12.99	25.86	70.55	9.33	12.11	37.68	14.57	27.27	27.72
transport	13.40	10.93	22.87	38.75	9.33	10.75	11.49	14.44	24.10	18.39
Mobile										
gsm	4.15	1.48	10.78	3.95	2.83	1.33	1.98	8.91	5.87	4.48
umts	5.79	1.84	12.98	5.68	4.19	2.42	2.23	11.31	6.61	5.73
lte	79.65	14.60	499.70	163.11	25.21	101.13	10.90	106.92	69.69	112.80

different mobile networks: GSM, UMTS and LTE. We construct a 0-1 distance variable for each network, which takes value 1 if the household is within a 2km radius from a cell tower and 0 otherwise. How far mobile base stations can broadcast a signal of good quality depends in general on the hardware used at the base station, the output power, terrain and the frequency on which the tower operates. For instance, LTE signals on 1800MHz frequency travel up to 5km from the base station and UMTS signals on 850MHz frequency may cover a radius of 60-120km. In this paper, we consider individuals who live within a 2km radius to have full coverage. The coverage by these different networks is highly correlated, where approximately 66% of individuals in our sample live within 2km from GSM tower, 64% from UMTS tower and 21% from LTE tower. There are large differences with respect to this statistics between countries in our data. There are large differences in coverage across countries, as shown in Table 5.

4.2 Reasons for not possessing a mobile phone

Survey respondents who declared not having a mobile phone were asked about the specific reasons, where multiple answers are possible. From the 3,796 individuals without a mobile phone, about 60% answered that they cannot afford a mobile phone. Lack of mobile coverage is a reason for not possessing a mobile phone for 10% of respondents and lack of electricity at home for charging the mobile phone was indicated by 25%. For another 15% the reason for not possessing a mobile phone was that the phone they owned before broke down or got stolen.

Table 4: Share of people within 2km distance from antennas

Country	GSM	UMTS	LTE
Ghana	68%	71%	19%
Kenya	77%	66%	46%
Mozambique	58%	57%	0%
Nigeria	64%	67%	7%
Rwanda	61%	50%	14%
Senegal	83%	78%	12%
South Africa	74%	71%	47%
Tanzania	59%	53%	32%
Uganda	54%	58%	14%
Total	66%	64%	21%

Table 5: Distribution of mobile phone type across technologies

	GSM		**UMTS**		**LTE**	
Country	Phone Basic	Smartphone	Phone Basic	Smartphone	Phone Basic	Smartphone
Ghana	66.7%	33.3%	67.5%	32.5%	51.6%	30.6%
Kenya	60.1%	39.9%	56.7%	43.3%	50.9%	49.1%
Mozambique	72.2%	27.8%	72.6%	27.4%		
Nigeria	78.6%	21.4%	78.0%	22.0%	67.5%	32.5%
Rwanda	84.7%	15.3%	80.1%	19.9%	67.8%	32.2%
Senegal	74.8%	25.2%	73.7%	26.3%	46.0%	54.0%
South Africa	50.6%	49.4%	50.0%	50.0%	45.9%	54.1%
Tanzania	70.0%	30.0%	66.9%	33.1%	63.8%	36.2%
Uganda	78.3%	21.7%	79.1%	20.9%	62.4%	37.6%
Total	67.7%	30.3%	68.8%	31.2%	54.6%	45.4%

Moreover, about 20% are not capable to use one, about 10% are not allowed to use one, and less than 5% have privacy concerns. Interestingly, among people who do not possess a mobile phone, about 30% own at least one active SIM card.

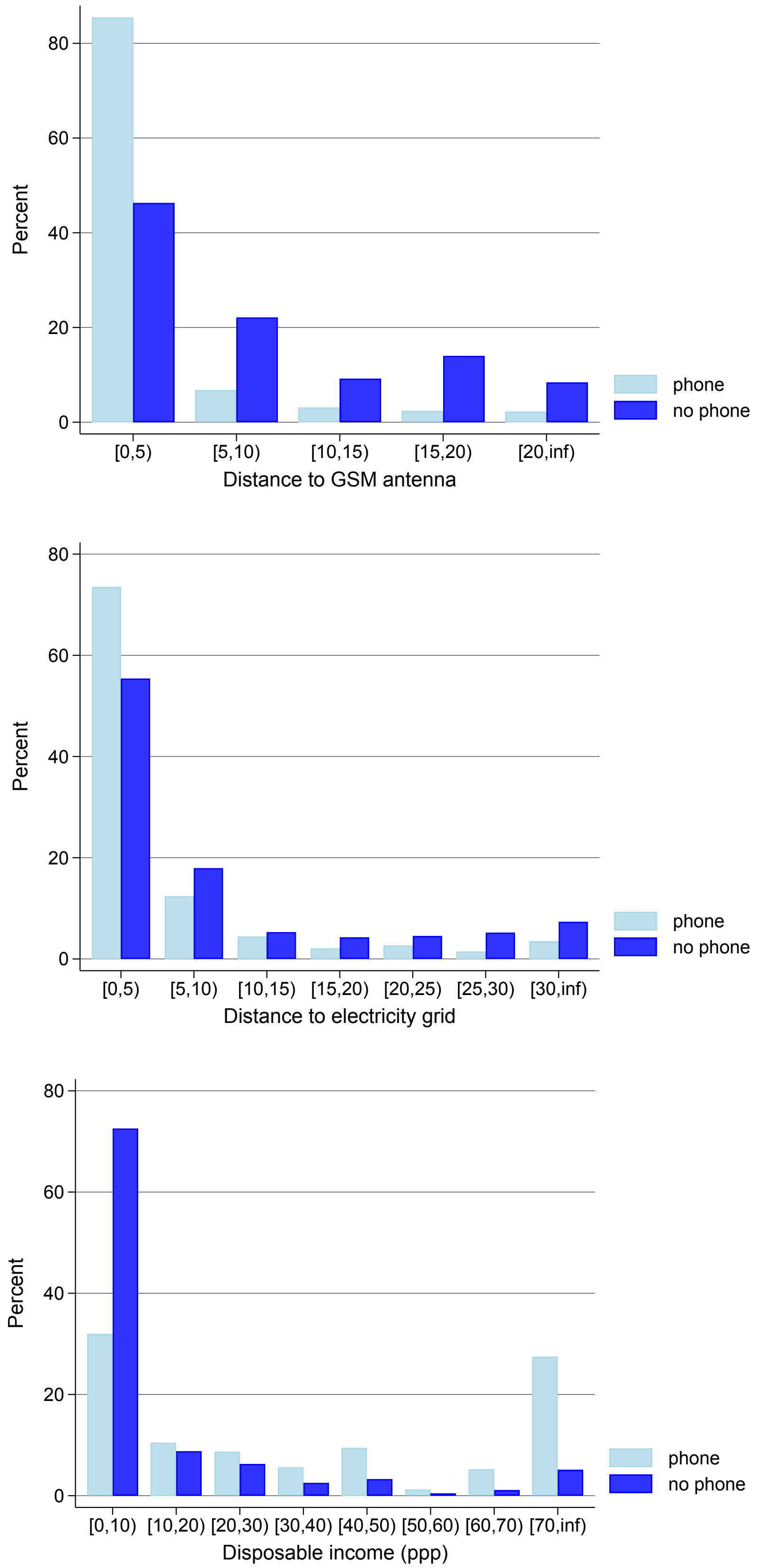
We can validate our geographic infrastructure variables and survey responses by comparing reasons for not possessing a mobile phone with the proximity of infrastructure. We do this for distance to mobile network towers and electricity grid. Figure 2 shows that individuals who declared not having a mobile phone because of lack of coverage, live further away from GSM antennas, as compared to people who have a mobile phone. Similarly, individuals who declared that lack of electricity is the reason for not having a mobile phone, live further away from electricity grid. We also cross-check the survey by comparing the income distribution for those who do not possess a mobile phone because they answered that they could not afford one and those who possess one. There substantially more individuals without income in the first group, as shown on Figure 2.

5 The Model

We estimate a number of different models for the decision to adopt a feature phone or a smartphone and for usage of mobile money services. Our decision model is estimated in two stages. In the first stage, consumers decide whether to adopt a mobile phone, which can be a feature phone, i.e., a phone without operating system and mobile Internet access, or a smartphone. In the second stage, those who adopted a mobile phone decide whether to use mobile money services. We also consider the decision to send or receive money in the second stage. In the first stage we estimate a standard multinomial logit. The selection correction models based on multinomial logit were developed by Lee (1984), Dubin & McFadden (1984), Dahl (2002) and more recently Bourguignon et al. (2007). We follow the approach by Dubin & McFadden (1984), which we discuss below.

As shown in Table 1, 70.2% of individuals in our sample declared having a mobile phone, where 22.8% have a smartphone. The penetration of smartphones in Sub-Saharan African countries was still very low in 2017 because the majority of people could not afford them. Also, people do not derive utility from a smartphone when there is no UMTS or LTE coverage at individual's location, which we take into account using distance to mobile infrastructure in the estimation.

Figure 2: Not having a mobile phone vs. geographical infrastructure and declared income



We model the decision to adopt a feature phone, denoted by subscript f or a smartphone with subscript s, where a consumer chooses a handset that maximizes his utility in a single period.[10] Thus, an individual $i = 1, ..., N$ from country $c = 1, ..., 9$ chooses alternative $j \in J \equiv \{f, s, o\}$, where subscript o denotes no handset at all, when $U_{icj} = \max_{k \in J} U_{ick}$. The decision problem of consumer i can be written using the following two equations:

$$U_{icj} = Z_{ic}\beta_j + \xi_j D_c + \epsilon_{icj} = V_{icj} + \epsilon_{icj} \quad (1)$$

$$y_{icj} = X_{ic}\gamma_j + u_{icj} \quad (2)$$

where the outcome variable y_{icj} is observed if and only if category $j \in \{f, s\}$ is chosen. The first equation (1) denotes a standard linear utility which consumer i derives from adopting a feature phone or a smartphone, where Z_{ic} includes a set of individual/household characteristics and infrastructure variables which determine adoption of different types of handsets. The alternative-specific coefficients, β_j, are estimated relative to the outside option of not having a mobile phone. The individual-specific valuation for alternative j, i.e., the 'logit error term', is represented by ϵ_{icj}. It is assumed to be identically and independently distributed over handsets and individuals according to the type I extreme value distribution. Finally, ξ_j denotes a vector of average country-specific valuation of a feature phone or a smartphone. Consumers have the same three choices in each country, but the range of available devices is different and hence also the utility which they derive from adopting a feature phone or a smartphone. We do not use prices of mobile phones in the estimation because we do not know the exact phone model used by individuals. Thus, we cannot estimate price elasticities of demand for feature phones and smartphones, but ξ_j should also control for the differences in average prices of handsets across countries.

The second equation (2) denotes the use of mobile money, which is determined by individual characteristics and infrastructure variables included in X_{ic} with handset-specific coefficients γ_j. The error term is denoted by u_{icj} and satisfies the condition $E(u_{icj}|Z_i, X_i) = 0$. We assume that the model is non-parametrically identified from exclusion of some of the variables in the choice equation, Z_i, from the variables in usage equation, X_i. In particular, we consider that the adoption of mobile phones is determined by network coverage, which does not affect usage of mobile services. While UMTS or LTE coverage is needed to access Internet on a smartphone,

[10]In reality, handsets are durable goods and consumers may be forward-looking, i.e., they may form expectations about the future range of products, their quality and prices.

it is not required to use mobile money. Once people can have GSM coverage and are able to use a feature phone, they can also use mobile money. We also estimate a similar two-stage model, where in the second stage individuals decide to send or receive funds via mobile money. For notational simplicity, we skip the subscript i for individuals and c for countries in the derivation of the model below.

In the second stage we take into account the selection correction term and follow the derivation in Bourguignon et al. (2007). Without loss of generality, a smartphone category s is chosen when $U_s > \max_{j \neq s} U_j$. We define ε_s as follows:

$$\begin{aligned} \varepsilon_s &= \max_{j \neq s}(U_j - U_s) \\ &= \max_{j \neq s}[(V_j + \epsilon_j) - (V_s + \epsilon_s)] \end{aligned}$$

Under this definition, smartphone is chosen when $\varepsilon_s < 0$. As shown by McFadden (1973), assuming that the error term ϵ_j has iid type I extreme value distribution, the choice probability for alternative s can be written as:

$$P_s\left(\varepsilon_s < 0|Z\right) = \frac{\exp\left(V_s\right)}{\sum_{j \in J} \exp\left(V_j\right)} \tag{3}$$

The parameters of utility function V_j can be estimated using the maximum likelihood estimator.

The problem is however with estimating mobile money usage equation (2) when there are unobserved characteristics of the individuals that affect both the handset choice and mobile money usage. Then the error term u_s is not independent of ϵ_s and for a continuous usage variable y_s, and normally distributed u_s, a simple ordinary least squares (OLS) regression of the usage equation would not be consistent.

Let us define the following vector $\Gamma = \{V_f, V_s, V_o\}$. For a generalized Heckman (1979) model, the correction bias can be based on the conditional mean of u_s:

$$E(u_s|\varepsilon_s < 0, \Gamma) = \int \int_{-\infty}^{0} \frac{u_s \cdot f(u_s, \epsilon_s|\Gamma)}{P(\varepsilon_s < 0|\Gamma)} d\epsilon_s du_s = \lambda(\Gamma) \tag{4}$$

where $f(u_s, \varepsilon_s|\Gamma)$ is the conditional joint density of u_s and ϵ_s. For notational simplicity, let us denote the probability that any alternative j is preferred by $P_j \equiv P_j(\varepsilon_j < 0|\Gamma)$. Given that the relation between the J components of Γ and the J corresponding probabilities is invertible, there is a unique function μ that can be substituted for λ such that:

$$E(u_s|\varepsilon_s, \Gamma) = \mu(P_f, P_s, P_o) \tag{5}$$

Therefore, consistent estimation of γ_j can be based on either regression:

$$\begin{aligned} y_j &= X\gamma_j + \mu(P_s, P_f, P_o) + \omega_j \\ &= X\gamma_j + \lambda(\Gamma) + \omega_j \end{aligned} \tag{6}$$

where ω_j is a residual that is mean-independent of the regressors.

For practical implementation, the literature proposed different restrictions over $\mu(.)$, or equivalently $\lambda(\Gamma)$ to deal with the issue dimensionality. Bourguignon et al. (2007) survey different approaches to selection bias correction. In this paper, we follow the approach by Dubin & McFadden (1984), in which the following linearity assumption is made with respect to the 'logit error term' ϵ_j:

$$E(u_s|\epsilon_f, \epsilon_s, \epsilon_o) = \sigma_u \sum_{j \in J} r_j(\epsilon_j - E(\epsilon_j)) \tag{7}$$

where $\sum_{j \in J} r_j = 0$. This assumption implies:

$$E(u_s|\epsilon_f, \epsilon_s, \epsilon_o) = \sigma_u \sum_{j \in \{f,o\}} r_j(\epsilon_j - \epsilon_s)) \tag{8}$$

For the multinomial logit model we can write for alternatives $j \neq s$:

$$E(\epsilon_j - \epsilon_s | U_s > \max_{k \neq s} U_k, \Gamma) = \frac{P_j ln(P_j)}{1 - P_j} + ln(P_s) \tag{9}$$

Given the assumption (7), the bias-corrected mobile money usage equation (2) for smartphone category s can be written as:

$$y_s = X\gamma_s + \sigma_u \sum_{j \in \{f,o\}} r_j \left(\frac{P_j ln(P_j)}{1 - P_j} + ln(P_s) \right) + \omega_s \tag{10}$$

and an analogous equation can be estimated for feature phone category f.[11] In the case of continuous usage variable y_s the estimation is done by means of OLS. Since our usage variable takes values zero when individuals use mobile money, and zero otherwise, we proceed by estimating bivariate logit model in the second stage.

6 The Estimation Results

6.1 Adoption of Mobile Phones

The vast majority of population in Sub-Saharan African countries relies on mobile phones to access Internet and use financial services. But due to low levels of income and relatively high costs of purchasing a smartphone, they cannot be afforded by many individuals. It is therefore important to analyze the factors which can contribute to a greater adoption smartphones and mobile financial services. We are in particular interested in estimating how network coverage impacts the adoption of different types of handsets. Currently, there are three different networks on which mobile services are provided: GSM, UMTS and LTE. The coverage of these networks is highly spatially correlated. About 66% of individuals in our sample live within 2km from GSM tower, 64% from UMTS tower and 21% from LTE tower, with large differences across countries. We estimate different model specifications, which include coverage by one or more networks. The models are estimated in two stages, as discussed above.

In the first stage, we estimate a discrete choice model for the decision to adopt a feature phone or a smartphone (see Table 6). We find that individuals who live within 2km radius from GSM, UMTS and LTE towers are more likely to adopt both a feature phone and a smartphone, where there is a greater impact of coverage on the adoption of smartphones. In Model I, we include in the estimation coverage by all three networks. In Models II, III and IV we use coverage for each network separately. The estimation results for all four specifications are comparable.

In the counterfactual simulations, we consider that the whole population lives within 2km from towers any of these networks. We find that in such case the adoption of smartphones would increase by between 12% and 32% depending on a country, as shown in Table 7. The smallest impact is estimated for South Africa, which had better network coverage and a higher

[11] Dubin & McFadden (1984) do not make any assumption on covariances between u_s and the error terms of the selection equation because all correlations, up to a normalization, are estimated in equation (10). As argued by Bourguignon et al. (2007), this assumption imposes a specific form of linearity between u_s and Gumbel distributions, thus restricting the class of allowed distributions for u_s. They suggest a variation of this assumption that can makes u_s linear on a set of normal distributions, allowing in particular u_s to be also normal.

share of smartphone users as of 2017. The biggest impact is estimated for Uganda and Rwanda. Moreover, when network coverage improves, the adoption of feature phones declines in most countries. Again, there are substantial differences across countries with a decrease by 7% in South Africa and an increase by 3% in Rwanda. Finally, the share of population without mobile phones would decline by between 8% and 18% depending on a country. Thus, our results emphasize the importance of investments in infrastructure on the adoption of smartphones and consequently on the use of mobile Internet and mobile financial services.

We include in the estimation a rich set of individual-specific variables. In particular, we find that females are less likely to adopt a feature phone or a smartphone. Individuals in younger age groups are more likely to adopt smartphones. People belonging to higher income groups are also more likely to adopt a mobile phone, and especially a smartphone. Married individuals are also more likely to use mobile phones, while people without education or with primary education are less likely to use a mobile phones. Employed and self-employed people are more likely to use mobile phones, while retired people are less likely. Students are less likely to use a feature phone but more likely to adopt a smartphone. People who own a house are less likely to use a mobile phone, but those who own a motorbike are more likely. Individuals who own a car or a laptop/computer are more likely to use a smartphone. Finally, individuals with a bank account are more likely to use both a feature phone and a smartphone. Overall, these variables have reasonable signs and interpretation.

6.2 Use of Mobile Money

In the second stage, conditional on the type of mobile phone used, we estimate the decision to use mobile money services. These services can be used both on a feature phone and a smartphone, but smartphones in addition give access to Internet and other financial services such as mobile banking. We estimate specifications with different infrastructure variables. In the first regressions, we consider the impact on use of mobile money of distance to bank branch and ATM, as shown in Tables 8 and 9. Overall, we find that individuals who live in areas which are reported as 'dark', i.e., without any nighttime light, are less likely to use mobile services. Living in less economically developed areas has a negative impact on the use of mobile money among feature phone users but not among smartphone users. Next, we find that smartphone users who live within 10km from a bank branch are less likely to use mobile money services, but this is not the case for users of feature phones. Furthermore, users of any type of handset who live within 25km from an ATM are also less likely to use mobile money services. In other two regressions, we consider the impact of distance to main road and town, as shown in Tables 10 and 11. We do not find that distance to the main road or town has impact on the use of mobile money. We conclude that while overall, there is less usage of mobile money in the areas which are less developed economically, a greater distance to banking facilities increases the incentives to use mobile money. Thus, mobile money eliminates the costs related to traveling to banking facilities in person to withdraw, deposit or transfer money.

The second stage estimations also include the correction terms from the first stage and the same set of individual-specific characteristics. Most of characteristics are however insignificant. The exceptions are a positive impact of owning a laptop/computer or being self-employed on the use of mobile money among smartphone users. There is also a positive impact of having a bank account or being a student among feature phone users. Importantly, the use of mobile money services is not influenced by the level of income directly.

In alternative model specification, we estimate two-stage model, where in the first stage individuals decide to adopt any type of mobile phone. In the second stage, we estimate the decision to adopt mobile money including the correction term from the first stage and distance to infrastructure. As above, there is also less use of mobile money in less developed economically areas. In this case, there is no impact of distance to bank branch on the use of mobile money but individuals living within distance of 25km to ATM are less likely to use mobile money, as shown in Tables 12 and 13. A number of individual characteristics becomes significant, as compared to the results shown in Tables 8 and 9. Finally, we do not find that distance to the main road has impact on the use of mobile money, while individuals living within 5km from town are less likely to adopt mobile money services, as shown in Tables 14 and 15.

6.3 Sending/Receiving Money

We also estimate second-stage regressions separately for the decisions to send or receive money via mobile wallet. We estimate these models without separating by the type of mobile phone used in the first stage. We find that people living in areas which are less developed economically are less likely to send money. Moreover, they are more likely to send money if they live within 2km from a bank branch but less likely if they live within 2km from an ATM, as shown in Tables 16. An easy access to ATM makes it possible to use cash instead of mobile money transfers. The positive impact of the proximity of bank branch is less clear. We also find that people living within 10km from town are less likely to send money via mobile wallet, as shown in Table 17. A number of individual characteristics are significant in these regressions. In particular, sending money is more likely among people who belong to younger age groups, are married, have secondary education, own a laptop/computer and bank account. Also, people from higher income groups are more likely to send money. But interestingly, people who own a car are less likely to send money even though they are better off financially.

The estimation results for receiving money via mobile money are different (see Tables 18 and 19). Living in areas which are less developed economically does not impact negatively receiving money, while the level of income is significant. Older people are more likely to receive money via mobile money, as well as females and married individuals. Thus, mobile money services enable transfers from richer to poorer areas, from richer to poorer people and from younger to older, which contributes to reduction in income inequality. A number of individual characteristics is significant in these regressions. People who own a car or motorbike are less likely to receive money, while those with a bank account are more likely. People who are employed are also more likely to receive money, which indicates that this may be a way of paying salaries. People who do not have any education are less likely to receive money which emphasizes the role of education and financial literacy for adoption and use of mobile money services. Finally, people who live within 2km from a bank branch are more likely to receive money, which may be because they are able to cash out money for others.

7 Conclusion

In this paper, we analyze how the proximity of mobile networks infrastructure and banking facilities impact the decision to adopt a mobile phone and to use mobile money services. We use a rich survey data of 12,735 individuals conducted in 2017 in nine Sub-Saharan African countries: Ghana, Kenya, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania and Uganda. We combine the survey data with detailed information on the proximity of physical infrastructure using information on geo-location of respondents. We approximate access to physical services and infrastructure, and the level of economic development using a number of variables. First, we use nighttime light intensity data to approximate the level of economic development at the location of survey respondents. Second, we approximate coverage using distance from the household location to mobile towers of GSM, UMTS and LTE networks. We also use variables such as proximity of bank branch, ATM, main road and town.

We estimate a two-stage model, where in the first stage consumers make the decision to adopt a mobile phone. We distinguish between feature phones which cannot access Internet and smartphones. In the second stage, depending on the type of handset adopted, they decide whether to use mobile money services. We find that network coverage has a significant impact on the decision to adopt a mobile phone. In particular, individuals who live within 2km radius from GSM, UMTS and LTE towers are more likely to adopt both a feature phone and a smartphone, where there is a greater impact on the adoption of a smartphone. In counterfactual simulations, we consider that the whole population lives within 2km radius from any of these networks. We find that in such scenario the adoption of smartphones would increase by 12-32% depending on a country. The adoption of feature phones would decline for most countries when network coverage expands. The share of population without mobile phones would decline by 8-18% depending on a country. Our results emphasize the role of investments in network coverage for reduction of digital divide and increasing the adoption of smartphones in African countries. To the best of our knowledge, this is the first paper which uses a very detailed individual-level data from a number of African countries with geo-location information that is combined with a detailed geographic data on infrastructure coverage.

Overall, individuals who live in areas which are less developed economically, i.e., where no nighttime light is observed, are less likely to use mobile money services. Next, we find that smartphone users who live within 10km from a bank branch are less likely to use mobile money services, but this is not the case for users of feature phones. Furthermore, users of any type of mobile phone who live within 25km from an ATM are also less likely to use mobile money services. Thus, while there is overall less mobile money usage in areas which are less developed economically, a greater distance to financial facilities increases the incentives to use mobile money. We also find that individuals who live in less developed areas are less likely to send money using mobile money services, but this is not the case with respect to receiving money. We conclude that mobile money services enable transfers from richer to poorer areas, from richer to poorer people and from younger to older, which contributes to reduction in income inequality.

add savings in addition to sending and receiving, drop SA and nigeria, add discussion of regulatory impact, the issue of endogeneity og infrastructure and identification

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8 Appendix

Table 6: Stage one: adoption of feature phones / smartphones

	Model I		Model II		Model III		Model IV	
	Feature	Smart	Feature	Smart	Feature	Smart	Feature	Smart
GSM	0.224***	0.503***	0.470***	1.082***				
	(0.073)	(0.115)	(0.051)	(0.082)				
UMTS	0.386***	0.696***			0.516***	1.142***		
	(0.074)	(0.116)			(0.051)	(0.081)		
LTE	-0.122	0.202**					0.177**	0.683***
	(0.082)	(0.097)					(0.077)	(0.090)
Female	-0.319***	-0.359***	-0.305***	-0.333***	-0.321***	-0.355***	-0.280***	-0.307***
	(0.052)	(0.071)	(0.052)	(0.070)	(0.052)	(0.071)	(0.051)	(0.070)
Age1	-0.155	1.927***	-0.172	1.879***	-0.158	1.916***	-0.209*	1.864***
	(0.112)	(0.247)	(0.111)	(0.245)	(0.112)	(0.246)	(0.111)	(0.246)
Age2	0.378***	2.175***	0.370***	2.138***	0.377***	2.167***	0.350***	2.157***
	(0.109)	(0.242)	(0.109)	(0.241)	(0.109)	(0.241)	(0.108)	(0.242)
Age3	0.421***	1.610***	0.419***	1.574***	0.419***	1.600***	0.407***	1.613***
	(0.113)	(0.247)	(0.113)	(0.246)	(0.113)	(0.246)	(0.113)	(0.247)
Age4	0.385***	1.206***	0.386***	1.165***	0.385***	1.200***	0.377***	1.213***
	(0.120)	(0.255)	(0.119)	(0.253)	(0.119)	(0.254)	(0.119)	(0.255)
Age5	0.443***	1.064***	0.448***	1.051***	0.440***	1.054***	0.442***	1.074***
	(0.121)	(0.250)	(0.121)	(0.249)	(0.121)	(0.250)	(0.120)	(0.250)
Income1	2.090***	0.575*	2.091***	0.513*	2.108***	0.529*	2.049***	0.548*
	(0.298)	(0.295)	(0.299)	(0.293)	(0.298)	(0.294)	(0.300)	(0.298)
Income2	2.339***	1.246***	2.343***	1.210***	2.355***	1.217***	2.314***	1.248***
	(0.302)	(0.297)	(0.302)	(0.296)	(0.302)	(0.297)	(0.303)	(0.300)
Income3	2.107***	1.572***	2.120***	1.553***	2.116***	1.544***	2.101***	1.601***
	(0.363)	(0.365)	(0.364)	(0.364)	(0.364)	(0.364)	(0.365)	(0.367)
Married	0.241***	0.208**	0.232***	0.188**	0.241***	0.198**	0.218***	0.169**
	(0.057)	(0.082)	(0.057)	(0.082)	(0.057)	(0.082)	(0.057)	(0.082)
hh2	0.013	0.068	0.021	0.094	0.008	0.065	0.019	0.076
	(0.095)	(0.127)	(0.095)	(0.127)	(0.095)	(0.127)	(0.095)	(0.126)
hh3	-0.103	-0.067	-0.093	-0.046	-0.105	-0.062	-0.086	-0.049
	(0.080)	(0.107)	(0.080)	(0.107)	(0.080)	(0.107)	(0.079)	(0.107)
none	-1.854***	-4.036***	-1.884***	-4.098***	-1.856***	-4.036***	-1.948***	-4.189***
	(0.139)	(0.205)	(0.139)	(0.205)	(0.139)	(0.205)	(0.138)	(0.204)
primary	-0.956***	-2.726***	-0.976***	-2.762***	-0.960***	-2.726***	-1.026***	-2.849***
	(0.130)	(0.146)	(0.130)	(0.146)	(0.130)	(0.146)	(0.129)	(0.145)
secondary	-0.209	-1.165***	-0.216*	-1.171***	-0.206	-1.151***	-0.207	-1.171***
	(0.128)	(0.131)	(0.128)	(0.131)	(0.128)	(0.131)	(0.128)	(0.131)
employed	0.511***	0.827***	0.518***	0.848***	0.512***	0.834***	0.552***	0.867***
	(0.101)	(0.126)	(0.101)	(0.125)	(0.101)	(0.125)	(0.101)	(0.125)
self employed	0.366***	0.457***	0.356***	0.453***	0.365***	0.463***	0.346***	0.431***
	(0.073)	(0.110)	(0.073)	(0.110)	(0.073)	(0.110)	(0.073)	(0.109)
housework	-0.136*	-0.007	-0.134*	-0.011	-0.137*	-0.017	-0.142*	-0.018
	(0.079)	(0.128)	(0.079)	(0.128)	(0.079)	(0.128)	(0.078)	(0.127)
student	-0.907***	-0.172	-0.892***	-0.154	-0.903***	-0.175	-0.864***	-0.111
	(0.099)	(0.124)	(0.099)	(0.124)	(0.099)	(0.124)	(0.098)	(0.123)
retired	-0.315***	-0.771***	-0.309**	-0.732***	-0.318***	-0.756***	-0.306**	-0.765***
	(0.121)	(0.221)	(0.121)	(0.219)	(0.121)	(0.220)	(0.121)	(0.221)
own house	-0.109*	-0.318***	-0.129**	-0.401***	-0.112*	-0.366***	-0.224***	-0.487***
	(0.058)	(0.077)	(0.057)	(0.076)	(0.058)	(0.076)	(0.057)	(0.075)
car	-0.013	0.486***	-0.001	0.540***	-0.010	0.505***	0.045	0.558***
	(0.129)	(0.140)	(0.129)	(0.140)	(0.129)	(0.140)	(0.129)	(0.140)
motobike	0.342***	0.413***	0.348***	0.397***	0.329***	0.393***	0.302***	0.336***
	(0.099)	(0.126)	(0.098)	(0.127)	(0.098)	(0.126)	(0.097)	(0.125)
laptop/computer	0.179	0.939***	0.200	0.974***	0.188	0.958***	0.263*	1.063***
	(0.139)	(0.144)	(0.139)	(0.143)	(0.139)	(0.144)	(0.138)	(0.143)
bank	1.022***	1.828***	1.034***	1.850***	1.019***	1.836***	1.050***	1.876***
	(0.084)	(0.099)	(0.084)	(0.099)	(0.084)	(0.099)	(0.084)	(0.098)
Observations	38,115	38,115	38,115	38,115	38,115	38,115	38,115	38,115

Table 7: Impact of coverage on adoption on handsets: simulation

	Base			Full coverage				Change	
Country	No phone	Feature	Smart	No phone	Feature	Smart	% No phone	% Feature	% Smart
Ghana	21.9%	52.3%	25.9%	18.7%	50.1%	31.2%	-14%	-4%	21%
Kenya	11.8%	54.7%	33.5%	9.6%	52.5%	37.8%	-18%	-4%	13%
Mozambique	41.6%	41.4%	17.0%	36.6%	41.6%	21.8%	-12%	0%	29%
Nigeria	34.6%	48.9%	16.5%	31.7%	47.1%	21.2%	-9%	-4%	29%
Rwanda	45.4%	43.9%	10.7%	40.7%	45.3%	14.0%	-10%	3%	31%
Senegal	18.9%	58.9%	22.1%	17.5%	56.3%	26.2%	-8%	-4%	18%
South Africa	14.5%	41.6%	43.9%	11.8%	38.8%	49.3%	-18%	-7%	12%
Tanzania	34.3%	45.4%	20.3%	29.0%	46.5%	24.5%	-15%	2%	20%
Uganda	43.1%	43.7%	13.2%	38.0%	44.6%	17.4%	-12%	2%	32%

Table 8: Stage two: distance to bank branch (adoption of mobile phones model)

	Feature phone				Smartphone			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
bank2	0.029				-0.431***			
	(0.098)				(0.153)			
bank5		0.016				-0.422***		
		(0.098)				(0.155)		
bank10			-0.078				-0.343**	
			(0.091)				(0.155)	
bank25				0.071				-0.186
				(0.096)				(0.185)
light1	-0.277**	-0.280**	-0.305***	-0.282***	-0.233	-0.249	-0.204	-0.120
	(0.110)	(0.112)	(0.108)	(0.106)	(0.200)	(0.199)	(0.195)	(0.192)
female	0.084	0.084	0.098	0.079	-0.087	-0.062	-0.053	-0.093
	(0.084)	(0.084)	(0.084)	(0.084)	(0.164)	(0.165)	(0.165)	(0.165)
age1	0.349	0.344	0.267	0.379	0.954	0.944	0.945	0.997
	(0.274)	(0.277)	(0.280)	(0.276)	(0.624)	(0.617)	(0.620)	(0.619)
age2	0.343	0.337	0.253	0.375	1.195*	1.131*	1.134*	1.225**
	(0.273)	(0.276)	(0.280)	(0.276)	(0.618)	(0.612)	(0.614)	(0.613)
age3	0.592**	0.587**	0.524**	0.614**	0.936	0.878	0.876	0.962
	(0.241)	(0.243)	(0.246)	(0.242)	(0.618)	(0.611)	(0.614)	(0.613)
age4	0.447*	0.444*	0.397*	0.464**	0.499	0.459	0.451	0.527
	(0.229)	(0.229)	(0.231)	(0.229)	(0.628)	(0.620)	(0.622)	(0.622)
age5	0.292	0.289	0.248	0.303	0.231	0.184	0.156	0.235
	(0.225)	(0.226)	(0.227)	(0.225)	(0.624)	(0.618)	(0.620)	(0.618)
income1	-0.585	-0.587	-0.590	-0.580	-0.980	-1.134	-1.171	-0.995
	(0.517)	(0.517)	(0.517)	(0.517)	(0.848)	(0.848)	(0.850)	(0.846)
income2	-0.404	-0.407	-0.432	-0.392	-0.922	-1.110	-1.154	-0.947
	(0.527)	(0.527)	(0.528)	(0.528)	(0.904)	(0.904)	(0.906)	(0.901)
income3	-0.744	-0.747	-0.779	-0.725	-0.841	-1.026	-1.072	-0.871
	(0.568)	(0.568)	(0.569)	(0.569)	(0.828)	(0.829)	(0.831)	(0.826)
married	0.048	0.047	0.040	0.051	-0.066	-0.077	-0.089	-0.060
	(0.088)	(0.088)	(0.088)	(0.088)	(0.171)	(0.171)	(0.172)	(0.171)
hh2	0.058	0.058	0.056	0.060	0.126	0.125	0.133	0.139
	(0.141)	(0.141)	(0.141)	(0.141)	(0.232)	(0.232)	(0.232)	(0.231)
hh3	0.054	0.054	0.056	0.053	-0.015	-0.008	-0.003	-0.009
	(0.119)	(0.119)	(0.119)	(0.119)	(0.197)	(0.197)	(0.197)	(0.197)
none	-0.774*	-0.769*	-0.636	-0.821**	-0.600	-0.438	-0.422	-0.630
	(0.404)	(0.411)	(0.417)	(0.407)	(0.704)	(0.706)	(0.707)	(0.701)
primary	-0.272	-0.268	-0.183	-0.306	-0.387	-0.275	-0.271	-0.394
	(0.297)	(0.302)	(0.305)	(0.300)	(0.403)	(0.405)	(0.406)	(0.402)
secondary	-0.190	-0.189	-0.154	-0.203	-0.249	-0.210	-0.210	-0.257
	(0.200)	(0.201)	(0.202)	(0.200)	(0.199)	(0.200)	(0.200)	(0.199)
employed	0.214	0.213	0.190	0.225	0.296	0.252	0.248	0.286
	(0.152)	(0.152)	(0.153)	(0.152)	(0.274)	(0.274)	(0.273)	(0.273)
self_employed	-0.004	-0.004	-0.019	0.004	0.600**	0.578**	0.573**	0.592**
	(0.114)	(0.115)	(0.115)	(0.115)	(0.256)	(0.256)	(0.255)	(0.255)
housework	-0.074	-0.074	-0.078	-0.072	0.234	0.244	0.250	0.243
	(0.126)	(0.126)	(0.126)	(0.126)	(0.265)	(0.265)	(0.266)	(0.265)
student	0.375**	0.374**	0.380**	0.369**	0.573	0.626*	0.647*	0.580
	(0.180)	(0.180)	(0.180)	(0.180)	(0.371)	(0.370)	(0.370)	(0.369)
retired	0.074	0.076	0.104	0.067	-0.307	-0.285	-0.302	-0.365
	(0.218)	(0.218)	(0.219)	(0.218)	(0.535)	(0.534)	(0.533)	(0.534)
own_house	-0.074	-0.075	-0.071	-0.079	0.026	0.043	0.063	0.063
	(0.094)	(0.094)	(0.094)	(0.094)	(0.140)	(0.139)	(0.139)	(0.139)
car	-0.025	-0.026	-0.045	-0.019	0.021	-0.005	-0.009	-0.003
	(0.198)	(0.199)	(0.199)	(0.199)	(0.174)	(0.173)	(0.173)	(0.174)
motorbike	0.158	0.156	0.134	0.166	-0.001	-0.041	-0.046	-0.007
	(0.146)	(0.146)	(0.147)	(0.146)	(0.231)	(0.230)	(0.231)	(0.230)
laptop_comp	0.200	0.198	0.169	0.210	0.433**	0.422**	0.407**	0.441**
	(0.182)	(0.182)	(0.183)	(0.182)	(0.183)	(0.183)	(0.183)	(0.183)
bank	0.381*	0.379*	0.317	0.405**	0.398	0.308	0.292	0.385
	(0.199)	(0.202)	(0.204)	(0.201)	(0.362)	(0.362)	(0.363)	(0.362)
mon2_1	-0.228	-0.230	-0.268*	-0.212	-0.209	-0.301	-0.322	-0.217
	(0.144)	(0.145)	(0.147)	(0.145)	(0.371)	(0.372)	(0.373)	(0.370)
mon2_3	0.156	0.158	0.202*	0.140	0.741	0.813	0.859	0.771
	(0.117)	(0.120)	(0.122)	(0.118)	(0.538)	(0.538)	(0.538)	(0.536)
Constant	2.084***	2.098***	2.245***	2.015***	3.454***	3.601***	3.623***	3.333***
	(0.653)	(0.656)	(0.657)	(0.657)	(1.107)	(1.107)	(1.115)	(1.114)
Observations	5,983	5,983	5,983	5,983	2,883	2,883	2,883	2,883

Table 9: Stage two: distance to ATM (adoption of feature phone / smartphone model)

	Feature phone				Smartphone			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
atm2	0.162				-0.271*			
	(0.112)				(0.150)			
atm5		0.198**				-0.324**		
		(0.099)				(0.142)		
atm10			-0.067				-0.423***	
			(0.092)				(0.142)	
atm25				-0.181**				-0.281*
				(0.086)				(0.152)
light1	-0.246**	-0.227**	-0.302***	-0.311***	-0.144	-0.195	-0.235	-0.158
	(0.109)	(0.110)	(0.108)	(0.106)	(0.193)	(0.196)	(0.195)	(0.192)
female	0.080	0.072	0.094	0.104	-0.108	-0.101	-0.071	-0.085
	(0.083)	(0.083)	(0.084)	(0.084)	(0.164)	(0.164)	(0.164)	(0.164)
age1	0.375	0.430	0.290	0.208	0.901	0.888	0.828	0.944
	(0.271)	(0.274)	(0.276)	(0.276)	(0.618)	(0.618)	(0.623)	(0.620)
age2	0.372	0.435	0.275	0.185	1.161*	1.141*	1.053*	1.171*
	(0.269)	(0.273)	(0.276)	(0.276)	(0.611)	(0.611)	(0.616)	(0.614)
age3	0.612**	0.652***	0.544**	0.484**	0.905	0.900	0.810	0.913
	(0.238)	(0.240)	(0.242)	(0.242)	(0.611)	(0.610)	(0.615)	(0.613)
age4	0.458**	0.488**	0.412*	0.367	0.476	0.458	0.385	0.489
	(0.227)	(0.228)	(0.229)	(0.229)	(0.620)	(0.619)	(0.624)	(0.622)
age5	0.306	0.329	0.261	0.222	0.204	0.201	0.114	0.192
	(0.224)	(0.224)	(0.225)	(0.225)	(0.616)	(0.616)	(0.621)	(0.619)
income1	-0.582	-0.601	-0.590	-0.615	-0.888	-0.961	-1.050	-1.046
	(0.516)	(0.514)	(0.517)	(0.517)	(0.843)	(0.845)	(0.843)	(0.845)
income2	-0.399	-0.400	-0.426	-0.467	-0.829	-0.904	-1.018	-0.998
	(0.526)	(0.524)	(0.528)	(0.527)	(0.897)	(0.900)	(0.898)	(0.899)
income3	-0.749	-0.745	-0.767	-0.813	-0.770	-0.839	-0.959	-0.918
	(0.567)	(0.566)	(0.569)	(0.568)	(0.823)	(0.825)	(0.823)	(0.825)
married	0.050	0.055	0.042	0.033	-0.050	-0.059	-0.084	-0.068
	(0.087)	(0.088)	(0.088)	(0.088)	(0.170)	(0.171)	(0.171)	(0.171)
hh2	0.058	0.054	0.058	0.055	0.133	0.140	0.148	0.139
	(0.142)	(0.142)	(0.141)	(0.142)	(0.231)	(0.232)	(0.232)	(0.231)
hh3	0.054	0.048	0.057	0.055	-0.011	-0.008	-0.002	-0.007
	(0.119)	(0.119)	(0.119)	(0.119)	(0.196)	(0.197)	(0.197)	(0.197)
none	-0.813**	-0.920**	-0.667	-0.515	-0.724	-0.605	-0.465	-0.577
	(0.398)	(0.405)	(0.411)	(0.411)	(0.698)	(0.700)	(0.701)	(0.701)
primary	-0.298	-0.368	-0.201	-0.094	-0.431	-0.373	-0.276	-0.355
	(0.294)	(0.298)	(0.302)	(0.302)	(0.400)	(0.402)	(0.403)	(0.402)
secondary	-0.201	-0.227	-0.163	-0.119	-0.264	-0.236	-0.198	-0.235
	(0.199)	(0.200)	(0.201)	(0.201)	(0.199)	(0.199)	(0.200)	(0.199)
employed	0.222	0.238	0.194	0.163	0.305	0.284	0.262	0.266
	(0.151)	(0.152)	(0.153)	(0.153)	(0.273)	(0.273)	(0.273)	(0.273)
self_employed	0.001	0.013	-0.016	-0.035	0.609**	0.588**	0.590**	0.580**
	(0.114)	(0.115)	(0.115)	(0.115)	(0.256)	(0.256)	(0.256)	(0.256)
housework	-0.074	-0.072	-0.076	-0.077	0.217	0.223	0.254	0.246
	(0.126)	(0.126)	(0.126)	(0.126)	(0.266)	(0.265)	(0.265)	(0.265)
student	0.373**	0.374**	0.376**	0.378**	0.541	0.543	0.588	0.587
	(0.180)	(0.180)	(0.179)	(0.179)	(0.369)	(0.369)	(0.368)	(0.368)
retired	0.065	0.035	0.100	0.126	-0.376	-0.369	-0.342	-0.370
	(0.217)	(0.218)	(0.218)	(0.218)	(0.535)	(0.534)	(0.535)	(0.532)
own_house	-0.073	-0.074	-0.074	-0.067	0.042	0.032	0.044	0.059
	(0.094)	(0.094)	(0.094)	(0.094)	(0.140)	(0.140)	(0.140)	(0.139)
car	-0.034	-0.020	-0.035	-0.041	0.023	0.025	0.023	0.009
	(0.198)	(0.198)	(0.198)	(0.199)	(0.174)	(0.174)	(0.174)	(0.174)
motorbike	0.169	0.183	0.142	0.122	-0.001	-0.010	-0.046	-0.031
	(0.146)	(0.146)	(0.146)	(0.146)	(0.230)	(0.230)	(0.230)	(0.231)
laptop_comp	0.204	0.228	0.177	0.149	0.447**	0.449**	0.421**	0.439**
	(0.181)	(0.182)	(0.182)	(0.182)	(0.183)	(0.183)	(0.183)	(0.183)
bank	0.398**	0.448**	0.330	0.260	0.437	0.414	0.340	0.371
	(0.196)	(0.199)	(0.203)	(0.202)	(0.359)	(0.359)	(0.359)	(0.360)
mon2_1	-0.220	-0.193	-0.260*	-0.299**	-0.166	-0.189	-0.269	-0.241
	(0.142)	(0.143)	(0.146)	(0.145)	(0.368)	(0.369)	(0.368)	(0.369)
mon2_3	0.140	0.103	0.192	0.241**	0.688	0.691	0.744	0.775
	(0.115)	(0.118)	(0.120)	(0.119)	(0.536)	(0.537)	(0.536)	(0.535)
Constant	1.992***	1.907***	2.205***	2.380***	3.281***	3.403***	3.563***	3.438***
	(0.647)	(0.649)	(0.652)	(0.653)	(1.094)	(1.097)	(1.102)	(1.104)
Observations	5,983	5,983	5,983	5,983	2,883	2,883	2,883	2,883

Table 10: Stage two: distance to roads (adoption of feature phones / smartphones model)

	Feature phone			Smartphone		
	Model I	Model II	Model III	Model I	Model II	Model III
road2	-0.051			-0.027		
	(0.075)			(0.123)		
road5		0.049			0.072	
		(0.084)			(0.150)	
road10			-0.071			0.275
			(0.101)			(0.219)
light1	-0.294***	-0.277***	-0.299***	-0.081	-0.065	-0.026
	(0.106)	(0.107)	(0.107)	(0.189)	(0.191)	(0.193)
female	0.089	0.082	0.093	-0.115	-0.122	-0.144
	(0.083)	(0.083)	(0.084)	(0.163)	(0.163)	(0.164)
age1	0.327	0.349	0.304	0.994	1.008	1.016
	(0.270)	(0.271)	(0.273)	(0.618)	(0.618)	(0.619)
age2	0.317	0.342	0.297	1.253**	1.272**	1.308**
	(0.268)	(0.269)	(0.271)	(0.611)	(0.611)	(0.613)
age3	0.572**	0.592**	0.556**	0.987	1.003	1.032*
	(0.238)	(0.238)	(0.240)	(0.611)	(0.611)	(0.612)
age4	0.431*	0.448**	0.420*	0.550	0.567	0.598
	(0.227)	(0.227)	(0.228)	(0.620)	(0.620)	(0.622)
age5	0.277	0.293	0.267	0.260	0.266	0.295
	(0.223)	(0.224)	(0.224)	(0.617)	(0.616)	(0.617)
income1	-0.589	-0.586	-0.594	-0.886	-0.868	-0.771
	(0.516)	(0.517)	(0.516)	(0.839)	(0.840)	(0.844)
income2	-0.414	-0.406	-0.425	-0.820	-0.804	-0.697
	(0.527)	(0.527)	(0.527)	(0.893)	(0.895)	(0.899)
income3	-0.758	-0.743	-0.770	-0.761	-0.738	-0.632
	(0.568)	(0.568)	(0.568)	(0.819)	(0.821)	(0.826)
married	0.046	0.047	0.044	-0.042	-0.040	-0.027
	(0.087)	(0.087)	(0.087)	(0.170)	(0.170)	(0.171)
hh2	0.054	0.060	0.054	0.135	0.140	0.132
	(0.142)	(0.142)	(0.142)	(0.231)	(0.231)	(0.231)
hh3	0.050	0.055	0.053	-0.015	-0.014	-0.020
	(0.119)	(0.119)	(0.119)	(0.196)	(0.196)	(0.196)
none	-0.744*	-0.771*	-0.706*	-0.723	-0.750	-0.819
	(0.396)	(0.397)	(0.401)	(0.695)	(0.698)	(0.701)
primary	-0.252	-0.270	-0.228	-0.450	-0.466	-0.512
	(0.292)	(0.293)	(0.295)	(0.398)	(0.400)	(0.402)
secondary	-0.182	-0.189	-0.173	-0.274	-0.281	-0.291
	(0.199)	(0.199)	(0.199)	(0.198)	(0.198)	(0.199)
employed	0.204	0.217	0.198	0.303	0.303	0.320
	(0.151)	(0.152)	(0.152)	(0.272)	(0.273)	(0.273)
self_employed	-0.008	-0.002	-0.012	0.590**	0.590**	0.603**
	(0.114)	(0.114)	(0.115)	(0.255)	(0.255)	(0.256)
housework	-0.078	-0.073	-0.079	0.228	0.225	0.224
	(0.126)	(0.126)	(0.126)	(0.265)	(0.265)	(0.265)
student	0.377**	0.375**	0.375**	0.544	0.530	0.483
	(0.180)	(0.180)	(0.180)	(0.367)	(0.368)	(0.370)
retired	0.078	0.078	0.086	-0.395	-0.401	-0.431
	(0.217)	(0.217)	(0.217)	(0.533)	(0.532)	(0.534)
own_house	-0.076	-0.073	-0.076	0.058	0.063	0.063
	(0.094)	(0.094)	(0.094)	(0.139)	(0.140)	(0.139)
car	-0.030	-0.027	-0.029	-0.002	-0.010	-0.013
	(0.198)	(0.198)	(0.198)	(0.174)	(0.174)	(0.174)
motorbike	0.154	0.152	0.153	0.023	0.027	0.048
	(0.145)	(0.145)	(0.145)	(0.229)	(0.229)	(0.229)
laptop_comp	0.195	0.197	0.185	0.452**	0.457**	0.465**
	(0.181)	(0.181)	(0.181)	(0.182)	(0.183)	(0.183)
bank	0.366*	0.379*	0.352*	0.443	0.450	0.490
	(0.195)	(0.196)	(0.197)	(0.358)	(0.358)	(0.361)
mon2_1	-0.239*	-0.228	-0.247*	-0.158	-0.148	-0.097
	(0.142)	(0.142)	(0.143)	(0.366)	(0.367)	(0.370)
mon2_3	0.166	0.157	0.180	0.713	0.709	0.649
	(0.114)	(0.114)	(0.116)	(0.534)	(0.534)	(0.536)
Constant	2.154***	2.064***	2.224***	3.090***	3.009***	2.719**
	(0.643)	(0.649)	(0.657)	(1.086)	(1.094)	(1.121)
Observations	5,983	5,983	5,983	2,883	2,883	2,883

Table 11: Stage two: distance to town (adoption of feature phone / smartphone model)

	Feature phone			Smartphone		
	Model I	Model II	Model III	Model I	Model II	Model III
town2	0.063			0.007		
	(0.092)			(0.155)		
town5		-0.051			-0.152	
		(0.079)			(0.128)	
town10			0.013			0.156
			(0.079)			(0.129)
light1	-0.287***	-0.287***	-0.287***	-0.078	-0.094	-0.053
	(0.106)	(0.106)	(0.106)	(0.189)	(0.189)	(0.190)
female	0.084	0.089	0.086	-0.117	-0.106	-0.124
	(0.083)	(0.083)	(0.083)	(0.163)	(0.163)	(0.164)
age1	0.348	0.326	0.337	0.998	0.984	0.997
	(0.270)	(0.270)	(0.270)	(0.618)	(0.620)	(0.617)
age2	0.340	0.317	0.330	1.258**	1.234**	1.275**
	(0.268)	(0.268)	(0.268)	(0.611)	(0.613)	(0.610)
age3	0.591**	0.571**	0.582**	0.991	0.971	1.001
	(0.238)	(0.238)	(0.238)	(0.611)	(0.613)	(0.610)
age4	0.448**	0.433*	0.440*	0.554	0.546	0.564
	(0.227)	(0.227)	(0.227)	(0.620)	(0.622)	(0.619)
age5	0.292	0.280	0.285	0.262	0.244	0.279
	(0.224)	(0.223)	(0.224)	(0.617)	(0.618)	(0.616)
income1	-0.578	-0.601	-0.583	-0.885	-0.921	-0.851
	(0.517)	(0.517)	(0.517)	(0.840)	(0.839)	(0.842)
income2	-0.395	-0.430	-0.405	-0.820	-0.866	-0.778
	(0.527)	(0.528)	(0.528)	(0.894)	(0.894)	(0.897)
income3	-0.727	-0.774	-0.744	-0.759	-0.806	-0.714
	(0.569)	(0.569)	(0.569)	(0.821)	(0.820)	(0.823)
married	0.048	0.045	0.047	-0.043	-0.052	-0.032
	(0.087)	(0.087)	(0.087)	(0.170)	(0.170)	(0.171)
hh2	0.059	0.054	0.058	0.136	0.138	0.134
	(0.141)	(0.142)	(0.142)	(0.231)	(0.231)	(0.231)
hh3	0.054	0.051	0.054	-0.013	-0.013	-0.017
	(0.119)	(0.119)	(0.119)	(0.196)	(0.196)	(0.196)
none	-0.780*	-0.729*	-0.756*	-0.726	-0.686	-0.791
	(0.398)	(0.396)	(0.398)	(0.696)	(0.694)	(0.700)
primary	-0.274	-0.246	-0.260	-0.452	-0.441	-0.474
	(0.294)	(0.293)	(0.293)	(0.398)	(0.398)	(0.400)
secondary	-0.192	-0.180	-0.185	-0.276	-0.270	-0.289
	(0.199)	(0.199)	(0.199)	(0.198)	(0.198)	(0.198)
employed	0.216	0.204	0.211	0.302	0.285	0.321
	(0.151)	(0.151)	(0.151)	(0.273)	(0.272)	(0.274)
self_employed	-0.003	-0.009	-0.005	0.590**	0.578**	0.601**
	(0.114)	(0.114)	(0.114)	(0.255)	(0.255)	(0.256)
housework	-0.076	-0.075	-0.075	0.228	0.231	0.215
	(0.126)	(0.126)	(0.126)	(0.265)	(0.265)	(0.266)
student	0.373**	0.374**	0.374**	0.542	0.556	0.533
	(0.180)	(0.180)	(0.180)	(0.367)	(0.367)	(0.369)
retired	0.073	0.087	0.079	-0.395	-0.394	-0.394
	(0.217)	(0.217)	(0.217)	(0.533)	(0.532)	(0.534)
own_house	-0.077	-0.074	-0.075	0.059	0.062	0.052
	(0.094)	(0.094)	(0.094)	(0.139)	(0.139)	(0.140)
car	-0.024	-0.032	-0.027	-0.005	-0.009	0.002
	(0.198)	(0.198)	(0.198)	(0.174)	(0.174)	(0.174)
motorbike	0.155	0.149	0.154	0.023	0.020	0.033
	(0.145)	(0.145)	(0.145)	(0.229)	(0.228)	(0.229)
laptop_comp	0.204	0.186	0.197	0.454**	0.443**	0.471**
	(0.181)	(0.181)	(0.181)	(0.182)	(0.182)	(0.183)
bank	0.380*	0.361*	0.373*	0.443	0.416	0.467
	(0.196)	(0.196)	(0.196)	(0.358)	(0.357)	(0.360)
mon2_1	-0.225	-0.242*	-0.233	-0.157	-0.187	-0.127
	(0.143)	(0.142)	(0.143)	(0.366)	(0.365)	(0.368)
mon2_3	0.156	0.170	0.163	0.714	0.738	0.697
	(0.114)	(0.114)	(0.114)	(0.534)	(0.534)	(0.535)
Constant	2.093***	2.158***	2.108***	3.077***	3.171***	2.969***
	(0.643)	(0.644)	(0.646)	(1.087)	(1.090)	(1.088)
Observations	5,983	5,983	5,983	2,883	2,883	2,883

Table 12: Stage two: distance to bank branch (adoption of mobile phones model)

	Model I	Model II	Model III	Model IV
bank2	-0.015			
	(0.078)			
bank5		-0.016		
		(0.077)		
bank10			-0.039	
			(0.072)	
bank25				0.079
				(0.081)
light1	-0.442***	-0.444***	-0.453***	-0.418***
	(0.087)	(0.089)	(0.086)	(0.081)
female	-0.020	-0.020	-0.018	-0.026
	(0.070)	(0.070)	(0.070)	(0.070)
age1	0.697***	0.698***	0.696***	0.700***
	(0.180)	(0.180)	(0.180)	(0.180)
age2	0.793***	0.793***	0.789***	0.804***
	(0.176)	(0.176)	(0.177)	(0.177)
age3	0.828***	0.828***	0.824***	0.836***
	(0.180)	(0.180)	(0.180)	(0.180)
age4	0.586***	0.586***	0.583***	0.592***
	(0.187)	(0.187)	(0.187)	(0.187)
age5	0.399**	0.400**	0.397**	0.402**
	(0.190)	(0.190)	(0.190)	(0.190)
income1	-0.405	-0.407	-0.416	-0.376
	(0.293)	(0.294)	(0.294)	(0.293)
income2	-0.138	-0.140	-0.151	-0.106
	(0.309)	(0.310)	(0.310)	(0.309)
income3	-0.301	-0.303	-0.315	-0.271
	(0.330)	(0.330)	(0.331)	(0.330)
married	0.001	0.001	-0.001	0.006
	(0.075)	(0.075)	(0.075)	(0.075)
hh2	0.081	0.081	0.082	0.080
	(0.119)	(0.119)	(0.119)	(0.119)
hh3	0.028	0.028	0.029	0.024
	(0.100)	(0.100)	(0.101)	(0.100)
none	-1.281***	-1.279***	-1.266***	-1.307***
	(0.253)	(0.254)	(0.255)	(0.254)
primary	-0.592***	-0.590***	-0.581***	-0.614***
	(0.191)	(0.192)	(0.192)	(0.192)
secondary	-0.193	-0.192	-0.187	-0.205
	(0.131)	(0.131)	(0.131)	(0.131)
employed	0.282**	0.281**	0.280**	0.288**
	(0.122)	(0.122)	(0.122)	(0.122)
self_employed	0.116	0.115	0.114	0.120
	(0.100)	(0.100)	(0.100)	(0.100)
housework	-0.021	-0.021	-0.021	-0.021
	(0.111)	(0.111)	(0.111)	(0.111)
student	0.345**	0.346**	0.350**	0.336**
	(0.142)	(0.142)	(0.142)	(0.142)
retired	-0.111	-0.110	-0.108	-0.114
	(0.191)	(0.191)	(0.191)	(0.191)
own_house	-0.076	-0.076	-0.077	-0.072
	(0.074)	(0.073)	(0.073)	(0.073)
car	-0.057	-0.057	-0.058	-0.057
	(0.123)	(0.123)	(0.123)	(0.123)
motorbike	0.148	0.148	0.144	0.159
	(0.116)	(0.116)	(0.116)	(0.116)
laptop_comp	0.343***	0.342***	0.339***	0.349***
	(0.123)	(0.123)	(0.123)	(0.123)
bank	0.622***	0.621***	0.614***	0.639***
	(0.146)	(0.146)	(0.146)	(0.146)
mon2_0	-0.086	-0.087	-0.096	-0.065
	(0.136)	(0.136)	(0.137)	(0.136)
Constant	1.790***	1.791***	1.803***	1.724***
	(0.381)	(0.381)	(0.380)	(0.382)
Observations	8,866	8,866	8,866	8,866

Table 13: Stage two: distance to ATM (adoption of mobile phones model)

	Model I	Model II	Model III	Model IV
atm2	0.015			
	(0.087)			
atm5		0.084		
		(0.077)		
atm10			-0.084	
			(0.072)	
atm25				-0.116*
				(0.070)
light1	-0.431***	-0.399***	-0.471***	-0.474***
	(0.083)	(0.086)	(0.085)	(0.082)
female	-0.022	-0.024	-0.015	-0.015
	(0.070)	(0.070)	(0.070)	(0.070)
age1	0.697***	0.695***	0.699***	0.699***
	(0.180)	(0.180)	(0.180)	(0.180)
age2	0.795***	0.798***	0.787***	0.785***
	(0.176)	(0.176)	(0.176)	(0.176)
age3	0.829***	0.829***	0.824***	0.825***
	(0.180)	(0.180)	(0.180)	(0.180)
age4	0.587***	0.586***	0.584***	0.584***
	(0.187)	(0.187)	(0.187)	(0.187)
age5	0.401**	0.400**	0.398**	0.397**
	(0.190)	(0.190)	(0.190)	(0.190)
income1	-0.398	-0.372	-0.437	-0.453
	(0.293)	(0.293)	(0.294)	(0.294)
income2	-0.131	-0.104	-0.172	-0.186
	(0.308)	(0.309)	(0.310)	(0.310)
income3	-0.296	-0.275	-0.332	-0.344
	(0.329)	(0.329)	(0.331)	(0.330)
married	0.002	0.005	-0.003	-0.005
	(0.075)	(0.075)	(0.075)	(0.075)
hh2	0.081	0.077	0.085	0.084
	(0.119)	(0.119)	(0.119)	(0.119)
hh3	0.027	0.023	0.032	0.031
	(0.100)	(0.101)	(0.101)	(0.101)
none	-1.285***	-1.302***	-1.251***	-1.240***
	(0.253)	(0.253)	(0.255)	(0.254)
primary	-0.595***	-0.607***	-0.569***	-0.558***
	(0.191)	(0.191)	(0.192)	(0.192)
secondary	-0.195	-0.201	-0.182	-0.176
	(0.130)	(0.130)	(0.131)	(0.131)
employed	0.283**	0.285**	0.276**	0.271**
	(0.122)	(0.122)	(0.122)	(0.122)
self_employed	0.116	0.118	0.111	0.108
	(0.100)	(0.100)	(0.100)	(0.100)
housework	-0.021	-0.022	-0.020	-0.019
	(0.111)	(0.111)	(0.111)	(0.111)
student	0.344**	0.340**	0.353**	0.355**
	(0.142)	(0.142)	(0.142)	(0.142)
retired	-0.112	-0.118	-0.104	-0.107
	(0.191)	(0.191)	(0.191)	(0.191)
own_house	-0.073	-0.067	-0.081	-0.081
	(0.073)	(0.073)	(0.073)	(0.073)
car	-0.059	-0.067	-0.051	-0.050
	(0.124)	(0.123)	(0.123)	(0.123)
motorbike	0.151	0.157	0.139	0.135
	(0.116)	(0.116)	(0.116)	(0.116)
laptop_comp	0.344***	0.344***	0.337***	0.337***
	(0.123)	(0.123)	(0.123)	(0.123)
bank	0.625***	0.634***	0.604***	0.598***
	(0.145)	(0.146)	(0.146)	(0.146)
mon2_0	-0.082	-0.071	-0.108	-0.114
	(0.135)	(0.135)	(0.137)	(0.136)
Constant	1.773***	1.728***	1.820***	1.844***
	(0.381)	(0.381)	(0.380)	(0.380)
Observations	8,866	8,866	8,866	8,866

Table 14: Stage two: distance to roads (adoption of mobile phones model)

	Model I	Model II	Model III
road2	-0.051		
	(0.063)		
road5		0.060	
		(0.072)	
road10			0.026
			(0.089)
light1	-0.443***	-0.421***	-0.429***
	(0.080)	(0.081)	(0.083)
female	-0.018	-0.025	-0.023
	(0.070)	(0.070)	(0.070)
age1	0.693***	0.700***	0.698***
	(0.180)	(0.180)	(0.180)
age2	0.788***	0.799***	0.796***
	(0.176)	(0.176)	(0.176)
age3	0.824***	0.834***	0.830***
	(0.180)	(0.180)	(0.180)
age4	0.580***	0.592***	0.588***
	(0.187)	(0.187)	(0.187)
age5	0.395**	0.404**	0.402**
	(0.190)	(0.190)	(0.190)
income1	-0.408	-0.391	-0.396
	(0.292)	(0.292)	(0.293)
income2	-0.142	-0.124	-0.129
	(0.308)	(0.308)	(0.308)
income3	-0.307	-0.285	-0.292
	(0.329)	(0.329)	(0.329)
married	0.002	0.003	0.002
	(0.075)	(0.075)	(0.075)
hh2	0.078	0.083	0.081
	(0.119)	(0.119)	(0.119)
hh3	0.024	0.027	0.027
	(0.100)	(0.100)	(0.100)
none	-1.278***	-1.294***	-1.289***
	(0.253)	(0.253)	(0.253)
primary	-0.589***	-0.602***	-0.597***
	(0.191)	(0.191)	(0.191)
secondary	-0.192	-0.198	-0.196
	(0.130)	(0.130)	(0.130)
employed	0.280**	0.286**	0.284**
	(0.122)	(0.122)	(0.122)
self_employed	0.115	0.119	0.117
	(0.100)	(0.100)	(0.100)
housework	-0.024	-0.020	-0.020
	(0.111)	(0.111)	(0.111)
student	0.349**	0.340**	0.343**
	(0.142)	(0.142)	(0.142)
retired	-0.114	-0.111	-0.112
	(0.191)	(0.191)	(0.191)
own_house	-0.076	-0.070	-0.073
	(0.073)	(0.073)	(0.073)
car	-0.054	-0.061	-0.058
	(0.123)	(0.123)	(0.123)
motorbike	0.149	0.148	0.149
	(0.116)	(0.116)	(0.116)
laptop_comp	0.343***	0.345***	0.344***
	(0.123)	(0.123)	(0.123)
bank	0.621***	0.628***	0.626***
	(0.145)	(0.145)	(0.145)
mon2_0	-0.088	-0.077	-0.080
	(0.135)	(0.135)	(0.135)
Constant	1.809***	1.734***	1.758***
	(0.380)	(0.382)	(0.386)
Observations	8,866	8,866	8,866

Table 15: Stage two: distance to town (adoption of mobile phones model)

	Model I	Model II	Model III
town2	0.007		
	(0.076)		
town5		-0.113*	
		(0.066)	
town10			0.030
			(0.065)
light1	-0.435***	-0.443***	-0.433***
	(0.079)	(0.079)	(0.079)
female	-0.021	-0.017	-0.022
	(0.070)	(0.070)	(0.070)
age1	0.697***	0.699***	0.698***
	(0.180)	(0.180)	(0.180)
age2	0.794***	0.795***	0.796***
	(0.176)	(0.176)	(0.176)
age3	0.829***	0.827***	0.830***
	(0.180)	(0.180)	(0.180)
age4	0.587***	0.588***	0.589***
	(0.187)	(0.187)	(0.187)
age5	0.401**	0.401**	0.402**
	(0.190)	(0.190)	(0.190)
income1	-0.400	-0.411	-0.397
	(0.292)	(0.293)	(0.292)
income2	-0.132	-0.150	-0.129
	(0.308)	(0.309)	(0.308)
income3	-0.296	-0.319	-0.291
	(0.329)	(0.330)	(0.329)
married	0.002	0.000	0.002
	(0.075)	(0.075)	(0.075)
hh2	0.081	0.076	0.082
	(0.119)	(0.119)	(0.119)
hh3	0.027	0.023	0.028
	(0.100)	(0.100)	(0.100)
none	-1.285***	-1.268***	-1.291***
	(0.253)	(0.253)	(0.253)
primary	-0.594***	-0.591***	-0.597***
	(0.191)	(0.191)	(0.191)
secondary	-0.195	-0.194	-0.196
	(0.130)	(0.130)	(0.130)
employed	0.283**	0.276**	0.284**
	(0.122)	(0.122)	(0.122)
self_employed	0.116	0.111	0.118
	(0.100)	(0.100)	(0.100)
housework	-0.021	-0.022	-0.022
	(0.111)	(0.111)	(0.111)
student	0.344**	0.346**	0.343**
	(0.142)	(0.142)	(0.142)
retired	-0.112	-0.107	-0.112
	(0.191)	(0.191)	(0.191)
own_house	-0.074	-0.076	-0.075
	(0.073)	(0.073)	(0.073)
car	-0.057	-0.060	-0.057
	(0.123)	(0.123)	(0.123)
motorbike	0.149	0.144	0.151
	(0.116)	(0.116)	(0.116)
laptop_comp	0.344***	0.335***	0.347***
	(0.123)	(0.123)	(0.123)
bank	0.624***	0.616***	0.627***
	(0.145)	(0.145)	(0.145)
mon2_0	-0.083	-0.095	-0.080
	(0.135)	(0.135)	(0.135)
Constant	1.780***	1.815***	1.765***
	(0.378)	(0.379)	(0.379)
Observations	8,866	8,866	8,866

Table 16: Sending money: distance to bank branch / ATM (adoption of mobile phones model)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
bank2/atm2	0.202***				-0.184**			
	(0.077)				(0.085)			
bank5/atm5		-0.035				-0.093		
		(0.081)				(0.076)		
bank10/atm10			0.066				-0.001	
			(0.076)				(0.072)	
bank25/atm25				0.163*				0.002
				(0.087)				(0.069)
light1	-0.237***	-0.360***	-0.312***	-0.312***	-0.418***	-0.385***	-0.340***	-0.339***
	(0.086)	(0.089)	(0.083)	(0.078)	(0.085)	(0.085)	(0.083)	(0.079)
female	0.104	0.121*	0.111	0.107	0.121*	0.121*	0.118*	0.117*
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
age1	0.801***	0.808***	0.808***	0.813***	0.803***	0.811***	0.806***	0.806***
	(0.214)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)
age2	0.914***	0.899***	0.910***	0.919***	0.895***	0.900***	0.901***	0.901***
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)
age3	0.820***	0.803***	0.813***	0.817***	0.799***	0.807***	0.805***	0.805***
	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)
age4	0.683***	0.671***	0.677***	0.682***	0.669***	0.673***	0.672***	0.672***
	(0.222)	(0.221)	(0.221)	(0.221)	(0.221)	(0.221)	(0.221)	(0.221)
age5	0.653***	0.643***	0.649***	0.646***	0.642***	0.646***	0.644***	0.644***
	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)
income1	0.472	0.404	0.451	0.466	0.408	0.382	0.422	0.423
	(0.317)	(0.320)	(0.319)	(0.318)	(0.317)	(0.318)	(0.319)	(0.319)
income2	0.649*	0.575*	0.627*	0.642*	0.585*	0.556*	0.594*	0.596*
	(0.331)	(0.333)	(0.333)	(0.332)	(0.331)	(0.331)	(0.333)	(0.332)
income3	0.723**	0.664*	0.711**	0.725**	0.683*	0.651*	0.682*	0.683*
	(0.355)	(0.356)	(0.356)	(0.355)	(0.355)	(0.355)	(0.356)	(0.356)
married	0.276***	0.265***	0.271***	0.273***	0.263***	0.263***	0.267***	0.267***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
hh2	-0.017	-0.014	-0.016	-0.016	-0.016	-0.013	-0.014	-0.014
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
hh3	-0.075	-0.067	-0.072	-0.075	-0.067	-0.065	-0.068	-0.069
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
none	-0.909***	-0.842***	-0.883***	-0.888***	-0.854***	-0.839***	-0.856***	-0.858***
	(0.251)	(0.252)	(0.252)	(0.251)	(0.250)	(0.250)	(0.252)	(0.251)
primary	-0.005	0.042	0.014	-0.001	0.035	0.045	0.033	0.032
	(0.180)	(0.181)	(0.181)	(0.181)	(0.180)	(0.180)	(0.180)	(0.181)
secondary	0.310***	0.343***	0.325***	0.317***	0.338***	0.344***	0.336***	0.336***
	(0.120)	(0.121)	(0.121)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
employed	0.182	0.166	0.175	0.182	0.171	0.167	0.169	0.169
	(0.119)	(0.119)	(0.119)	(0.119)	(0.118)	(0.118)	(0.119)	(0.119)
self_employed	0.092	0.087	0.092	0.098	0.089	0.085	0.088	0.088
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)
housework	0.047	0.047	0.049	0.050	0.049	0.049	0.048	0.048
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
student	-0.035	-0.014	-0.026	-0.033	-0.017	-0.014	-0.019	-0.019
	(0.145)	(0.145)	(0.145)	(0.145)	(0.144)	(0.144)	(0.145)	(0.145)
retired	-0.131	-0.105	-0.113	-0.108	-0.103	-0.102	-0.108	-0.109
	(0.224)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)
own_house	-0.003	-0.028	-0.021	-0.022	-0.038	-0.033	-0.025	-0.025
	(0.073)	(0.073)	(0.073)	(0.072)	(0.073)	(0.073)	(0.073)	(0.072)
car	-0.309**	-0.303**	-0.307**	-0.306**	-0.288**	-0.294**	-0.304**	-0.304**
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
motorbike	0.122	0.101	0.113	0.119	0.090	0.097	0.104	0.105
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
laptop_comp	0.393***	0.368***	0.382***	0.389***	0.377***	0.370***	0.372***	0.373***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
bank	0.598***	0.556***	0.582***	0.591***	0.562***	0.555***	0.565***	0.565***
	(0.151)	(0.151)	(0.151)	(0.151)	(0.150)	(0.150)	(0.151)	(0.151)
mon2_0	0.119	0.068	0.097	0.107	0.074	0.066	0.078	0.079
	(0.132)	(0.133)	(0.133)	(0.132)	(0.131)	(0.131)	(0.132)	(0.132)
Constant	-1.234***	-1.103***	-1.175***	-1.259***	-1.007**	-1.052***	-1.128***	-1.130***
	(0.404)	(0.406)	(0.406)	(0.408)	(0.406)	(0.406)	(0.405)	(0.404)
Observations	8,866	8,866	8,866	8,866	8,866	8,866	8,866	8,866

Table 17: Sending money: distance to roads / town (adoption of mobile phones model)

	Road			Town		
	Model I	Model II	Model III	Model I	Model II	Model III
road2/town2	0.018			-0.026		
	(0.063)			(0.075)		
road5/town5		0.024			-0.008	
		(0.070)			(0.065)	
road10/town10			0.107			-0.132**
			(0.088)			(0.066)
light1	-0.337***	-0.334***	-0.310***	-0.341***	-0.341***	-0.350***
	(0.077)	(0.078)	(0.080)	(0.076)	(0.076)	(0.077)
female	0.117*	0.117*	0.111	0.118*	0.118*	0.123*
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
age1	0.808***	0.807***	0.813***	0.807***	0.807***	0.799***
	(0.213)	(0.213)	(0.214)	(0.213)	(0.213)	(0.213)
age2	0.903***	0.903***	0.910***	0.901***	0.901***	0.890***
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)
age3	0.807***	0.807***	0.813***	0.805***	0.805***	0.794***
	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)
age4	0.674***	0.674***	0.678***	0.671***	0.672***	0.666***
	(0.222)	(0.221)	(0.222)	(0.221)	(0.221)	(0.221)
age5	0.646***	0.645***	0.651***	0.644***	0.644***	0.639***
	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)
income1	0.421	0.423	0.435	0.421	0.422	0.393
	(0.317)	(0.317)	(0.317)	(0.317)	(0.317)	(0.316)
income2	0.594*	0.595*	0.609*	0.592*	0.594*	0.563*
	(0.330)	(0.331)	(0.331)	(0.331)	(0.331)	(0.330)
income3	0.683*	0.683*	0.704**	0.677*	0.680*	0.645*
	(0.354)	(0.354)	(0.355)	(0.355)	(0.355)	(0.354)
married	0.267***	0.267***	0.269***	0.267***	0.267***	0.266***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
hh2	-0.013	-0.014	-0.011	-0.015	-0.015	-0.019
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
hh3	-0.067	-0.069	-0.068	-0.069	-0.069	-0.073
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
none	-0.857***	-0.859***	-0.875***	-0.852***	-0.855***	-0.834***
	(0.250)	(0.250)	(0.251)	(0.251)	(0.250)	(0.250)
primary	0.032	0.030	0.021	0.034	0.033	0.043
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
secondary	0.336***	0.335***	0.330***	0.338***	0.337***	0.344***
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
employed	0.170	0.170	0.173	0.167	0.168	0.159
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)
self_employed	0.089	0.090	0.092	0.087	0.088	0.077
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)
housework	0.049	0.049	0.052	0.048	0.047	0.047
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
student	-0.019	-0.019	-0.025	-0.017	-0.019	-0.013
	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)
retired	-0.108	-0.107	-0.106	-0.107	-0.108	-0.108
	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)	(0.223)
own_house	-0.024	-0.023	-0.017	-0.025	-0.025	-0.023
	(0.072)	(0.073)	(0.073)	(0.072)	(0.072)	(0.072)
car	-0.305**	-0.305**	-0.306**	-0.306**	-0.305**	-0.309**
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
motorbike	0.105	0.105	0.106	0.104	0.104	0.098
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
laptop_comp	0.372***	0.373***	0.375***	0.370***	0.372***	0.366***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
bank	0.565***	0.566***	0.574***	0.562***	0.564***	0.549***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
mon2_0	0.078	0.080	0.091	0.074	0.077	0.062
	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
Constant	-1.139***	-1.147***	-1.227***	-1.129***	-1.127***	-1.040**
	(0.404)	(0.405)	(0.410)	(0.402)	(0.402)	(0.404)
Observations	8,866	8,866	8,866	8,866	8,866	8,866

Table 18: Receiving money: distance to bank branch / ATM (adoption of mobile phones model)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
bank2/atm2	0.131*				0.054			
	(0.079)				(0.086)			
bank5/atm5		0.017				-0.031		
		(0.083)				(0.077)		
bank10/atm10			0.023				0.008	
			(0.077)				(0.074)	
bank25/atm25				0.182**				-0.027
				(0.089)				(0.071)
light1	-0.065	-0.122	-0.122	-0.101	-0.109	-0.146*	-0.128	-0.140*
	(0.087)	(0.090)	(0.084)	(0.079)	(0.085)	(0.086)	(0.084)	(0.080)
female	0.204***	0.211***	0.210***	0.202***	0.212***	0.214***	0.212***	0.215***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
age1	0.234	0.237	0.239	0.246	0.239	0.240	0.238	0.240
	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)
age2	0.345*	0.338*	0.340*	0.357*	0.339*	0.337*	0.338*	0.336*
	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)
age3	0.266	0.258	0.260	0.270	0.259	0.258	0.257	0.257
	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)
age4	0.291	0.285	0.286	0.295	0.285	0.285	0.285	0.284
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)
age5	0.434**	0.429**	0.430**	0.430**	0.429**	0.429**	0.428**	0.427**
	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)
income1	0.705**	0.681**	0.682**	0.718**	0.675**	0.658*	0.676**	0.658*
	(0.340)	(0.342)	(0.341)	(0.340)	(0.339)	(0.341)	(0.341)	(0.341)
income2	1.028***	1.001***	1.003***	1.042***	0.994***	0.978***	0.996***	0.977***
	(0.354)	(0.356)	(0.355)	(0.354)	(0.353)	(0.354)	(0.355)	(0.355)
income3	0.813**	0.795**	0.797**	0.831**	0.786**	0.776**	0.791**	0.775**
	(0.380)	(0.381)	(0.381)	(0.380)	(0.379)	(0.380)	(0.381)	(0.380)
married	0.161**	0.157**	0.157**	0.162**	0.157**	0.155**	0.156**	0.155**
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
hh2	0.077	0.078	0.078	0.077	0.079	0.078	0.078	0.078
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)
hh3	-0.046	-0.043	-0.043	-0.049	-0.043	-0.041	-0.043	-0.042
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
none	-1.120***	-1.093***	-1.095***	-1.118***	-1.086***	-1.080***	-1.089***	-1.076***
	(0.250)	(0.251)	(0.251)	(0.249)	(0.249)	(0.249)	(0.250)	(0.250)
primary	-0.330*	-0.310*	-0.312*	-0.341*	-0.305*	-0.301*	-0.307*	-0.298
	(0.183)	(0.184)	(0.184)	(0.183)	(0.182)	(0.183)	(0.183)	(0.184)
secondary	0.141	0.155	0.154	0.137	0.158	0.161	0.157	0.163
	(0.122)	(0.123)	(0.123)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
employed	0.268**	0.261**	0.261**	0.274**	0.258**	0.259**	0.260**	0.257**
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
self_employed	0.149	0.147	0.148	0.158	0.146	0.146	0.147	0.145
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
housework	0.053	0.054	0.055	0.057	0.054	0.055	0.054	0.055
	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)
student	0.171	0.179	0.178	0.166	0.181	0.183	0.180	0.185
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
retired	0.009	0.021	0.021	0.024	0.021	0.024	0.021	0.024
	(0.219)	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)
own_house	-0.032	-0.045	-0.045	-0.044	-0.043	-0.049	-0.046	-0.047
	(0.075)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
car	-0.459***	-0.458***	-0.459***	-0.460***	-0.462***	-0.455***	-0.459***	-0.456***
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
motorbike	-0.240**	-0.249**	-0.248**	-0.236*	-0.247**	-0.252**	-0.250**	-0.254**
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)
laptop_comp	0.110	0.098	0.099	0.115	0.094	0.096	0.097	0.093
	(0.131)	(0.131)	(0.131)	(0.131)	(0.130)	(0.130)	(0.131)	(0.131)
bank	0.669***	0.652***	0.653***	0.676***	0.648***	0.644***	0.649***	0.640***
	(0.152)	(0.153)	(0.153)	(0.152)	(0.152)	(0.152)	(0.153)	(0.153)
mon2_0	0.267**	0.245*	0.247*	0.273**	0.241*	0.236*	0.242*	0.233*
	(0.134)	(0.135)	(0.134)	(0.134)	(0.133)	(0.133)	(0.134)	(0.134)
Constant	-0.224	-0.170	-0.173	-0.299	-0.193	-0.131	-0.162	-0.142
	(0.418)	(0.420)	(0.419)	(0.421)	(0.420)	(0.420)	(0.418)	(0.417)
Observations	8,866	8,866	8,866	8,866	8,866	8,866	8,866	8,866

Table 19: Receiving money: distance to roads / town (adoption of mobile phones model)

	Road			Town		
	Model I	Model II	Model III	Model I	Model II	Model III
road2/town2	-0.067			0.069		
	(0.064)			(0.077)		
road5/town5		0.042			0.035	
		(0.071)			(0.066)	
road10/town10			0.028			0.028
			(0.088)			(0.067)
light1	-0.142*	-0.121	-0.123	-0.129*	-0.129*	-0.129*
	(0.078)	(0.079)	(0.082)	(0.077)	(0.078)	(0.078)
female	0.215***	0.211***	0.211***	0.211***	0.211***	0.212***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
age1	0.234	0.240	0.240	0.237	0.237	0.240
	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)
age2	0.330*	0.340*	0.339*	0.337*	0.336*	0.339*
	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)
age3	0.253	0.260	0.259	0.259	0.258	0.260
	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)	(0.202)
age4	0.277	0.287	0.286	0.286	0.284	0.286
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)
age5	0.424**	0.430**	0.430**	0.429**	0.428**	0.429**
	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)
income1	0.676**	0.673**	0.675**	0.674**	0.674**	0.679**
	(0.339)	(0.339)	(0.339)	(0.339)	(0.339)	(0.340)
income2	0.995***	0.992***	0.995***	1.000***	0.996***	0.999***
	(0.353)	(0.353)	(0.353)	(0.353)	(0.353)	(0.353)
income3	0.785**	0.790**	0.793**	0.801**	0.794**	0.795**
	(0.379)	(0.379)	(0.380)	(0.380)	(0.380)	(0.380)
married	0.156**	0.157**	0.156**	0.156**	0.156**	0.156**
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
hh2	0.073	0.080	0.079	0.080	0.079	0.079
	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)	(0.108)
hh3	-0.047	-0.042	-0.042	-0.041	-0.041	-0.041
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
none	-1.084***	-1.091***	-1.091***	-1.098***	-1.091***	-1.090***
	(0.249)	(0.249)	(0.249)	(0.249)	(0.249)	(0.249)
primary	-0.304*	-0.310*	-0.308*	-0.311*	-0.307*	-0.308*
	(0.182)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
secondary	0.160	0.156	0.157	0.154	0.157	0.157
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
employed	0.257**	0.262**	0.260**	0.263**	0.262**	0.261**
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
self_employed	0.144	0.149	0.148	0.149	0.149	0.149
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
housework	0.050	0.056	0.056	0.053	0.055	0.055
	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)
student	0.180	0.180	0.179	0.178	0.181	0.180
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
retired	0.018	0.024	0.023	0.018	0.020	0.022
	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)
own_house	-0.049	-0.043	-0.044	-0.046	-0.046	-0.047
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
car	-0.455***	-0.459***	-0.458***	-0.454***	-0.456***	-0.457***
	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)	(0.143)
motorbike	-0.253**	-0.249**	-0.250**	-0.251**	-0.249**	-0.249**
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)
laptop_comp	0.097	0.097	0.097	0.103	0.099	0.097
	(0.130)	(0.130)	(0.130)	(0.131)	(0.130)	(0.130)
bank	0.646***	0.650***	0.650***	0.655***	0.651***	0.651***
	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)
mon2_0	0.238*	0.244*	0.244*	0.250*	0.244*	0.243*
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
Constant	-0.122	-0.188	-0.183	-0.155	-0.165	-0.177
	(0.417)	(0.419)	(0.423)	(0.416)	(0.416)	(0.419)
Observations	8,866	8,866	8,866	8,866	8,866	8,866