Tsukuba Economics Working Papers
No. 2022-001

Is Better Access to Mobile Networks Associated with Increased Mobile Money Adoption? Evidence from the Micro-data of Six Developing Countries

by

Hisahiro Naito

Shinnosuke Yamamoto

January 2022

UNIVERSITY OF TSUKUBA
Program in Economic and Public Policy
1-1-1 Tennodai
Tsukuba, Ibaraki 305-8571
JAPAN

Is Better Access to Mobile Networks Associated with Increased Mobile Money Adoption? Evidence from the Micro-data of Six Developing Countries

Hisahiro Naito *†

Graduate School of Humanities and Social Sciences

University of Tsukuba

Shinnosuke Yamamoto *‡

College of International Studies

University of Tsukuba

December 17, 2021

*The authors appreciate the comments from Yuko Nakano and ZengFei Yu.

†Email: naito@dpipe.tsukuba.ac.jp. Address: Tennodai 1-1-1 University of Tsukuba, Tsukuba City, Ibaraki Prefecture Japan

‡Email: shinno6132@gmail.com Address: Tennodai 1-1-1, Tsukuba City, Ibaraki Prefecture, Japan

Abstract

In several developing countries in Sub-Saharan Africa, accessibility to digital financial services is increasing because of the development of mobile money services. People previously excluded from the financial system have started to have access to financial services such as receiving and sending remittances, saving, and borrowing. This study examines the effect of network accessibility on the use of mobile money in six developing countries (Bangladesh, Kenya, Nigeria, Pakistan, Tanzania, and Uganda) using GPS information on each household and mobile phone network coverage maps. We find that among these six countries, network accessibility is associated with the use of mobile money in a robust way only in Pakistan and Tanzania. In those two countries, when a household location becomes 10 km closer to the center of the area with multiple mobile networks, the probability of using mobile money increases by 10 percent. In the other countries, we did not find a robust relationship between the use of mobile money and network accessibility. This suggests that increasing network accessibility may not be an efficient method for increasing mobile money adoption in certain countries. The fact that mobile money use rates differ between Tanzania and Pakistan also suggests that the effect of mobile networks is unrelated to the overall level of mobile money adoption.

1 Introduction

Mobile phone networks are rapidly becoming an important infrastructure in developing countries. For example, in Asia and Africa, the mobile phone use rate is more than 90 percent (Figure A1). However, the percentage of people with bank accounts remains low. For example, the proportion of adults in developing countries that have a bank account is 63 percent compared with 94 percent in developed countries. Interestingly, among the approximately 1.7 billion "unbanked" people, about one billion have mobile phones (Demirguc-Kunt, Klapper, Singer, Ansar and Hess, 2018).

Economics research emphasizes the importance of financial inclusion: the concept that individuals and entities can access convenient and affordable financial services that meet their needs for transactions, payments, savings, credit, and insurance provided through responsible and sustainable means. The literature argues that financial inclusion is expected to promote economic growth (Aggarwal and Klapper, 2013) and improve quality of life in developing regions (Demirguc-Kunt et al., 2018).

Financial inclusion in some African countries has recently started to change despite their low rate of bank account ownership due to the growth in mobile money services, which enable individuals to send, receive, and save using a mobile phone (Hughes and Lonie, 2007; GSM Association, 2020). For example, in 2017, only 55, 19, and 17 percent of adults had a bank account in Kenya, Tanzania, and Zimbabwe, respectively, whereas 58, 32, and 32 percent already had mobile money accounts. The growth in mobile money services has been dizzying, too. In Tanzania, mobile money was officially introduced in 2008. In 2009, the user rate was just 1.1 percent; however, this rose to 32 percent in 2013 and 55.8 percent in 2017 (World Bank, 2014). Globally, the number of mobile money agents tripled between 2014 and 2019, reaching seven times the number of ATMs and 20 times the number of bank branches (GSM Association, 2020).

Yet, this high proliferation of mobile money is not universal in developing countries. According to the Global Financial Inclusion database of the World Bank, the mobile money penetration rate in 2017 was below 10 percent in more than half of the 77 countries surveyed (Figure A2). India, which has the largest population in the South Asian region, had a use rate of about 2 percent, while Nigeria, with the largest population in Africa, had a use rate of 5.6 percent.

One natural question that arises is what prevents the adoption of mobile money and resulting financial inclusion in developing countries. Several studies have examined this issue (Evans and Pirchio, 2014; Mothobi and Grzybowski, 2017; Lashitew, van Tulder and Liasse, 2019; Asongu, Biekpe and Cassimon, 2020). One of the issues that has attracted the attention of researchers and policymakers is the role of mobile networks. Broadband coverage such as 3G and 4G, which are common communication technologies in developed countries, are limited to urban and densely populated areas, while 2G (GSM), which is slower than 3G and 4G, is commonly used in rural areas (Perlman and Wechsler, 2019). Although 2G has wider coverage than other faster networks, it does not cover all areas far from cities and national highways or areas not yet served by electricity. For example, in the survey of Nigerian households conducted by Tonuchi (2020), 65 percent of the 300 offline respondents and 83 percent of the 200 online respondents cited the network as the biggest barrier to using mobile money services. Thus, network accessibility may have an important effect on the use of mobile money. Lashitew, van Tulder and Liasse (2019) show that network coverage does not have a statistically or economically significant effect on mobile money adoption, while Asongu, Biekpe and Cassimon (2020) show that it has a statistically and economically significant effect.[1]

Thus, given the importance of this issue and lack of evidence using micro-data and information on individual-level network accessibility, we empirically examine the effect of accessibility to mobile networks on the use of mobile money using micro-data as well as GPS information on household locations and network coverage map data, which have recently become available. Examining such issues is important for several reasons. First, from the perspective of the government, such information is critical. Past research shows that the use of mobile money has many positive effects on the economy such as smoothing consumption, increasing the receipt of remittances, improving the

[1]Perlman and Wechsler (2019) discuss how different mobile network providers use different types of networks in developing countries.

welfare system, and increasing human capital. (Jack and Suri, 2014; Muralidharan et al., 2016; Munyegera and Matsumoto, 2016; Aker et al., 2016; Abiona and Koppensteiner, 2020). On the other hand, the mobile phone market is often dominated by several companies due to the high initial cost of the network infrastructure. Thus, how to regulate this industry is an important issue. If the expansion of mobile phone networks is likely to enhance the use of mobile money, then the government might need to formulate a policy that encourages mobile phone operators to make additional investments in mobile phone networks.

Second, from the perspective of mobile money operators, it is critical to know whether expanding mobile networks is likely to affect the use of mobile money. Since the cost of expanding mobile phone networks is substantial, such information is critical for the investment decisions of mobile phone operators.

Finally, several satellite-based Internet constellations are planned by large companies such as Amazon (Project Kuiper) and Space X (Starlink). A satellite-based Internet constellation is thousands of mass-produced small satellites in low earth orbit, which allow people to access the Internet everywhere at any place on Earth at any time through satellites. If the expansion of mobile phone networks has changed financial inclusion in developing countries, the spread of Internet networks could affect financial inclusion in those countries in the future. [2] To predict the degree to which this new technology will affect financial inclusion, it is important to know how mobile phone networks have affected financial inclusion in the past.

One might think that the results of this study would be obvious. Since people need to be connected to mobile networks to use mobile money, readers might speculate that expanding networks always increases its adoption. However, such an argument can be misleading for several reasons. First, people can use mobile money even when no mobile network is available at home. People living outside network coverage areas often use mobile phones when they visit urban areas for work or to buy groceries. Thus, living outside a network-covered area does not imply that people cannot use mobile

[2] For example, Asian Development Bank (2021) discusses the potential impact of those constellations for developing countries in Asia and the Pacific region.

money. Second, if the decision not to use mobile money is driven by other reasons such as low service quality and a culture of relying on cash transactions, increasing accessibility to mobile networks would be unlikely to increase the use of mobile money. Indeed, in many developing countries, the rate of mobile phone use is more than 90 percent but that of mobile money use is low.

One strand of the literature examines the cause of adopting mobile money in developing countries. Batista and Vicente (2020) conduct a field experiment that introduces mobile money to residents and examine the factors behind its adoption. Evans and Pirchio (2014) show that heavy regulation on mobile money operators is the key barrier to the growth of mobile money adoption. Murendo, Wollni, De Brauw and Mugabi (2018) analyze the effect of social networks on mobile money adoption in Uganda. Lashitew, van Tulder and Liasse (2019) use macro-data to identify that ATM penetration and bank concentration have a negative effect on mobile money adoption, while mobile network connectivity does not have a significant effect. Moreover, Asongu, Biekpe and Cassimon (2020) show that ATM penetration, mobile subscription rates, GDP growth, mobile phone connectivity, and the rate of urbanization all have a positive effect on mobile money adoption, again using macro data. Afawubo, Couchoro, Agbaglah and Gbandi (2020) show that factors related to education and sex and being clients of a bank or microfinance institution are key determinants of mobile money adoption. Akinyemi and Mushunje (2020) find that young, educated, and rural dwellers tend to use mobile money in Africa. Tonuchi (2020) identifies infrastructure as a key challenge to the expansion of digital financial services in Nigeria. Mothobi and Grzybowski (2017) examine whether the infrastructure—proxied by the level of night light—influences mobile money adoption using microeconomic data. They find that the adoption of mobile phones is higher in areas with a better physical infrastructure.[3]

In addition, another strand of the literature examines the effect of the use of mobile money on economic outcomes. Aker et al. (2016) and Muralidharan et al. (2016)

[3]The literature is expanding rapidly (Hasbi and Dubus, 2020; N'dri and Kakinaka, 2020; Akinyemi and Mushunje, 2020; Kabengele and Hahn, 2021). For example, Kabengele and Hahn (2021) analyze the institutional factors behind mobile money adoption and Akinyemi and Mushunje (2020) examine the determinants of adopting mobile money technology in rural areas of Africa.

analyze the role of secure payments in Niger and India, respectively. Blumenstock et al. (2015) conduct a randomized experiment to test the effectiveness of using mobile money to pay salaries. Dupas and Robinson (2013) analyze the role of mobile money as a secure way to deposit daily cash in microenterprises in Kenya. Jack and Suri (2014) empirically demonstrate that, in Kenya, a household that uses mobile money does not decrease consumption when faced with a negative income shock. Munyegera and Matsumoto (2016) show that, in Uganda, a mobile money user receives remittances more frequently and has higher real per capita consumption than a non-user. Blumenstock et al. (2016) and Riley (2018) analyze whether mobile money is useful to smooth consumption for households that experience negative shocks. Suri and Jack (2016) analyze the long-run effect of the use of mobile money and find that 2 percent of Kenyan households have moved out of poverty since its availability in the country because of increases in saving and financial resilience. Abiona and Koppensteiner (2020) analyze how the use of mobile money affects education expenditure in Tanzania. Riley (2020) finds, using field experiments, that disbursing loans through a mobile money account to female business borrowers has a more significant effect on profit than disbursing loans in cash.

We contribute to this literature in two ways. First, we examine the effect of accessibility to mobile networks on the use of mobile money using GPS data on household location and micro-data that include household characteristics. Previous studies that examine the relationship between network accessibility and mobile money adoption rely on macro-data.[4] By contrast, using GPS information and micro-data, we can directly measure accessibility to mobile networks and control for various confounding factors. To the best of our knowledge, our study is the first to combine mobile network maps and household GPS information to examine the effect of accessibility to mobile networks on the use of mobile money. In addition, we can quantify the extent to which people live in areas with multiple mobile network connections. We find that about 70 percent of sample households live in an area with multiple mobile networks. This

[4] One exception is the study by Mothobi and Grzybowski (2017). However, their key explanatory variable is night light level as opposed to network accessibility.

information can be useful for considering a mobile money policy. Second, we use various geographically referenced data such as satellite night light data and the population density map constructed by CIESIN (2015) to control for confounding factors such as income level and population density and thus provide a causal interpretation of the estimates.

The remainder of our paper is organized as follows. In Section 2, we discuss our dataset. In Section 3, we describe the estimating equation. In Section 4, we present the estimation results. In Section 5, we discuss our results and conclude.

2 Dataset

2.1 Household Datasets

This study uses household survey data published by Financial Inclusion Insights, a research program funded by the Bill & Melinda Gates Foundation. Financial Inclusion Insights provides data on household living conditions and finance in Africa and Asia for use in consumer demand-side research and policy interventions (Financial Inclusion Insights Program, 2017).

Among the datasets available from Financial Inclusion Insights, we select datasets based on the following inclusion criteria: GPS information on household location is available, mobile network information is available, and mobile money is introduced in this country. The countries that satisfy these criteria are Bangladesh, Kenya, Nigeria, Pakistan, Tanzania, and Uganda, and we choose the datasets of those countries in 2017. Figure A3 shows the bank account and mobile phone ownership rates in those six countries. Each dataset is an interview-based survey of randomly selected households aged 15 years and above and includes questions on personal and household characteristics such as the age, sex, occupation, and education level of respondents as well as questions on financial inclusion such as access to and usage of bank accounts and mobile money. In addition, GPS information and the distances to banks and ATMs are available. In our study, the GPS information in this micro-level dataset is combined with the map data described below as spatial information. We convert this information into numerical information and use it as the variables.

2.2 Map Data on Network Coverage

In addition to the Financial Inclusion Insights data, we use map data on network coverage published by the GSM Association. The GSM Association asks the mobile operators in each country to provide network coverage maps and publishes the network coverage map of each operator in each country to the public.[5]

The key variable to quantify network accessibility is the shortest distance to the border of the area with multiple mobile networks. This distance takes a negative value if a household is located within the area with multiple mobile networks and takes a positive value otherwise. Thus, for a household in the center of area with multiple mobile networks, this value is a large negative number. For a household on the border of the area with multiple mobile networks, this value is zero. For a household outside the area with multiple mobile networks, the value is high and positive. When the distance to the area with multiple mobile networks is a high negative value, it implies that a household is living in an area covered by multiple mobile networks. Thus, when a member of the household visits a nearby place for shopping or work, this person's location is still covered by multiple mobile networks. On the other hand, when the number is positive and high, it implies that this person is not covered by multiple mobile networks regardless of the direction in which they are moving.

One of the major motivations for using mobile money is to send and receive money (Jack and Suri, 2014; Munyegera and Matsumoto, 2016). When a person needs to send or receive money, this person naturally wants to use the same brand of mobile money service as her or his friends and family use. If multiple mobile networks are available, the probability that the same brand of mobile money service as the friends and family use is available in this area becomes high. In such a case, this person has a strong motivation to use mobile money. On the other hand, when only one mobile network is available, the brand of mobile money service available in this area could differ from

[5] Available at `https://www.gsma.com/coverage/` (2020/11/05 accessed).

that used by their friends and family. In such a case, the person has less incentive to adopt mobile money.

To calculate the shortest distance to the border of the area with multiple mobile networks, we first list mobile network providers whose market shares are in the top three in their respective countries. Then, we select mobile network providers whose market share is at least 80 percent. Table A1 shows the market share of mobile phone companies in each country.

We select Banglalink and Robi Axiata in Bangladesh; Safaricom and Airtel in Kenya; MTN, Airtel, and Glo in Nigeria; Jazz and Zong in Pakistan; Airtel and Tigo in Tanzania; and MTN and Airtel in Uganda.[6] Then, for each country, we identify the intersection of the network areas covered by the selected network providers. Once we identify such an area for each country, for each household location, we measure the shortest distance to the boundary of the area covered by multiple mobile networks. When a household is inside (outside) this area, we code it with a negative (positive) value. We use this distance variable as the proxy for the network accessibility of each household. As an example, Figure A4 shows the intersection of the network coverage map of three mobile network providers in Uganda. The yellow area is the area in which multiple mobile networks are available and the blue points are the locations of households.

2.3 Map Data on Population Density and Night Light Intensity

We add population density and night light intensity around each household as control variables to more accurately estimate the impact of network accessibility on households' adoption of mobile money while controlling for the effect of other covariates. Population density is used as a proxy of the urbanicity of the area and night light intensity is used as a proxy of income level following a recent study measuring income at the sub-regional

[6]Bangladesh's Grameenphone has the largest market share in the country (52 percent), but is excluded from the analysis because it covers the entire country and using its network-covered area does not offer additional information. Telenor in Pakistan, which has the second largest market share in the country (21.9 percent), is also excluded since no adequate coverage map is available.

level (Henderson et al., 2012).[7] Because these datasets are not included in the Financial Inclusion Insights data, we create those variables by overlaying the GPS information of each household onto the population density and night light maps.

For population density, we use the map data published by the Center for International Earth Science Information Network (CIESIN) at Columbia University (CIESIN, 2015). These map data are available in a raster format. To each 30-second square (about 1 km near the equator) cell, the map assigns a value from 0 to 455,159 to estimate population density based on census and population registries. This population dataset has been updated every five years since 2000. We use data on 2005, before the deployment of mobile money services, to avoid the endogenous effect of network coverage on population movement.

The National Oceanic and Atmospheric Administration at the National Geophysical Data Center processes and archives night light data acquired by the U.S. Air Force Defense Meteorological Satellite Program Operational Linescan System from 1992 to 2013 (NOAA, 2015). These satellite data are available in raster format. Each 30-second square cell is assigned a value from 0 to 63 depending on night light intensity. As with the mapping data for population density, we use the dataset on 2005 to avoid the endogeneity from the mobile network to income and night light. Figure A6 shows the night light map of 2005 used in our analysis.

3 Estimation Strategy

To analyze the impact of network accessibility on the use of mobile money, we estimate the following linear probability model using ordinary least squares estimation:

$$\text{Mobile Money}_i = \beta_0 + \beta_1 \text{Distance}_i + \gamma X_i + \varepsilon_i \tag{1}$$

[7] Several economists have recently used night light level to approximate income when information on income at the sub-regional level is unavailable. For example, see Alesina, Michalopoulos and Papaioannou (2016), Storeygard (2016) and Pfeifer et al. (2018).

where Mobile Money is a dummy variable equal to one if a household used a mobile money service in the past 90 days. i is an index of each household. The explanatory variable Distance$_i$ is the shortest distance (in kilometers) from the household's location to the boundary of the area covered by multiple mobile networks, which is negative (positive) if the household is inside (outside) an area with multiple mobile networks. X_i is a set of control variables.

We estimate the above equation separately for the six countries since the estimated coefficients of the explanatory variables are unlikely to be the same across these countries.

There are several concerns when using ordinary least squares to estimate equation (1). The first is omitted variable bias because the distance to the mobile network could be correlated with other covariates such as education, income, and urban/rural location. Since those variables are also directly correlated with the use of mobile money, the estimated coefficient would be biased and would not measure the effect of the distance to the mobile network.

The second concern is the measurement error problem. The data provided by mobile network operators may not be sufficiently accurate since this is a theoretical value calculated from the location of the mobile network tower and strength of its radio waves.

The third concern is endogeneity. The mobile network operator may build a mobile network tower in an area in which demand for using mobile money is high. In such a case, our estimated coefficient of the distance to the mobile network would be upward biased. This implies that when the estimated coefficient is significant, we need to carefully interpret the estimated coefficient of the key explanatory variable, namely, the distance to mobile network areas.

To address the first issue, we include a large set of control variables in X_i in equation (1): age, sex, marital status, status in the household, employment status, education level (14 categories), residential location (urban or rural), distance to the nearest bank branch, and distance to an ATM. To control for the average income of the area and population density, we include in X_i population density and average night light intensity within a radius of 10 km from each household's location. To control for the potential effect of the mobile network on population density and economic activity, we measure population density and average night light intensity in 2005.

To address the second issue, we first identify the areas covered by multiple mobile networks and assume that the mobile connection is stable and strong in those areas. To measure network accessibility, the areas covered by the multiple mobile networks suffer less measurement error than those covered by a single company's mobile network.

To address the third issue, we conduct the so-called coefficient stability test originally proposed by Altonji, Elder and Taber (2005) and later refined by Oster (2019). This method gradually increases the number of control variables that could be correlated with the error term and examines how the estimated coefficient of the key explanatory variable changes. If the change in the estimated coefficient of the key explanatory is relatively small, this test concludes that the chance of the estimated coefficient being biased due to endogeneity is low.[8]

4 Results

4.1 Description of the Data

Table 1 shows the summary statistics of the dataset of the Financial Inclusion Insights and map data. We examine a sample of 18,340 households from the six countries. The dependent variable is a dummy variable for the use of mobile money, coded 1 if the household has used any mobile money service within the past 90 days and 0 otherwise. The main explanatory variable is the shortest distance from the household location to the boundary of the areas covered by multiple mobile networks. This distance is positive (negative) if the household is outside (inside) the area covered by

[8]The coefficient stability test proposed by Altonji, Elder and Taber (2005) and Oster (2019) has become influential in empirical research. For example, Oster (2019) already had more than 1600 citations in Google Scholar by January 2021. Their technique is now widely used in papers published in major economics journals. For recent applications, see Mian and Sufi (2014) and Michalopoulos and Papaioannou (2016).

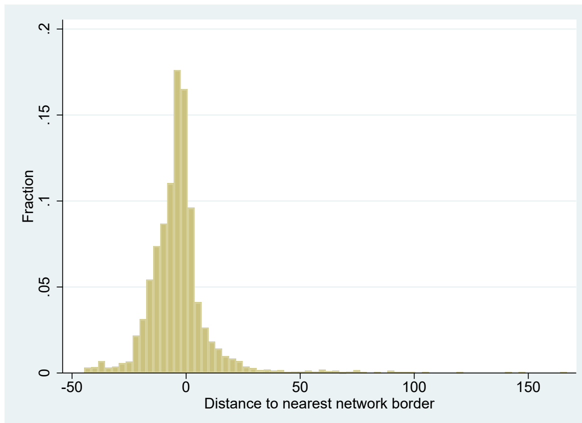
Table 1. Summary Statistics of Selected Variables in Pooled Data Set

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.228	0.420	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-3.092	15.28	-44.61	166.9
(Control Variables)				
Age of respondant	33.86	7.962	22	50
Gender dummy (Male=1, Female=0)	0.440	0.496	0	1
Marriage dummy (Married=1, Otherwise=0)	0.751	0.433	0	1
Head dummy (Head=1, Otherwise=0)	0.416	0.493	0	1
Working dummy (Working=1, Otherwise=0)	0.624	0.484	0	1
Location dummy (Urban=1, Rural=0)	0.341	0.474	0	1
Farmer dummy	0.503	0.500	0	1
Log of population density	6.261	1.636	-2.461	10.83
Log of night light	1.731	0.897	0.693	4.143
(Variables for Reference)				
Multiple Networks coverage dummy	0.714	0.452	0	1
Bank account dummy	0.230	0.421	0	1
Mobile Phone Owership dummy	0.702	0.457	0	1
N	18,340			

multiple mobile networks. Since the mean value of the explanatory variable is -3.081, households live 3.081 km inside the boundary of the network area covered by multiple mobile networks on average. The mean value of the network coverage dummy is 0.714, indicating that 71.4 percent of households live in an area in which multiple mobile networks are available.

The control variables are the respondent's age, sex, marital status, and education level (14 categories). We also include as control variables a male-headed dummy, currently working dummy, urban dummy, and farmer dummy as well as the distance to a bank (five categories), distance to an ATM (five categories), and the natural logs of population density and night light intensity at the household location. Population density and night light intensity are measured within a radius of 10 km from the household location using the population density map and night light map from 2005.[9] To save space in Table 1, we pool the descriptive statistics of the six countries. Tables A2–A7 in the Appendices shows the descriptive statistics for each country. Figure

Figure 1: Histogram of the Distance from the Border of the Area with Multiple Mobile Networks



Notes: The above histogram uses the pooled observations of the six countries. The horizontal axis is the shortest distance from the border of the area with multiple mobile networks. The unit is km.

1 shows the histogram of our key explanatory variable, the distance to the area with multiple mobile networks. This variable takes a negative value if the household location is in the network area and a positive value if it is outside. The histogram confirms that about 70 percent of households live in an area with multiple mobile networks.

To check the differences in the characteristics between countries, Table 2 shows the mean values of the variables related to mobile money for each country. The average use rate of the mobile money dummy varies among the six countries. The highest rate is Kenya's 78 percent and the second highest rate is Tanzania's 45.2 percent. The countries with a low use rate of mobile money are Nigeria and Pakistan, whose rates are 2.1 percent and 2.8 percent, respectively. The overall average use rate is 22.8 percent. Thus, there is substantial variation in the mobile money use rate among the six countries. In contrast, the differences in mobile network coverage and mobile phone

[9] We do not include a bank account ownership dummy or a mobile phone ownership dummy because of the possible endogeneity of these variables.

ownership between countries are small and do not deviate significantly from the overall average.

Table 2. Mean of Mobile Money Related Variables by Country

Country	Mobile money use dummy	Bank account dummy	Distance to nearest network border (km)	Multiple Networks coverage dummy	Mobile Phone Ownership dummy	N
Bangladesh	0.155	0.236	-10.16	0.791	0.724	3,995
Kenya	0.780	0.364	-2.668	0.800	0.841	2,034
Nigeria	0.0211	0.379	1.201	0.594	0.697	3,843
Pakistan	0.0282	0.130	-1.937	0.690	0.653	4,538
Tanzania	0.452	0.122	-0.270	0.709	0.692	2,029
Uganda	0.446	0.127	-3.135	0.769	0.644	1,901
All	0.228	0.23	-3.092	0.714	0.702	18,340

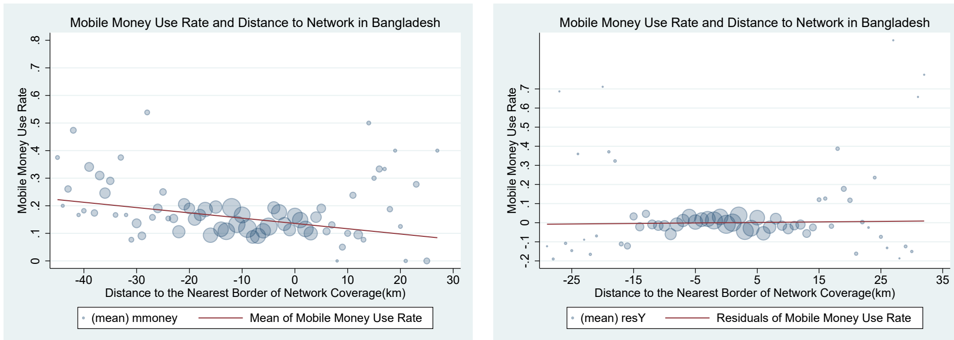
4.2 Results Using the Bangladesh Dataset

Figures 2(a) and 2(b) show the relationship between the distance from the border of the area with multiple mobile networks and the average mobile money use rate in Bangladesh. The size of each circle shows the sample size at each distance. In Figure 1(a), we do not control for any of the covariates; however, in Figure 2(b), we control for all the control variables: the respondent's age, sex, marital status, and education level (14 categories); a male-headed dummy, currently working dummy, urban dummy, and farmer dummy; distance to a bank (five categories) and distance to an ATM (five categories); and the natural logs of population density and night light intensity at the household location.

When we do not control for any of the control variables, there is a clear negative relationship between the distance from the border of the area with multiple mobile networks and the average mobile money use rate. However, once we control for the control variables, Figure 2(b) shows no clear relationship between those two variables.

Table 3 shows the regression results. In column (1) of Table 3, we do not include any of the control variables. In columns (1) to (4), we increase the number of control variables. When there are no other control variables, column (1) shows that if a

Figure 2: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Bangladesh



(a) Before Control

(b) After Control

Notes: In Figure 2(a), for each bin, the average mobile money use rate is calculated for a bin size of 0.5 km. Then, the scatterplot of the average mobile money use rate and fitted line are displayed with the average use rate of mobile money on the vertical axis and the distance variable on the horizontal axis. The size of the circle is the sample size in each bin. On the right of Figure 2(b), the horizontal axis is the residual of the regression regressing the distance on all the covariates. The vertical axis is the residual of the regression regressing the mobile money use dummy on all the covariates. The size of the bin is 0.5 km. the covariates are the respondent's age, sex, marital status, and education level (14 categories); a male-headed dummy, currently working dummy, urban dummy, and farmer dummy; distance to a bank (five categories) and distance to an ATM (five categories); and the natural logs of population density and night light intensity at the household location.

household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 1.81 percentage points. However, column (4) shows that such a relationship between the two variables disappears once we control for several confounding factors, especially population density and average night light intensity, which are proxies of income and urbanicity. Column (4) shows that the estimated coefficient of the distance from the area with multiple mobile networks to the use of mobile money is low, positive (in the opposite direction), and not significant. Thus, we cannot confirm that better accessibility to mobile networks increases the use of mobile money.

Table 3. The Effect of Distance to the Area with Multiple Mobile Networks in Bangladesh

Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.00191***	-0.000903*	-0.00103**	0.000270
	(0.000499)	(0.000478)	(0.000487)	(0.000702)
R-squared	0.005	0.100	0.103	0.105
N	3,995	3,995	3,995	3,995
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

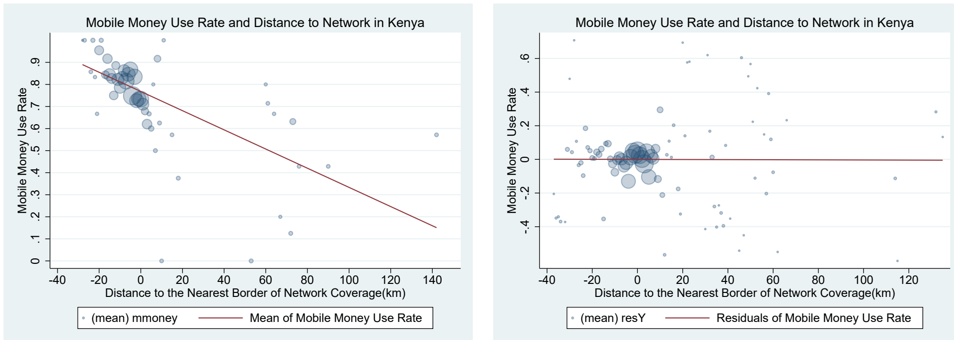
Notes: Robust standard errors in parentheses. Demographic characteristics are the respondent's age, sex, marital status, and education level (14 categories) as well as a male-headed dummy, currently working dummy, urban dummy, and farmer dummy, . Both the distance to a bank and the distance to an ATM are categorical variables (five categories). *** p<0.01, ** p<0.05, * p<0.1.

4.3 Results Using the Kenya Dataset

Figures 3(a) and 3(b) show the relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money in Kenya. In Figure 3(a), we do not control for any of the control variables, whereas we include all the control variables used in Bangladesh's figure in Figure 3(b). When we do not include any of the control variables, there is a clear negative relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money. However, once we control for the effect of the control variables, Figure 3 (b) shows no clear relationship between the two variables.

Table 4 shows the regression results. When we do not control for any of the control variables, column (1) shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 4.35 percentage points. However, column (2) shows that the statistically significant relationship dis-

Figure 3: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Kenya



(a) Before Control (b) After Control

Note: Notes of Figure 2 apply.

Table 4. The Effect of Distance to the Area with Multiple Mobile Networks in Kenya

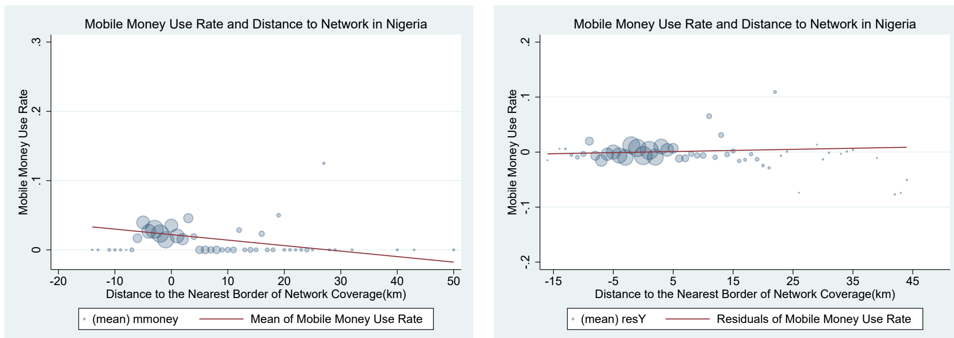
Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.00435***	-0.00111*	-0.00107	-6.19e-05
	(0.000650)	(0.000659)	(0.000676)	(0.000735)
R-squared	0.035	0.169	0.175	0.180
N	2,034	2,034	2,034	2,034
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

appears once we control for the demographic factors. Columns (3) and (4) show that when we control for the distances to a bank and an ATM, population density, and night light intensity, the estimated coefficient becomes low and not statistically significant. This shows that when a household becomes 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by -6.19e-04 percentage points. Given that the average use rate of mobile money in Kenya is 78 percent, the effect is practically zero.

4.4 Results Using the Nigeria Dataset

Figure 4: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Nigeria



(a) Before Control (b) After Control

Note: Notes of Figure 2 apply.

Table 5. The Effect of Distance to the Area with Multiple Mobile Networks in Nigeria

Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.000753***	7.12e-05	0.000275	0.000184
	(0.000250)	(0.000269)	(0.000280)	(0.000299)
R-squared	0.001	0.073	0.080	0.080
N	3,843	3,843	3,843	3,843
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

Nigeria has the lowest mobile money use rate (2.1 percent; Table 2). Figures 4(a) and 4(b) show the relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money in Nigeria. In Figure 4(a), we do not control for any of the control variables, whereas we include all the control variables used in Figure 1 in Figure 4(b). When we do not include any of the control variables, there is a negative relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money. However, once we control for the effect of the control variables, Figure 4(b) shows no clear relationship between the two variables.

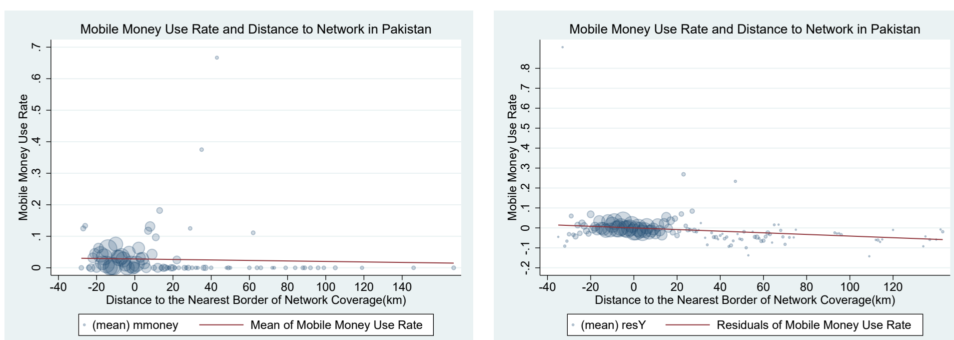
Table 5 shows the regression results. When we do not include any of the control variables, column (1) shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 0.75 percentage points. However, column (2) shows that the statistically significant relationship disappears and the estimated coefficient becomes virtually zero once we control for the demographic factors. Columns (3) and (4) show that when we control for the distances to a bank and an ATM, population density, and night light intensity, the estimated coefficient becomes low, positive (having the opposite sign) and not statistically significant. Thus, we cannot confirm that increasing accessibility to mobile networks increases the use of mobile money in Nigeria.

4.5 Results Using the Pakistan Dataset

Pakistan has a low mobile money use rate, almost as low as that of Nigeria (2.8 percent; Table 2). Figures 5(a) and 5(b) show the relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money in Pakistan. In Figure 5(a), we do not control for any of the control variables, whereas we include all the control variables used in the previous figures in Figure 5(b). When we do not control for any of the control variables, there is no clear relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money. However, once we control for the effect of the control variables, Figure 5(b) shows a solid relationship between the two variables.

Table 6 shows the regression results. When there are no control variables, column (1) shows that the effect of increasing network accessibility is practically zero. However, once we control for the demographic variables, there is a statistically significant relationship between the distance to the area with multiple networks and the use of mobile money. Column (2) of Table 6 shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 0.33 percentage points. Column (4) shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 0.4 percentage points. Although this 0.4 percentage point effect looks small, the average mobile money use rate in Pakistan is just 2.8 percent. Thus, if a household location becomes 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by $(0.4/2.8) \times 100 = 14.3$ percent, which is not small economically.

Figure 5: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Pakistan



(a) Before Control

(b) After Control

Note: Notes of Figure 2 apply.

4.6 Results Using the Tanzania Dataset

The mobile money use rate in the Tanzania dataset is 45.2 percent, making it one of the six countries with relatively high use along with Uganda. Figures 6(a) and 6(b)

Table 6. The Effect of Distance to the Area with Multiple Mobile Networks in Pakistan

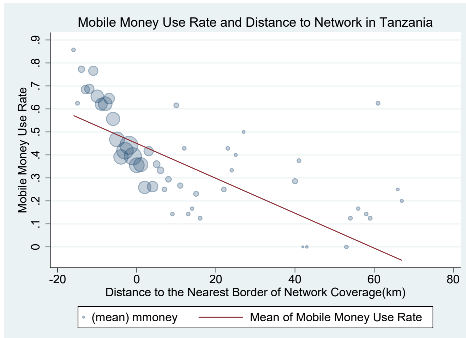
Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-7.56e-05	-0.000334***	-0.000372***	-0.000406***
	(8.61e-05)	(9.19e-05)	(9.55e-05)	(0.000119)
R-squared	0.000	0.053	0.056	0.061
N	4,538	4,538	4,538	4,538
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

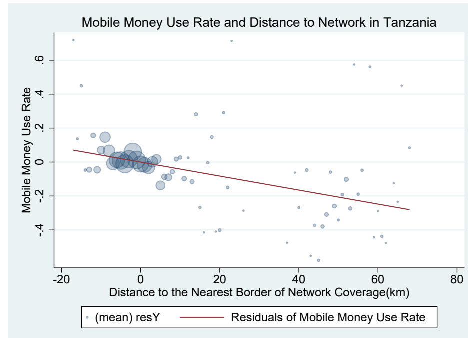
show the relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money in Tanzania. In Figure 6(a), we do not include any of the control variables, whereas we include all the control variables used in the previous figures in Figure 6(b). When we do not control for any of the covariates, there is a clear negative relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money. Further, even when we control for the effect of the control variables, Figure 6(b) shows a clear relationship between the two variables.

Table 7 shows the regression results. When we do not include any of the control variables, column (1) shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 7.6 percentage points, statistically significant at the 1 percent level. Column (4) shows that even when we include all the control variables and when a household's location becomes 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 4.16 percentage points, statistically significant at the 1 percent

Figure 6: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Tanzania



(a) Before Control



(b) After Control

Note: Notes of Figure 2 apply.

level. Since the average use rate of mobile money in Tanzania is 45.2 percent, this implies that if a household location becomes 10 km closer, the probability of using mobile money rises by $(4.16/45.2) \times 100 = 9.2$ percent.

Table 7. The Effect of Distance to the Area with Multiple Mobile Networks in Tanzania

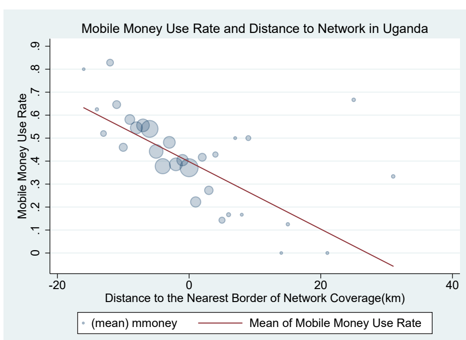
Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.00759***	-0.00477***	-0.00463***	-0.00416***
	(0.000833)	(0.000803)	(0.000797)	(0.000803)
R-squared	0.037	0.188	0.201	0.206
N	2,029	2,029	2,029	2,029
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

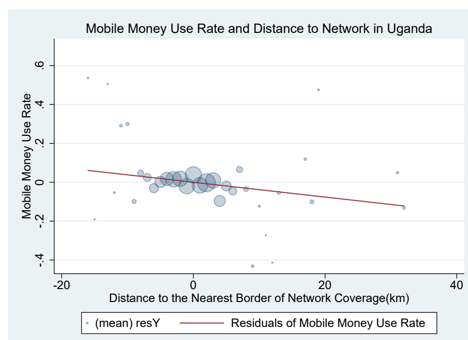
4.7 Results Using the Uganda Dataset

The mobile money use rate in Uganda is 44.6 percent, similar to the rate in Tanzania. Figures 7(a) and 7(b) show the relationship between the distance from the border of the area in which multiple mobile networks are available and the average use rate of mobile money. In Figure 7(a), we do not include any of the control variables, whereas we include all the control variables used in the previous figures in Figure 7(b). When we do not include any of the control variables, there is a clear negative relationship between the distance from the border of the area with multiple mobile networks and the average use rate of mobile money. Further, even if we control for the effect of the control variables, Figure 7(b) shows a clear relationship between the two variables.

Figure 7: Relationship between the Mobile Money Usage Rate and Distance to the Network Area in Uganda



(a) Before Control



(b) After Control

Note: Notes of Figure 2 apply.

Table 8 shows the regression results. When we do not include any of the control variables, column (1) shows that if a household is 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 11.1 percentage points, statistically significant at the 1 percent level. Column (4) shows that when we control for the effect of all the control variables and when a household's location becomes 10 km closer to the area with multiple mobile networks, the probability of using mobile money increases by 3.95 percentage points, statistically significant at the 10 percent level. Since the average use rate of mobile money in Uganda is 44.6 percent,

Table 8. The Effect of Distance to the Area with Multiple Mobile Networks in Uganda

Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.0151***	-0.00634***	-0.00514***	-0.00395*
	(0.00213)	(0.00181)	(0.00186)	(0.00209)
R-squared	0.030	0.217	0.228	0.229
N	1,901	1,901	1,901	1,901
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

this implies that if a household location becomes 10 km closer, the probability of using mobile money increases by 8.8 percent.

4.8 Robustness Checks

In the previous subsection, we examined the relationship between the distance from the area with multiple mobile networks and the use of mobile money. The analysis showed that in Uganda, Tanzania, and Pakistan, there are statistically and economically significant relationships between the distance from the area with multiple mobile networks and the use of mobile money. In this subsection, we examine the robustness of those results.

Using the Probit model and Restricting the Sample to within 20 km of the Border

Table 9 shows the results of the robustness check when using a different model and different samples. The rows in Table 9 show the estimation results using the datasets of the different countries. To compare the estimation results of the Probit model with those of the linear probability model, we show column (4) of the estimation results of the linear probability model in column (1) of Table 9. Column (2) of Table 9 shows the estimation results using the Probit model. To estimate the Probit model, we include all the control variables used in the linear probability model. Column (2) of Table 9 presents the marginal effect of the distance from the border of the area with multiple mobile networks, showing that the estimated coefficients of the Probit model are similar to those of the linear probability model.

Column (3) of Table 9 shows the estimation results when we restrict the sample to households who live within 20 km of the border of the area with multiple mobile networks regardless of whether they live inside or outside the network area. The idea is that if we include a remote household, it might differ substantially from households that live close to the border of the network. In such a case, the estimated coefficient might represent not only the distance effect but also the household heterogeneity effect. To prevent such a possibility, we restrict the sample to households that live within 20 km of the border of the network area regardless of whether they live inside or outside the network area.

The estimation results in column (3) show that the estimated coefficients change little even if we restrict the sample to households that live within 20 km of the border of the network area in this way. In Pakistan's case, the statistical significance disappears, although the estimated coefficient is similar. This is likely due to the smaller sample size and resulting higher standard error. Thus, we conclude that the results in the previous subsection are robust to using a Probit model estimation and restricting the sample to households that live within 20 km of the area with multiple mobile networks.

Oster's Coefficient Stability Test

Table 10 presents the results of the coefficient stability test. The different rows show the estimation results using the datasets of the different countries. Column (1) shows the estimated coefficient of the distance from the area with multiple mobile networks, its standard error, and its R-squared value when no control variables are included in the estimating equation. The standard errors are in parentheses and the R-squared values are in square brackets. Column (2) shows the estimated coefficient of this distance

Table 9. Comparison of the Estimated Coefficient of Distance in the Different Specifications

Dependent Variable	Mobile Money Use Dummy		
	(1)	(2)	(3)
Estimation Model	LPM	Probit	LPM
Sample	All	All	Within 20km from the border
Country			
Bangladesh	0.000270	0.000130	0.000896
	(0.000702)	(0.000881)	(0.000937)
	[3995, 0.105]	[3955, 0.118]	[3214, 0.088]
Kenya	-6.19e-05	7.51e-05	-0.000310
	(0.000735)	(0.000580)	(0.00234)
	[2034, 0.180]	[2034, 0.178]	[1881, 0.167]
Nigeria	0.000184	0.000258	0.000498
	(0.000299)	(0.000325)	(0.000408)
	[3843, 0.080]	[3843, 0.277]	[3734, 0.080]
Pakistan	-0.000406***	-0.000453***	-0.000306
	(0.000119)	(0.000159)	(0.000393)
	[4538, 0.061]	[4538, 0.237]	[3920, 0.061]
Tanzania	-0.00416***	-0.00447***	-0.00736***
	(0.000803)	(0.000948)	(0.00254)
	[2029, 0.206]	[2029, 0.164]	[1915, 0.204]
Uganda	-0.00395*	-0.00400*	-0.00561**
	(0.00209)	(0.00210)	(0.00264)
	[1901, 0.229]	[1901, 0.187]	[1877, 0.229]

Notes: Each cell shows the estimated coefficient of the distance from the border of the network area, its standard error, the sample size, and the R-squared value. In all the regressions, the dependent variable is the mobile money use dummy and the regression equation includes all the control variables used in column (4) in the previous tables. In the Sample row, "all" implies that there is no restriction on the data. Within 20km from the border means that the sample is restricted to households within 20 km of the border of the network area. Standard errors are shown in parentheses and the sample size and R-squared value are shown in square brackets. *** p<0.01, ** p<0.05, * p<0.1.

variable, its standard error, and its R-squared value when all the control variables are used.

Column (3) shows the R-max, which is a hypothetical R-squared when all the

Table 10: Coefficient Robustness to Unobservable Factors

	(1)	(2)	(3)	(4)	(5)
	Baseline Effect (Std. Err), [R2]	Controlled Effect (Std Err),[R2]	R-max	δ for b =0	Identified Set of b
Bangladesh	-0.00191***	0.00027	0.136	-0.17	[0.00027, 0.00326]
	(0.000499),[0.005]	(0.000702),[0.105]			
Kenya	-0.00435***	-6.19E-05	0.234	0.025	[-6.19e-05, 0.00284]
	(0.000650),[0.035]	(0.000735),[0.180]			
Nigeria	-0.000753***	0.000184	0.105	-0.47117	[0.000184, 0.00066]
	(0.000250),[0.001]	(0.000299),[0.080]			
Pakistan	-7.56e-05	-0.000406***	0.079	-4.47	[-0.00062 , -0.000406]
	(8.61e-05), [0.000]	(0.000119),[0.061]			
Tanzania	-0.00759***	-0.00416***	0.268	2.32	[-0.00416, -0.00263]
	(0.000833), [0.037]	(0.000803),[0.206]			
Uganda	-0.0151***	-0.00395*	0.298	0.67	[-0.00395, 0.00230]
	(0.00213), [0.030]	(0.00209),[0.229]			

Notes: The table shows the coefficient robustness to unobservable factors based on Oster (2019). The rows show the estimation results using each country's dataset. Column (1) shows the estimated coefficient of the distance from the border of the area with multiple mobile networks, its standard error, and the R-squared value in the baseline model. Standard errors are in parentheses and the R-squared value is in square brackets. Column (2) shows the estimated coefficient of the same variable, its standard error, and the R-squared value when all the control variables are used. Column (3) shows the R-max value, the maximum R-squared value when all unobservable factors are hypothetically included in the control variables. Oster (2019) argues that 1.3 multiplied by the R-squared value when all observable control variables are used is appropriate. Thus, we follow Oster's recommendation. Column (4) shows the degree to which unobservable factors need to be important to zero out the estimated coefficient of the distance. Column (5) shows the potential region of the estimated coefficient of the distance when unobservable factors are correlated with the distance as observable control variables.

observable and *unobservable* control variables are included in the estimating equation.[10]

[10] Since our dependent variable is a dummy variable, it is reasonable that the R-max does not become 1 even if all the unobservable control variables are included.

Oster argues that it is reasonable to assume that the R-max is equal to 1.3 multiplied by the R-squared value of the estimation when all *observable* control variables are included. Following Oster's recommendation, we calculate the R-max as the R-squared value of column (2) multiplied by 1.3. Column (4) includes Altonji et al. (2005) and Oster (2019)'s δ, which show the degree to which unobservable factors need to affect the estimated coefficient of the distance variable compared with the degree to which observable control variables affect the estimated coefficient of the distance variable to zero out the latter. For example, if δ is 2, this implies that unobservable factors need to affect the estimated coefficient of the distance variable twice as much as the degree to which observable factors affect it to make the estimated coefficient zero. Altonji, Elder and Taber (2005) and Oster (2019) argue that if δ is above one, then it is unlikely that unobservable factors make the estimated coefficient of the distance variable zero. Moreover, if δ is negative, this implies that as more observable control variables are added, the estimated coefficient becomes further away from zero and more significant. As a result, to make the estimated coefficient zero, unobservable factors must affect the estimated coefficient in the opposite direction to observable control variables. Since such a case is unlikely, when δ is above one or negative, we can conclude that it is unlikely that unobservable factors will zero out the estimated coefficient of the distance variable. Column (5) shows the robust region of the true value of the coefficient of the distance variable assuming that unobservable factors affect the estimated coefficient to the same degree as the observable control variables. If this robust region is within the negative (positive) region, it implies that the estimated coefficient in column (2) is robust (not robust) to unobservable factors.

Investigating columns (4) and (5) of Table 10, we can conclude that the estimation results using the Pakistan and Tanzania datasets are robust to potential unobservable factors. Regarding Uganda, however, we cannot reject the possibility that unobservable factors might make the estimated coefficient of the distance variable zero.

Analysis Using Different Network Maps

In the regression analysis using the Kenyan dataset, we obtain the network area by taking the intersection of the network areas of Safaricom (90.4 percent market share) and Airtel (21.2 percent). However, since the network area of Airtel is much smaller than that of Safaricom, one might argue that such a method is unsuitable since 90 percent of people in Kenya use Safaricom. Thus, as a robustness check, we use only the network area of Safaricom. We measure the shortest distance to the network area of Safaricom and use it as the distance to the network area in the regression analysis. Table 11 shows the regression results using the distance to the network of Safaricom as the key explanatory variable. We see that the results are similar to those when the distance variable is created using the intersection of the network areas of Safaricom and Airtel (see Table 4). In column (4), where all the control variables are included, the results do not reach significance and the sign is the opposite to that in Table 4. This result confirms that there is no significant relationship between the distance to the network area and the use of mobile money in Kenya, where the mobile money use rate is above 70 percent.

Table 11. Robustness Check for Kenya (Only Safaricom)

Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	-0.00354***	-0.000928*	-0.000928*	6.58e-06
	(0.000553)	(0.000563)	(0.000563)	(0.000618)
R-squared	0.025	0.175	0.175	0.180
N	2,034	2,034	2,034	2,034
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

Similarly, in Nigeria, MTN (64.1 percent market share), Airtel (31.7 percent), and Glo (22.8 percent) are the major mobile network operators. One might think that the inclusion of Glo, which has a small market share, reduces the network area since we use the intersection of these three mobile network operators. To check the robustness of this result, we remove the network map of Glo. Thus, the network area is the intersection of only two companies, MTN and Airtel. Then, we measure the shortest distance to the area with multiple mobile networks and rerun the regression. Table 12 shows that there is no significant relationship between the two variables, confirming the results in Table 5.

Table 12. Robustness Check for Nigeria (Only Two Mobile Operators)

Dependent Variable	Mobile Money Use Dummy			
Estimation Model	LPM			
	(1)	(2)	(3)	(4)
Distance	8.28e-06	0.000187	0.000227*	0.000189
	(0.000111)	(0.000117)	(0.000120)	(0.000128)
R-squared	0.000	0.030	0.080	0.080
N	3,843	3,843	3,843	3,843
Control Variables				
Demographic Characteristics		Yes	Yes	Yes
Distances to Bank & ATM			Yes	Yes
Population Density				Yes
Night Light Luminosity				Yes

Notes: Robust standard errors in parentheses. Notes of Table 3 apply. *** p<0.01, ** p<0.05, * p<0.1.

5 Discussion and Conclusion

In this study, we examine the effect of network accessibility on the use of mobile money using GPS data on household location and the network coverage maps of mobile network providers. To quantify network accessibility, we measure the shortest distance from each household location to the border of the areas in which several mobile networks are available and use it as an index of network accessibility. To control for confounding factors, we use various individual and household characteristics as well as night light intensity and population density at the household location. To avoid the reverse causality running from the use of mobile money to night light intensity and population density, we use the night light and population density maps for 2005 (i.e., before the introduction of mobile money). We find that 70 percent of households in each country live in areas with multiple mobile networks.

The estimation results found in this study indicate that the effect of network accessibility on the use of mobile money is not universal in developing countries. More specifically, among the six countries (Bangladesh, Kenya, Nigeria, Pakistan, Tanzania, and Uganda), there is a negative relationship between the distance to the area with multiple mobile networks and the use of mobile money in five countries. However, once we control for demographic factors, distances to a bank and an ATM, population density, and night light intensity, we find a negative relationship between those two variables only in Pakistan, Tanzania, and Uganda. Furthermore, for Uganda, our coefficient stability test indicates that we cannot reject the possibility that unobservable factors generate this negative relationship between the distance to the network area and the use of mobile money. Thus, we find a robust relationship between the distance to the network area and use of mobile money only in Pakistan and Tanzania.

In our six countries, the use rates of mobile money differ substantially. The highest rate is 78 percent in Kenya and the lowest rate is 2.1 percent in Nigeria. Among the two countries in which the effect of network accessibility on the adoption of mobile money is robust (Tanzania and Pakistan), the mobile money use rate in Tanzania is 45 percent, while that in Pakistan is 3 percent. Thus, the overall mobile money adoption rate does not seem to affect how mobile networks impact on the use of mobile money. This suggests that the impediment of the use of mobile money is not likely to come from the poor infrastructure but other reasons such as the reliability of mobile network providers, inconvenience, or culture.

Our estimation results explain why studies using macro-data on network coverage, which treat one country's data as one observation, sometimes provide different results on how network accessibility affects the use of mobile money. For example, Lashitew, van Tulder and Liasse (2019) show that network coverage does not affect the use of mobile money using macro-data, while Asongu, Biekpe and Cassimon (2020) show that network connectivity has a positive effect. Our results indicate that the effect of network accessibility can differ by country. Thus, the assumption of cross-country studies that in principle assume that the effect of network accessibility is the same across countries is unlikely to hold.

Quantitatively, our results show that in Tanzania and Pakistan, if a household's location becomes 10 km closer to the area with multiple mobile networks or moves 10 km inside such an area, the probability of using mobile money increases by 10 percent. Although the overall mobile money use rates in Pakistan and Tanzania differ, these effects are similar in both countries, which may suggest that similar economic mechanisms are working regarding mobile network and mobile money adoption in these two countries.

However, our analysis had two limitations. First, the lack of panel data prevented us from examining the dynamic aspect of the effect of the network on mobile money adoption. The second limitation of our study was the number of countries used in our analysis due to the lack of detailed network coverage maps in other countries. Owing to this limitation, we restricted our analysis to six countries. This prevented us from conducting a more extensive analysis, as discussed below.

Our results may have important policy implications for the expansion of mobile networks. Recent economics research shows that mobile money offers various benefits to the economy. For instance, it enhances consumption smoothing in the presence of shocks (Jack and Suri, 2014; Blumenstock et al., 2016; Riley, 2018), encourages the receipt of remittances (Munyegera and Matsumoto, 2016), economizes the welfare system (Aker et al., 2016), and increases human capital accumulation (Abiona and Koppensteiner, 2020). Given such benefits, one might be tempted to suggest that the government should encourage the expansion of mobile networks despite this approach needing substantial initial investment, given that mobile network coverage is insufficient in the rural areas of many developing countries. In addition, as we discussed in the Introduction, several companies are planning satellite-based Internet constellations, which can increase accessibility to the Internet. However, our results may indicate that increasing network accessibility does not always raise the use of mobile money in developing countries.

An important future research question is which country, a government should increase network coverage to have the largest effect on financial inclusion and economic activities. This information would be useful for obtaining the largest benefit from the given investment. When the number of countries in the analysis increases through the availability of network coverage maps, such an analysis will be feasible.

References

Abiona, Olukorede and Martin Foureaux Koppensteiner (2020) "Financial Inclusion, Shocks, and Poverty: Evidence from the Expansion of Mobile Money in Tanzania," *Journal of Human Resources*, pp. 1018–9796R1.

Afawubo, Komivi, Mawuli K Couchoro, Messan Agbaglah, and Tchapo Gbandi (2020) "Mobile money adoption and households vulnerability to shocks: Evidence from Togo," *Applied Economics*, Vol. 52, pp. 1141–1162.

Aggarwal, Shilpa and Leora Klapper (2013) "Designing government policies to expand financial inclusion: Evidence from around the world," *The Journal of Finance*, Vol. 56, pp. 1029–51.

Aker, Jenny C, Rachid Boumnijel, Amanda McClelland, and Niall Tierney (2016) "Payment Mechanisms and Antipoverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger," *Economic Development and Cultural Change*, Vol. 65, pp. 1–37.

Akinyemi, Babatope E and Abbyssinia Mushunje (2020) "Determinants of mobile money technology adoption in rural areas of Africa," *Cogent Social Sciences*, Vol. 6, p. 1815963.

Alesina, Alberto, Stelios Michalopoulos, and Elias Papaioannou (2016) "Ethnic inequality," *Journal of Political Economy*, Vol. 124, pp. 428–488.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber (2005) "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of political economy*, Vol. 113, pp. 151–184.

Asian Development Bank (2021) "Five ways low earth orbit satellites will impact Asia and the Pacific," `https://www.adb.org/news/features/five-ways-low-earth-orbit-satellites-impact-asia-pacific`.

Asongu, Simplice A, Nicholas Biekpe, and Danny Cassimon (2020) "Understanding the greater diffusion of mobile money innovations in Africa," *Telecommunications Policy*, Vol. 44, p. 102000.

Batista, Catia and Pedro C Vicente (2020) "Adopting mobile money: Evidence from an experiment in rural Africa," in *AEA Papers and Proceedings*, Vol. 110, pp. 594–98.

Blumenstock, Joshua E, Michael Callen, Tarek Ghani, and Lucas Koepke (2015) "Promises and pitfalls of mobile money in Afghanistan: evidence from a randomized control trial," in *Proceedings of the Seventh International Conference on Information and Communication Technologies and Development*, p. 15, ACM.

Blumenstock, Joshua E, Nathan Eagle, and Marcel Fafchamps (2016) "Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters," *Journal of Development Economics*, Vol. 120, pp. 157–181.

Center for International Earth Science Information Network - CIESIN - Columbia University (2015) "Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision UN WPP Country Totals, Revision 11.," `https://doi.org/10.7927/H4F47M65` accessed in 2021 January 21.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess

(2018) *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*: The World Bank.

Dupas, Pascaline and Jonathan Robinson (2013) "Savings constraints and microenterprise development: Evidence from a field experiment in Kenya," *American Economic Journal: Applied Economics*, Vol. 5, pp. 163–92.

Evans, David S and Alexis Pirchio (2014) "An empirical examination of why mobile money schemes ignite in some developing countries but flounder in most," *Review of Network Economics*, Vol. 13, pp. 397–451.

Financial Inclusion Insights Program (2017) "Financial Inclusion Insights Data Set," `http://finclusion.org/data_fiinder/` accessed in 2021 January 21.

GSM Association (2020) "State of the Industry Report on Mobile Money 2019," https://www.gsma.com/sotir/wp-content/uploads/2020/03/GSMA-State-of-the-Industry-Report-on-Mobile-Money-2019-Full-Report.pdf, Accessed January 15th 2021.

Hasbi, Maude and Antoine Dubus (2020) "Determinants of mobile broadband use in developing economies: Evidence from Sub-Saharan Africa," *Telecommunications Policy*, Vol. 44, p. 101944.

Henderson, J Vernon, Adam Storeygard, and David N Weil (2012) "Measuring economic growth from outer space," *American economic review*, Vol. 102, pp. 994–1028.

Hughes, Nick and Susie Lonie (2007) "M-PESA: mobile money for the unbanked turning cellphones into 24-hour tellers in Kenya," *Innovations: technology, governance, globalization*, Vol. 2, pp. 63–81.

Jack, William and Tavneet Suri (2014) "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution," *The American Economic Review*, Vol. 104, pp. 183–223.

Kabengele, Christian and Rüdiger Hahn (2021) "Institutional and firm-level factors for mobile money adoption in emerging markets–A configurational analysis," *Technological Forecasting and Social Change*, Vol. 171, p. 120934.

Lashitew, Addisu A, Rob van Tulder, and Yann Liasse (2019) "Mobile phones for financial inclusion: What explains the diffusion of mobile money innovations?" *Research Policy*, Vol. 48, pp. 1201–1215.

Mian, Atif and Amir Sufi (2014) "What explains the 2007–2009 drop in employment?" *Econometrica*, Vol. 82, pp. 2197–2223.

Michalopoulos, Stelios and Elias Papaioannou (2016) "The long-run effects of the scramble for Africa," *American Economic Review*, Vol. 106, pp. 1802–48.

Mothobi, Onkokame and Lukasz Grzybowski (2017) "Infrastructure deficiencies and adoption of mobile money in Sub-Saharan Africa," *Information Economics and Policy*, Vol. 40, pp. 71–79.

Munyegera, Ggombe Kasim and Tomoya Matsumoto (2016) "Mobile money, remittances, and household welfare: panel evidence from rural Uganda," *World Development*, Vol. 79, pp. 127–137.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar (2016) "Building state capacity: Evidence from biometric smartcards in India," *American Economic Review*, Vol. 106, pp. 2895–2929.

Murendo, Conrad, Meike Wollni, Alan De Brauw, and Nicholas Mugabi (2018) "Social network effects on mobile money adoption in Uganda," *The Journal of Development Studies*, Vol. 54, pp. 327–342.

National Oceanic and Atmospheric Administration, National Geophysical Data Center (2015) "DMSP data collected by the US Air Force Weather Agency," `https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html` accessed in 2021 January 21.

N'dri, Lasme Mathieu and Makoto Kakinaka (2020) "Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso," *Telecommunications Policy*, Vol. 44, p. 101926.

Oster, Emily (2019) "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, Vol. 37, pp. 187–204.

Perlman, Leon and Michael Wechsler (2019) "Mobile Coverage and its Impact on Digital Financial Services," *Available at SSRN 3370669*.

Pfeifer, Gregor, Fabian Wahl, and Martyna Marczak (2018) "Illuminating the world cup effect: night lights evidence from South Africa," *Journal of regional science*, Vol. 58, pp. 887–920.

Riley, Emma (2018) "Mobile money and risk sharing against village shocks," *Journal of Development Economics*, Vol. 135, pp. 43–58.

——— (2020) "Resisting Social Pressure in the Household Using Mobile Money: Experimental Evidence on Microenterprise Investment in Uganda," *University of Oxford, May*, Vol. 25.

Storeygard, Adam (2016) "Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa," *The Review of economic studies*, Vol. 83, pp. 1263–1295.

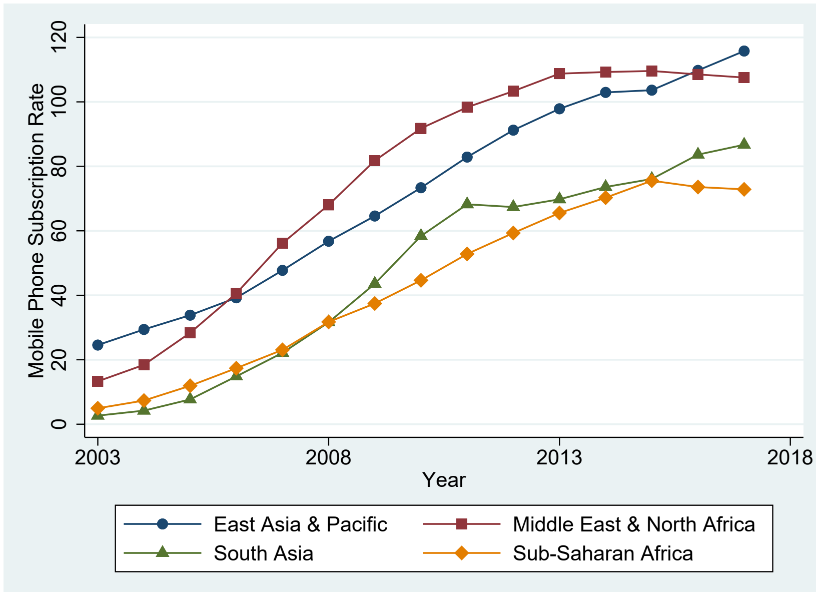
Suri, Tavneet and William Jack (2016) "The long-run poverty and gender impacts of mobile money," *Science*, Vol. 354, pp. 1288–1292.

Tonuchi, Joseph E (2020) "How to Improve Mobile Money Service Usage and Adoption by Nigerians in the Era of COVID-19," *International Journal of Finance, Insurance and Risk Management*, Vol. 10.

World Bank (2014) "Financial Inclusion Data Global Findex," `http://datatopics.worldbank.org/financialinclusion/`.

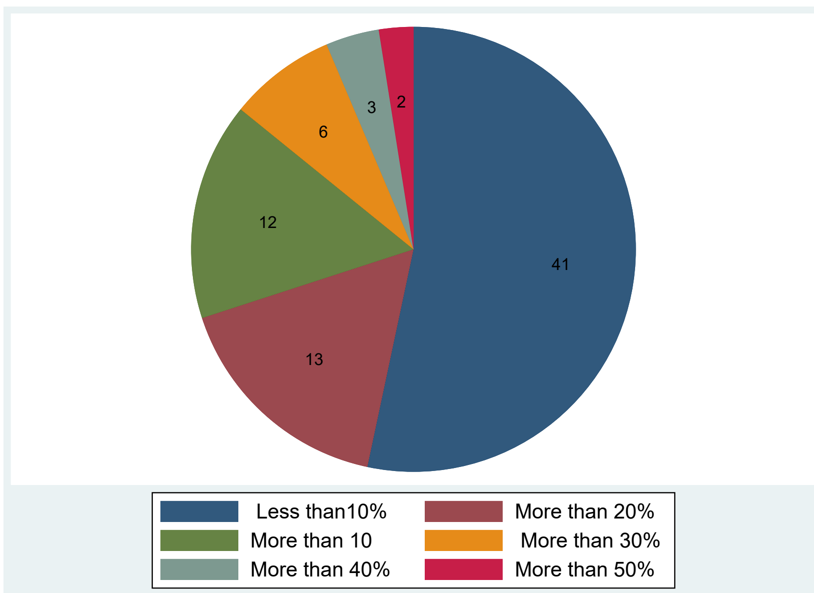
Appendices

Figure A1: Mobile Phone Subscriptions Globally (Percentage of the Population)



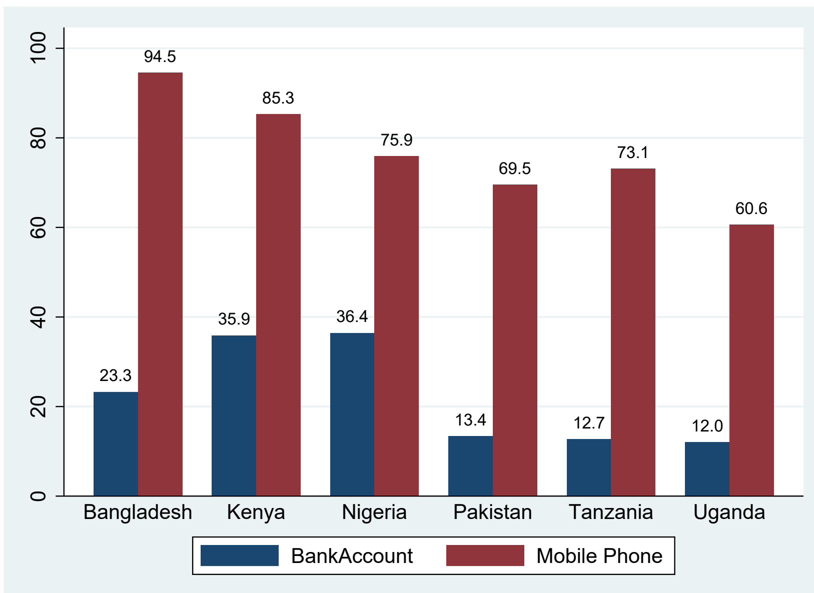
Note: Based on the authors' calculation from the World Development Indicators.

Figure A2: The Spread of Mobile Money Globally



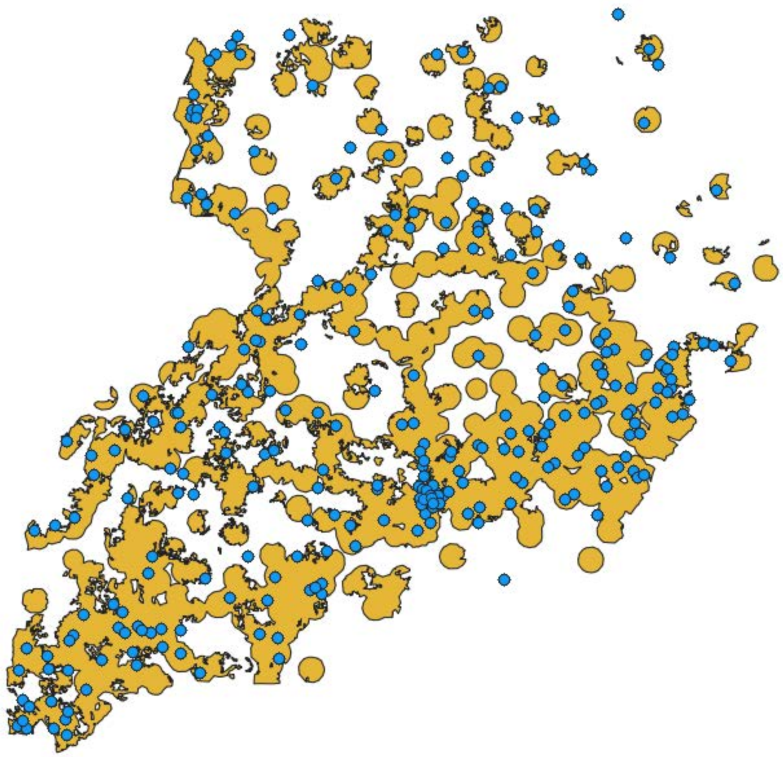
Note: Based on the authors' calculation from the Global Findex Report. The number of sample countries is 77. This graph shows that of the 77 sample countries, the mobile money use rate is less than 10 percent in 41 and less than 20 percent in 54.

Figure A3: Bank Account and Mobile Phone Ownership Rates in the Six Countries (Percentage of the Population)



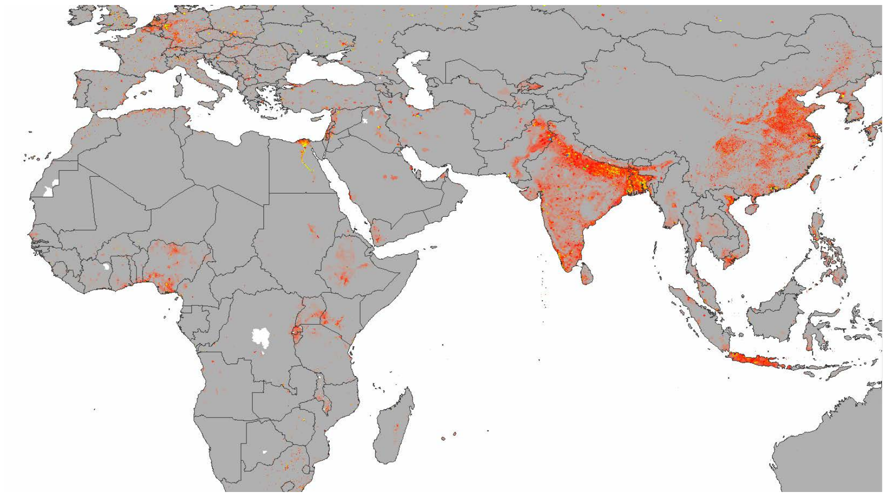
Note: Based on the authors' calculation from the Findex Survey and World Development Indicators. The numbers of bank accounts and mobile phones are the percentage of the population above age 15.

Figure A4: Mobile Network Coverage Map and Household Locations in Uganda



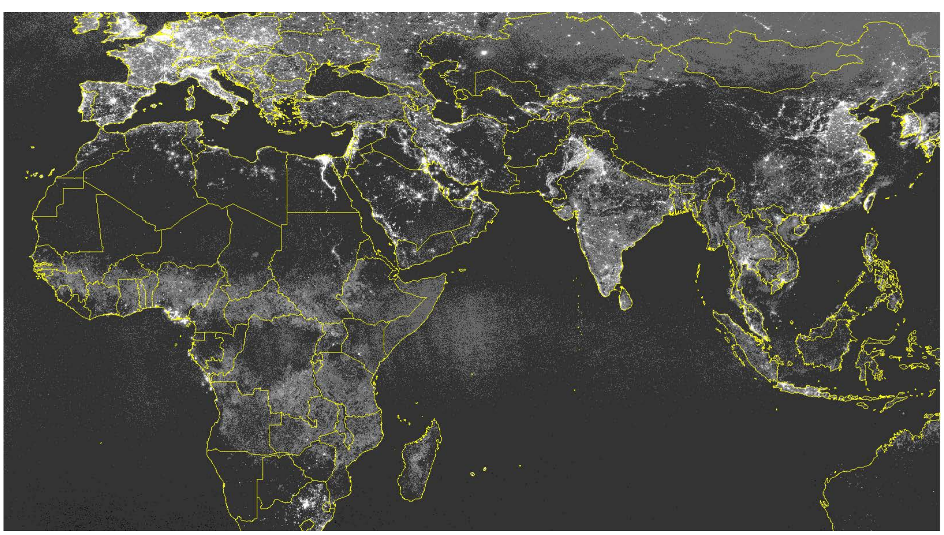
Note: Constructed by the authors. Overlaying the maps of the three mobile networks, we select the area of their intersection and then overlay household locations (blue points).

Figure A5: Population Density Map



Source: CIESIN Gridded Population of the World, v4UN WPP-Adjusted Population Density, v4.11 (2005).

Figure A6: Night Light Map



Source: NOAA

Table A1. Mobile Phone Operators and Market Shares

Country	Mobile Phone		
	Rank	Operator	Share
	(1)	Grameenphone	52.0%
Bangladesh	(2)	Banglalink	22.0%
	(3)	Robi Axiata	20.6%
	(1)	Safaricom	90.4%
Kenya	(2)	Airtel	21.1%
	(3)	Orange	8.3%
	(1)	MTN	64.1%
Nigeria	(2)	Airtel	31.7%
	(3)	Glo	22.8%
	(1)	Jazz	32.8%
Pakistan	(2)	Telenor	21.9%
	(3)	Zong	12.3%
	(1)	Vodacom	48.4%
Tanzania	(2)	Airtel	40.1%
	(3)	Tigo	35.0%
	(1)	MTN	58.4%
Uganda	(2)	Airtel	39.9%
	(3)	Africell	5.3%

Table A2. Summary Statistics of Selected Variables of Bangladesh Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.155	0.362	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-10.16	12.84	-44.61	26.69
(Control Variables)				
Age of respondant	33.99	7.922	22	50
Gender dummy (Male=1, Female=0)	0.440	0.496	0	1
Marriage dummy (Married=1, Otherwise=0	0.902	0.298	0	1
Head dummy (Head=1, Otherwise=0)	0.386	0.487	0	1
Working dummy (Working=1, Otherwise=(	0.426	0.495	0	1
Location dummy (Urban=1, Rural=0)	0.283	0.451	0	1
Farmer dummy	0.601	0.490	0	1
Log of population density	7.394	0.971	6.012	10.83
Log of night light	1.607	0.792	0.693	3.809
(Variables for Reference)				
Multiple Networks coverage dummy	0.791	0.407	0	1
Bank account dummy	0.236	0.424	0	1
Mobile Phone Owership dummy	0.724	0.447	0	1
N	3,995			

Table A3. Summary Statistics of Selected Variables of Kenya Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.780	0.415	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-2.668	17.74	-27.89	142.4
(Control Variables)				
Age of respondant	32.60	7.756	22	50
Gender dummy (Male=1, Female=0)	0.339	0.474	0	1
Marriage dummy (Married=1, Otherwise=0	0.566	0.496	0	1
Head dummy (Head=1, Otherwise=0)	0.488	0.500	0	1
Working dummy (Working=1, Otherwise=(	0.706	0.456	0	1
Location dummy (Urban=1, Rural=0)	0.414	0.493	0	1
Farmer dummy	0.390	0.488	0	1
Log of population density	6.197	1.791	-2.461	10.01
Log of night light	1.469	0.837	0.705	3.654
(Variables for Reference)				
Multiple Networks coverage dummy	0.800	0.400	0	1
Bank account dummy	0.364	0.481	0	1
Mobile Phone Owership dummy	0.841	0.366	0	1
N		2,034		

Table A4. Summary Statistics of Selected Variables of Nigeria Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.0211	0.144	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	1.201	7.160	-14.06	49.52
(Control Variables)				
Age of respondant	33.54	7.853	22	50
Gender dummy (Male=1, Female=0)	0.503	0.500	0	1
Marriage dummy (Married=1, Otherwise=0)	0.710	0.454	0	1
Head dummy (Head=1, Otherwise=0)	0.425	0.494	0	1
Working dummy (Working=1, Otherwise=0)	0.732	0.443	0	1
Location dummy (Urban=1, Rural=0)	0.408	0.491	0	1
Farmer dummy	0.441	0.497	0	1
Log of population density	5.873	1.615	2.836	10.18
Log of night light	1.759	0.886	0.694	3.949
(Variables for Reference)				
Multiple Networks coverage dummy	0.594	0.491	0	1
Bank account dummy	0.379	0.485	0	1
Mobile Phone Owership dummy	0.697	0.460	0	1
N		2,034		

Table A5. Summary Statistics of Selected Variables of Pakistan Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.0282	0.166	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-1.937	21.53	-27.83	166.9
(Control Variables)				
Age of respondant	34.88	7.942	22	50
Gender dummy (Male=1, Female=0)	0.497	0.500	0	1
Marriage dummy (Married=1, Otherwise=0	0.888	0.315	0	1
Head dummy (Head=1, Otherwise=0)	0.331	0.471	0	1
Working dummy (Working=1, Otherwise=(	0.515	0.500	0	1
Location dummy (Urban=1, Rural=0)	0.327	0.469	0	1
Farmer dummy	0.552	0.497	0	1
Log of population density	6.260	1.421	2.188	10.53
Log of night light	2.251	0.921	0.693	4.143
(Variables for Reference)				
Multiple Networks coverage dummy	0.690	0.463	0	1
Bank account dummy	0.130	0.337	0	1
Mobile Phone Owership dummy	0.653	0.476	0	1
N	4,538			

Table A6. Summary Statistics of Selected Variables of Tanzania Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.452	0.498	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-0.270	12.67	-16.00	67.24
(Control Variables)				
Age of respondant	33.42	8.046	22	50
Gender dummy (Male=1, Female=0)	0.356	0.479	0	1
Marriage dummy (Married=1, Otherwise=0	0.602	0.490	0	1
Head dummy (Head=1, Otherwise=0)	0.489	0.500	0	1
Working dummy (Working=1, Otherwise=(	0.777	0.416	0	1
Location dummy (Urban=1, Rural=0)	0.333	0.471	0	1
Farmer dummy	0.516	0.500	0	1
Log of population density	5.296	1.964	0.535	9.866
Log of night light	1.389	0.696	0.744	3.660
(Variables for Reference)				
Multiple Networks coverage dummy	0.709	0.454	0	1
Bank account dummy	0.122	0.327	0	1
Mobile Phone Owership dummy	0.692	0.462	0	1
N		2,029		

Table A7. Summary Statistics of Selected Variables of Uganda Data Set

	(1)	(2)	(3)	(4)
VARIABLES	mean	sd	min	max
(Main Dependent Variable)				
Mobile money use dummy (use=1, not=0)	0.446	0.497	0	1
(Main Explanatory Variable)				
Distance to nearest network border (km)	-3.135	5.723	-15.90	31.22
(Control Variables)				
Age of respondant	33.64	8.155	22	50
Gender dummy (Male=1, Female=0)	0.375	0.484	0	1
Marriage dummy (Married=1, Otherwise=C	0.542	0.498	0	1
Head dummy (Head=1, Otherwise=0)	0.509	0.500	0	1
Working dummy (Working=1, Otherwise=(	0.835	0.371	0	1
Location dummy (Urban=1, Rural=0)	0.293	0.455	0	1
Farmer dummy	0.415	0.493	0	1
Log of population density	5.766	1.405	2.247	9.114
Log of night light	1.341	0.738	0.697	3.381
(Variables for Reference)				
Multiple Networks coverage dummy	0.769	0.422	0	1
Bank account dummy	0.127	0.333	0	1
Mobile Phone Owership dummy	0.644	0.479	0	1
N	1,901			