Disruptive Technologies in South Africa and Sub-Saharan Africa: The Case of Mobile Telecommunications Services

Lukasz Grzybowski

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List of abbreviations and acronyms

ATM	Automated Teller Machine
BLP	Berry. Levinsohn and Pakes estimator
CCP	Conditional Choice Probability
CPU	Central Processing Unit
DCDP	Discrete Choice Dynamic Programming
DMSP	Defense Meteorological Satellite Programme
EOG	Earth Observations Group
GB	GigaByte
GMM	Generalized Method of Moments
GPU	Graphics Processing Unit
GSM	Global System for Mobile communication
ICT	Information and Communications Technology
IDC	International Data Company
IID	Identically and Independently Distributed
IMEI	International Mobile Equipment Identity
IT	Information Technology
LCD TV	Liquid Crystal Display Television
LTE	Long Term Evolution
MB	Megabyte
MNO	Mobile Network Operator
NFP	Nested Fixed Point
NGDC	National GeoData Centre
NIDS	National Income Dynamic Survey
NOAA	National Oceanic and Atmospheric Administration
NTL	Night-time Lights
OSM	Open Street Map
OLS	Ordinary Least Squares
PPP	Purchasing Power Parity
RAM	Random Access Memory
RCT	Randomized Controlled Trial
SALDRU	Southern Africa Labour and Development Research Unit
SMS	Short Message Service
UCT	University of Cape Town
UMTS	Universal Mobile Telecommunications System
USDA	United States Department of Agriculture
VAT	Value-Added Tax

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1.0 Introduction

The last decade around the world has been marked by digital transformation of the economies and societies. In most developed countries, almost every single household got fast broadband Internet connection, while mobile operators have been covering the globe with LTE networks, which offer high-speed Internet connections on mobile devices. These investments in telecommunications infrastructure and increasing number of people with fast Internet connections on fixed or mobile networks resulted in explosion of innovative Internet services, which impacted the functioning of almost every single traditional industry including the media, retail, and transportation. The impact of digital markets on individuals, households, and small business is gaining a momentum with the emergence and rapid growth of online social platforms, peer-to-peer lending, crowd-funding services, and many other online platforms.

These recent changes take place at different pace in developed and developing countries, which is largely due to differences in the availability of infrastructure, affordability of Internet access, level of education, and technological literacy as well as social and economic development. But even though developing countries are lagging behind, the rapid deployment of mobile Internet services in the last years allows them to overcome poor or non-existent fixed-line infrastructure for Internet access. A digital literacy and digital divide between poor and richer areas and between segments of the societies still remains a key issue to overcome.

Access to mobile Internet can dramatically improve standard of living in developing countries by saving wasted trips, providing information about prices or serving as a conduit to banking, health care and other services. There are different ways through which mobile services can benefit people and economies in developing countries. First, mobile services can improve the functioning of markets by improving access to information and thus increasing transparency. Second, better communication can improve management of supplies and improve the efficiency of firms. Third, mobile phones may facilitate services which are in general not available to low-income households, such as mobile phone-based financial, agricultural, health, and educational services. Fourth, communications applications used on mobile phones, such as Facebook messenger, Skype, Viber, WhatsApp and others, not only cut the expenses on telecommunications services of low-income households, but they may also facilitate the coordination and cooperation of communities without access to other means of communications.

To date, there is only scarce research on how people in developing countries use mobile phones and Internet to access different mobile services and, consequently, how this impacts their wellbeing and the functioning of different markets. This is largely due to the shortage of individual-level data on the use of mobile services in these countries.

In this paper, we fill this research gap by conducting three research studies. In the first study, we analyse adoption of smartphones among individuals with different levels of income in South Africa. We comment on policies which may reduce digital divide and stimulate access to smartphones and mobile Internet among poorest individuals. In the second one, we analyse how the proximity of mobile networks infrastructure and banking facilities impact the decision to adopt a mobile phone and to use mobile money services in selected countries in sub-Saharan Africa. In the third study, we analyse the impact of mobile phone ownership on change in employment status in South Africa.

2.0 Adoption of smartphones and digital divide between rural and urban areas in South Africa

Introduction

Mobile communications offer a major opportunity to advance economic growth in developing countries, where fixed-line infrastructure is non-existent or of limited coverage. Even when fixed networks exist, they are typically available in urban areas and to better-off households who are the minority.

Therefore, the majority of population has to rely on mobile networks to access the Internet. As the main communications technology, mobile phones can stimulate inclusive economic growth, and reduce poverty and inequality through different mechanisms, for example: by saving wasted trips; providing information about prices; improving management of supplies; and increasing productive efficiency of firms (see Aker & Mbiti, 2010). They can also serve as a channel for provision of services which are in general not available to poor people, such as mobile-based financial, health, educational, and agricultural services.[1]

Yet, mobile phones, and especially smartphones, are still expensive and not affordable to the majority of population in low-income countries. Many poor people in these countries do not have stable jobs or work in informal sector. Thus, they are not eligible for tariff plans which would enable them to pay off the cost of a smartphone over one or two years. Because of limited budgets, they also cannot afford purchasing bigger bundles of data and minutes at one time and instead make frequent purchases of small bundles. This increases the average price they pay for mobile services. Overall, poor households spend a relatively high share of their income on telecommunications services. Another problem is that mobile networks, which enable high-speed Internet access, are first rolled out in densely populated urban areas which tend to be richer on average. This further contributes to widening the digital divide between rich and poor and between urban and rural areas.

1 For evidence on the impact of mobile phones on economic development, see papers by Jensen (2007), Muto and Yamano (2009) and Aker and Mbiti (2010).

In this paper, we use biannual panel data of subscribers of mobile telecommunications services in South Africa to analyse how the price of smartphones impacts the adoption decision in different income groups. This is important because, as mentioned above, a smartphone is the only means of accessing the Internet by poor people, which has economic and societal consequences. The governments and international organizations such as the World Bank have been trying to design policies to increase smartphone penetration and Internet access among poor people in Africa and in other low-income countries. The potential policies are lower taxes on the imports and sale of smartphones, or smartphone subsidy schemes, which could lower the prices paid by poor consumers. But, the effectiveness of these policies cannot be evaluated without knowing how price responsiveness varies across different income groups. We are especially interested on how demand responds to price among poorest people who should be targeted by these policies. But the price of smartphones is not the only factor which impacts adoption. There is little value in having a smartphone in areas without coverage with 3G or 4G/LTE technologies, i.e., without mobile Internet access. Also, the cost of mobile data may determine the adoption decision.

We estimate a number of discrete choice models, where we take into consideration the fact that smartphones are durable goods and consumers are forward-looking. In doing this, we follow the paper by De Groote and Verboven (2019), who develop a simple dynamic model of new technology adoption. Similar to other technological products, the quality of smartphones has been increasing over time (better processor, memory size, quality of camera, etc.), while the quality-adjusted price has been declining. Therefore, modelling demand for smartphones requires a dynamic framework, where in each period consumers decide whether to adopt a smartphone or to postpone this decision until prices go further down and quality increases. A static model will underestimate the price elasticities when consumers indeed postpone the adoption decision (see Gowrisankaran & Rysman, 2012). We comment whether this is the case in our setup by comparing dynamic and static adoption models.

We do not have information about the exact income of individuals in our sample. However, in South Africa, the suburb in which people live enables a very good approximation of the income level of households because of racial segregation policies during Apartheid. Even though underprivileged and wealthy suburbs often share a border with one another, there is virtually no mobility between them. The differences in property prices and rents are extreme and people remain segregated due to structural poverty and inequality. We have information on the location of mobile antenna to which each individual in our sample was connected most of the time in the time period observed. We use this information to identify the suburbs in which individuals live. Next, use location information to combine with our sample, a very detailed census data on 5,090 so called 'sub-places'. This allows us to retrieve information about the average household income as well as other statistics, such as the share of population having a fixed-line connection or a computer. We use the income information obtained from this data to construct five income groups. The first group corresponds to individuals living in areas where the income is below the national poverty line. The remaining individuals are divided into four income groups based on the four quartiles of the distribution of income for people living above the poverty line.

We analyse the characteristics of smartphones used by individuals belonging to five income groups. There are substantial differences in the type, quality and price of smartphones across these groups. Therefore, in our model consumers have different choice sets of handsets depending on their income group. In general, consumers with stable jobs and stream of income have access to long-term contracts with handset subsidies and can afford more expensive handsets. In the earlier literature, the choice set is commonly specified at the level of geographic market, or eventually based on different product segments. In this paper, we define separate markets and choice sets for different income groups. We proceed by aggregating the individual data at the income group level which we use in the estimation. This approach allows us to estimate the group-specific price coefficients, which we then use in the counterfactual simulations.

We find that there is digital divide in the population because poor people live in areas without network coverage, while the cost of smartphones does not have significant impact on adoption. In particular, if poor and richer areas were fully covered by LTE networks in the period of our data, the adoption of smartphones would increase from 57.1% to 76.0% among people below poverty line, while it would only change from 81.5% to 82.2% in the richest group of consumers as of 1st quarter of 2018. This is precisely because richer areas have almost full LTE coverage, while poorer regions are only partially covered. At the same time, removing 15% VAT on smartphones would increase adoption only to 57.7% among people below poverty line, and to 81.7% among richest consumers as of 1st quarter of 2018. The price effect has only marginal impact on adoption in all income groups. We conclude that, to reduce digital divide, it is critical to develop LTE infrastructure in poorer areas and people will respond by adopting smartphones irrespective of their income. Our static and dynamic models yield comparable results suggesting that consumers do not take future price and quality into account when purchasing smartphones.

Literature review

Our paper is methodologically related to the stream of literature dedicated to discrete choice dynamic programming models (DCDP). Methods to estimate such models have been reviewed by Aguirregabiria and Mira (2010) and Arcidiacono and Ellickson (2011) and can be classified in two types. The first one includes estimations using full solution methods, i.e., GMM approaches relying on the Nested Fixed Point (NFP) algorithm suggested by Rust (1987), and the BLP contraction mapping proposed by Berry et al. (1995). The second type are estimations relying on a simplification of Rust's algorithm, with the seminal paper by Hotz and Miller (1993) and more recent papers by Aguirregabiria and Mira (2002) and Arcidiacono and Miller (2011).] The second stream of literature relies on the Conditional Choice Probability (CCP) estimators, which is a relatively easy way to estimate dynamic discrete choice models. The type of data used in these estimations is aggregate market or individual-level data.

In the seminal paper, Rust (1987) formulates a simple regenerative optimal stopping model of bus engine replacement. The optimal stopping rule is the solution to a stochastic dynamic programming problem that formalizes the trade-off between the conflicting objectives of minimizing maintenance costs versus minimizing unexpected engine failures. The paper proposes a “nested fixed point” algorithm for estimating discrete choice dynamic programming models. For each combination of parameters, a fixed-point algorithm is used to compute value functions which characterize the expected future utility associated with the choices. Hotz and Miller (1993) develop a method for estimating the structural parameters of DCDP models. Under some conditions, this method avoids the computation of the value functions and is computationally less burdensome. Their method relies on the realization that the value functions can be represented as an easily computed function of the state variables, structural parameters, and the probabilities of choosing alternative actions for states that are feasible in the future. They estimate a dynamic model of parental contraceptive choice and fertility to illustrate application of this method. Subsequent work and extensions of these two seminal papers are surveyed in Aguirregabiria and Mira (2010) and Arcidiacono and Ellickson (2011).

Dynamic discrete choice models are estimated for various choices made by agents such as occupational choices (Miller, 1984), patent renewal (Pakes, 1986) or fertility choices (Wolpin, 1984; Hotz & Miller, 1993). One category of decision that is of particular interest for us is the adoption of durable goods, for which prices tend to decrease over time and quality increases. For example, Nair (2007) estimates the demand for video games when consumers forward-looking and firms use inter-temporal price discrimination. Schiraldi (2011) estimates a model for new and used cars where consumers decide to replace their automobile when a secondary market exists. In another paper, Conlon (2012) estimates a dynamic demand model for LCD TVs. Gowrisankaran and Rysman (2012) estimate dynamic demand for cameras for video recording (camcorders) which experienced rapid price declines and quality improvements at the same time. In their paper, they consider a dynamic decision that involves endogenous repeat purchases over time (Rust, 1987), when a large number of differentiated products are available on the market (Berry et al., 1995). They highlight significant differences in the price and characteristics elasticities depending on whether the model is static or dynamic, with more intuitive results obtained with the dynamic one. This observation suggests that accounting for dynamic decisions is important and should be implemented when one needs to compute the welfare gains associated with the introduction of these products. The market of smartphones which we study is similar to camcorders in that consumers choose from many differentiated products and they can rationally expect that over time prices will decline and the quality will increase. Thus, consumers face the trade-off between adopting now or waiting for the next period. However, in contrast to their work that focuses on replacement of product, we study the adoption of products.

Our paper follows closely the adoption decision framework derived in De Groote and Verboven (2019). In their paper, they formulate the expected next period ex ante value function as the realized value function plus a prediction error, which is uncorrelated with any variables known by the household at the time of the adoption decision. Then, they show how to invert the demand model to solve for the unobserved error term, which yields a linear regression equation. The current adoption rate then depends on current and next period prices, as well as on the next period adoption rate. The model can be estimated using a standard nonlinear GMM estimator to account for the endogeneity of several variables. They apply the model to a programme which promotes adoption of solar photovoltaic systems in Belgium and find that households significantly discounted the future benefits from the new technology. This implies that an upfront investment subsidy programme would have promoted the technology at a much lower budgetary cost. The model is estimated using aggregate market data and does not allow for household heterogeneity. This aggregate approach is similar as in Scott (2013). He uses the CCP estimator developed by Hotz and Miller (1993) to study a change in land use in US where landowners optimize dynamically. He allows for unobservable heterogeneity and avoids the burden of explicitly modelling the evolution of market-level state variables like input and output prices. He then uses the model to estimate long-run cropland-price elasticity. He concludes that the estimation of a static, myopic model yields to understating the long-run acreage elasticities, and therefore of the long-run land use effects and environmental costs. In this paper, we use aggregate data and follow the approach by Scott (2013) and De Groote and Verboven (2019), which allows us to address our research question in a relatively simple way. Estimating a dynamic demand model with micro-data is more challenging to implement, but it allows accounting for individual heterogeneity. We leave the estimation of a dynamic model of demand for smartphones with individual-level data to a future research.

Finally, our paper contributes to the literature on consumer's choices in the telecommunications markets, which in the last years has been undergoing dramatic technological innovation. This includes deployment of mobile broadband networks (3G, 4G, and soon 5G) and launch of smartphones. The usage and adoption of mobile services has been extensively studied as well as the adoption dynamics of mobile services and handsets due to switching costs (e.g., Cullen & Scherbakov, 2010); Grzybowski & Liang, 2014; Grzybowski & Nicolle, 2020). A novel aspect in our setting is that most consumers already use a mobile phone and decide to upgrade to a new product, which enables them to use mobile broadband services. Only a few papers estimated demand for smartphones in a structural framework for various purposes. For example, Sun (2012) explores the impact of the application stores on the brand value of operating systems. Sinkinson (2014) estimates price elasticities for smartphones and carriers and studies the implications of exclusive contracts for smartphones. Hiller et al. (2018) simulate the impact of different hypothetical smartphone patent infringements on equilibrium outcomes. Fan and Yang (2020) explore the relationship between competition on the smartphone market and the number of products offered.

They assess the welfare impact of various mergers between manufacturers, accounting for price and quality of products released. Finally, Luo (2018) explores the existence of OS-specific network effects in the smartphone industry. She also assesses the impact of long-term contracts offered by operators in this framework.

The adoption of mobile services in developing countries attracted much interest because of the potential which they have for the economic development (see, for example, Aker & Mbiti, 2010). In a recent paper, Bjorkegren (2019) develops a method to estimate and simulate the adoption of a network good. The demand for mobile phones is modelled as a function of individuals' social networks, coverage and prices. He uses transaction data over 4.5 years for nearly the entire mobile subscribers' base in Rwanda. The model is then used to simulate the effects of two policies. First, a requirement to serve rural areas by the operators resulted in lower profits but increased net social welfare. Second, he finds that a shift from handset to usage taxes would have increased the surplus of poorer users by at least 26%. In another recent paper, Shreeti (2019) uses aggregate data from the period 2007–2018 to explore the determinants of smartphone adoption in India. She exploits two shocks that occurred in the Indian market over the period of her study. First, the entry of a Chinese manufacturer resulted in a sharp decline of device prices. Second, the entry of a new mobile network operator (MNO) decreased mobile broadband prices. She concludes that the availability of cheap devices was not sufficient to allow for the adoption of smartphones to take-off. Her results suggest that both cheap smartphones and cheap data services are needed to stimulate adoption.

Our paper makes the following contributions to the literature discussed above. First, we apply the dynamic technology adoption model proposed by De Groote and Verboven (2019) to the case of smartphones in developing country with large income inequality. We account for heterogeneity in price responsiveness in different income groups. We then use our estimates to conduct counterfactual simulations and comment on what should be the most effective policies to stimulate adoption of smartphones and access to Internet among poor consumers. This is the first paper which sheds light on how consumers from different income groups choose smartphones.

Data

Data set construction: We combine different data sets for the purpose of this analysis. There are four mobile network operators in South Africa. We use data from one of them with full geographic coverage. The original data set consists in 293,193 observations of 83,964 individuals who used mobile services between March 2016 and September 2018. We observe consumers twice per year in March and September. We observe the model of handset used by these individuals. Such information is recorded in our database because the SIM card used by a consumer automatically detects and registers the model of a handset based on a unique international code called the IMEI (International Mobile Equipment Identity). From this data, we drop all observations of devices which are not phones, which leave us with 200,942 observations. We also drop consumers who subscribed to post-paid contracts because they can be bundled with a handset subsidized by the operator. In South Africa, the majority of consumers use mobile communications services with prepaid SIM cards. Thus, the remaining data set has 182,989 observations.

Next, we merge this data with detailed information on network coverage for 2G, 3G, and 4G networks at the main place level (2,434 unique geographic areas). There is substantial variation in coverage across geographic regions, as presented in Table A2. While coverage for 2G and 3G has reached very high levels over the whole territory with a few exceptions, the roll-out of 4G network is much more heterogeneous. We use this variation to identify how the development of high-speed networks, in particular 4G, impacts consumers' utility and smartphone adoption. Finally, we use the codes for sub-places to add information on average household income from the National Census of 2011, which covered about 10% of the country population. We lose a few observations at this stage, which leaves us with 181,934 observations.

This data is then merged with historical prices of handsets obtained from a price comparison website and complemented by data purchased from the firm International Data Company (IDC). For some handsets and periods, information on price is missing. We fill the data gaps using linear interpolation at the model level, or if not possible, at the brand-level. After dropping missing observations, we are left with 144,613 observations (79.49%). We further merge this data with handset characteristics from Imei.info, which does not result in further loss of data.

The society in South Africa is multi-racial, multi-lingual and highly segmented with respect to income, which results in differences in the affordability of mobile telecommunications services. The operator market shares vary by income group. Our data set is for a single operator and after cleaning described above it is not representative for the whole country. Still, it provides a solid basis to study the role of income for smartphone adoption decisions. We also show in the appendix that the individuals in our data set are not significantly different from those surveyed in the representative national census in terms of socio-demographic characteristics (see Table A1).

After this process of merging and data cleaning, our data set consists of 144,613 observations and 53,037 unique individuals. We observe different patterns in terms of initial choice of handset and switching between feature phones and smartphones, as described in Table A2 (in the appendix). We focus our analysis on consumers who in the time period of our data: (i) never adopted a smartphone; or (ii) switched from a feature phone to a smartphone. Therefore, we drop observations related to consumers who upgraded from a feature phone to a smartphone before the beginning of our sample. The final sample consists in 68,412 observations. For the small share of consumers who upgrade and then downgrade, we drop the observations related to downgrade, which reduces the sample to 62,196 observations on 25,930 unique consumers observed in the period between March 2016 and September 2018.

We use information on average income at the sub-place level to form income groups. The first group corresponds to individuals living in areas where the income is below the national poverty line. The remaining individuals are divided into four income group based on the four quartiles of the income distribution above the poverty line.[2] We use these groups to define markets as discussed below.

Aggregation of the data: We estimate the model for two levels of data aggregation. First, we aggregate the data at the market-level, which yields 135-162 observations for different smartphone models per period and 614 observations in total. The range of smartphone models which are available to consumers varies over time but not across individuals with different income level. Second, we divide all individuals into five income groups and aggregate the data at the income-group level, which yields 1040 observations in total. Here, we consider that people who live in locations with different average income level choose from a different set of handsets, which also varies over time.

Even though Apartheid ended about 30 years ago, as a result of this policy South African society is the most unequal in terms of income in the world. People with extreme differences in income live in segregated neighbourhoods with essentially no mobility between them. The rationale for grouping consumers by income and hence by location is to capture the differences in budget, tastes and usage of mobile services. The income of individuals constrains the choice of handsets. Thus, the aggregation at the income-group level allows us to identify how income affects the price sensitivity and preferences for product characteristics.

Descriptive statistics: We observe 25,930 unique consumers, among whom about 83% live in an urban area. They switch their handsets between 0 and 5 times over the two-year period which we study (0.4 on average). They consume per month between 0 and 31 GB of data (with an average of 97 MB), make between 0 and 4805 minutes of calls (with an average of 198 minutes) and send between 0 and 1,431 text messages (with an average of 12 texts).

In our sample, there are 394 unique handset types which belong to 20 brands. We group 11 small brands together and define 10 main manufacturers including 'small brands' in the subsequent analysis. Table A3 (in the appendix) presents the average characteristics of handsets which were observed at least once in our data over the period. On average, a handset costs about €200, with a minimum of €14 and a maximum of €1,110. On average, the phones selected by the consumers in the sample were released 4.2 years prior to purchase. About 68% of handsets are

2 In 2019 in South Africa, an individual living with less than roughly US$ 47 per month was considered to be poor. Based on the national poverty line obtained from official sources and the average number of individuals living in a household (3.3 persons), we can identify the areas where individuals are likely to live below the poverty line.

smartphones and 34% are compatible with LTE networks. Figure A3 and Figure A4 (in the appendix) show the differences in the distribution of prices and ages for two categories of handsets: feature phones and smartphones.

Table A4 (in the appendix) shows how the characteristics of selected phones differ across income groups. We observe that individuals who belong to higher income groups choose smartphones with more desirable characteristics such as LTE compatibility, bigger memory, higher quality camera, greater CPUs and display size, etc. Also, the data usage increases with income, while the usage of text messages decreases. This can be explained by the substitution between text messages and data, which depends on the income level and hence on the contract and handset type.

The sample which we use for the estimation at the market-level consists of 614 observations, with 135 observations for September 2016, 162 for March 2017, and 159 observations for September 2017 and 159 for March 2018. The sample we use for the estimation at the income-group level consists of 1,040 observations in total. At each period of time, we observe between, 32 and 81 models of smartphones, with the largest variety being observed for the first income group (see Table A5 in the appendix).

Model

We follow De Groote and Verboven (2019) and specify a dynamic adoption model which can be estimated with aggregate market-level data. As discussed above, we create five income groups in the population based on the average income information linked to geographic location of individuals in our sample. Next, we define the choice set of smartphones which is specific to each income group. An individual i_m from income group m may decide to adopt a smartphone from the set of devices available for this income group[3] at period t, denoted with j, with $j_m = 1, \ldots, J_m$. Alternatively, the individual may choose to continue using a feature phone denoted by $j_m = 0$. In this notation, we ignore the fact that the choice set may differ between periods. Also, to simplify the notation in the further derivation we ignore the subscript for the income segment m.

Given that we have individual-level data, we know the feature phone which is used by each individual. The utility derived from using a feature phone depends on its quality and price, and also on individual's taste. Since we estimate the model using aggregate income-group level data, we need to approximate this utility using the same value for all consumers belonging to group m. Also, we make different assumptions regarding the value of continued use of a feature phone and test how they impact our estimates. First, we normalize the utility of using a feature phone to zero, for all individuals. Second, we assume that the utility of choosing a feature phone is determined by the characteristics and price of the most-used feature phone in each income group, at each period of time. Third, we compute an arithmetic average

3 Available here means that we observe the specific smartphone being chosen at least once by one individual from the income group

based on the characteristics and price of the 50 top-used feature phones in each group, at each period. This way, we create a time-varying and group-specific 'average feature phone', which is used by consumers as an alternative to smartphones. In De Groote and Verboven (2019), non-adoption is associated with zero utility, as in our first approach. In the last two approaches, the utility derived from using a feature phone varies across income groups and declines over time. Also, the utility derived from adopting different smartphone models increases over time due to decreasing prices and improved quality.

There is no individual heterogeneity in the model apart from taste shock, which is i.i.d. type I extreme value distribution. This assumption implies that the correlation of preferences across individuals for similar smartphones is not permitted. But we estimate group-specific price coefficients to account for differences in price responsiveness of individuals with different level of income.

We assume that at each period t, individuals choose the alternative j which maximizes their random utility denoted by $\delta_{ijt} + \epsilon_{ijt}$, where δ_{ijt} depends on smartphone characteristics and ϵ_{ijt} is the taste shock specific to individual i. The adoption of a smartphone is terminating state, and we ignore the fact that a small group of consumers switches back to a feature phone, as shown in Table [patterns]. For the sake of simplicity, we drop these observations from the data. The indirect utility derived by an individual from owning a smartphone, which consists in a stream of utilities for a certain number of time periods can be specified as:

$$\delta_{ijt} = x_j \gamma - \alpha p_{jt} + \theta c_t + \xi_{jt} \tag{1}$$

Where: x_{jt} is a vector of characteristics of smartphone j, which do not change over time, p_{jt} is the smartphone price variable, c_t is 3G network coverage which varies over time and by income segment, and ξ_{jt} is the unobserved quality of alternative j in period t. We do not use fixed effects for smartphone models which cannot be estimated together with other smartphone characteristics. But we use a set of dummy variables for the main brands and operating systems.

The conditional value of not adopting a smartphone can be written as:

$$\delta_{i0t} = u_{0t} + \beta E_t(\overline{V}_{t+1}) \tag{2}$$

Where: u_{0t} denotes the utility in period t and $\overline{V}_{t+1}$ is the ex-ante value function, i.e., the continuation value from behaving optimally from period $t+1$ onward, before the random taste shocks are revealed. This value function captures the expected utility of making a decision to switch or not in the next period. With a type I extreme value distribution for the random taste shocks ϵ_{ijt}, the ex-ante value function $\overline{V}_{t+1}$ has the well-known closed-form logsum expression:

$$\overline{V}_{t+1} = 0.577 + \ln \textstyle\sum_{j=0}^{J} exp(\delta_{jt+1}) \tag{3}$$

Where: 0.577 is Euler's constant (the mean of the extreme value distribution).

The random utility maximization yields the following choice probabilities or predicted market shares for each alternative $j = 0, \ldots, J$ in period t:

$$S_{jt} = s_{jt}(\delta_t) \equiv \frac{exp(\delta_{jt})}{\sum_{k=0}^{J} exp(\delta_{kt})} \tag{4}$$

Where: following Berry (1994), the predicted market share $s_{jt}(\delta_t)$ corresponds to the observed market shares S_{jt} because of the inclusion of unobserved quality ξ_{jt} for every product and period. The observed market share of smartphone j in period t is defined as $S_{jt} = q_{jt}/N_t$, where q_{jt} is the observed number of users of this smartphone and N_t is the total number of individuals in our sample in period t. Since the adoption of a smartphone is terminal action, the potential number of adopters in period t is the total number of individuals in our sample, N, less the number of individuals that adopted a smartphone in the past, i.e., $N_t = N - \sum_{\tau=1}^{t-1}\sum_{j=1}^{J} q_{j\tau}$. The aggregate market share of not adopting is $S_{0t} = 1 - \sum_{j=1}^{J} S_{jt}$.

De Groote and Verboven (2019) show how to obtain an analytic expression for the expected future value term $E_t(\bar{V}_{t+1})$, which enters the conditional value for not adopting given by (2) and is recursively defined by (3). The usual approach to compute $E_t(\bar{V}_{t+1})$ is by specifying an explicit stochastic process of the state transitions. Instead, they follow Scott (2013) and decompose $E_t(\bar{V}_{t+1})$ into the realized ex-ante value function $\bar{V}_{t+1}$ and a short-run prediction error $\eta_t \equiv \bar{V}_{t+1} - E_t(\bar{V}_{t+1})$. Assuming that individuals' expectations are on average correct, so that $\eta_t\eta_t$ is mean zero, Equation 2 can be written as:

$$\delta_{0t} = u_{0t} + \beta(\bar{V}_{t+1} - \eta_t) \tag{5}$$

The next step follows Hotz and Miller (1993) who show how to write $\bar{V}_{t+1}$ in terms of the conditional choice probabilities. When the decision problem has a terminal action as in our setup, we can take the next period CCP for an arbitrary terminating choice, e.g. $j = 1$, as given by $s_{1t+1}(\delta_{t+1}) \equiv exp(\delta_{1t+1})/\sum_{j=0}^{J} e\,xp(\delta_{jt+1})$. This expression after taking logs becomes:

$$\ln \sum_{j=0}^{J} e\,xp(\delta_{jt+1}) = \delta_{1t+1} - \ln s_{1t+1}(\delta_{t+1}) \tag{6}$$

After substituting (6) into (3), we obtain the following expression for the ex-ante value function at $t+1$:

$$\bar{V}_{t+1} = 0.577 + \delta_{1t+1} - \ln s_{1t+1}(\delta_{t+1}) \tag{7}$$

When substituting (7) into the mean utility from not adopting (5) we get:

$$\delta_{0t} = u_{0t} + \beta(0.577 + \delta_{1t+1} - \ln s_{1t+1}(\delta_{t+1}) - \eta_t) \tag{8}$$

After normalizing $u_{0t} + \beta 0.577 = 0$ and given that the CCP at the realized mean utilities is equal to the observed market share ($S_{1t+1} = s_{1t+1}(\delta_{t+1})$), we get:

$$\delta_{0t} = \beta(\delta_{1t+1} - \ln S_{1t+1} - \eta_t) \tag{9}$$

Next, the market share equation can be inverted following Berry (1994). The choice probabilities S_{jt} for each $j = 1, \ldots, J$ given by the market share expressions (4) are divided by S_{0t} and after taking logs become:

$$\ln(S_{jt}/S_{0t}) = \delta_{jt} - \delta_{0t} \tag{10}$$

We get the following main estimating equation after substituting the expressions for the mean utilities (9) and (1) into (10):

$$ln(S_{jt}/S_{0t}) = (x_{jt} - \beta x_{1t+1})\gamma + \theta(c_t - \beta c_{t+1}) - \alpha(p_{jt} - \beta p_{1t+1}) + \beta ln(S_{1t+1}) + \epsilon_{jt} \tag{11}$$

Where: the econometric error term is defined as:

$$\epsilon_{jt} \equiv \xi_{jt} - \beta(\xi_{1t+1} - \eta_t)$$

When the discount factor $\beta = 0$, the model and error term simplify to standard static logit model as in Berry (1994). We follow De Groote and Verboven (2019) and assume that $\beta = 0.99$, for which Equation 11 is a regression of the change in the number of new adopters on the change in price and possibly other characteristics. In the model above, the outside option is normalized to zero. We also estimate alternative model specifications, where the utility of outside option, $u_{0t} + \beta 0.577 \neq 0$, is determined by the most-used fea

$$ln(\frac{S_{jt}/S_{1t+1}^{\beta}}{S_{0t}}) = (x_{jt} - \beta x_{1t+1} - x_{Ft})\gamma + \theta(c_t - \beta c_{t+1}) - \alpha(p_{jt} - \beta p_{1t+1} - p_{Ft}) - \beta 0.577 + \epsilon_{jt}$$

Where: x_{Ft} and p_{Ft} denote a vector of characteristics and price of top-used feature phone in period t. In another specification, instead of top-used feature phone, we use the average characteristics and price of 50 top-used feature phones. The arbitrary terminating product choice, $j = 1$, differs between income groups and over time. For example, for the income group below poverty line, we use Vodafone Smart Kicka as the arbitrary product in the first three periods, Vodafone Kicka 3 in March 2018 and Vodafone Kicka 4 in September 2018.

A vector of characteristics of smartphone j at time t is denoted by x_{jt} and includes: (i) brand; (ii) operating system; (iii) age of the model, (iv) a dummy for not having CPU, (v) dimensions in terms of height, width and thickness, (vi) weight.[4] Furthermore, p_{1t+1} denotes the price and x_{1t+1} denotes a vector of characteristics of the arbitrary terminating choice, $j = 1$, at time $t + 1$.

Estimation results

We estimate the model using the Ordinary Least Squares (OLS) and the Generalized Method of Moments (GMM), where we instrument the handset price with two handset characteristics: a dummy variable for Graphics Processing Unit (GPU) and Random Access Memory (RAM).[5] These characteristics are responsible for the performance of smartphone and determine the cost of production. We do not include them as determinants of the utility function because consumers may be unaware of these technical features. Thus, while they are correlated with the price of smartphone as cost drivers, they should not be correlated with the error term which corresponds to the unobserved quality in our model.

Each observation represents a smartphone purchased in a given income group and period. In case the smartphone model was purchased in more than one income group and period, there are multiple observations on this model with different market shares. In our base specification, the outside option, which is the utility of feature phone, is normalized to zero in each period. In two alternative specifications, which we report in the appendix, the outside option is determined by the characteristics of: (i) top selling feature phone; (ii) the average characteristics of feature phones available on the market in a given time.

4 A smartphone CPU core is an individual processing unit found on the central processing unit (CPU) of a mobile phone. It is responsible for receiving and executing instructions that are sent from the user to the phone.

5 The main purpose of GPU is to perform graphics processing operations or do floating point calculations. In simple terms, it is a specialized circuit whose main job is to generate images for the device to display. Every smartphone has a GPU in some form to generate pictures.

First, we estimate a static demand model, where the discount factor $\beta = 0$ in Equation 11. The estimation results are shown in Table A7 (in the appendix). We pool together the data for five income groups (column All), and then estimate the model separately for two groups with the lowest income (column Poor) and three groups with the highest income (column Well-off). The estimation results for OLS are shown in columns (1)-(3) and for GMM in columns (4)-(6). Next, we estimate a dynamic demand model where the discount factor $\beta = 0.99$ in Equation 11. The estimation results for OLS and GMM are shown in Table A8 (in the appendix).

The estimation results of both static and dynamic models are comparable in terms of signs and significance of variables. The price coefficient is significant and negative in both specifications. It is greater in absolute terms for poor consumers, as compared to the group of well-off consumers. The price coefficient increases when GMM is estimated for all three regressions. This suggests that, in the OLS regression, the price coefficient is biased downwards due to endogeneity. The coverage with LTE networks increases the adoption of smartphones with comparable impact for both poor and well-off consumers in the static framework. In the dynamic framework, there seem to be bigger impact for well-off consumers. Thus, investment in LTE coverage stimulates adoption of smartphones.

The age of smartphones reflects the quality, and as expected, newer smartphones are more valued by consumers. We include four dummy variables for one, two, three, and four years passed since the release date. The estimates of these dummy variables are relative to smartphones released five or more years before. Smartphones without CPU are less valued relative to those with CPU. The dimensions of smartphones impact the utility with preference for smaller ones, where those with height of 120mm and less are valued more, width of 63mm and less are valued more, and weight of 120g and less are valued more. The smartphones produced by Apple and Blackberry are valued more than other brands. These two manufacturers rely on own operating systems, as compared to other brands which use Android, Windows and other OS. There is no difference in the valuation of these operating systems because dummy variables for Android and Windows are not significant. We also include in the estimation a set of dummy variables for top selling brands and models, which are not shown in the table due to space constraints.

Counterfactual scenarios

We use the model for the following counterfactual simulations. First, we consider that to stimulate adoption among poorest consumers, the government eliminates VAT on smartphones, which is now 15%. This corresponds to price reduction of smartphones by 1/1.15=13%, while the price of feature phones remains unchanged, and thus the utility of outside option. Second, we consider that there was full LTE coverage from the first period in our data. The investment in deployment of LTE networks is a relatively slow process starting from urban and densely populated areas. Thus, individuals living in rural areas who are generally poorer are disadvantaged with respect to access to mobile Internet. This causes a digital divide between geographic regions.

In the static model, we compute the share of smartphone adopters in each period in the sample used in the estimation, which includes only individuals without a smartphone in the first period. Next, we use this information to calculate smartphone adoption path for different income groups using full data set, which includes users of smartphones and feature phones. The adoption paths are show in Table A9(in the appendix) for price reduction, and in Table A10 (in the appendix) for LTE coverage. In the dynamic model, we follow the same procedure but the formula for the share of smartphone adopters differs, as shown in the appendix. We then also calculate smartphone adoption path for different income groups using full data set. The adoption path for price reduction is shown in Table A11 (in the appendix). The results are comparable to the static model, which suggests that consumers do not take future price and quality into account when purchasing smartphones. We are not able to estimate the effect of LTE coverage in dynamic framework when assuming full coverage over the whole period. This is because in Equation 11 coverage comes as a difference between periods t and $t+1$.

We find that there is digital divide in the population because poor people live in areas without network coverage, while the cost of smartphones does not have significant impact on adoption. In particular in the static framework, if poor and richer areas were fully covered by LTE networks in the period of our data, the adoption of smartphones would increase from 57.1% to 76.0% among people below poverty line, while it would only change from 81.5% to 82.2% in the richest group of consumers as of 1st quarter of 2018. This is precisely because richer areas have almost full LTE coverage, while poorer regions are only partially covered. At the same time, removing 15% VAT on smartphones would increase adoption only to 57.7% among people below poverty line, and to 81.7% among richest consumers as of 1st quarter of 2018. The price effect has only marginal impact on adoption in all income groups. We conclude that, to reduce digital divide, it is critical to develop LTE infrastructure in poorer areas and people will respond by adopting smartphones irrespective of their income.

Conclusions

In this paper, we construct a unique database of adopters of smartphones with different levels of income in South Africa, which is a developing economy with large income inequality. We estimate a static and dynamic model of smartphone adoption for different income groups. We use the model to assess policies which can stimulate adoption of smartphones among people living below poverty line. We find that the main driver of adoption is coverage by LTE networks, while the price of smartphones has only marginal impact. We conclude that, to reduce digital divide, it is critical to develop LTE infrastructure in poorer areas and people will respond by adopting smartphones irrespective of their income. The static and dynamic models yield comparable results, suggesting that consumers do not take future price and quality into account when purchasing smartphones.

3.0 Usage of mobile money and online financial services

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 chapter, 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. 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 on 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 of phone and differences in adoption on detailed geographic level. In this paper, we contribute to this literature by analysing how investments in mobile network coverage and proximity of banking facilities impacts the adoption of mobile phones and use of 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 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 night-time 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 OpenStreetMap (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 analyse 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 economically less developed areas, i.e., without night-time 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.

Literature review

There is a growing body of literature on the adoption and use of mobile services in low income countries. 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 and Weil (2015) analyse 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 and 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 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 and Matsumoto (2016) use data on 846 rural households to analyse 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 and 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 and Singh (2013) use data on 37,000 individuals from 35 countries to analyse 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 analyse 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 and 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 and Jeziorski (2017) 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, 2018) or to small-scale entrepreneurs (Aggarwal et al., 2020). Batista and 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 and 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 analyse 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 and 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 and 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 analysed by Dinkelman (2011) for South Africa. She shows that electrification increases female employment. Similar effects are found by Grogan and 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 example, Duflo and 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 analyse how availability of infrastructure influences adoption of mobile phones and use of mobile money services is scarce. Mothobi and Grzybowski (2017) combine a micro-level survey data conducted in 2011 for 11 African countries with night-time 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 phones for financial transactions. They conclude that mobile phones improve the livelihood of individuals residing in remote areas.

Our analysis 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 night-time 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.

Mobile money in sub-Saharan Africa

Mobile banking is a financial service, 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, and 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. In 2019, the number of active mobile money accounts increased to 54.8 million and the agent network grew to about 222,000.[6] 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.

The regulatory approach in other East African countries was similar to Kenya. In Tanzania for example, 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.[7] Inter-operability between mobile money services is also the main regulatory focus in other African countries.

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

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

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

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 that this year.

A number of banks in Africa rolled out a similar service called e-wallet. The difference to M-PESA is 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. 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.

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. 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 is Night-time 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. In the earlier economic literature, initiated by Henderson et al. (2011), the Defense Meteorological Satellite Programme (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 Night-time Lights data have been widely exploited by the scientific community. However, the Night-time Lights 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 (≈ 465m × 465m at the equator, or ≈ 465m × 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 this 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 in- habitants. 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.

Statistics

Table 1 shows penetration of mobile phones, usage of banking services and Night-time Lights 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. 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 example, 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 which 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 lit at night. There is substantial variation in economic development approximated by night-time lights 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.

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

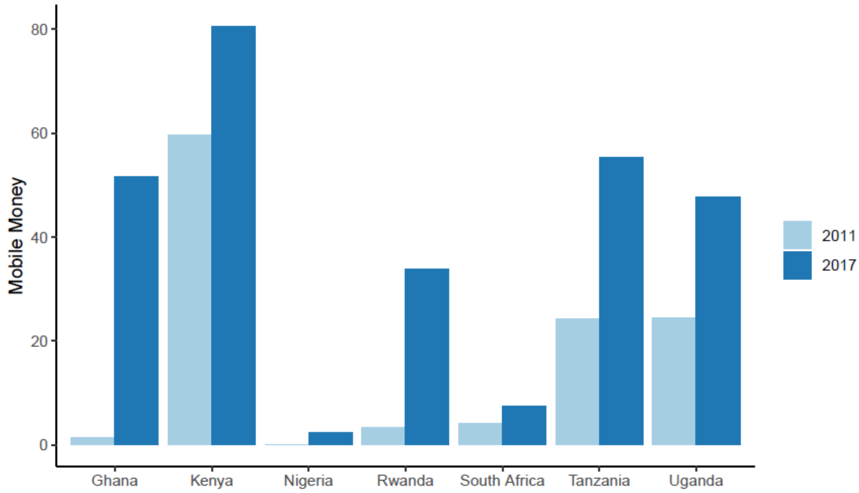
Table 1: Adoption of mobile phones, smartphones, mobile money and bank accounts

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

Figure 2 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.

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.

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 laptop/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 night-time lights 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 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 example, 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.

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

Variable	No Phone	Phone Types Basic Phone	Smartphone	Dark No	Yes	Mobile Money 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

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	54.1	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	163.1	25.21	101.1	10.90	106.92	69.69	112.8

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. 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.

Table 4: Distribution of mobile phone type across technologies

	GSM (%)		UMTS (%)		LTE (%)	
Country	Phone Basic Smartphone		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

Table 5: 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

Econometric 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 and McFadden (1984), Dahl (2002), and more recently Bourguignon et al. (2007). We follow the approach by Dubin and 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.

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 $i = 1, \ldots, N$ from country $c = 1, \ldots, 9$ 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:

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.

$$U_{icj} = Z_{ic}\beta_j + \xi_j D_c + \epsilon_{icj} = V_{icj} + \epsilon_{icj}$$
$$y_{icj} = X_{ic}\gamma_j + u_{icj}$$

Where: the outcome variable y_{icj} is observed if and only if category $j \in \{f,s\}$ is chosen. The first equation (utility) 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 (usage) 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, 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 r receive funds via r bile money. For notational simplicity, we skip the subscript ii for individuals and cc 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:

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

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 (usage) 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 model, the correction bias can be based on the conditional mean of u_s:

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

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:

$$E(u_s|\varepsilon_s, \Gamma) = \mu(P_f, P_s, P_o)$$

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

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

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 and McFadden (1984), in which the following linearity assumption

$$E(u_s|\epsilon_f, \epsilon_s, \epsilon_o) = \sigma_u \sum_{j \in J} r_j (\epsilon_j - E(\epsilon_j))$$ erm’ ϵ_j:

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

$$E(\epsilon_j - \epsilon_s|U_s > \max_{k \neq s} U_k, \Gamma) = \frac{P_j ln(P_j)}{1 - P_j} + ln(P_s)$$ r alternatives $j \neq sj \neq s$:

Given the assumption (cond5), the bias-corrected mobile money usage equation (usage) for smartphone category s can be written as:

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

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.

Estimation results

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 analyse the factors which can contribute to a greater adoption of 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 C.4). 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 the counterfactual simulations, we consider that the whole population lives within 2km from towers of 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 5. The smallest impact is estimated for South Africa, which had better network coverage and a higher 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 will decline 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

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

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 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.

Table 6: 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

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 C.6 and C.7. Overall we find that individuals who live in areas which are reported as 'dark', i.e., without any night-time 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 C.8 and Table C.9 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 the 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 economically less developed 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 C.10 and C.11.

A number of individual characteristics becomes signi_cant, as compared to the results shown in Tables C.6 and C.7. Finally, we do not _nd 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 C.12 and C.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 difference in mobile money usage.

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 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 Table C.14. 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 wallet, as shown in Table C.15. 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 C.16 and C.17). 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 are 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.

Finally, in the regressions for saving money via mobile wallet are shown in Tables C.18 and C.19. People who live in areas which are less developed economically save less money in this way. Interestingly, people with higher income (relative to base category) save less on mobile wallet, which suggests that they have alternative means of saving or investing money. People in younger age groups save more money compared to the oldest age category. People without education save less, which was also the case with respect to sending and receiving money. Self-employed people and students save more on mobile wallet as well as people who have access to laptop or PC. Finally, people who live within 10km from an ATM or 25km from a bank branch tend to save more money on mobile wallet, and similarly people who live within 10km from town. Thus, people who live in rural areas with poor access to infrastructure tend to have fewer saving on mobile wallet, which again emphasizes the role of mobile money transfers between geographic areas for supporting daily expenses and reducing income differences.

Conclusion

In this study, we analyse 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 night-time 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 night-time 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.

4.0 Mobile phones and labour market in South Africa

The deployment and adoption of mobile phones and Internet services have broad implications for the economies of developing countries. This includes improved market efficiency (see Jensen, 2007; Aker & Mbiti, 2010), increased employment (Hjort & Poulsen, 2019), and reduced household poverty levels (see Bahia et al., 2020, 2021). In this study, we provide further evidence on the impact of mobile phones on employment in the case of South Africa, where unemployment rates have been persistently high and even increased in the last decade from 22.4% in 2008 to 29.2% in 2020.[12]

One of the key problems of the labour market in South Africa is the spatial distribution of supply and demand for labour. Due to spatial laws developed during Apartheid, many people live in rural areas which are far away from towns and cities where jobs are located (Bhorat, 2012). Moreover, search costs and limited access to information make it difficult for people living in rural areas to find jobs. As suggested by Festus et al. (2016), based on Quarterly Labour Force Survey conducted in South Africa in 2015, seeking assistance from family or friends and enquiring at workplaces were the most popular channels for unemployed individuals to search for work. Mobile phones and Internet access can help people to find jobs by improving access to information and reducing search costs. They can search for jobs online and call potential employers instead of personal inquiries, and be called back when opportunities arise.

In this chapter, we study whether change in employment status over time can be attributed to some extent to ownership of mobile phones. We use five waves of panel data from the National Income Dynamic Survey (NIDS), which was conducted in South Africa from 2008 to 2017. In the estimation, we control for a set of individual characteristics such as race, age, gender, physical health, educational attainment, place of living, among others. The panel data structure allows us to account for unobserved heterogeneity amongst individuals. During the period covered by our data, Internet usage among South Africans increased from 8.4% in 2008 to 68.2% of the population in 2019.[13] Mobile devices are the most popular means of accessing the Internet with 64.1% of South African households using mobile broadband, as

12 World Bank, 2021. World Development Indicators.

13 Source: ibidem

compared to 8.3% that access the Internet using fixed broadband at home.[14][15] Our estimation results suggest that mobile phone ownership has a positive impact on the change in employment status from unemployed to being employed. On the other hand, ownership of a computer by a household and computer literacy do not have a significant impact on the change in employment status. We also find that having a mobile phone and ownership of a computer by a household reduce the likelihood of becoming unemployed.

This chapter is organized as follows. In the next section, we provide an overview of the relevant literature. The third describes our data. The fourth section discusses the econometric methodology, followed by the fifth section which discusses estimation results. Finally, the sixth section concludes.

Literature review

There is a growing body of research on the economic impact of mobile phones and Internet access on the wellbeing of people in developing countries.[16] One of the channels is through the functioning of the labour markets. In general, the Internet made labour markets more efficient as information about job openings can now reach a much broader audience while reducing search costs (Autor, 2001). But at the same time, empirical evidence suggests that access to the Internet and digitization benefits educated and skilled workers more than those who are unskilled (Atasoy, 2013).

In an earlier paper, Kuhn and Skuterud (2004) use the Current Population Survey data in the U.S. coupled with data on Internet job search to investigate its impact on unemployment duration. Surprisingly, they do not find that using the Internet to search for work results in shorter unemployment periods as compared to non-Internet users. In their estimation, they account for observable characteristics of the unemployed and postulate that this result could be due to Internet job searchers being negatively selected on unobservable characteristics. This result is similar to Kroft and Pope (2014) who find that the expansion of Craigslist, a U.S. website that provides a platform for people to advertise jobs and apartment rentals among other things, did not have any effect on employment. These results are also confirmed by

14 General Household Survey 2020. Statistics South Africa.

15 Using mobile devices to access the Internet includes access on mobile phones and on other devices via 3G or 4G SIM cards.

16 In an earlier paper, 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 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 and Mbiti (2010) study how the introduction of mobile phone between 2001 and 2006 affected grain prices in Niger. In another paper for Tanzania, Sife et al. (2010) find that mobile phones can aid with poverty reduction and help improve the way rural traders do business. These papers emphasize the importance of rolling out mobile network infrastructure for improving economic efficiency of markets.

Kuhn and Mansour (2014) when using the same data set as Kuhn and Skuterud (2004). But when they use the National Longitudinal Survey of Youth (NLSY97), which was conducted in 2008–2009, they find that using the Internet for job search decreased unemployment duration by 25%. One of the reasons given for these contradictory findings is that the two surveys were conducted almost a decade apart allowing for job search sites and Internet penetration to improve.

In another paper, Atasoy (2013) uses U.S. county level panel data that spans from 1999 to 2007 and finds that increased broadband penetration led to a 1.8 percentage point increase in employment. He also suggests that broadband adoption complements skilled labour as counties with a greater proportion of college educated individuals had higher employment rates. In addition, broadband access increases employment in industries that have a greater share of college educated individuals but had the opposite effect in some lower skilled industries. On the other hand, Ivus and Boland (2015) studied the deployment of fixed broadband in Canada over the period 1997–2011 and find that broadband deployment promotes employment in rural areas and not in urban areas. The results are more pronounced in information technology (IT) intensive industries. These results are contrary to the findings of Kandilov and Renkow (2010), who analysed the United States Department of Agriculture's (USDA) Pilot Broadband Loan Programme and Broadband Loan Programme and found that neither one promoted employment in rural areas, even though the programmes were created to develop telecommunications in rural America. Furthermore, Czernich (2014) finds that broadband availability among German households does not lead to a reduction in unemployment. Given this counterintuitive result, the author notes that broadband Internet can impact the labour market in ways which are not analysed by the author, such as improving the efficiency of job searches for currently employed individuals or increase employment for those who are unemployed but not registered as such. In another paper, Dettling (2017) uses data from U.S. census current population survey from 2000 to 2009 and finds that married women with access to high speed Internet are more likely to join the labour force relative to men and single women. In particular, the impact is greater for married women who are college educated, which provides further evidence that broadband benefits skilled labour. Akerman et al. (2015) use rich Norwegian firm-level data and estimate production functions, where firms can change their technology by adopting broadband Internet. They conclude that, broadband Internet complements skilled workers in executing non-routine abstract tasks, and substitutes for unskilled workers in performing routine tasks. Finally, by exploiting the gradual arrival of submarine Internet cables on the coast in Africa, Hjort and Poulsen (2019) show that Internet coverage increases employment. Similarly to developed countries, there is also a bias towards higher-skilled occupations.

The labour market papers discussed above focus on the deployment of fixed broadband in developed economies, with the exception of Hjort and Poulsen (2019). There are, however, fewer studies which focus on the impact of mobile coverage on labour markets in developing countries, in which there is small or no fixed broadband coverage at all. One exception is an earlier unpublished paper by Klonner and Nolen

(2010), who find that the rollout of mobile networks in rural areas in South Africa has a positive impact on employment. In localities which moved from no coverage to full coverage, employment increased by 15 percentage points, with a greater impact on women employment. In another recent paper by Bahia et al. (2020) for Nigeria, the authors combine survey and coverage data in years the 2010–2016 which showed that greater mobile broadband coverage increases household consumption and reduces poverty. They attribute these results to increased labour force participation and wage-based employment.

This chapter contributes to the literature by studying the impact of having a mobile phone on the change in employment status. We use a unique panel data of South African individuals which consists of five waves and covers the period between 2008 and 2017. In each period, we observe whether people are employed or unemployed and thus whether they changed their employment status. These employment dynamics could not be analysed in previous studies due to unavailability of panel data.

Data

Our analysis is based on the National Income Dynamics Survey (NIDS), which is the first nationwide panel survey data in South Africa collected by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town (UCT). This survey was conducted in five waves in the years: 2008, 2010–2011, 2012, 2014–2015, and 2017. The data includes information on a representative sample of households and their members living across the country.[17]

The survey combines household-level interviews (administered to the oldest woman in the household) with questionnaires addressed to individual household members. There are separate questionnaires for adults (aged 15 or older) and children (directed to the mother or the care-giver). In this analysis, we only consider questionnaires from adult household members and from proxies. A proxy is a knowledgeable household member who is interviewed when it is not possible to interview the relevant individual (aged 15+) in person.

The first wave of the survey completed in December 2008 includes successful interviews of 7,296 households and 17,381 adults. The second wave was completed approximately two years later between May 2010 and September 2011 including 6,781 households and 18,725 adults. The third wave was completed in 2012 including 8,031 households with 21,399 adults. The fourth wave ran from October 2014 to August 2015, with 9,615 households and 24,334 adults successfully interviewed. In 2017, NIDS conducted its fifth wave of interviews totalling 10,842 households and 25,813 adults. Table 7 shows the number of successful households and adults interviewed in all the five waves.

17 For a description of the sampling method, see fieldwork manual which is available at http://www.nids.uct.ac.za from where the data was downloaded.

Table 7: Number of successfully interviewed households and adults across all five waves

	Households	Adults
Wave 1	7,296	17,381
Wave 2	6,781	18,725
Wave 3	8,031	21,399
Wave 4	9,615	24,334
Wave 5	10,842	25,813

Each questionnaire consists of several modules with questions related to household expenditure and consumption, demographics, education, personal asset ownership and debt, various income sources, and intra-household decision-making, among others.

Employment status: Our main variable of interest is employment status, y_{it}, which in the data takes four values: (i) not economically active; (ii) discouraged unemployment; (iii) strict unemployment; and (iv) employed. We exclude individuals who are not economically active since they do not actively seek for work. Unemployed individuals, $y_{it} = 0$, belong to two categories: (ii) discouraged unemployed and (iii) strict unemployed. Employed individuals, $y_{it} = 1$, belong to the last category.

We create two dependent variables for change in employment status. Our first variable is a change from unemployed to being employed between two consecutive waves, Y_{it}, which takes on the value zero when individuals who were unemployed in wave t remained unemployed in wave t+1 (y_{it} =0 and y_{it+1} =0), and value one when they change status to employed (y_{it} =0 and y_{it+1} =1). We only keep observations on individuals who are unemployed in period t. Thus, our data has repeated information on individuals who remain unemployed in two or more consecutive waves. When they change status to employed, then they are dropped from the data in the next wave, independently of whether they subsequently keep or lose employment. Our second dependent variable takes on the value zero when individuals who were employed in wave t remained employed in wave t+1 (y_{it} =1 and y_{it+1} =1), and value one when they change status to unemployed (y_{it} =1 and y_{it+1} =0). In this case, we only keep observations on individuals who are employed in period t and when they change status to unemployed then they are dropped from the data in the next wave. Table 8 shows the number of people changing employment status by wave.

Table 8: Number people changing employment status by wave

	Remain unempl.	Become empl.	Total	Remain empl.	Become unempl.	Total
Wave 2	681	651	1,332	2,878	525	3,403
Wave 3	673	703	1,376	2,919	489	3,408
Wave 4	803	1,154	1,957	4,299	518	4,817
Wave 5	694	946	1,640	5,221	675	5,896
Total	2,851	3,454	6,305	15,317	2,207	17,524

Mobile phones: Our main explanatory variable is ownership of a mobile phone by an individual which is a binary variable. Mobile phone adoption increased over the period covered by the NIDS data. The overall penetration changed from 57.0% in the first wave to 59.8% in the second wave, 77.4% in the third wave, 76.2% in the fourth wave, and 79.8% in the fifth wave. Unfortunately, we are not able to analyse how Internet connectivity impacts change in employment status because questions about Internet access were not asked in the survey. We also do not know whether mobile phones are smartphones, which could be used to approximate Internet access. But as suggested by the statistics on the growth of Internet users in South Africa, which increased from 8.4% in 2008 to 68.2% of the population in 2019, the majority of mobile phone users have access to the Internet. We account for the increase in the number of smartphone owners and Internet users by interacting the mobile phone variable with a set of wave dummy variables.

Other variables: In the estimation, we include a set of individual characteristics which may determine employment such as: gender, race, age, educational attainment, physical health, place of living, among others. We drop from the sample individuals who are outside the working age, younger than 15 years and older than 65 years. Table 9 shows the summary statistics of the variables used in our estimation, split by change in employment status defined above. The data shows that, there are more individuals with a mobile phone who changed their employment status than those who have not. There are also significant differences between both groups with respect to gender, race, geographical location, and physical health. Figure 2 shows how the change in employment status varies between those with mobile phones and those without mobile phones. A greater proportion of adults that own a mobile phone have shifted from being unemployed to being employed across the different waves, relative to adults that do not own a mobile phone. The difference between the two groups is more pronounced in waves 2 and 4. Furthermore, Table 10 shows that a greater share of individual who lost employment do not own a mobile phone, which can be also seen on Figure 3.

Table 9: Summary statistics of adults who remained unemployed and those who became employed

Variables	Remain Unemp		Become employ	
	Mean	Std	Mean	Std
Mobile Phone	0.714	0.452	0.753	0.431
Female	0.646	0.478	0.538	0.499
Age	29.3	9.1	30.9	9.7
Race African	0.890	0.313	0.853	0.354
White	0.004	0.060	0.007	0.083
Coloured	0.100	0.300	0.134	0.340
Asian/Indian	0.006	0.080	0.006	0.079
Education <Primary	0.111	0.314	0.112	0.316
Primary	0.619	0.486	0.547	0.498
Secondary	0.205	0.403	0.226	0.418
Tertiary	0.065	0.247	0.115	0.319
Health Poor-fair	0.077	0.267	0.064	0.244
Good-Very Good	0.547	0.498	0.545	0.498
Excellent	0.376	0.484	0.391	0.488
Household Computer	0.065	0.247	0.094	0.292
Computer Literate	0.288	0.453	0.351	0.477
Geographic Location Urban	0.457	0.498	0.534	0.499
Non-Urban	0.543	0.498	0.466	0.499
Province Western Cape	0.060	0.237	0.103	0.304
Eastern Cape	0.137	0.344	0.111	0.314
Northern Cape	0.081	0.273	0.084	0.278
Free State	0.063	0.243	0.073	0.260
KwaZulu Natal	0.290	0.454	0.246	0.431
North West	0.087	0.282	0.067	0.251
Gauteng	0.109	0.312	0.135	0.342
Mpumalanga	0.081	0.273	0.085	0.279
Limpopo	0.092	0.289	0.095	0.293
Observations		2 474		3 013

Figure 2: Proportion of adults who became employed over time by mobile phone ownership

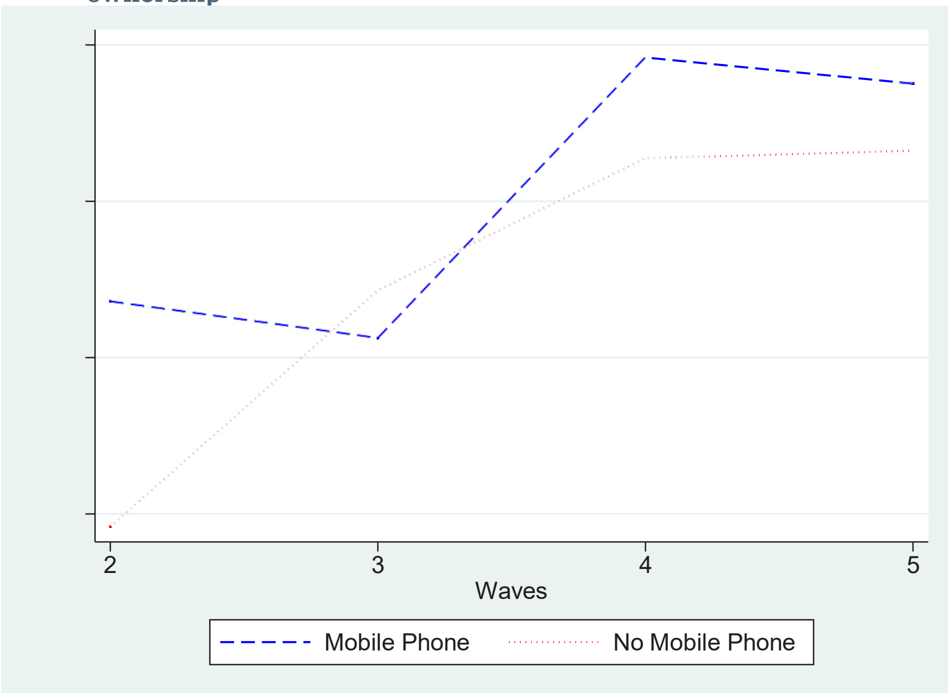
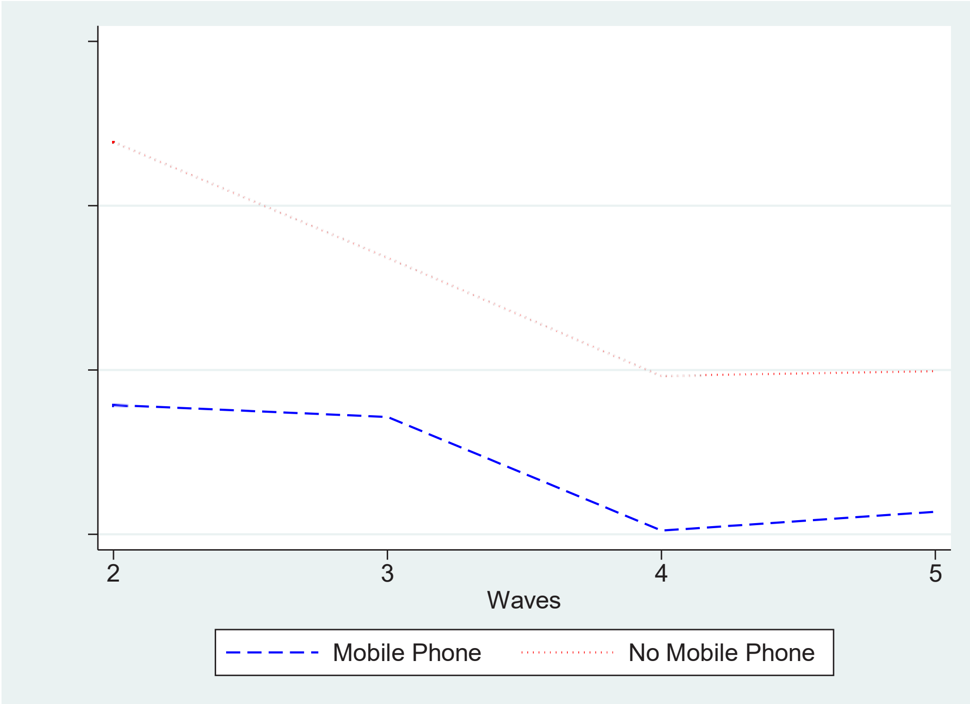


Table 10: Summary statistics of adults who remained employed and those who became unemployed

Variables	Become empl		Become unempl	
	Mean	Std	Mean	Std
Mobile Phone	0.851	0.356	0.777	0.416
Female	0.482	0.500	0.528	0.499
Age	37.6	10.7	32.7	10.2
Race African	0.746	0.435	0.819	0.385
White	0.045	0.207	0.008	0.092
Coloured	0.195	0.397	0.164	0.371
Asian/Indian	0.014	0.117	0.008	0.089
Education <Primary	0.144	0.352	0.134	0.341
Primary	0.446	0.497	0.577	0.494
Secondary	0.191	0.393	0.191	0.393
Tertiary	0.219	0.413	0.098	0.298
Health Poor-fair	0.080	0.271	0.096	0.294
Good-Very Good	0.571	0.495	0.539	0.499
Excellent	0.349	0.477	0.365	0.482
Household Computer	0.205	0.404	0.096	0.294
Computer Literate	0.438	0.496	0.333	0.471
Geographic Location Urban	0.649	0.477	0.562	0.496
Non-Urban	0.351	0.477	0.438	0.496
Province Western Cape	0.175	0.380	0.134	0.341
Eastern Cape	0.085	0.279	0.112	0.315
Northern Cape	0.082	0.275	0.081	0.273
Free State	0.070	0.256	0.066	0.248
KwaZulu Natal	0.208	0.406	0.260	0.439
North West	0.060	0.238	0.060	0.237
Gauteng	0.169	0.374	0.125	0.331
Mpumalanga	0.083	0.276	0.087	0.282
Limpopo	0.067	0.250	0.075	0.263
Observations		13 855		2 003

Figure 3: Proportion of adults who became unemployed over time by mobile phone ownership



Econometric model

We estimate a probit model with a binary dependent variable where the probability of a change in employment status, Y_{it}, is explained by a vector of individual and household characteristics. In another specification, we also allow for unobservable het ogeneity by means of individual random effects. The probability that an individual ii takes up employment in wave $t = 1, \ldots, T_i$ can be written as:

$$Pr(Y_{it} = 1|X_{it}, \xi_i) = \Phi(X_{it}\beta + \xi_i)$$

Where: X_{it} denotes a vector of individual and household characteristics, ξ_i are unobserved individual-specific effects assumed to be normally distributed and $\Phi(.)$ is the standard normal cumulated distribution function of the error term ε_{it}. Note that the panel data is unbalanced because we lose some individuals over time and new ones join the sample. Also, when individuals become employed they are dropped from the sample.

The probability of a particular pattern of employment status for an individual i over the whole period when she/he is present in our data can be written as:

$$l_i(\beta|X_{it},\xi_i) = \prod_{t=1}^{T_i} \Phi\,(X_{it}\beta + \xi_i)^{Y_{it}}\,(1 - \Phi(X_{it}\beta + \xi_i))^{1-Y_{it}}$$

In a model with unobserved heterogeneity, ξ_i, it is necessary to integrate the conditional probability $l_i(\beta|X_{it},\xi_i)$ over the normal distribution of $\xi_i \sim N(\mu_\xi,\sigma_\xi)$

$$P_i = \int_\xi l_i(\beta,\xi_i) f(\xi) d\xi,$$

Assuming that the decisions of individuals $i = 1,\ldots,N$ are independent, the probability that each individual in the sample has the sequence of changes in employment status as observed can be written as the log-likelihood function:

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

The vector of all parameters which are estimated is denoted by θ and includes the parameters of the distribution of random effects $\xi_i \sim N(\mu_\xi,\sigma_\xi)$. The maximum likelihood estimator is the value of the parameter vector θ that maximizes the likelihood function $\mathcal{L}$ given by equation ([loglik]).

There is a potential issue of endogeneity for mobile phone possession. Individuals who own a mobile phone may be more likely to get employed, but those who are employed and have income are more likely to own a mobile phone. This should not be a problem in our regression for becoming employed because we study only individuals who are not employed in period t and whether they become employed in period $t + 1$. But there may still be unobserved factors which determine both having a mobile phone and the likelihood to change employment status in the future, such as being more entrepreneurial. This potential problem should be mitigated to some extent by estimating a model with individual random effects. In the second regression, in period t, everyone is employed and has income for which a mobile phone can be purchased. There may be again unobserved individual characteristics correlated with having a mobile phone and keeping employment, which should be mitigated to some extend by the inclusion of individual random effects. Similar issues concern the ownership of a computer by the household and computer literacy.

Estimation results

First, we estimate a simple probit model to show how a change in employment status depends on consumer and household characteristics. Second, we estimate a probit model with individual random effects, which accounts for unobserved heterogeneity. Each of these models is estimated in three specifications. The first one includes a binary variable for the possession of a mobile phone. The second specification in addition includes binary variables for the possession of a computer by the household and for individual computer literacy. The third specification includes interaction terms between mobile phone ownership and survey wave dummy variables to approximate the growing adoption of smartphones and Internet usage. The estimation results for becoming employed are shown in Table 11, where models 1 to 3 are probit models while models 4 to 6 are probit models with random effects. The models build progressively on one another with Model 2 being the same as Model 1 but with the addition of the home computer and computer literacy variables. Model 3 builds on Model 2 with the addition of the mobile phone and wave interaction terms. The same progression applies to Model 5 and Model 6 which build on Model 4. The models for becoming unemployed in Table 12 are constructed in the same manner as in Table 11. Now, the dependent variable takes on a value of one when an individual who was employed in period t becomes unemployed in period t+1. Based on the log-likelihood values, the preferred specifications are models with individual random effects. Our findings are as follows.

In all model specifications, we find that having a mobile phone has a positive impact on employment status. This is in line with the statistics in Figure 2, which shows that a greater proportion of people who have a mobile phone in wave t find employment in wave t+1, relative to those who do not own a mobile phone. On the other hand, having a computer in the household and computer literacy are both statistically insignificant. Even though relatively more people who change employment have a computer in the household and are computer-literate, as shown in Table 9. Individual characteristics have a significant impact on the change in employment status. Females are less likely to become employed relative to men. Older individuals have a greater chance of becoming employed as compared to individuals who are less than 25 years old. This makes intuitive sense, as older individuals tend to have more work experience and are therefore more marketable in the labour market.

There are no differences between race groups in the probability of becoming employed. Both secondary and tertiary educated individuals are more likely to become employed relative to those with less than a primary education. Individuals with excellent health conditions are more likely to become employed as well as people living in urban areas. Over time, chances to become employed increase and are greater in waves 4 and 5 than in waves 3 and 2. There are significant differences in the probabilities of becoming employed for people living in different geographic regions across the country, with individuals in the Western Cape having the highest chances of becoming employed, compared to other provinces.

The interaction terms between mobile phone possession and the wave dummy variables are significant and negative for wave 3 but insignificant for waves 4 and 5, which suggest that the impact of having a mobile phone on change in employment status increases over time. We interpret this result as an increase in the adoption of smartphones and Internet usage.

Table 11: Estimation results of owning a mobile phone and becoming employed

	Probit Model			Probit Model with Random Effects		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Mobile phone	0.070*	0.077*	0.164**	0.070	0.078*	0.164*
	(0.041)	(0.042)	(0.077)	(0.046)	(0.046)	(0.085)
Home computer		0.062	0.061		0.072	0.071
		(0.069)	(0.069)		(0.077)	(0.077)
Computer literate		0.019	0.023		0.024	0.028
		(0.044)	(0.044)		(0.049)	(0.049)
Female	-0.330***	-0.328***	-0.330***	-0.364***	-0.363***	-0.366***
	(0.036)	(0.036)	(0.036)	(0.042)	(0.042)	(0.042)
Urban	0.087**	0.086*	0.085*	0.097*	0.096*	0.095*
Age categories	(0.044)	(0.045)	(0.045)	(0.050)	(0.051)	(0.051)
25-35	0.149***	0.147***	0.148***	0.180***	0.181***	0.182***
	(0.041)	(0.041)	(0.041)	(0.046)	(0.047)	(0.047)
35-50	0.320***	0.326***	0.328***	0.380***	0.390***	0.392***
	(0.048)	(0.049)	(0.049)	(0.056)	(0.058)	(0.058)
50-65	0.415***	0.406***	0.411***	0.476***	0.468***	0.474***
Race	(0.093)	(0.097)	(0.097)	(0.106)	(0.110)	(0.111)
African	-0.171	-0.132	-0.134	-0.232	-0.190	-0.193
	(0.244)	(0.247)	(0.247)	(0.280)	(0.285)	(0.286)
Coloured	-0.074	-0.035	-0.040	-0.122	-0.079	-0.085
	(0.248)	(0.251)	(0.251)	(0.284)	(0.290)	(0.290)
Asian/Indian	-0.208	-0.194	-0.184	-0.234	-0.220	-0.207
	(0.326)	(0.327)	(0.327)	(0.373)	(0.377)	(0.378)
Education						
Primary	-0.044	-0.037	-0.041	-0.052	-0.044	-0.049
	(0.058)	(0.060)	(0.060)	(0.066)	(0.068)	(0.068)
Secondary	0.147**	0.143**	0.140**	0.161**	0.158**	0.154*
	(0.067)	(0.070)	(0.070)	(0.076)	(0.080)	(0.080)
Tertiary	0.397***	0.381***	0.375***	0.440***	0.423***	0.417***
Health	(0.081)	(0.088)	(0.088)	(0.093)	(0.100)	(0.100)
Good-Very Good	0.109	0.106	0.105	0.115	0.111	0.110
	(0.070)	(0.071)	(0.071)	(0.078)	(0.079)	(0.079)
Excellent	0.149**	0.146**	0.146**	0.161**	0.157*	0.157*
	(0.073)	(0.074)	(0.074)	(0.080)	(0.082)	(0.082)
Wave 3	0.011	0.002	0.131	0.052	0.044	0.186*
	(0.052)	(0.053)	(0.087)	(0.057)	(0.059)	(0.097)
Wave 4	0.207***	0.201***	0.231**	0.264***	0.257***	0.273**
	(0.050)	(0.050)	(0.100)	(0.057)	(0.057)	(0.111)
Wave 5	0.183***	0.175***	0.226**	0.255***	0.249***	0.294***
	(0.050)	(0.051)	(0.094)	(0.059)	(0.060)	(0.105)
Mobile phone x Waves 3			-0.203*			-0.222*
			(0.109)			(0.121)
Mobile phone x Waves 4			-0.058			-0.042
			(0.115)			(0.128)
Mobile phone x Waves 5			-0.083			-0.075
			(0.111)			(0.123)
Provinces	yes	yes	yes	yes	yes	yes
Constant	0.266	0.215	0.170	0.333	0.278	0.236
	(0.265)	(0.268)	(0.271)	(0.303)	(0.308)	(0.312)

lnsig2u				-1.498	-1.432	-1.426
				(0.286)	(0.278)	(0.278)
σu				0.473	0.489	0.490
				(0.068)	(0.068)	(0.068)
ρ				0.183	0.193	0.194
				(0.043)	(0.043)	(0.043)
Observations	5,549	5,487	5,487	5,549	5,487	5,487
Log likelihood	-3670	-3626	-3625	-3660	-3616	-3614

Notes: The dependent variable is a binary variable which takes a value of one when an individual moves from being unemployed to being employed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), and provinces. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Estimation results of owning a mobile phone and becoming unemployed

	Probit Model			Probit Model with Random Effects		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Mobile phone	-0.196***	-0.185***	-0.229***	-0.239***	-0.226***	-0.265***
	(0.035)	(0.035)	(0.064)	(0.046)	(0.046)	(0.083)
Home computer		-0.160***	-0.161***		-0.198***	-0.199***
		(0.044)	(0.044)		(0.058)	(0.058)
Computer literate		-0.055	-0.055		-0.072	-0.072
		(0.034)	(0.034)		(0.045)	(0.045)
Female	0.181***	0.181***	0.181***	0.252***	0.252***	0.252***
	(0.027)	(0.027)	(0.027)	(0.039)	(0.039)	(0.039)
Urban	-0.068**	-0.060*	-0.059*	-0.108**	-0.097**	-0.096**
	(0.032)	(0.032)	(0.032)	(0.045)	(0.046)	(0.046)
Age categories						
25-35	-0.296***	-0.300***	-0.299***	-0.360***	-0.364***	-0.364***
	(0.036)	(0.036)	(0.036)	(0.048)	(0.048)	(0.048)
35-50	-0.629***	-0.634***	-0.634***	-0.788***	-0.795***	-0.795***
	(0.037)	(0.038)	(0.038)	(0.054)	(0.055)	(0.055)
50-65	-0.822***	-0.844***	-0.844***	-1.057***	-1.084***	-1.084***
	(0.054)	(0.056)	(0.056)	(0.078)	(0.080)	(0.080)
Race						
African	0.533***	0.431***	0.429***	0.743***	0.612***	0.610***
	(0.113)	(0.116)	(0.116)	(0.157)	(0.159)	(0.159)
Coloured	0.355***	0.273**	0.270**	0.508***	0.403**	0.401**
	(0.116)	(0.118)	(0.118)	(0.160)	(0.162)	(0.162)
Asian/Indian	0.271	0.245	0.243	0.386	0.356	0.354
	(0.175)	(0.175)	(0.175)	(0.242)	(0.242)	(0.242)
Education						
Primary	0.074*	0.086**	0.087**	0.097*	0.119**	0.120**
	(0.041)	(0.043)	(0.043)	(0.059)	(0.060)	(0.060)
Secondary	-0.130***	-0.091*	-0.089*	-0.195***	-0.136*	-0.134*
	(0.050)	(0.053)	(0.053)	(0.071)	(0.074)	(0.074)
Tertiary	-0.423***	-0.343***	-0.341***	-0.574***	-0.465***	-0.464***
	(0.054)	(0.060)	(0.060)	(0.077)	(0.084)	(0.084)
Health						
Good-Very Good	-0.191***	-0.198***	-0.197***	-0.227***	-0.238***	-0.237***

	(0.049)	(0.049)	(0.049)	(0.063)	(0.064)	(0.064)
Excellent	-0.158***	-0.163***	-0.162***	-0.181***	-0.190***	-0.189***
	(0.051)	(0.052)	(0.052)	(0.067)	(0.067)	(0.067)
Wave 3	-0.035	-0.026	-0.097	0.017	0.023	-0.042
	(0.041)	(0.042)	(0.086)	(0.051)	(0.052)	(0.109)
Wave 4	-0.222***	-0.212***	-0.235***	-0.233***	-0.225***	-0.249**
	(0.040)	(0.040)	(0.090)	(0.050)	(0.050)	(0.115)
Wave 5	-0.198***	-0.179***	-0.219***	-0.221***	-0.197***	-0.233**
	(0.037)	(0.038)	(0.077)	(0.047)	(0.048)	(0.099)
Mobile phone x Waves 3			0.093			0.085
			(0.098)			(0.124)
Mobile phone x Waves 4			0.034			0.034
			(0.100)			(0.128)
		Probit Model		Probit Model with Random Effects		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Mobile phone x Waves 5			0.054			0.048
			(0.088)			(0.113)
Provinces	yes	yes	yes	yes	yes	yes
Constant	-0.813***	-0.717***	-0.686***	-1.121***	-0.999***	-0.970***
	(0.137)	(0.139)	(0.144)	(0.191)	(0.193)	(0.199)
lnsig2u				-0.298	-0.312	-0.314
				(0.138)	(0.141)	(0.142)
σu				0.862	0.856	0.854
				(0.060)	(0.060)	(0.060)
ρ				0.426	0.423	0.422
				(0.034)	(0.035)	(0.035)
Observations	16,105	15,858	15,858	16,105	15,858	15,858
Log likelihood	-5671	-5570	-5570	-5612	-5514	-5514

Notes: The dependent variable is a binary variable which takes a value of one when an individual moves from being employed to being unemployed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), and provinces. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In the regressions in Table 12, we find that owning a mobile phone and having a home computer decreases the probability of becoming unemployed. This corroborates the pattern in Figure 3, which shows that a larger proportion of individuals who own a mobile phone remain employed over time relative to those who do not own a mobile phone. Furthermore, living in an urban area, being older, having a tertiary or secondary education and being in good health are all contributing factors in decreasing the probability of losing one's job. In terms of gender and race, the results show that women are more likely to become unemployed relative to men, while African and Coloured adults are more likely to become unemployed relative to White adults.

Conclusions

In this chapter, we study whether the change in employment status over time can be attributed to mobile phone ownership. We use five waves of panel data from the National Income Dynamic Survey (NIDS), which was conducted in South Africa from 2008 to 2017. During the period covered by our data, Internet usage among South Africans increased from 8.4% in 2008 to 68.2% of the population in 2019, which is driven by the adoption of smartphones and use of mobile broadband.

Our estimation results suggest that mobile phone ownership has a positive impact on changing status from unemployed to being employed. The impact is greater in the last waves of the survey. On the other hand, ownership of a computer by a household and computer literacy do not have a significant impact on the change in employment status. In our estimation, we control for a set of individual characteristics such as race, age, gender, physical health, educational attainment, place of living, among others. The panel data allows us to account for unobserved heterogeneity amongst individuals. We also find that having a mobile phone and ownership of a computer by a household reduce the likelihood of becoming unemployed.

This chapter contributes to the growing body of research on the impact of mobile phones and Internet on the labour market. This is particularly important in developing countries where search costs for jobs are high due to the lack of physical infrastructure amongst others. We show that mobile phones have the potential to reduce this inefficiency to some extent. It is, therefore, critically important to develop policies which stimulate their adoption. The key factors for this are expanding network coverage, affordable prices of smartphones and mobile devices, and low prices of mobile data services. In this chapter we focused on the impact of mobile phones on employment. But as shown by some of the earlier research, there are other channels through which mobile phones impact the economy, including increased market efficiency, access to financial services, and overall reduction in poverty.

5.0 Report conclusions

In this report, we address the following questions with respect to the impact of mobile phones and Internet services on markets in South Africa and sub-Saharan Africa. First, we analyse adoption of smartphones among individuals with different levels of income in South Africa. We construct a unique database of adopters of smartphones with different levels of income in South Africa, which is a developing economy with large income inequality. We use our model to assess the impact of policies which aim at stimulating the adoption of smartphones by people living below the poverty line. We find that the main driver of adoption is coverage by LTE networks, while the price of smartphones has only marginal impact. We conclude that, to reduce digital divide, it is critical to develop LTE infrastructure in poorer areas and people will respond by adopting smartphones irrespective of their income. The static and dynamic models yield comparable results suggesting that consumers do not take future price and quality into account when purchasing smartphones.

Second, we analyse 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 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. Overall, individuals who live in areas which are less developed economically, i.e., where no night-time 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.

Third, we analyse the impact of mobile phone ownership on change in employment status using NIDS panel data conducted among individuals and households in South Africa. Our estimation results suggest that mobile phone ownership has positive impact on employment status. The impact is greater in the last waves of the survey. On the other hand, ownership of a computer by a household and computer literacy do not have a significant impact on the change in employment status. In the estimation, we control for a set of individual characteristics such as race, age, gender, physical health, educational attainment, place of living, among others. We also find that having a mobile phone and ownership of a computer by a household reduce the likelihood of becoming unemployed. The panel data allows us to account for unobserved heterogeneity amongst individuals.

In the absence of fixed broadband infrastructure which is accessible to broad masses of consumers, smartphones and mobile Internet are the key disruptive technologies in Africa. As demonstrated empirically in this report on the example of financial services and labour market, mobile network infrastructure and mobile phones have critical impact on reducing digital divide and enabling poor individuals to participate in the economy.

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Appendixes

Appendix A: Tables and figures for Chapter 2

Table A1: Summary statistics on the full sample of individuals

Variable	Mean	Std	Min	Max
Usage of SMS (units)	17.1	75.92	0	4238
Usage of voice (minutes)	211.57	327.63	0	6459.75
Usage of data (MB)	464.3	1576.9	0	82430.28
Smartphone 0/1	0.55	0.5	0	1
Handset = Samsung	0.32	0.47	0	1
Handset = Nokia	0.23	0.42	0	1
Handset = Apple	0.03	0.18	0	1
Living in urban area (0/1)	0.85	0.35	0	1
Average income	121886.5	126736.4	0	1311958.4
2G coverage	0.99	0.03	0.02	1.01
3G coverage	0.98	0.07	0	1
4G coverage	0.71	0.41	0	1
Percent of black people	0.75	0.33	0	1
Percent of coloured people	0.09	0.21	0	0.98
Percent of white people	0.15	0.25	0	1

Note: All the variables are individual-specific, except those presented in the lower part (from average income), which are related to the residence area of individuals.

Table A2: Summary statistics on the sample of individuals used for estimation (N=65,556)

Variable	Mean	Std	Min	Max
Usage of SMS (units)	13.76	70.95	0	2648
Usage of voice (minutes)	220.02	323.99	0	5250.7
Usage of data (MB)	116.17	663.1	0	44243.42
Smartphone 0/1	0.09	0.29	0	1
Handset = Samsung	0.22	0.42	0	1
Handset = Nokia	0.5	0.5	0	1
Handset = Apple	0	0.03	0	1
Living in urban area (0/1)	0.83	0.38	0	1
Average income	94308.7	103648.4	0	1311958.4
2G coverage	0.99	0.03	0.16	1.01
3G coverage	0.97	0.08	0	1
4G coverage	0.63	0.44	0	1
Percent of black people	0.82	0.29	0	1
Percent of coloured people	0.07	0.18	0	0.98
Percent of white people	0.1	0.2	0	0.99

Figure A1: Share of smartphones among used devices, per income groups

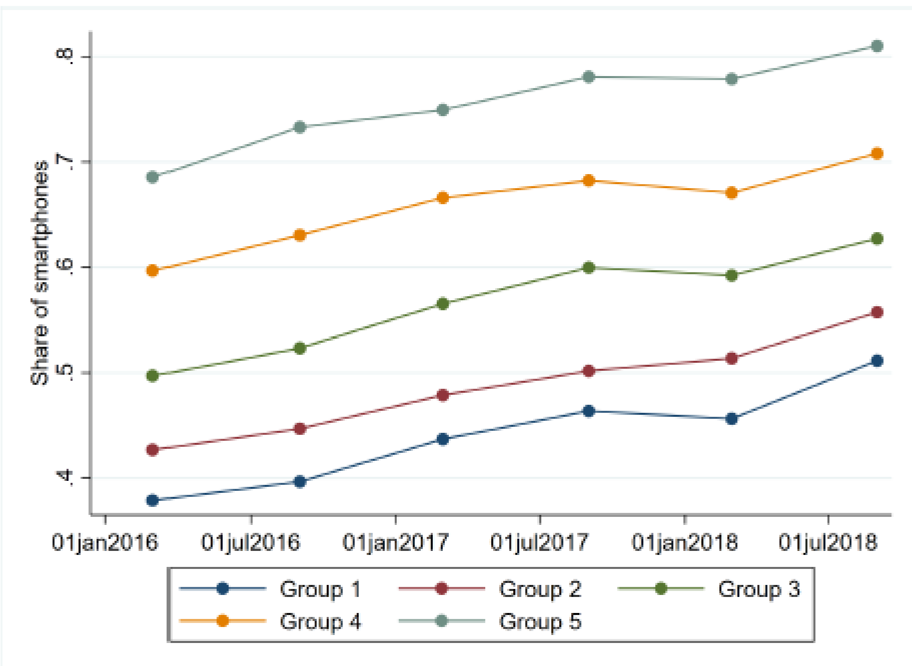


Figure A2: Share of smartphone adopters, per income groups

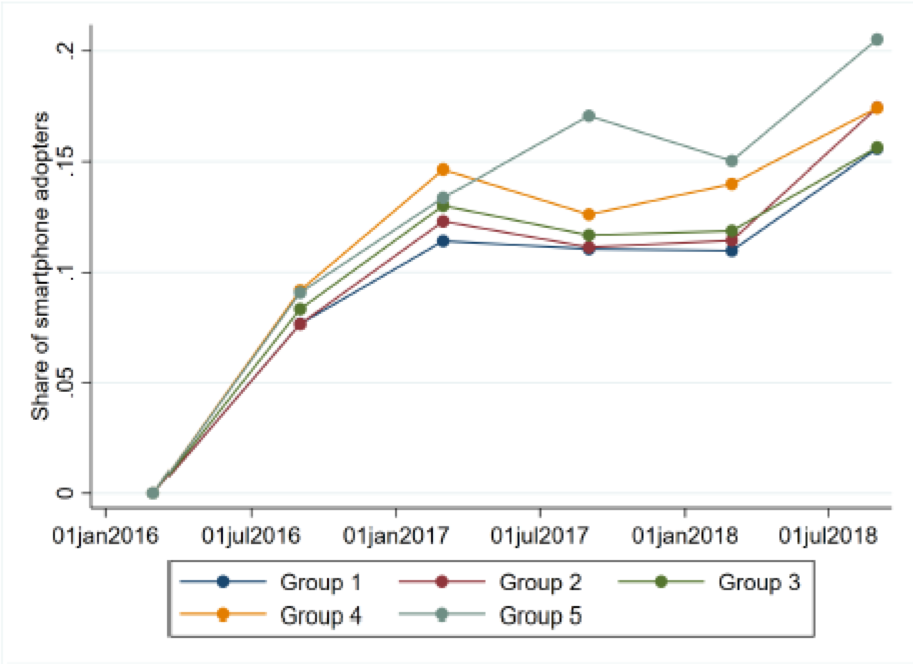
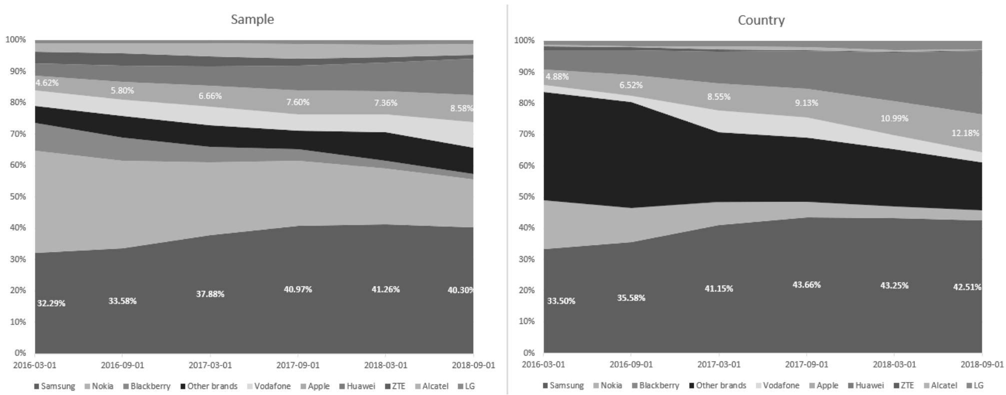


Figure A3: Manufacturers market share



Source: Statscounter. Other brands include Alcatel, ZTE, Motorola, and other small marginal brands. Percentages shown are for Samsung (bold type) and for Apple.

Figure A4: Coverage by geographic area

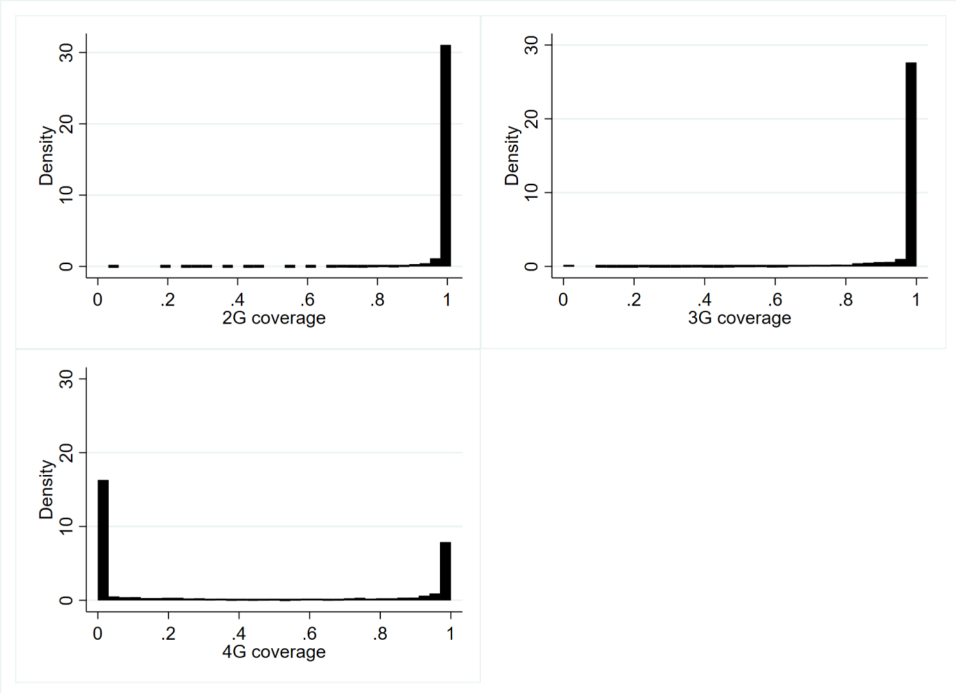


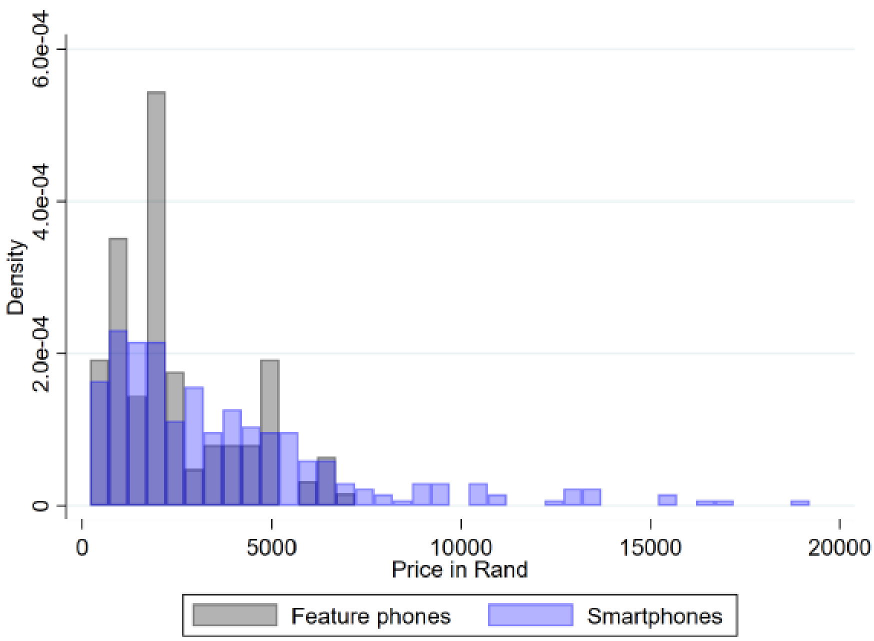
Table A3: Switching patterns in the full data set

	Freq.	Percent
Stays with smartphone	23,569	44.44
Stays with feature phone	20,825	39.27
Upgrade to smartphone	4,332	8.17
Downgrade to feature phone	2,629	4.96
Other switching patterns	1,682	3.16
Total	53,037	100

Table A4: Characteristics of handsets

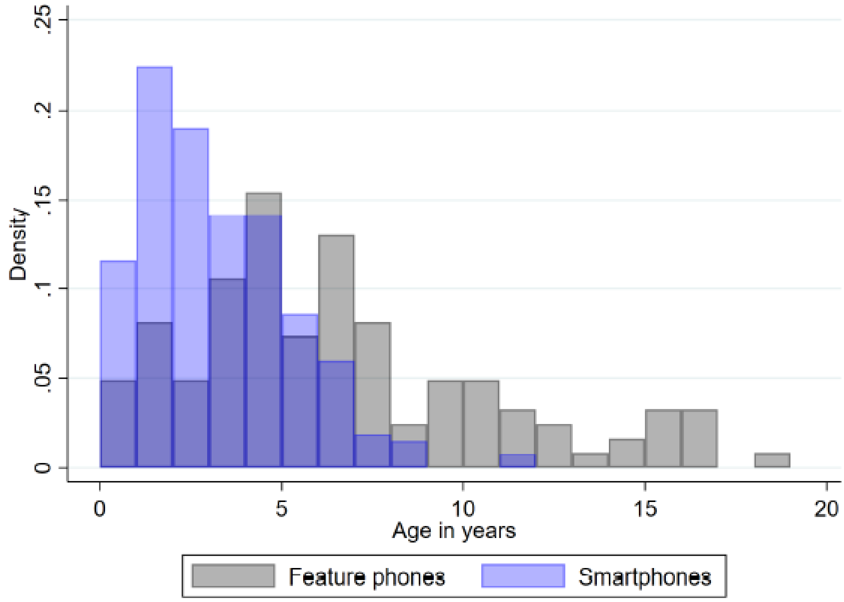
	Mean	Std	Min	Max	N
Price in thousands RAND	3.41	3.01	0.24	19	394
Average age over the period in years	4.2	3.29	0.08	18.18	391
Smartphone	0.68	0.47	0	1	394
LTE compatible	0.34	0.47	0	1	393
Height in mm	125.42	18.86	80	165	377
Width in mm	63.15	14.53	39	255.5	377
Thickness in mm	11.13	3.33	5.9	22.5	377
Weight in grams	124.76	31.76	59	220	368
Internal memory in GB	11.08	18.8	0	128	394
RAM in GB	0.91	1.17	0	6	394
Camera quality in Mpx	5.89	4.74	0	22.57	394
Second camera quality in Mpx	2	3.2	0	23.79	394
Number of CPUs	0.70	0.64	0	3	394
Number of GPUs	0.26	0.44	0	1	394
Display resolution (Mpx)	0.69	0.88	0.01	4.26	355
Battery power in mAh	1829.73	858.21	400	4100	360
Apple	0.04	0.19	0	1	394
Samsung	0.3	0.46	0	1	394
Android OS	0.51	0.5	0	1	394
Blackberry OS	0.06	0.23	0	1	394
Windows OS	0.05	0.22	0	1	394
Other OS: Symbian, Bada, Tizen	0.03	0.16	0	1	394

Figure A5: Histogram of handset prices



Note: Average price in RAND over the whole time period for 394 unique models.

Figure A6: Histogram of models age



Note: Average age of models computed over the whole time period for 394 unique models.

Table A5: Characteristics of choices, per income group

	Gr1	Gr.2	Gr.3	Gr.4	Gr.5
Price in thousands RAND	2.23	2.29	2.27	2.39	2.66
Data usage in MB	61.24	77.23	84.19	124.29	208.81
Voice usage in minutes	226.61	223.30	219.84	192.22	192.32
Text usage in units	14.15	11.35	10.89	11.73	14.79
Age of the model in years	5.00	5.04	5.17	5.51	6.02
Smartphone	0.08	0.08	0.08	0.08	0.10
LTE compatible	0.03	0.03	0.03	0.03	0.05
Height	111.30	111.33	111.10	110.50	109.60
Width	52.62	52.85	52.76	52.65	52.04
Thickness	13.48	13.47	13.55	13.67	13.88
Weight	89.79	90.13	90.63	91.10	90.85
Internal memory	0.77	0.88	0.89	0.99	1.46
RAM	0.14	0.15	0.15	0.16	0.18
Camera quality	1.29	1.35	1.39	1.51	1.63
Second camera quality	0.11	0.14	0.14	0.17	0.27
Number of CPUs	0.14	0.15	0.15	0.15	0.15
Number of GPUs	0.02	0.02	0.02	0.02	0.03
Display size	0.11	0.11	0.12	0.12	0.15
Battery power	1097	1102	1111	1118	1111
Apple	0.000	0.000	0.000	0.001	0.004
Samsung	0.18	0.20	0.20	0.23	0.29
Android OS	0.06	0.07	0.07	0.07	0.08
Blackberry OS	0.01	0.01	0.01	0.01	0.01
Windows OS	0.00	0.00	0.00	0.00	0.00
Other OS	0.00	0.01	0.01	0.00	0.00

Note: Computed on 62,196 observations.

Table A6: Number of unique model in the choice set of various income groups

Group	Mean	Std	P50	Min	Max
1	72.75	7.37	73	64	81
2	53.25	6.40	55.5	44	58
3	47.5	9.85	51	33	55
4	46.5	9.71	51	32	52
5	40	8.49	39	32	50
Total	52	13.73	51.5	32	81

Figure A7: Histograms of prices for the two extreme income groups

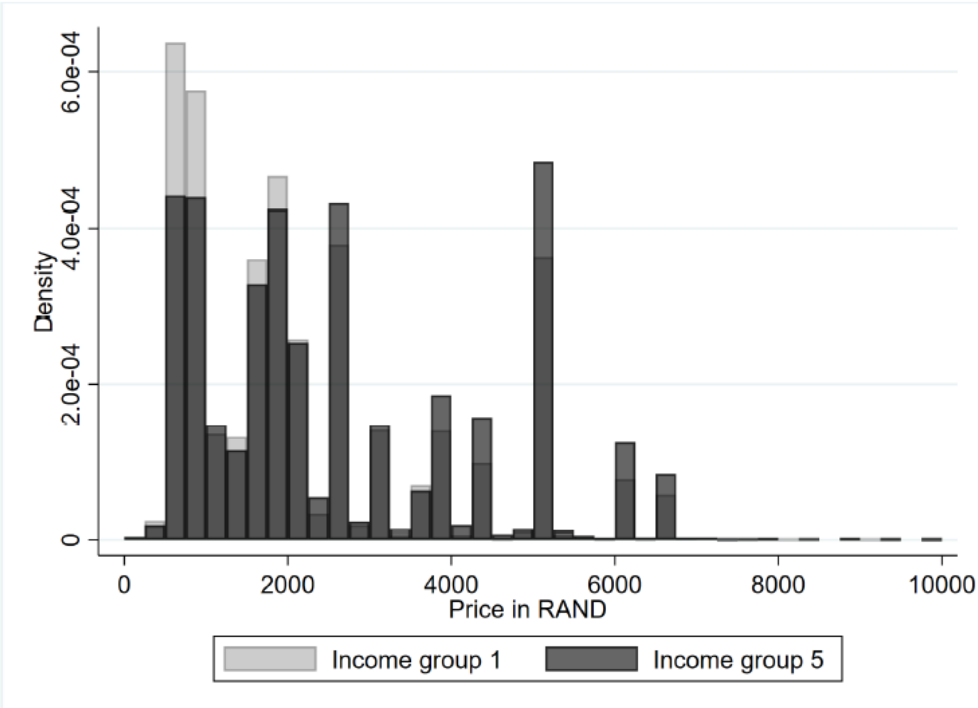


Table A7: Static demand model

	OLS			GMM		
	All	Poor	Well-off	All	Poor	Well-off
price	-0.027***	-0.038***	-0.021***	-0.078***	-0.130***	-0.066***
	(0.008)	(0.015)	(0.008)	(0.024)	(0.047)	(0.025)
Coverage LTE	2.254***	2.173***	1.998***	2.294***	2.322***	2.060***
	(0.105)	(0.261)	(0.187)	(0.105)	(0.259)	(0.186)
Handset age: 1 year	0.715***	0.934***	0.488***	0.712***	0.933***	0.485***
	(0.077)	(0.132)	(0.088)	(0.077)	(0.134)	(0.088)
Handset age: 2 year	0.708***	0.911***	0.520***	0.713***	0.910***	0.532***
	(0.069)	(0.113)	(0.078)	(0.069)	(0.111)	(0.078)
Handset age: 3 year	0.510***	0.653***	0.379***	0.488***	0.612***	0.359***
	(0.065)	(0.104)	(0.076)	(0.065)	(0.103)	(0.076)
Handset age: 4 year	0.289***	0.379***	0.183***	0.281***	0.367***	0.174***
	(0.058)	(0.090)	(0.067)	(0.058)	(0.088)	(0.067)
CPU=0	-0.291***	-0.367***	-0.218***	-0.298***	-0.388***	-0.221***
	(0.066)	(0.102)	(0.082)	(0.065)	(0.101)	(0.081)
Height <120mm	0.262***	0.504***	0.053	0.267***	0.534***	0.054
	(0.060)	(0.093)	(0.075)	(0.059)	(0.091)	(0.074)
Width <63mm	0.144**	0.161*	0.108	0.136**	0.157*	0.093
	(0.059)	(0.092)	(0.074)	(0.058)	(0.091)	(0.074)
Weight <120	0.261***	0.319***	0.229***	0.229***	0.254***	0.197***
	(0.055)	(0.086)	(0.065)	(0.057)	(0.091)	(0.067)
Thickness <8mm	0.018	-0.068	0.066	0.187*	0.244	0.222**
	(0.065)	(0.111)	(0.073)	(0.099)	(0.186)	(0.104)
Apple	0.396**	0.468	0.264	0.522***	0.642*	0.369
	(0.179)	(0.291)	(0.216)	(0.195)	(0.349)	(0.232)
Blackberry	0.837***	0.953***	0.678***	0.806***	0.917***	0.643***
	(0.161)	(0.251)	(0.200)	(0.163)	(0.258)	(0.203)
	(0.108)	(0.182)	(0.119)	(0.114)	(0.198)	(0.125)
Os Android	0.215	0.290	0.098	0.181	0.267	0.040
	(0.157)	(0.246)	(0.194)	(0.161)	(0.264)	(0.199)
OS Windows	0.378***	0.455**	0.234	0.292*	0.300	0.145
	(0.145)	(0.206)	(0.193)	(0.151)	(0.224)	(0.200)
Constant	-9.707***	-10.006***	-9.112***	-9.576***	-9.837***	-9.000***
	(0.177)	(0.296)	(0.247)	(0.189)	(0.318)	(0.256)
Product dummies	yes	yes	yes	yes	yes	yes
Observations	1,519	691	828	1,519	691	828
R-squared	0.487	0.487	0.403	0.486	0.481	0.400

Table A8: Dynamic demand model

	OLS			GMM		
	All	**Poor**	**Well-off**	**All**	**Poor**	**Well-off**
price	-0.032***	-0.045***	-0.025**	-0.124***	-0.213***	-0.091***
	(0.010)	(0.016)	(0.010)	(0.032)	(0.056)	(0.031)
Coverage LTE	2.098***	1.058**	2.103*	2.176***	1.156**	2.307**
	(0.388)	(0.457)	(1.074)	(0.386)	(0.462)	(1.054)
Handset age: 1 year	1.125***	1.148***	0.879***	1.116***	1.129***	0.870***
	(0.088)	(0.144)	(0.093)	(0.090)	(0.151)	(0.095)
Handset age: 2 year	0.755***	0.818***	0.623***	0.781***	0.850***	0.642***
	(0.082)	(0.126)	(0.087)	(0.085)	(0.132)	(0.090)
Handset age: 3 year	0.482***	0.521***	0.386***	0.456***	0.456***	0.363***
	(0.078)	(0.119)	(0.084)	(0.079)	(0.122)	(0.084)
Handset age: 4 year	0.299***	0.290***	0.214***	0.300***	0.289***	0.205***
	(0.069)	(0.104)	(0.077)	(0.070)	(0.107)	(0.077)
CPU=0	-0.155*	-0.213*	-0.034	-0.206**	-0.278**	-0.061
	(0.084)	(0.117)	(0.092)	(0.084)	(0.115)	(0.093)
Height <120mm	0.640***	0.902***	0.352***	0.635***	0.946***	0.351***
	(0.067)	(0.099)	(0.074)	(0.068)	(0.101)	(0.076)
Width <63mm	-0.467***	-0.612***	-0.317**	-0.435***	-0.572***	-0.298***
	(0.053)	(0.074)	* (0.060)	(0.054)	(0.077)	(0.062)
Weight <120	0.446***	0.479***	0.384***	0.386***	0.340***	0.323***
	(0.066)	(0.098)	(0.074)	(0.069)	(0.106)	(0.077)
Thickness <8mm	-0.001	-0.097	0.014	0.323**	0.479**	0.262**
	(0.080)	(0.114)	(0.086)	(0.131)	(0.207)	(0.132)
Apple	0.496**	0.232	0.492*	0.707***	0.535	0.602**
	(0.222)	(0.282)	(0.252)	(0.254)	(0.413)	(0.278)
Blackberry	0.645***	0.560**	0.632***	0.619***	0.495*	0.582**
	(0.192)	(0.253)	(0.230)	(0.203)	(0.287)	(0.238)
Os Android	0.024	-0.027	0.034	0.004	-0.062	-0.033
	(0.195)	(0.260)	(0.229)	(0.211)	(0.314)	(0.239)
OS Windows	0.093	0.029	0.116	-0.049	-0.294	-0.010
	(0.168)	(0.202)	(0.223)	(0.183)	(0.244)	(0.235)
Constant	-1.113***	-1.338***	-1.075***	-1.064***	-1.285***	-1.019***
	(0.082)	(0.170)	(0.099)	(0.079)	(0.161)	(0.098)
Product dummies	yes	yes	yes	yes	yes	yes
Observations	1,519	691	828	1,519	691	828
R-squared	0.461	0.510	0.401	0.453	0.476	0.392

Table A9: Static model: Simulation of removing 15% VAT

	Penetration					Simulations				
	inc 1	inc 2	inc 3	inc 4	inc 5	inc 1	inc 2	inc 3	inc 4	inc 5
2016q3	41.6%	46.0%	53.0%	63.1%	71.4%	41.7%	46.1%	53.1%	63.2%	71.5%
2017q1	47.7%	51.7%	57.6%	68.0%	75.3%	48.0%	51.9%	57.8%	68.2%	75.4%
2017q3	52.4%	56.2%	61.5%	71.7%	78.8%	52.8%	56.6%	61.7%	71.9%	79.0%
2018q1	57.1%	60.2%	65.1%	75.3%	81.5%	57.7%	60.7%	65.4%	75.5%	81.7%

Table A10: Static model: Simulation of full LTE coverage

	Penetration					Simulations				
	inc 1	inc 2	inc 3	inc 4	inc 5	inc 1	inc 2	inc 3	inc 4	inc 5
2016q3	41.6%	46.0%	53.0%	63.1%	71.4%	51.7%	53.3%	56.8%	65.0%	72.0%
2017q1	47.7%	51.7%	57.6%	68.0%	75.3%	62.6%	62.5%	63.5%	70.5%	75.9%
2017q3	52.4%	56.2%	61.5%	71.7%	78.8%	69.9%	69.3%	68.6%	74.5%	79.5%
2018q1	57.1%	60.2%	65.1%	75.3%	81.5%	76.0%	74.6%	73.0%	78.3%	82.2%

Table A11: Dynamic model: Simulation of removing 15% VAT

	Penetration					Simulations				
	inc 1	inc 2	inc 3	inc 4	inc 5	inc 1	inc 2	inc 3	inc 4	inc 5
2016q3	41.7%	46.5%	52.8%	63.2%	70.6%	41.8%	46.6%	52.8%	63.3%	70.7%
2017q1	45.6%	52.1%	58.8%	67.2%	74.1%	45.9%	52.3%	59.0%	67.3%	74.1%
2017q3	48.8%	57.0%	63.8%	70.5%	77.4%	49.3%	57.4%	63.9%	70.7%	77.5%
2018q1	56.2%	61.9%	68.8%	74.6%	79.9%	56.9%	62.4%	69.0%	74.9%	80.0%

Appendix B: Model predictions derivation

The equation which we estimate in dynamic framework for product j is given by:

$$ln(\frac{S_{jt}/S_{1t+1}^{\beta}}{S_{0t}}) = (x_{jt} - \beta x_{1t+1} - x_{Ft})\gamma + \theta(c_t - \beta c_{1t+1}) - \alpha(p_{jt} - \beta p_{1t+1} - p_{Ft}) - \beta 0.577 + \epsilon_{jt}$$

which can be written as:

$$\ln(S_{jt}/S_{0t}) = \beta\ln(S_{1t+1}) + \Delta_{jt}$$

where: Δ_{jt} depends on the characteristics of j at time t as well as on the characteristics of arbitrary product denoted by 1 at time $t+1$. We compute Δ_{jt} using data and estimated parameters, where ϵ_{jt} is assumed to be zero-mean. We can further write this equation as:

$$S_{jt}/S_{0t} = \exp(\beta\ln(S_{1t+1}) + \Delta_{jt})$$

and using as: $S_{0t} = 1 - \sum_{i=1}^{N} S_{it}$

$$\frac{S_{jt}}{1 - \sum_{i=1}^{N} S_{it}} = \exp(\beta\ln(S_{1t+1}) + \Delta_{jt})$$

Summing up for all products and solving for the share of all smartphones we get:

$$\sum_{i=1}^{N} S_{it} = \frac{\sum_{i=1}^{N}(\beta \ln(S_{1t+1}) + \Delta_{jt})}{1 + \sum_{i=1}^{N}(\beta \ln(S_{1t+1}) + \Delta_{jt})}$$

In the case of static model, the starting equation is:

$$ln(S_{jt}/S_{0t}) = x_{jt}\gamma + \theta c_t - \alpha p_{jt} + \epsilon_{jt} = \delta_{jt} + \epsilon_{jt}$$

Where: δ_{jt} is computed using data and estimated parameters and assuming that ϵ_{jt} is zero-mean. After taking exponential and summing up for all products, we can write this equation as:

$$\frac{\sum_{j=1}^{N} S_{jt}}{1 - \sum_{j=1}^{N} S_{jt}} = \exp(\delta_{jt})$$

which can be solved for the share of all smartphones:

$$\sum_{i=1}^{N} S_{it} = \frac{\sum_{i=1}^{N} \delta_{jt}}{1 + \sum_{i=1}^{N} \delta_{jt}}$$

Appendix C: Tables and figures for Chapter 3

Table C.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)
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)	28(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 C.5: 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 C.6: Stage two: distance to bank branch (feature phones / smartphones adoption)

	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 C.7: Stage two: distance to ATM (feature phones / smartphones adoption)

	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 C.8: Stage two: distance to roads (feature phones / smartphones adoption)

	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 C.9: Stage two: distance to town (feature phones / smartphones adoption)

	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 C.10: Stage two: distance to bank branch (handset adoption)

	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 C.11: Stage two: distance to ATM (handset adoption)

	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 C.12: Stage two: distance to roads (handset adoption)

	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 C.13: Stage two: distance to town (handset adoption)

	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 C.14: Sending money: distance to bank branch / ATM (handset adoption)

	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 C.15: Sending money: distance to roads / town (handset adoption)

	Road Model I	Model II	Model III	Town 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 C.16: Receiving money: distance to bank branch / ATM (handset adoption)

	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 C.17: Receiving money: distance to roads / town (handset adoption)

	Road Model I	Model II	Model III	Town 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

Table C.18: Saving money: distance to bank branch / ATM (handset adoption)

	Bank				ATM			
	Model I	Model II	Model III	Model IV	Model I	Model II	Model III	Model
IV bank2/atm2	0.023				0.176**			
	(0.072)				(0.078)			
bank5/atm5		0.008				0.252***		
		(0.074)				(0.070)		
bank10/atm10			0.039				0.121*	
			(0.070)				(0.067)	
bank25/atm25				0.204***				0.032
				(0.078)				(0.065)
light1	-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)
age1	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)
age2	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)
age3	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)
age4	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)
age5	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)
income1	-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)
income2	-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)
income3	-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)
hh2	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)
hh3	-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 comp	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	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)
mon2 0	-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

Table 19: Saving money: distance to roads / town (handset adoption)

	Road			Town		
	Model I	Model II	Model III	Model I	Model II	Model III
road2/town2	-0.035			0.041		
	(0.059)			(0.071)		
road5/town5		-0.001			-0.006	
		(0.066)			(0.062)	
road10/town10			-0.092			0.153**
			(0.083)			(0.061)
light1	-0.451***	-0.446***	-0.472***	-0.444***	-0.446***	-0.437***
	(0.073)	(0.074)	(0.076)	(0.072)	(0.072)	(0.072)
female	0.077	0.076	0.081	0.075	0.076	0.071
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
age1	0.566***	0.568***	0.564***	0.568***	0.569***	0.575***
	(0.183)	(0.183)	(0.183)	(0.182)	(0.182)	(0.183)
age2	0.580***	0.584***	0.578***	0.584***	0.584***	0.593***
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
age3	0.669***	0.672***	0.667***	0.673***	0.672***	0.682***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
age4	0.425**	0.429**	0.424**	0.430**	0.429**	0.437**
	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)	(0.190)
age5	0.188	0.192	0.187	0.193	0.192	0.197
	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)	(0.195)
income1	-0.909***	-0.907***	-0.916***	-0.904***	-0.907***	-0.891***
	(0.290)	(0.290)	(0.291)	(0.290)	(0.290)	(0.290)
income2	-0.569*	-0.567*	-0.577*	-0.562*	-0.567*	-0.548*
	(0.302)	(0.302)	(0.303)	(0.302)	(0.302)	(0.303)
income3	-0.745**	-0.740**	-0.756**	-0.732**	-0.741**	-0.713**
	(0.325)	(0.325)	(0.325)	(0.325)	(0.325)	(0.325)
married	-0.028	-0.029	-0.030	-0.029	-0.029	-0.027
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
hh2	0.055	0.058	0.056	0.059	0.058	0.062
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
hh3	-0.037	-0.034	-0.034	-0.033	-0.034	-0.030
	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
none	-0.633***	-0.634***	-0.622***	-0.640***	-0.633***	-0.661***
	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)	(0.232)
primary	-0.241	-0.242	-0.234	-0.244	-0.242	-0.253
	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)
secondary	-0.035	-0.035	-0.031	-0.037	-0.035	-0.043
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
employed	0.110	0.111	0.108	0.113	0.111	0.121
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
_self employed	0.155*	0.156*	0.153*	0.157*	0.155*	0.167*
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
housework	-0.060	-0.058	-0.061	-0.059	-0.058	-0.058
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
student	0.363***	0.362***	0.367***	0.360***	0.362***	0.358***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
retired	-0.015	-0.014	-0.015	-0.015	-0.013	-0.013
	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)	(0.196)
own house	-0.057	-0.055	-0.062	-0.055	-0.055	-0.056
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
car	-0.079	-0.081	-0.079	-0.079	-0.082	-0.075
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
motorbike	-0.014	-0.013	-0.013	-0.014	-0.013	-0.008
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
laptop comp	0.211*	0.211*	0.209*	0.214*	0.211*	0.224*
	(0.115)	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)
bank	0.202	0.203	0.197	0.205	0.202	0.218
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
_mon2 0	-0.276**	-0.274**	-0.283**	-0.270**	-0.275**	-0.258**
	(0.124)	(0.124)	(0.124)	(0.124)	(0.124)	(0.124)
Constant	0.809**	0.788**	0.873**	0.783**	0.789**	0.703*
	(0.368)	(0.370)	(0.375)	(0.366)	(0.367)	(0.368)
Observations	8,866	8,866	8,866	8,866	8,866	8,866

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

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