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Mobile money and financial inclusion in Sub-Saharan Africa*

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Abstract

In this paper, we utilize survey data collected in 2017 from 12,735 individuals across nine Sub-Saharan African countries. We merge the survey data with geographic information related to the proximity of mobile network towers and banking facilities, based on the geo-locations of the respondents. Our estimation approach comprises a two-stage model. In the first stage, consumers make choices between adopting a feature phone or a smartphone. In the second stage, they make decisions regarding the use of mobile money services. Our findings reveal that network coverage significantly influences the adoption of mobile phones. Moreover, we observe that mobile money services are more favored by younger and relatively wealthier individuals for sending money, while older individuals and those with lower incomes tend to use mobile wallets for receiving money. Consequently, mobile money services facilitate younger migrant workers residing in areas with better infrastructure in providing support to their older relatives in less developed regions.

Keywords: Mobile money; Sub-Saharan Africa; Financial inclusion

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

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1 Introduction

Mobile communications offer a major opportunity to advance economic growth in developing countries by providing information about prices, improving the management of supplies, increasing the productive efficiency of firms, reducing transportation costs, and other means (see Aker & Mbiti (2010) and Jensen (2007)). Mobile phones can also serve as a channel for the provision of services that are generally not available to poor people living in remote areas without infrastructure, such as mobile-based financial, educational, health, and agricultural services.

In this paper, our focus is on the role of mobile money in expanding access to financial services and facilitating money transfers among individuals residing in areas with varying levels of economic development in nine Sub-Saharan African countries: Ghana, Kenya, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Uganda. This is an important research question because the banking sector in Sub-Saharan Africa remains underdeveloped with significant differences across geographic areas. According to the 2017 survey conducted by Research ICT Africa, which we utilize in this analysis, only 29% of individuals in nine Sub-Saharan African countries had a bank account, significantly below the global average for developing countries.[1] The primary reasons for the lack of access to financial services may include deficient infrastructure, inaccessibility, and financial illiteracy.

The absence of access to formal banking systems has compelled a significant portion of the financially excluded population to resort to alternative means of money transfer. They rely on services such as MoneyGram, Western Union, postal offices, or send cash through personal contacts and public transport. These transfer methods are associated with substantial service fees and transactional costs for both the sender and the recipient. Furthermore, to protect themselves against unforeseen disruptions, these individuals frequently depend on traditional, inefficient savings methods, which include holding cash and non-liquid assets.

The proliferation of mobile phones in developing countries offers an efficient, affordable, and secure method through which financially underserved individuals can engage in money transfers, receipts, and savings using so-called mobile money wallets. Mobile money has the potential to create a positive economic impact by expanding financial inclusion, enhancing risk management, promoting savings, and facilitating access to credit. This is particularly important in regions

[1] Demirguc-Kunt et al. (2018) report that in 2017 the share of adults having an account with a financial institution or through a mobile money provider was 69% globally (up from 51% in 2011). In high-income countries, 94% of adults had an account, compared to 63% in developing economies.

where traditional financial services are limited.

Our study contributes to the literature by analyzing how investments in mobile network coverage and the proximity of banking facilities impact the adoption of mobile phones and the use of mobile money services. Specifically, the purpose of the study is to examine the potential role that mobile money can play in facilitating transactions between individuals living in relatively developed areas and those living in areas with poor infrastructure based on available geo-location information. The earlier literature on financial inclusion and mobile money usually relied on survey data from a single country, which did not include geo-location information.

We combine rich survey data from 12,735 individuals conducted in 2017 across nine Sub-Saharan African countries with nighttime light intensity information 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. We also use the distance from the household to mobile network towers to estimate the impact of coverage on the adoption of smartphones. Furthermore, we use the distance from the household to banking facilities such as a bank branch and ATM to estimate how the proximity to physical infrastructure impacts the use of mobile money services.

Our results suggest that UMTS and LTE network coverage significantly influences the decision to adopt a mobile phone, especially a smartphone. Therefore, investments in network coverage are crucial for increasing smartphone penetration in Sub-Saharan African countries and reducing the digital divide. In particular, we observe that individuals who reside in less economically developed areas—with no nighttime light at all—are less likely to use mobile phones. This could be attributed to the income effect but may also result from a lack of access to electricity.

Regarding financial infrastructure, we have observed that smartphone users who reside within 10km of a bank branch are less inclined to use mobile money services. Conversely, this pattern does not hold true for feature phone users. Furthermore, individuals using any type of handset, irrespective of their location, are also less likely to employ mobile money services if they live within 25km of an ATM. While less mobile money usage is generally evident in less economically developed areas, greater distances to financial facilities tend to amplify the reliance on mobile money services.

We also find that mobile money is more likely to be used by younger and relatively wealthier individuals residing in urban areas for sending money. In contrast, the elderly and those with lower incomes living in rural areas are more inclined to receive remittances via mobile money, reducing the need to rely on risky cash-in-transit methods. Consequently, our results suggest that mobile money services strengthen support networks by enabling younger and wealthier migrant workers, located in areas with better infrastructure, to provide care for their elderly family members in less developed regions. The affordable and secure flow of remittances holds significant importance in developing countries, where public forms of social support are limited.

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

Our paper contributes to the literature on the adoption and use of mobile services and financial inclusion. The empirical literature focused on the adoption of mobile phones is already relatively old and mature (see, for example, Grzybowski (2015); Forenbacher et al. (2019)). However, this literature, in general, relied on aggregate country-level data or surveys without geo-location information. Thus, the question of the geographic digital divide could only be studied to a limited extent.

The growing body of empirical literature on mobile money and and its contribution in promoting financial inclusion and development, with a focus on Sub-Saharan Africa, was recently reviewed in Ahmad et al. (2020). Among earlier studies that analyze the impact of mobile money on financial inclusion, many have focused on M-Pesa in Kenya, the first and most prominent mobile money service in Sub-Saharan Africa.[2] In particular, Jack & Suri (2014) used two waves of about three thousands households in Kenya to study transactional networks and concluded that there is more remittance activity in households with M-Pesa users than in those without users. They also found that households which use M-Pesa are more likely to remit for routine support, credit, and insurance purposes. They concluded that mobile money allows households to spread risk more efficiently through deeper financial integration and expanded informal networks. Mbiti & Weil (2015) analyzed the use and economic impact of M-Pesa in Kenya using two waves of individual-level data on financial access. They found that M-Pesa positively impacts individual

[2] The name originates from combining M for mobile and Pesa for money in Swahili.

welfare by promoting banking and increasing money transfers. In another paper focused on Kenya, Suri et al. (2021) used administrative and survey data to investigate the adoption and impacts of one of the world's most popular digital loan products, M-Shwari. They concluded that these loans enhance household resilience, with households being 6.3 percentage points less likely to cut down on expenses due to adverse shocks. In a recent paper, Yao et al. (2023) utilized data from the "M-PESA Household Survey," a national survey conducted in Kenya from 2008 to 2014. The findings suggest that improved access to mobile money significantly enhances development resilience in households experiencing severe shocks, helping them maintain their status above the asset poverty line.

The empirical studies for other African countries are less common due to the lower adoption rate of mobile money and limited data availability. For example, Munyegera & Matsumoto (2016) used data on 846 rural households in Uganda to analyze the adoption of mobile money, remittance activity, and household welfare. They found a positive and significant effect of mobile money access on household welfare. Similar to Jack & Suri (2014), they concluded that households using mobile money are more likely to receive remittances than non-user households. They also found that the total value of remittances received by households using mobile money is significantly higher than for non-user households. In another paper,Mothobi & Grzybowski (2017) analyzed how the availability of infrastructure influences the adoption and use of mobile phones in eleven Sub-Saharan African countries using survey data and nighttime lights intensity data as a proxy for economic development in individual locations. They found that people residing in relatively developed areas are more likely to adopt mobile phones than those living in areas with poor infrastructure. Additionally, they found that individuals living in areas with relatively poor infrastructure are more likely to use mobile phones for financial transactions.

Our paper contributes to this literature by examining how the proximity of physical banking infrastructure influences the use of mobile money services. Importantly, we utilize detailed geo-location information to analyze the direction of money transfers between areas of varying economic development.

The papers discussed above rely on surveys of individuals or households. There are also recent studies that apply a randomized controlled trial (RCT) to estimate the causal effects of mobile money. Randomized access to mobile money is either given directly to individuals (see Batista & Vicente (2013); Batista & Vicente (2018)) or to small-scale entrepreneurs (see (Aggarwal et al., 2020)). Batista & Vicente (2013) conducted an experiment involving a set of individual dissemination activities, including explanations of the services and functionalities, as well as hands-on experiences with trial money in rural Mozambique. They found that remittances increased within rural households in experimental locations. In a follow-up study, Batista & Vicente (2018) demonstrated the economic effects of their experiment. They identified the potential of mobile money to improve the economic welfare of rural households, as they are less affected by negative shocks in terms of consumption and vulnerability, such as severe floods and hunger episodes. Furthermore, households appeared to shift away from investments in agriculture towards investments in migration. Aggarwal et al. (2020) conducted their RCT on access to mobile money among micro-entrepreneurs in urban Malawi, where mobile money usage was still modest. Treated individuals received assistance and basic training for opening a mobile money account. The treatment significantly increased usage, primarily due to savings rather than lower costs of interpersonal transfers. Wieser et al. (2019) randomized access to mobile money through the roll-out of mobile money agents. They analyzed how access to mobile money agents impacted poor households in rural northern Uganda and concluded that the agent roll-out 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.

Empirical studies relying on surveys and randomized controlled trials could be complemented with analysis of data from mobile network operators, which are rarely accessible for research purposes. An exception is the paper by Economides & Jeziorski (2017), which uses data on mobile financial transactions among subscribers of a major mobile phone service provider in Tanzania for three months. They estimate price elasticities for different types of transactions and find that the demand for long-distance transfers is less elastic than for short-distance transfers. This finding suggests that mobile networks actively compete with antiquated cash transportation systems in addition to competing with each other. They then use the demand estimates to provide measures of willingness to pay to avoid carrying cash in their pocket while traveling and keeping cash at home.

There is limited research on the regulatory aspects of mobile money in relation to financial inclusion. Bourreau & Valletti (2015) employ a qualitative approach to evaluate the economic aspects of mobile payment systems in low-income countries and suggest that mobile money has the potential to enhance financial inclusion among low-income households at a minimal cost. Lashitew et al. (2019) uses a combination of quantitative and qualitative research methods to analyze the development and adoption of mobile money innovations both within and across countries. Their findings emphasize the pivotal role of a supportive regulatory framework in guiding innovations and expediting the spread of mobile money in Kenya.

The earlier literature, in general, often neglects to consider infrastructure availability and coverage. Moreover, studies examining the factors influencing mobile phone ownership and usage frequently fail to differentiate between mobile phone types (feature phones or smartphones), which have significant economic implications. Our study contributes to this literature in two ways: firstly, by assessing how proximity to cell towers affects the adoption of both smartphones and feature phones, and secondly, by providing evidence of how physical infrastructure influences the use of mobile money services and transactional flows among individuals residing in areas with varying levels of infrastructure and economic development.

3 Mobile Money in Sub-Saharan Africa

The term mobile banking combines financial services which enables consumers to access their bank account, transfer money, make payments, and perform other financial operations on their mobile phones. A mobile phone can also serve as a virtual bank card, point of sale terminal, or 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 partner to provide mobile banking.

On the other hand, mobile money services are linked to a unique mobile phone number and provided entirely on the mobile network. They enable users to cash in money using a mobile account called a mobile wallet. Subscribers can use mobile wallets for various financial services including domestic and international money transfers, bill payments, airtime top-ups, and others. Transactions are settled through the network of agents that an MNO establishes. Several banks in Africa rolled out a similar service called e-wallet. The difference to mobile money is that e-wallet requires the sender to have a bank account, while the receiver can cash out money only at ATMs using their mobile phone number and a pin.[3]

The most common mobile money service in Sub-Saharan Africa is M-Pesa, first launched in 2007 in Kenya by Safaricom and Vodacom, and a year later in April 2008 in Tanzania. Today, M-Pesa is the most popular mobile money service in East African countries including

[3]See www.bocra.org.bw

Kenya, Tanzania, Uganda, Rwanda, and Burundi. It has been increasingly used in other African countries such as Cote d'Ivoire, Senegal, Madagascar, Mali, Niger, Botswana, Cameroon, and South Africa, as well as outside Africa in Jordan and Afghanistan. For example, as of 2008 in Kenya, there were about 2.7 million registered active mobile money users and more than 3 thousands M-Pesa agents. In 2019, the number of active mobile money accounts increased to 54.8 million and the agent network grew to about 222 thousands.

Initially, mobile money services were not regulated. For example, the Central Bank of Kenya (CBK) issued clearance to mobile operators wishing to launch mobile money services in the form of "letter of no objection". However, the pressure to regulate and protect customers' funds stored within mobile money systems has been growing over time. To guard against losses, in 2014, the CBK passed the National Payment Systems Regulations, which was much more onerous than the original "letter of no objection" and covered capital, interoperability, governance, reporting, and other obligations. Similarly, the Bank of Tanzania also passed in 2015 the E-Money Regulations and Payment Systems Licensing and Approval Regulations.[4]

Another growing concern has been the issue of interoperability of mobile money services, which can be achieved at various levels. Firstly, there is account-to-account (A2A) interoperability, which enables mobile money customers to transfer funds between accounts held at different mobile money providers or between a mobile money provider and a bank. In such case agents have non-exclusive agreements with mobile money providers. Secondly, interoperability at the agent level allows agents to represent multiple mobile money providers. Thirdly, interoperability at the merchant level enables consumers to transact at any retailer, regardless of the account held by the merchant. Lastly, interoperability at the mobile network level enables subscribers of one network operator to access mobile money services provided by another network operator.

Recognizing the significance of interoperability, regulators, particularly in East African countries, have taken steps to direct mobile money operators to inter-operate. Notably, in 2016, Tanzania set a pioneering example by becoming the first African country to achieve interoperability between mobile money providers, even though the Bank of Tanzania opted for a market-based solution instead of formally mandating interoperability.[5] All mobile money operators agreed to enable mobile money senders to transfer funds directly from their wallet to the receiver's wallet in real-time, eliminating intermediary steps and regardless of whether the transaction is on- or

[4] www.bot.go.tz

[5] See CGAP, 2018

off-net.[6]

Another milestone was reached in 2018 when mobile money operators in Kenya - Safaricom, Airtel, and Telekom Kenya - agreed to interoperate. During the trial pilot stage, operators waived surcharges on mobile money transactions between networks, resulting in mobile money users being charged the same amount for remittances within or outside their networks.[7] The CBK adopted a similar interoperability approach to that of the Bank of Tanzania, where operators use a multilateral agreement for the rules, but on the technical level, they connect bilaterally.[8] Interoperability between mobile money services has also been a primary regulatory focus in other African countries. In general, the aim of these regulations has been to mitigate the first-mover advantage which can be observed in these markets.

In contrast to most East African countries, which allowed MNOs to innovate and launch mobile money services, in Nigeria these services were introduced by banks. As argued by the Central Bank of Nigeria, the objective was to control their rollout and prevent money laundering. The adoption of mobile money in Nigeria was much slower, and eventually, in September 2019, licenses were also granted to MNOs. In South Africa, on the other hand, mobile money services are less popular due to competition with existing financial institutions that offer mobile banking services. For instance, in 2017, the mobile network operator MTN discontinued its mobile money services, which had been launched earlier that year, due to low uptake. Importantly, the use of mobile banking services necessitates LTE network coverage and consumer adoption of smartphones.

4 Data

In this analysis, we combine a few different data sets and use a single-period cross-section of 12,778 individuals from nine African countries. The first data set is a survey of individuals and households conducted in 2017 by Research ICT Africa (RIA) in the following countries: Ghana, Kenya, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania and Uganda. The data collection was part of a multi-country research initiative "After Access Survey" including in total

[6] In September 2014, Airtel and Tigo reached a bilateral interoperability agreement and their off-net transfer services were launched commercially in February 2015. In December 2014, Tigo and Zantel also signed an interoperability agreement. Finally, one year later in February 2016, the market leader, Vodacom, signed bilateral agreements with Airtel and Tigo.

[7] centralbank.go.ke

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

surveys from 22 countries in the Global South that look at the challenges of digital inequality beyond that of simple connectivity.[9] Table 1 shows the number of individuals surveyed in each country. 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 is Nighttime Lights (NTL) stemming from the Visible Infrared Imaging Radiometer Suite (VIIRS) from the *Suomi* satellite provided by the Earth Observations Group (EOG), Payne Institute for Public Policy. We apply the yearly cloud-free averaged data from 2016. The VIIRS data is very precise in the light intensity measures and 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 the aurora, fires, boats, and other temporal lights were filtered out by EOG.

The third database comes from OpenStreetMap (OSM), a collaborative effort to set up a free database with geographic information. 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 major roads. We used the geo-location information to calculate distances to the surveyed households. Cities and towns are defined by the national, state, or provincial government. Cities often have more than 100,000 inhabitants including capital cities. Towns are smaller and have between 10,000 and 100,000 inhabitants. Major roads contain motorways/freeways, trunks, and national, regional, and local roads.

The fourth database on the cell tower location was downloaded from OpenCelliD.[10] Besides 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 constructed before 2017 to ensure that individuals in our survey could use these antennas. For each household, we calculate the distance to the closest antenna of each technology.

[9] The data collection was supported financially by Canada's International Development Research Centre (IDRC) and the Swedish International Development Agency (SIDA). For details on the sampling and data collection see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/765.

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

4.1 Descriptive Statistics

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

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

	Phone		**Infrastructure**	**Financial**			
Country	Feature phone	Smartphone	Dark	Mobile Money	Bank	Card	N
Ghana	52.2%	25.8%	23.9%	51.6%	30.6%	8.03%	1,196
Kenya	54.7%	33.6%	50.1%	80.5%	42.2%	19.9%	1,216
Mozambique	41.4%	17.0%	41.0%	23.9%	24.4%	20.6%	1,220
Nigeria	48.8%	16.5%	45.7%	2.49%	38.2%	31.0%	1,804
Rwanda	43.9%	10.7%	69.2%	33.9%	32.7%	8.96%	1,217
Senegal	59.0%	22.1%	34.6%	32.8%	10.6%	4.7%	1,233
South Africa	41.6%	43.9%	22.4%	7.58%	57.2%	33.2%	1,794
Tanzania	45.4%	20.3%	51.6%	55.4%	17.4%	10.6%	1,200
Uganda	43.7%	13.2%	75.2%	47.8%	2.7%	6.79%	1,855
Total	47.4%	22.8%	46.4%	34.8%	28.9%	17.0%	12,735

Source: Own calculation based on 2017 Research ICT Africa survey & VIIRS data.

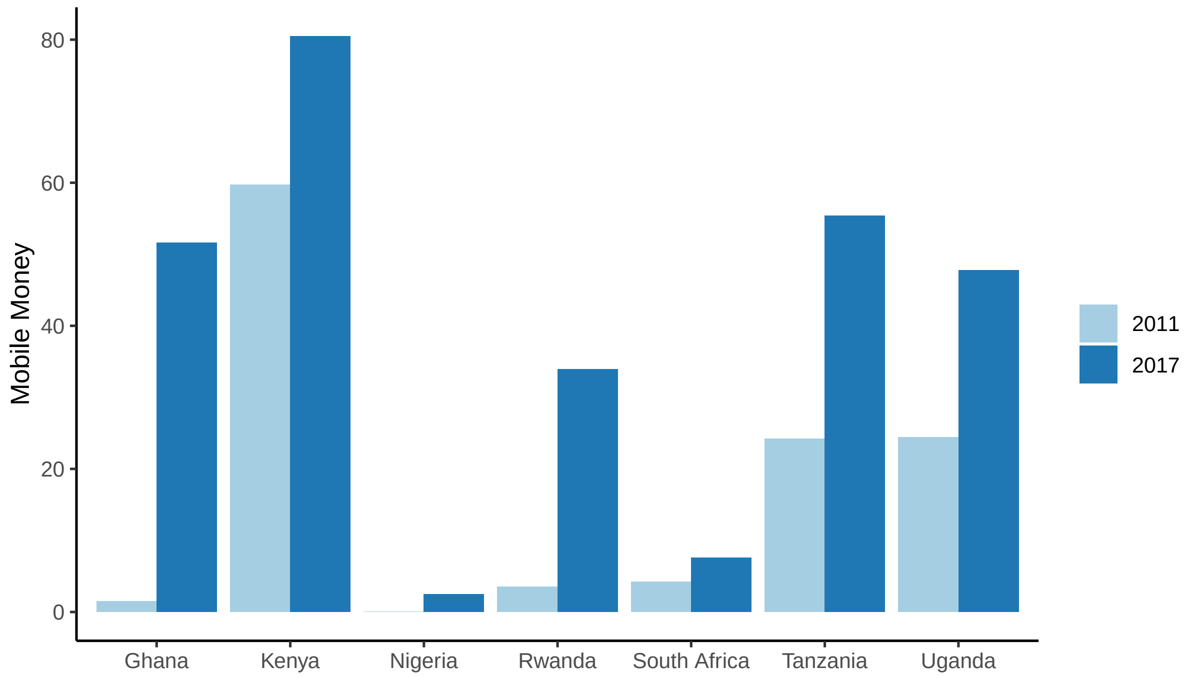
There are substantial differences in the usage of mobile phones and smartphones across countries. For instance, the highest penetration of mobile phones was in Kenya (88.3%) and the lowest was in Rwanda (54.6%). In South Africa, 85.5% of the population had a mobile phone, among whom 43.9% were smartphone users. The lowest smartphone penetration was in Rwanda at 10.7% among 54.6% of mobile phone users.

Concerning mobile money usage, Kenya was at the top (80.5%) followed by Tanzania (55.4%). More economically developed countries, South Africa and Nigeria, had the lowest share of mobile money users, respectively 7.6% and 2.5%. As discussed earlier, this may be due to the relatively high penetration of bank accounts in South Africa (57.2%). In Nigeria, very low usage of mobile money could be attributed to regulation, due to which initially only banks were allowed to provide mobile money services in the early years.

According to NTL satellite data, 46.4% of the individuals in our sample resided in areas designated as 'dark' because they were not illuminated at night. There is substantial variation in economic development approximated by nighttime light data. In Uganda and Rwanda, the highest share of people in our sample lived in 'dark' areas, respectively 75.2% and 69.2%. On the other side were South Africa and Ghana, where only 22.4% and 23.9% of the respondents lived in 'dark' places.

Figure 1 compares the use of mobile money in 2017 with the earlier survey conducted by Research ICT Africa in 2011.[11] Kenya had a substantial mobile money penetration already in 2011 which increased further. In South Africa and Nigeria, a very low penetration remained almost unchanged. In Uganda and Tanzania, the use of mobile money doubled from a relatively high level of nearly 25% in 2011 to about 48% and 55% in 2017. A substantial increase in the use of mobile money was also observed in Rwanda from 3.5% to 33.9% and in Ghana from 1.5% to 51.6%. A significant increase in adoption in these countries can be attributed to the development of inter-operable mobile money payment systems. The network of mobile money agents has been also growing substantially.

Figure 1: Evolution of mobile money usage between 2011 and 2017 by country.



Source: Own calculation based on 2017 Research ICT Africa survey.

[11] 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 compares the control variables we use in our estimation across handset types, between 'dark' and 'light' 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 the number of people in the household, house ownership, disposable income in US$ PPP, access to laptop/computer, car, motorbike, and bank account. The statistics show that women tend to use mobile money slightly less. In particular, we observe that in the group that does not use mobile money, the majority (56%) are women, while in the group that uses mobile money, women's shared is 48%. The opposite is true for married people who use mobile money slightly 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 use mobile money less.

Table 2: Individual characteristics for phone types, infrastructure and use of mobile money

	Phone Types			**Dark**		**Mobile Money**	
Variable	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

Source: Own calculation based on 2017 Research ICT Africa survey.

Table 3 shows significant differences in average light intensity, and similarly, variations exist in the average distance to banking and telecommunications infrastructure among individuals from different countries in our sample. The lowest average light intensity is observed in Uganda and Rwanda, while the highest values are found in South Africa, Mozambique, and Kenya. In general, individuals in all countries are reasonably close to road infrastructure, but there are notable differences in proximity to the nearest city, town, or both. Kenya has, on average, the shortest distance to bank branches, while Nigeria has the longest. Conversely, Rwanda has the shortest average distance to ATMs, whereas again Nigeria has the longest. Concerning telecommunications infrastructure, Senegal and Kenya are the best in terms of average distance to GSM and UMTS antennas, while South Africa leads in the average distance to LTE antennas. Mozambique, on the other hand, exhibits the worst mobile infrastructure in terms of average distance to antennas.

Table 3: Average distance to infrastructure across countries

	Ghana	Kenya	Mzbq	Nigeria	Rwanda	Senegal	S. Africa	Tanzania	Uganda	Total
Infrastructure										
Lights-viirs	5.9	7.6	8.3	4.5	1.4	6.1	12.9	4.4	1.0	5.8
Road	0.9	1.3	1.4	0.8	0.7	0.4	0.8	0.7	0.9	0.9
Town	7.1	10.5	16.0	20.4	6.5	8.8	12.2	23.3	13.7	13.5
City	54.2	25.2	58.5	34.2	26.4	29.2	47.8	57.3	35.0	40.5
City-town	5.6	6.1	9.3	12.2	5.4	3.6	11.1	16.5	8.0	8.9
Finance										
Bank	18.2	6.8	23.1	57.4	14.5	14.8	18.7	19.8	17.4	22.6
ATM	40.4	33.7	40.1	103.8	18.7	38.1	26.1	24.5	39.8	42.8
Finance	18.0	6.6	19.6	56.8	13.9	14.0	15.7	17.9	16.9	21.3
Mobile										
GSM	4.2	1.5	10.8	3.9	2.8	1.3	2.0	8.9	5.9	4.5
UMTS	5.8	1.8	13.0	5.7	4.2	2.4	2.2	11.3	6.6	5.7
LTE	79.7	14.6	499.7	163.1	25.2	101.1	10.9	106.9	69.7	112.8

Source: Own calculation based on 2017 Research ICT Africa survey & Open Street Map data.

Infrastructure variables include: (a) nighttime light data (Lights-viirs); and distance in km to: (b) major road (Road); (c) town; (d) city; (e) towns/cities (City-town); (f) automatic teller machine (ATM); (g) bank branch (Bank); (h) ATM or bank branch (Finance); (i) GSM antenna, (j) UMTS antenna; and (k) LTE antenna.

5 The Model

We model consumer decisions in two stages. In the first stage, they decide whether to adopt a mobile phone, which can either be a feature phone (without an operating system and Internet access) or a smartphone. As indicated in Table 1, 70.2% of individuals in our sample reported having a mobile phone, with 22.8% of them owning a smartphone. In the second stage, individuals who have adopted a mobile phone decide whether to use mobile money services. In additional second-stage regressions, we also consider the decisions related to sending, receiving, and saving money in a mobile wallet. In the first stage, we estimate a multinomial logit or a simple logit model. The second-stage selection correction models, based on multinomial logit, were developed by Lee (1984), Dubin & McFadden (1984), Dahl (2002), and more recently by Bourguignon et al. (2007). We adopt the approach proposed by Dubin & McFadden (1984), which is described below.

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. 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:

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

$$y_{icj} = X_{ic}\gamma_j + u_{icj} \tag{2}$$

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 that consumer i derives from adopting a feature phone or a smartphone, where Z_{ic} includes a set of individual/household characteristics and infrastructure variables that determine the 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 the 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 that they derive from adopting a feature phone or a smartphone. We do not use the 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 control for the differences in average quality and 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 by the exclusion of some of the variables in the choice equation, Z_i, from the variables in the usage equation, X_i. In particular, we consider that the adoption of mobile phones is determined by network coverage, which does not affect the usage of mobile money services. While UMTS or LTE coverage is needed to access the Internet on a smartphone, it is not required to use mobile money. Once people have GSM coverage and can use a feature phone, they can also use mobile money. We also estimate a similar two-stage model, where individuals decide to send, receive or save funds using a mobile money wallet in the second stage. To simplify notation, we skip the subscript i for individuals and c for countries in the derivation of the model below. In the second stage, we account for the selection correction term and follow the derivation shown in Bourguignon et al. (2007).

There is, however, a problem with estimating the 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_j is not independent of ϵ_j and for a continuous usage variable y_j and normally distributed u_j, a simple ordinary least squares (OLS) regression of the usage equation is inconsistent. Let us define the following vector $\Gamma = \{V_f, V_s, V_o\}$. For a generalized Heckman (1979) model, the correction bias can be written using the conditional mean of u_s, for example, without loss of generality:

$$E(u_s|\varepsilon_s < 0, \Gamma) = \int \int_{-\infty}^{0} \frac{u_s \cdot f(u_s, \epsilon_s|\Gamma)}{P(\varepsilon_s < 0|\Gamma)} d\epsilon_s du_s = \lambda(\Gamma) \tag{3}$$

where $f(u_s, \varepsilon_s|\Gamma)$ is the conditional joint density of u_s and ϵ_s. To simplify notation, 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:

$$E(u_s|\varepsilon_s, \Gamma) = \mu(P_f, P_s, P_o) \tag{4}$$

Therefore, consistent estimation of γ_j can be based on the following equation:

$$\begin{aligned} y_j &= X\gamma_j + \lambda(\Gamma) + \omega_j \qquad (5) \\ &= X\gamma_j + \mu(P_s, P_f, P_o) + \omega_j \end{aligned}$$

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 of dimensionality. Bourguignon et al. (2007) survey different approaches to selection bias correction. In this paper, we follow the approach by Dubin & McFadden (1984). The parameters of the utility function V_j can be estimated using the maximum likelihood estimator. In the case of continuous usage variable y_s the estimation of the second stage equation (5) 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 the bivariate logit model in the second stage.

6 The Estimation Results

6.1 Adoption of Mobile Phones

Most of the population in Sub-Saharan African countries relies on mobile phones to access the Internet and use financial services. Therefore, it is important to analyze the factors that contribute to a greater adoption of smartphones. We are particularly 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. We estimate in two stages different model specifications which include coverage by one or more networks.

In our models, network coverage is considered to be exogenous, even though networks are initially deployed in richer urbanized areas. First, these three different network technologies: GSM, UMTS, and LTE, were deployed at different times, and there were coverage obligations in place. In particular, GSM and UMTS were deployed before the time period of our analysis and before the adoption of smartphones took off. About 66% of individuals in our sample live within 2km of a GSM tower, 64% from a UMTS tower, and 21% from an LTE tower, with large differences across countries. Moreover, we include in the regressions nighttime light data as a proxy for economic development as well as an income variable and other variables related to possessions, which should control for the income effect of handset adoption.

In the first stage, we estimate a discrete choice model for the decision to adopt a feature phone or a smartphone (Table 4), or any type of handset (Table 5). In Model I, we include the coverage variables by all three networks. Models II, III, and IV use coverage for each network separately. The estimation results for all four specifications are comparable. We find that individuals who live within a 2km radius of GSM, UMTS, and LTE towers are more likely to adopt both a feature phone and a smartphone, where there is a stronger impact of coverage on the adoption of smartphones.

In the counterfactual simulations, we consider that the whole population lives within 2km of towers of any of these three networks. We find that in such case, the adoption of smartphones would increase by between 12% and 32% depending on the country, as shown in Table 6. The smallest impact is estimated for South Africa, which had better network coverage and a higher share of smartphone users as of 2017. The most significant 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 of 7% in South Africa and an increase of 3% in Rwanda. Finally, the share of the population without mobile phones declines by between 8% and 18% depending on the country. Thus, our results emphasize the importance of investments in infrastructure in the adoption of smartphones and consequently in the use of mobile Internet and mobile financial services.

We include in the estimation a rich set of individual and household-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 from higher income groups are also more likely to adopt a mobile phone, 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 phone. 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. 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. These results are consistent with the previous literature which indicate that inequalities in access and ownership of mobile phones are underpinned by the urban-rural divide, gender disparities, income, and educational inequalities (see Jamil (2021)).

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, as shown in Tables 7 and 8. These services can be used both on a feature phone and a smartphone, but smartphones also give access to the Internet and other financial services such as mobile banking. In these regressions, we consider that the use of mobile money may be impacted by distance to bank branches and ATMs. However, it is not impacted by network coverage directly, which is our exclusion restriction. When network coverage is included in the second stage regression, its impact on the use of mobile money is not significant, which supports using this variable as an exclusion restriction.

There may be a spatial correlation between mobile money adoption and the location of banking facilities due to income effect. Banking facilities are located in richer urbanized areas, in which there are also more mobile phone and mobile money users. The first-stage correction term should account for selection bias in handset adoption. Moreover, in the second-stage regressions we include nighttime lights as a proxy of economic development, which should control for the correlation due to income effect.

We find that living in areas with no nighttime light, reported as 'dark,' negatively impacts the use of mobile money among feature phone users but not among smartphone users. There is also a significant and negative impact on the use of mobile money in 'dark' locations when people choose any type of handset in the first stage regression (see Table 9).

Next, we find that smartphone users who live within 10km of a bank branch and within 25km of an ATM are less likely to use mobile money, but this is not the case for users of feature phones. Furthermore, users of any type of handset who live within 25km of an ATM are also less likely to use mobile money (see Table 9), but distance to bank branches has no significant impact.

We conclude that, on the whole, mobile money usage is lower in economically less developed areas. However, a greater distance to banking facilities increases the incentive to rely on it.[12]

The second-stage regressions include the correction terms from the first stage and the same set of individual- and household-specific characteristics. Most of the characteristics are however insignificant. The exceptions are the 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 directly influenced by the level of income. This means that once people get a mobile phone, mobile money is used by all income groups. In the alternative

[12]In two other regressions, we examined the impact of distance to the main road and town. We found that distance to the main road or town does not affect the use of mobile money. These results are not reported in the paper due to space constraints.

specification presented in Table 9, certain individual characteristics become significant, which differs from the results shown in Tables 7 and 8.[13]

6.3 Sending, Receiving and Saving Money on Mobile Wallet

We also estimate second-stage regressions separately for the decisions to send, receive, or save money via a mobile wallet, considering the adoption of any handset in the first stage. Consistent with Islam et al. (2022), we find that people living in less economically developed areas are less likely to send money. Moreover, they are more likely to send money if they live within 2km of a bank branch but less likely if they live within 2km of an ATM, as shown in Table 10. Easy access to ATMs makes using cash instead of mobile money transfers possible. The positive impact of the proximity of bank branches is less clear, but this may be related to the fact that bank branches are located in wealthier areas.

Several individual characteristics are significant in these regressions. Sending money is more likely among younger, married individuals with secondary education who own a laptop or computer and have a bank account. Additionally, higher-income individuals are more inclined to send money, while those without any formal education are less likely to do so. Individuals who own a car are less likely to send money, despite their better financial status. However, previous studies have found that individuals living in households with a car are more likely to engage in formal banking services transactions (see Fitzpatrick (2015)). This might be also due to the convenience of using a car to transport and distribute cash in developing countries, which is faster and safer than other means of transportation.

The estimation results for receiving money via mobile money differ (see Table 11). Living in less economically developed areas does not have a negative impact on receiving money, but income level is significant. Moreover, older individuals, females, and married individuals are more likely to receive money via mobile money. This indicates that mobile money provides a virtual infrastructure through which relatively wealthier individuals, primarily the young and the educated living in economically developed areas, can remit money directly to the older generation without the need for a third party or the use of expensive and risky cash-in-transit methods. This is critically important in developing countries where public forms of social welfare measures have been weak and national social security systems are underdeveloped.

[13] Since Nigeria and South Africa have much lower use of mobile money, as shown in Table 1, as a robustness check we estimate the models without these two countries. The estimation results are comparable because country-fixed effects control for differences in mobile money usage.

Our results reinforce previous evidence on the positive impacts of mobile money technologies on improving the livelihoods of the poor and its potential to smooth household shocks and consumption via increased transactions between household members (see Jack & Suri (2014)). Furthermore, our results are consistent with the findings of Suri & Jack (2016), who posit that women in male-headed households, who are mostly secondary income earners, are more likely to receive money via the mobile money platform.

Several other individual characteristics are significant in these regressions. People who own a car or motorbike are less likely to receive money, which was also the case with sending money. These results are a further indication that relatively richer individuals are more likely to transact using formal banking services. Moreover, our results also indicate that individuals with a bank account are more likely to receive money. Employed people are also more likely to receive money, which indicates that this may be a way of paying salaries. Conversely, individuals without any formal education are less likely to receive money, underscoring the importance of education and financial literacy in the adoption and use of mobile money services. This positive relationship between education and mobile money usage is consistent with findings in Munyegera & Matsumoto (2016) and Mothobi & Grzybowski (2017). Lastly, individuals living within 2km of a bank branch are more likely to receive money.

The estimation results for saving money via mobile wallet are shown in Table 12. People who live in less economically developed areas save less money in this way. Interestingly, people with higher incomes (relative to the base category) save less on mobile wallets, which suggests that they have alternative means of saving or investing money. People without education save less, which was also the case concerning sending and receiving money. People in younger age groups save more money compared to the oldest age category. Self-employed people and students save more on mobile wallets as well as people who have access to a laptop or PC. Finally, people who live within 10km of an ATM or 25km of a bank branch tend to save more money on mobile wallets.

Consistent with Jack & Suri (2014) and Riley (2018), our results indicate that the younger generation and self-employed individuals, who often provide financial support to the elderly and less affluent, are more likely to use mobile money as a safeguard against unexpected shocks. Conversely, the lack of savings in mobile wallets among the poor aligns with Cuneo (2019), who argue that lower transaction costs and easy access to mobile money agents might disincentivize users, particularly the poor and elderly, from saving, as they rely on their support networks.

7 Conclusion

In this paper, we analyze how the proximity of mobile network infrastructure and banking facilities impacts the decision to adopt a mobile phone and to use mobile money services. We use 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 the geo-location of respondents. We approximate the level of economic development and access to physical infrastructure using several 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 the proximity of bank branches and ATMs.

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 and smartphones. In the second stage, depending on the type of handset adopted, consumers decide whether to use mobile money services. We find that network coverage significantly impacts the decision to adopt a mobile phone. In particular, individuals who live within a 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 a 2km radius of any of these networks. We find that in such scenarios the adoption of smartphones would increase by 12-32% depending on the country.

Overall, individuals who live in areas that 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 of 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 mobile phone who live within 25km of an ATM are also less likely to use mobile money services. Thus, while there is overall less mobile money usage in less economically developed areas, 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 concerning receiving money.

Overall, our findings emphasize the critical role that investment in mobile network coverage plays in facilitating financial inclusion and in bridging the digital divide. We also show that mobile money services effectively enhance social support networks. They enable younger and relatively wealthier migrant workers, situated in areas with better infrastructure, to provide care for elderly family members residing in less developed regions. In the context of developing countries where traditional forms of public social welfare are limited, the availability of an affordable and secure remittance flow is critically important. Thus, widespread and reliable telecommunications infrastructure, along with affordable mobile money services, serves as a crucial tool for fostering economic cohesion.

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8 Appendix

Table 4: 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)
Age < 25	-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)
Age $25-35$	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)
Age $25-45$	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)
Age $45-55$	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)
Age $55-65$	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)
Income < 20USD	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)
Income $20-100$USD	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)
Income $100-300$USD	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)
HH size$=2$	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)
HH size>2	-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 account	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 5: Stage one: adoption of handsets

	Model I	Model II	Model III	Model IV
GSM	0.261***	0.558***		
	(0.072)	(0.051)		
UMTS	0.422***		0.608***	
	(0.073)		(0.051)	
LTE	0.001			0.317***
	(0.080)			(0.075)
Female	-0.323***	-0.306***	-0.322***	-0.282***
	(0.051)	(0.051)	(0.051)	(0.050)
Age < 25	0.048	0.032	0.046	-0.006
	(0.113)	(0.112)	(0.112)	(0.112)
Age $25 - 35$	0.538***	0.529***	0.537***	0.511***
	(0.110)	(0.110)	(0.110)	(0.110)
Age $35 - 45$	0.496***	0.493***	0.493***	0.482***
	(0.115)	(0.115)	(0.115)	(0.114)
Age $45 - 55$	0.433***	0.431***	0.431***	0.426***
	(0.122)	(0.122)	(0.122)	(0.121)
Age $55 - 65$	0.459***	0.464***	0.455***	0.459***
	(0.123)	(0.123)	(0.123)	(0.123)
Income < 20USD	1.567***	1.547***	1.562***	1.550***
	(0.253)	(0.253)	(0.252)	(0.256)
Income $20 - 100$USD	1.886***	1.876***	1.883***	1.890***
	(0.256)	(0.256)	(0.255)	(0.259)
Income $100 - 300$USD	1.820***	1.820***	1.814***	1.838***
	(0.321)	(0.321)	(0.321)	(0.324)
Married	0.242***	0.232***	0.242***	0.217***
	(0.057)	(0.057)	(0.057)	(0.057)
HH size $= 2$	0.026	0.037	0.020	0.030
	(0.095)	(0.094)	(0.094)	(0.094)
HH size > 2	-0.102	-0.091	-0.105	-0.085
	(0.079)	(0.079)	(0.079)	(0.079)
None	-2.380***	-2.419***	-2.388***	-2.495***
	(0.136)	(0.136)	(0.136)	(0.135)
Primary	-1.502***	-1.529***	-1.510***	-1.587***
	(0.126)	(0.126)	(0.126)	(0.125)
Secondary	-0.646***	-0.654***	-0.643***	-0.648***
	(0.123)	(0.123)	(0.123)	(0.123)
Employed	0.562***	0.576***	0.568***	0.609***
	(0.100)	(0.100)	(0.100)	(0.100)
Self-employed	0.389***	0.379***	0.389***	0.367***
	(0.073)	(0.073)	(0.073)	(0.072)
Housework	-0.126	-0.126	-0.129*	-0.132*
	(0.078)	(0.078)	(0.078)	(0.078)
Student	-0.643***	-0.628***	-0.642***	-0.597***
	(0.093)	(0.092)	(0.093)	(0.092)
Retired	-0.388***	-0.380***	-0.390***	-0.375***
	(0.124)	(0.123)	(0.123)	(0.123)
Own house	-0.130**	-0.166***	-0.146***	-0.257***
	(0.057)	(0.056)	(0.056)	(0.056)
Car	0.177	0.195	0.185	0.233*
	(0.125)	(0.125)	(0.125)	(0.125)
Motobike	0.356***	0.359***	0.342***	0.312***
	(0.097)	(0.097)	(0.097)	(0.096)
Laptop/computer	0.569***	0.589***	0.578***	0.644***
	(0.133)	(0.133)	(0.133)	(0.132)
Bank account	1.215***	1.230***	1.215***	1.246***
	(0.083)	(0.083)	(0.083)	(0.082)
Observations	12,620	12,620	12,620	12,620

Table 6: Simulation: impact of coverage on handset adoption

	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 7: Stage two: mobile money and distance to bank branch (stage one: feature phones / smartphones adoption)

	Feature phone				Smartphone			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
Bank 2km	0.029				-0.431***			
	(0.098)				(0.153)			
Bank 5km		0.016				-0.422***		
		(0.098)				(0.155)		
Bank 10km			-0.078				-0.343**	
			(0.091)				(0.155)	
Bank 25km				0.071				-0.186
				(0.096)				(0.185)
Dark	-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)
Age $<$ 25	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)
Age $25-35$	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)
Age $35-45$	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)
Age $45-55$	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)
Age $55-65$	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)
Income $<$ 20USD	-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)
Income $20-100$USD	-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)
Income $1000-300$ USD	-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)
HH size $=2$	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)
HH size >2	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/computer	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 account	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)
Corr. feature	-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)
Corr. smart	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 8: Stage two: mobile money and distance to ATM (stage one: feature phones / smartphones adoption)

	Feature phone				Smartphone			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
ATM 2km	0.162				-0.271*			
	(0.112)				(0.150)			
ATM 5km		0.198**				-0.324**		
		(0.099)				(0.142)		
ATM 10km			-0.067				-0.423***	
			(0.092)				(0.142)	
ATM 25km				-0.181**				-0.281*
				(0.086)				(0.152)
Dark	-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)
Age < 25	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)
Age $25-35$	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)
Age $33-45$	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)
Age $45-55$	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)
Age $55-65$	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)
Income < 20USD	-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)
Income $20-100$USD	-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)
Income $100-300$USD	-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)
HH size $= 2$	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)
HH size > 2	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/computer	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 account	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)
Corr. feature	-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)
Corr. smart	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 9: Stage two - mobile money and distance to bank branch / ATM (stage one: handset adoption)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
Bank/ATM 2km	-0.015				0.015			
	(0.078)				(0.087)			
Bank/ATM 5km		-0.016				0.084		
		(0.077)				(0.077)		
Bank/ATM 10km			-0.039				-0.084	
			(0.072)				(0.072)	
Bank/ATM 25km				0.079				-0.116*
				(0.081)				(0.070)
Dark	-0.442***	-0.444***	-0.453***	-0.418***	-0.431***	-0.399***	-0.471***	-0.474***
	(0.087)	(0.089)	(0.086)	(0.081)	(0.083)	(0.086)	(0.085)	(0.082)
Female	-0.020	-0.020	-0.018	-0.026	-0.022	-0.024	-0.015	-0.015
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
Age < 25	0.697***	0.698***	0.696***	0.700***	0.697***	0.695***	0.699***	0.699***
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
Age $25 - 35$	0.793***	0.793***	0.789***	0.804***	0.795***	0.798***	0.787***	0.785***
	(0.176)	(0.176)	(0.177)	(0.177)	(0.176)	(0.176)	(0.176)	(0.176)
Age $35 - 45$	0.828***	0.828***	0.824***	0.836***	0.829***	0.829***	0.824***	0.825***
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
Age $45 - 55$	0.586***	0.586***	0.583***	0.592***	0.587***	0.586***	0.584***	0.584***
	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
Age $55 - 65$	0.399**	0.400**	0.397**	0.402**	0.401**	0.400**	0.398**	0.397**
	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)
Income < 20USD	-0.405	-0.407	-0.416	-0.376	-0.398	-0.372	-0.437	-0.453
	(0.293)	(0.294)	(0.294)	(0.293)	(0.293)	(0.293)	(0.294)	(0.294)
Income $20 - 100$USD	-0.138	-0.140	-0.151	-0.106	-0.131	-0.104	-0.172	-0.186
	(0.309)	(0.310)	(0.310)	(0.309)	(0.308)	(0.309)	(0.310)	(0.310)
Income $100 - 300$USD	-0.301	-0.303	-0.315	-0.271	-0.296	-0.275	-0.332	-0.344
	(0.330)	(0.330)	(0.331)	(0.330)	(0.329)	(0.329)	(0.331)	(0.330)
Married	0.001	0.001	-0.001	0.006	0.002	0.005	-0.003	-0.005
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
HH size $= 2$	0.081	0.081	0.082	0.080	0.081	0.077	0.085	0.084
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)
HH size > 2	0.028	0.028	0.029	0.024	0.027	0.023	0.032	0.031
	(0.100)	(0.100)	(0.101)	(0.100)	(0.100)	(0.101)	(0.101)	(0.101)
None	-1.281***	-1.279***	-1.266***	-1.307***	-1.285***	-1.302***	-1.251***	-1.240***
	(0.253)	(0.254)	(0.255)	(0.254)	(0.253)	(0.253)	(0.255)	(0.254)
Primary	-0.592***	-0.590***	-0.581***	-0.614***	-0.595***	-0.607***	-0.569***	-0.558***
	(0.191)	(0.192)	(0.192)	(0.192)	(0.191)	(0.191)	(0.192)	(0.192)
Secondary	-0.193	-0.192	-0.187	-0.205	-0.195	-0.201	-0.182	-0.176
	(0.131)	(0.131)	(0.131)	(0.131)	(0.130)	(0.130)	(0.131)	(0.131)
Employed	0.282**	0.281**	0.280**	0.288**	0.283**	0.285**	0.276**	0.271**
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
Self-employed	0.116	0.115	0.114	0.120	0.116	0.118	0.111	0.108
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)
Housework	-0.021	-0.021	-0.021	-0.021	-0.021	-0.022	-0.020	-0.019
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Student	0.345**	0.346**	0.350**	0.336**	0.344**	0.340**	0.353**	0.355**
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)
Retired	-0.111	-0.110	-0.108	-0.114	-0.112	-0.118	-0.104	-0.107
	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)
Own house	-0.076	-0.076	-0.077	-0.072	-0.073	-0.067	-0.081	-0.081
	(0.074)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)
Car	-0.057	-0.057	-0.058	-0.057	-0.059	-0.067	-0.051	-0.050
	(0.123)	(0.123)	(0.123)	(0.123)	(0.124)	(0.123)	(0.123)	(0.123)
Motorbike	0.148	0.148	0.144	0.159	0.151	0.157	0.139	0.135
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
Laptop/computer	0.343***	0.342***	0.339***	0.349***	0.344***	0.344***	0.337***	0.337***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)
Bank account	0.622***	0.621***	0.614***	0.639***	0.625***	0.634***	0.604***	0.598***
	(0.146)	(0.146)	(0.146)	(0.146)	(0.145)	(0.146)	(0.146)	(0.146)
Corr. handset	-0.086	-0.087	-0.096	-0.065	-0.082	-0.071	-0.108	-0.114
	(0.136)	(0.136)	(0.137)	(0.136)	(0.135)	(0.135)	(0.137)	(0.136)
Constant	1.790***	1.791***	1.803***	1.724***	1.773***	1.728***	1.820***	1.844***
	(0.381)	(0.381)	(0.380)	(0.382)	(0.381)	(0.381)	(0.380)	(0.380)
Observations	8,866	8,866	8,866	8,866	8,866	8,866	8,866	8,866

Table 10: Stage two: sending money (stage one: handset adoption)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
Bank/ATM 2km	0.202***				-0.184**			
	(0.077)				(0.085)			
Bank/ATM 5km		-0.035				-0.093		
		(0.081)				(0.076)		
Bank/ATM 10km			0.066				-0.001	
			(0.076)				(0.072)	
Bank/ATM 25km				0.163*				0.002
				(0.087)				(0.069)
Dark	-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)
Age < 25	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)
Age $25-35$	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)
Age $35-45$	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)
Age $44-55$	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)
Age $55-65$	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)
Income < 20USD	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)
Income $20-100$USD	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)
Income $100-300$USD	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)
HH size = 2	-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)
HH size > 2	-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/computer	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 account	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)
Corr. handset	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 11: Stage two: receiving money (stage one: handset adoption)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
Bank/ATM 2km	0.131*				0.054			
	(0.079)				(0.086)			
Bank/ATM 5km		0.017				-0.031		
		(0.083)				(0.077)		
Bank/ATM 10km			0.023				0.008	
			(0.077)				(0.074)	
Bank/ATM 25km				0.182**				-0.027
				(0.089)				(0.071)
Dark	-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)
Age < 25	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)
Age $25-35$	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)
Age $35-45$	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)
Age $45-55$	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)
Age $55-65$	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)
Income < 20USD	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)
Income $20-100$USD	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)
Income $100-300$USD	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)
HH size $= 2$	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)
HH size > 2	-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/computer	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 account	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)
Corr. handset	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 12: Stage two: saving money (stage one: handset adoption)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model IV
Bank/ATM 2km	0.023				0.176**			
	(0.072)				(0.078)			
Bank/ATM 5km		0.008				0.252***		
		(0.074)				(0.070)		
Bank/ATM 10km			0.039				0.121*	
			(0.070)				(0.067)	
Bank/ATM 25km				0.204***				0.032
				(0.078)				(0.065)
Dark	-0.435***	-0.442***	-0.428***	-0.405***	-0.382***	-0.327***	-0.392***	-0.436***
	(0.080)	(0.084)	(0.079)	(0.074)	(0.078)	(0.080)	(0.078)	(0.075)
Female	0.074	0.075	0.072	0.062	0.072	0.068	0.067	0.074
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Age < 25	0.568***	0.568***	0.570***	0.579***	0.574***	0.560***	0.564***	0.567***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.182)
Age $25-35$	0.585***	0.584***	0.589***	0.611***	0.594***	0.593***	0.593***	0.586***
	(0.180)	(0.180)	(0.180)	(0.181)	(0.180)	(0.180)	(0.180)	(0.180)
Age $35-45$	0.674***	0.673***	0.677***	0.693***	0.681***	0.673***	0.677***	0.673***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
Age $45-55$	0.430**	0.429**	0.432**	0.445**	0.433**	0.427**	0.431**	0.429**
	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)
Age $55-65$	0.193	0.192	0.195	0.200	0.197	0.189	0.195	0.193
	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)
Income < 20USD	-0.900***	-0.903***	-0.891***	-0.845***	-0.881***	-0.825***	-0.856***	-0.892***
	(0.291)	(0.292)	(0.292)	(0.291)	(0.290)	(0.291)	(0.292)	(0.292)
Income $20-100$USD	-0.560*	-0.563*	-0.549*	-0.498	-0.544*	-0.486	-0.513*	-0.552*
	(0.303)	(0.304)	(0.304)	(0.303)	(0.302)	(0.303)	(0.304)	(0.304)
Income $100-300$USD	-0.734**	-0.737**	-0.724**	-0.674**	-0.728**	-0.676**	-0.691**	-0.727**
	(0.325)	(0.326)	(0.326)	(0.325)	(0.324)	(0.325)	(0.326)	(0.326)
Married	-0.028	-0.028	-0.026	-0.019	-0.025	-0.019	-0.022	-0.027
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
HH size $= 2$	0.058	0.058	0.057	0.055	0.058	0.053	0.055	0.058
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
HH size > 2	-0.035	-0.034	-0.036	-0.044	-0.036	-0.044	-0.041	-0.035
	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
None	-0.640***	-0.637***	-0.652***	-0.691***	-0.642***	-0.686***	-0.681***	-0.646***
	(0.232)	(0.234)	(0.234)	(0.233)	(0.232)	(0.233)	(0.233)	(0.233)
Primary	-0.246	-0.244	-0.254	-0.293*	-0.249	-0.280*	-0.276	-0.251
	(0.170)	(0.171)	(0.171)	(0.171)	(0.170)	(0.170)	(0.171)	(0.171)
Secondary	-0.038	-0.037	-0.042	-0.064	-0.039	-0.056	-0.053	-0.040
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Employed	0.113	0.112	0.115	0.129	0.113	0.117	0.121	0.114
	(0.111)	(0.111)	(0.111)	(0.112)	(0.111)	(0.111)	(0.111)	(0.111)
Self-employed	0.156*	0.156*	0.158*	0.168*	0.155*	0.164*	0.163*	0.158*
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
Housework	-0.058	-0.058	-0.057	-0.056	-0.059	-0.061	-0.060	-0.059
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
Student	0.360***	0.361***	0.357***	0.342***	0.359***	0.350***	0.351***	0.359***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
Retired	-0.016	-0.014	-0.017	-0.016	-0.019	-0.032	-0.025	-0.016
	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)
Own house	-0.053	-0.055	-0.053	-0.052	-0.043	-0.036	-0.048	-0.054
	(0.068)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Car	-0.082	-0.081	-0.081	-0.082	-0.099	-0.105	-0.091	-0.084
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
Motorbike	-0.011	-0.012	-0.007	0.011	0.001	0.009	0.002	-0.009
	(0.106)	(0.106)	(0.107)	(0.107)	(0.106)	(0.106)	(0.106)	(0.106)
Laptop/computer	0.213*	0.212*	0.216*	0.230**	0.210*	0.217*	0.221*	0.213*
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
Bank account	0.207	0.205	0.213	0.242*	0.210	0.234*	0.233*	0.211
	(0.136)	(0.137)	(0.137)	(0.137)	(0.136)	(0.136)	(0.137)	(0.137)
Corr. handset	-0.270**	-0.272**	-0.262**	-0.229*	-0.267**	-0.240*	-0.241*	-0.266**
	(0.124)	(0.125)	(0.125)	(0.125)	(0.124)	(0.124)	(0.125)	(0.125)
Constant	0.774**	0.782**	0.764**	0.634*	0.677*	0.617*	0.725**	0.770**
	(0.369)	(0.369)	(0.369)	(0.371)	(0.369)	(0.369)	(0.368)	(0.368)
Observations	8,866	8,866	8,866	8,866	8,866	8,866	8,866	8,866

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