Does Use of Mobile Money Affect Saving Decision? Evidence from the Data in Zimbabwe

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Abstract

According to estimates by the World Bank, only 63% of adults in developing countries have a bank account due to reasons such as the distance to financial institutions. Lacking a formal bank account makes it difficult for households to save safely and prepare for potential future negative shocks. However, recent technological developments have started to change the financial access of non-bank users due to the development of mobile money technology. This study examines the effect of the use of mobile money on saving and borrowing using information on mobile phone network coverage and 2SLS estimation strategy Zimbabwe. I find that the use of mobile money increases the probability of saving and borrowing by 14 percent and 12 percentage points. I also find that the use of mobile money increase the probability of receiving remittance by 45 percentage point. On the other hand, the effect of negative shock on borrowing and receiving remittance does not depend on the use of mobile money. This implies the use of mobile money increases the opportunity of saving, the probability of receiving remittance, borrowing money regardless of the negative shocks. Finally, we also found that the use of mobile money increase in saving in mobile money account but it does not increase saving in a bank account. In short, the availability of the mobile network makes households more accessible to mobile money and make them more financially active and increase saving, borrowing and receiving remittance. In our data, the mobile money is not used to buffer negative shocks, contrary to the claims of the previous studies such as Jack and Suri (2014) and Riley (2018).

1 Introduction

According to estimates by the World Bank, 94% of adults in developed countries have a bank account, while only 63% of adults in developing countries have a bank account due to reasons such as the distance to financial institutions. Lacking a formal bank account makes it difficult for households to save safely and prepare for potential future negative shocks. However, recent technological developments have started to change the financial access of non-bank users due to the development of mobile money technology. Mobile money allows the holder of a SIM card of a mobile phone to transfer money to another holder with a different SIM card.[1] In addition, mobile money operators often offer a savings account in which customers can save with a reasonable interest rate by depositing money with the nearest mobile money agent.[2]

According to a financial inclusion survey by the World Bank (World Bank, 2019), only 55, 19, and 17 percent of adults have a bank account in Kenya, Tanzania, and Zimbabwe, respectively, whereas 58, 32, and 32 percent of adults already have mobile money accounts.

The mobile money has proliferated at an accelerated pace. In Zimbabwe, mobile money was officially introduced in 2011, and, by 2015, the amount of money transferred through mobile money was almost the same as the amount of money circulating in the traditional banking system. In Tanzania, mobile money was officially introduced in 2008. In 2009, the user rate of mobile money was just 1.1 percent; however, this rose to 32 percent in 2013 and 55.8 percent in 2017.

Given this high speed market penetration, a natural question is to what degree mobile money affects the saving and borrowing of households. In developing countries, the lack of access to a safe method of saving can lead to insufficient saving. Insufficient saving and insufficient credit access in the face of negative shocks make it difficult for

[1] A mobile money account is attached to a mobile phone SIM card, not the mobile phone itself. In developing countries, each individual often owns a SIM card, but shares a mobile phone with others, especially in rural areas. Hence, even in such cases, it is possible for each individual to hold his or her own mobile money account as long as he or she owns a SIM card.

[2] The cost of the equipment needed to become a mobile money agent is much lower than the cost of setting up a bank branch or ATM. One needs only a personal computer and mobile network access to become a mobile money agent. In sub-Saharan countries, owners of small grocery shops often become mobile money agents. This implies that mobile money agents are more available than bank branches and ATMs.

a household to buffer negative shocks. Hence, the availability of safe saving methods through mobile money might make it easier to smooth consumption.

Theoretically, there are several channels through which the use of mobile money affects saving. First, when a household lacks access to a formal financial institution, mobile money can allow households to save in a safe and liquid way, thereby preparing them for negative shocks(new source channel). Second, on the contrary, if a household already has access to saving methods from a formal financial institution, the use of mobile money allows it to switch the source of those saving methods to a mobile money operator (substitution channel). This, however, would not affect the probability and the amount of saving. Third, having a mobile money account makes it easy for a household to saving from relatives or friends in the face of negative shocks because of the low transfer fee, which decrease the need of saving(connection channel). Fourth, the presence of low-cost money transfers might increase the possibility of households forming mutual insurance groups (Jack and Suri, 2014) (insurance channel). This insurance effect is likely to increase the amount of saving as a group. Fifth, a mobile money user can receive more remittances because of the low cost of transferring money for altruistic reasons (Agarwal and Horowitz, 2002; Vanwey, 2004). Hence, when a household can receive more remittances, the need for saving for precautionary reason falls (remittance precautionary effect). On the other hand, receiving more remittance can increase household disposable income, which in turn can increase the amount of saving.

Regarding borrowing behavior, similar arguments hold. The new source effect will increase borrowing. The substitution effect will not change the total amount of borrowing but the composition of different saving methods will. The insurance effect will decrease borrowing. The income effect is likely to decrease borrowing. Thus, from these theoretical points, it is not clear whether the use of mobile money will increase or decrease saving and borrowing.

Therefore, in this study, first I examine the causal effect of the use of mobile money on saving by using Finscope Survey 2014 in Zimbabwe. For estimating the causal effect of mobile money, several considerations are needed. First, using mobile money is a choice variable. It is possible that a household that is financially distressed might set up a mobile money account. This would introduce endogeneity bias. Second, an important variable, which is not in the list of control variables, that might affect the schooling decision might be correlated with mobile money usage. This would lead to omitted variable bias.

To treat those problems, in this study, I apply the 2SLS estimation and use information on the G2 mobile phone network coverage as an instrumental variable while including the observed demographic characteristics and enumeration area dummies as control variables. In other words, I use the cross-sectional variation of the mobile phone network coverage near the border of the network in each enumeration area as the key exogenous variation. In the two-staged stratified sampling, each enumeration area is constructed to ensure that households within each enumeration area is homogenous. In Zimbabwe, each enumeration area is constructed to ensure that it includes 150 households in the national sampling frame based on the census, and those households are expected to be very similar in terms of household demographic characteristics. This implies that after I control the enumeration area, restrict the sample to households who live near the border of the network area, and control observed demographic characteristics, the unobserved household characteristics is not likely to be correlated with the network dummy and the outcome variable.

In addition, to examine the robustness of my estimates, I conduct several robustness checks. First, in another specification, I restrict the sample to the households who live close to the border of the network area (within 10km, 8km, or 6km from the border), and run 2SLS with control variables including enumeration area dummies and household characteristics. The idea to use those who live close the border of the mobile network is that the household who live in those area are relatively more similar and the bias due to unobserved characteristics seem less likely.

Second, I conduct the coefficient stability test which is proposed by Altonji, Elder and Taber (2005) and later refined by Oster (2019). The potential criticism to the identification strategy of my 2SLS estimation is that there might be some unobserved differences between those who live in the network covered area and those who live in the uncovered area and those unobserved differences affect the outcome variable even if I restrict the sample households to those who live within 6km from the border of the network. The coefficient stability test proposed by Altonji, Elder and Taber (2005) and

Oster (2019) address this issue directly.[3] The coefficient stability test shows that even if unobservable variables as strongly affect as all observed variables, the estimated confidence interval of the effect of the use mobile money does not include the zero treatment effect.

Although my robustness checks show the estimated coefficients are robust, one might still argue that there is unobserved difference of the household characteristics of those who live under the mobile network coverage and those without mobile network coverage even though they live within 6km from the border and that those differences might affect the outcome. In addition, one might argue that although the use of mobile money might ease the financial difficulty in sending children to school, the use of mobile money might not improve the education outcome since the effect on educational outcome is not strong enough.

The identification strategy in this study raises the question whether the instrumental variable, the network coverage dummy, causes substantial variation in the use of mobile money after I include the enumeration area dummies and observed characteristics as control variables. However, even after including enumeration area dummies and observed demographic characteristics, the instrumental variable, the G2 mobile phone network coverage dummy, has a very strong predictive power for explaining the mobile money usage (Kleibergen-Paap rank Wald statistics, which is the robust F-value in this case, > 600); it shows that the instrumental variables pass the standard test of the weak instrumental variable.

This study contributes to the existing literature in three ways. First, I estimate the causal effect of the use of mobile money on saving and borrowing. Although many studies examine the effect of the use of mobile money on receiving remittance, the effect on saving and borrowing is quite limited. Second, I use the network coverage map as the source of exogenous variation. My identification assumption is that once I control the enumeration fixed effect, the variation of the coverage of the mobile network is exogenous. Using this information, I construct the network coverage dummy and

[3]The coefficient stability test proposed by Altonji, Elder and Taber (2005) and Oster (2019) become very influential in empirical research. For example, Oster (2019), which was published in 2019, has more than 1000 citations in January 2020 in google scholar. Their technique is now widely used in papers published major economic journals (Mian and Sufi, 2014; Michalopoulos and Papaioannou, 2016).

use it as an instrumental variable while controlling enumeration areas and restricting the sample to the households who live close to the border of the network area. The households that live very close to the border of the network area in the same enumeration area will be very similar, irrespective of whether they live inside or outside the network area. This instrumental variable turns out to be a very powerful instrumental variable, and the estimated coefficients are quite stable with various specifications. This instrumental variable can be used for conducting different research in future.

Third, I use detailed information of the data on remittance, borrowing, and saving. This information allows me to examine whether mobile money only increases remittance or it also increases borrowing and saving.

Regarding the main results, using the coverage by mobile phone network as the instrumental variable while controlling enumeration areas and other covariates, I find that a household whose location is covered by the network has a 74 percentage points higher probability of using mobile money than a household whose location is not covered by the network. The 2SLS estimates consistently show that using mobile money increases the probability of receiving remittances, borrowing money, and saving by 45, 12, and 14 percentage points, respectively.

The remainder of this paper is organized as follows. In section 2, I discuss the historical development of mobile money and the educational system in Zimbabwe. In section 3.1, I explain my data set. In section 3.2, I discuss the empirical strategy. In sections 4.1, I present summary statistics and the results of the ordinary least squares (OLS) and 2SLS estimations. In Subsection 4.2, I explore a possible mechanism. Section 5 provides a discussion and conclusions.

2 Literature Review

Our study is related to several strands of the literature. Given the rapid increase in mobile money usage, researchers have started to examine its effect on the economy (Aker et al., 2016; Muralidharan et al., 2016; Asongu and Asongu, 2018; Asongu, 2018; Okello Candiya Bongomin et al., 2018; Okello Candiya Bongomin and Munene, 2021; Blumenstock et al., 2015; Dupas and Robinson, 2013a; Jack and Suri, 2014; Munyegera and Matsumoto, 2016; Blumenstock et al., 2016; Riley, 2018; Gosavi, 2018; Suri and

Jack, 2016; Abiona and Koppensteiner, 2020; Riley, 2020).Aker et al. (2016) and Muralidharan et al. (2016) analyze the role of the secure payment method in Niger and India, respectively. Asongu and Asongu (2018) examine the effect of mobile money usage on economic development. Asongu (2018) analyze the determinants of mobile money penetration in African countries. Okello Candiya Bongomin et al. (2018) and Okello Candiya Bongomin and Munene (2021) examine the role of the social context for the adoption of mobile money. Blumenstock et al. (2015) conduct a randomized experiment to test the effectiveness of using mobile money to pay salaries. Dupas and Robinson (2013a) analyze the role of mobile money as a secure way to deposit daily cash in microenterprises in Kenya. Jack and Suri (2014) theoretically show that the development of mobile money decreases the transaction cost of risk sharing and increases the means to absorb a negative income shock on a household through an increase in remittances. Additionally, the authors 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. Gosavi (2018) studies the effect of the usage of mobile money for firms' financing. 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) analyzes the effect of the use of mobile money on 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. Naito et al. (2021) examine the effect of the use of mobile money on saving, borrowing and receiving remittance in Tanzania when a household experience a negative shocks. They found that the use of mobile money increase the probability of saving and receiving remittance. They also found that the effect of negative shock on receiving remittance does not depends on the use of mobile money.

To the best of our knowledge, however, no study focuses solely on the effect of mobile money on household saving, saving methods, and borrowing except my own paper with co-authors.

Second, several studies examine the effect of having a bank account on financial behavior. Burgess and Pande (2005) find that the state-led bank expansion in rural India has reduced poverty. Bruhn and Love (2009) analyze the expansion of a Mexican bank that offered both saving and credit products. They estimate that the new bank opening led to 7 percent higher income for both men and women. Dupas and Robinson (2013b) show that providing a safe place to save increases health-related saving by 60 percent in Kenya. Agarwal et al. (2017) analyze the effect of a large financial inclusion program in India and find that the region exposed to the program now lends more to borrowers. Dupas et al. (2018) analyze the effect of having a bank account on saving using field randomization in three countries, Uganda, Malawi, and Chile. They find no discernible intention-to-treat effects on savings, but a large treatment-on-the-treated effect due to the low take-up rate.

3 Institutional Background in Zimbabwe

In 2000s, the economy of Zimbabwe experienced some ups and downs. In November 2008, the monthly inflation rate peaked and it reached 500 billion percent (Hanke and Kwok, 2009). To address this ultra-hyperinflation, the government of Zimbabwe abandoned its own currency in 2009. Consequently, the inflation rate became normal and the economy started to grow by more than 10 percent from 2009. The annual growth rate from 2009 to 2012 was more than 12 percent. However, due to the lack of foreign currency, the economy went into recession from 2013 and the economic growth rate became 2.0 percent in 2013. In 2016, the government of Zimbabwe issued an order on the daily limit of cash withdrawals from formal financial institutions. However, in 2014 and 2015, years in which the survey of Finscope data and Demographics Health Survey 2015 were conducted, there was no official limit on cash withdrawal, although the economy was in the recession.

In Zimbabwe, for most of the population, how to transfer money safely and cheaply is a very important issue. In our sample, in the last 12 months, 36 percent of the households sent remittance to someone in Zimbabwe, and 1.5 percent of households

Table 1: Economic Condition of Zimbabwe after Hyperinflation

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GDP Growth Rate (%)	-3.7	-17.7	12	12.6	15.4	14.8	5.5	2.1	1.7	0.6
Inflation Rate (%)	24411.0	89 S	n.a.	3.0	3.3	3.9	1.6	-0.2	-2.4	-1.6
Lending Interest Rate (%)	579	1175	n.a.	n.a.	n.a.	11.6	9.7	8.5	7.1	9.5

Source: IMF fanancial statistics with the exception of the 2008-inflation rate.

Notes: The 2008-inflation rate is taken from the study by Hanke and Kwok (2015). They estimated that the inflation of Zimbabwe in 2008 is 89 sextillion percent; n.a. shows that the data is not available because of the chaotic situation of the country. All numbers are annual rates.

sent remittance to foreign countries. For receiving remittance, in the last 12 months, 46 percent of the households received remittance from someone in Zimbabwe, and 13 percent of the households received remittance from someone from other countries.

There are three major mobile network operators (MNOs) in Zimbabwe : Telecel, NetOne, and Econet. In September 2011, Econet, the largest mobile operator in Zimbabwe, introduced a mobile money service called Ecocash.[4] Econet Wireless has registered significant success signing up users to its EcoCash mobile money service, with 1.7 million subscribers just a year after launch. As of 2015, the market share of the total transaction value of mobile money of the three MNOs, Telecel, Netone, and Econet, are, 3.1 percent, 0.01 percent, and 96.9 percent, respectively (Postal and Telecommunications Regulatory Authority of Zimbabwe, 2015).[5] By 2015, the amount of money transferred through the mobile money system had grown to match the amount of money circulating in the traditional banking system (See Table 2). Given that mobile money system was officially introduced in 2011, the mobile money system has proliferated in Zimbabwe at an accelerated pace.

Econet wireless acquired the Steward Bank in February 2013; this allowed the account holders of the Steward bank to link their bank accounts with their mobile

[4]Before 2011, mobile network operators had started small-scale projects using mobile money to test the implementation of mobile money. This implies the existence of a few mobile money businesses before 2011. However, the size of the mobile money market was very small compared to its size in later years. For statistics on the development of mobile money, see Table 1.

[5]Note that as in many other developing countries, in Zimbabwe consumers often own several SIM cards and register to multiple mobile money companies but do not rarely use some of mobile money companies. For example, the share of subscription of Netone is 11.1 percent but people rarely use it to transfer money. As a result, the market share of the transaction value is 0.01 percent. Thus, it is more appropriate to use the transaction value based market share instead of the subscription based market share. The subscription-based market shares of Telecel, Netone, and Econet are 14.3 percent, 11.1 percent and 74.3 percent.

money accounts. Other MNOs made similar arrangements. The partnership between mobile money operators and traditional banks implies that mobile money can be either a substitute for or a complement to traditional banks.[6]

Table 2: Development of Mobile Money and M3 in Zimbabwe

Year	Mobile Money	M3*	Mobile Money/M3*
2009	0.62	1,381.25	0.000
2010	1.21	2,327.61	0.001
2011	7.87	3,100.40	0.003
2012	381.61	3,719.00	0.103
2013	2,091.01	3,888.00	0.538
2014	3,634.40	4,377.00	0.830
2015	4,645.89	4,736.00	0.981

Source: Internal documents of the Ministry of Finance of Zimbabwe

Notes: The unit of mobile money and M3* is US million dollars. M3* is the amount of M3 minus the amount of mobile money. For calculating M3, the IMF definition of M3 is used. Although mobile money was officially introduced in Zimbabwe in 2011, the mobile network operators started small-scale projects on mobile money to test the implementation of mobile money even before 2011. Thus, the amount of mobile money before 2011 is not zero.

According to a financial inclusion survey by the World Bank in 2014 (World Bank, 2014), in Zimbabwe, 32 percent of the adults have mobile money accounts, while the proportion of the adult population with traditional bank accounts is 17 percent.

Concerning the ownership of mobile phones, the ownership rate of a mobile phone is 85 percent, although only 62 percent of the households' locations are covered by the mobile phone network. This implies that many households would still use a mobile phone even if their residential location is not covered by the mobile phone network. However, as we demonstrate in the first stage regression of the 2SLS estimation, when the households' locations are covered by the mobile phone network, the probability that a household would use mobile money is about 70 percentage point higher than a household whose location is not covered by the mobile phone network, even after controlling enumeration area and observed characteristics.

[6]Currently, Econet has a partnership with the Western Union. This implies the possibility of transferring the money from foreign countries to a domestic mobile money account in Zimbabwe by linking two accounts in the Western Union and Econet. For example, a customer who has an account in the Western Union in Zimbabwe can link own Western Union bank account with own mobile money account. When a relative or a friend who lives abroad sends the money to the Western Union's bank account in Zimbabwe, the money is automatically transferred to the mobile money account. Many mobile money operators in other countries have similar services.

4 Data set and Empirical Strategy

4.1 Data set

The data set that I use in this study is the Finscope data 2014, which was commissioned by the Ministry of Finance of Zimbabwe and the National Statistical Agency of Zimbabwe. The survey was conducted by FinMark, an independent trust.[7] The sampling frame was developed by the National Statistics Agency of Zimbabwe based on a master frame developed from the 2002 Population Census of Zimbabwe. The sampling frame was constructed and the weighting of the data undertaken to obtain a representative individual-based sample of each province of Zimbabwe for the population aged 18 years and older. The sampling was based on a two-stage stratified sampling, and 662 enumeration areas were selected. Among the 662 enumeration areas, 4000 households were interviewed.

Administratively, there are 10 provinces in Zimbabwe, each comprising 59 districts, and each district is composed of 1200 wards (municipalities). In each ward, there are enumeration areas. The enumeration area is selected in the first stage in a two-stage stratified sampling method. Enumeration areas are delineated to ensure that households in each enumeration area are homogeneous. There are about 150 households in each enumeration area in the national sampling frame based on the census sample.

In the analysis, I construct two samples: the main sample and subsample. For the main sample, I restrict to households that have at least one household member who is younger than 18 years of age and that provide information on the financial difficulty in sending children to school and information on demographic characteristics. This main sample contains 2,621 households. For the subsample, I drop households that did not answer the question about the distance to school. The size of subsample is 1,789 households.

The Finscope data 2014 collects information on income, remittances, financial inclusion, location, distance, transportation methods to specific locations, such as a market and school, schooling of children, and demographic characteristics. However, the ques-

[7]FinMark Trust, an independent trust based in Johannesburg, South Africa, was established in March 2002 and is funded primarily by UKaid from the Department for International Development (DIFD) through its Southern Africa office. For information on this trust, see `http://www.finmark.org.za/`.

tion about income is not specific enough to exclude the amount of remittance received. It is possible that the respondent includes the amount of remittance received in own income when answering questions about income. Thus, I did not use this information in this study.

The main dependent variable is the following variables: having saved in the last 12 months, having borrowed in the last 12 months, having received remittance in the last 12 months.

For distance and transportation methods to school and market, the data set provides information as categorical variables. For distance, it provides 5 categories (less than 10 minutes, 11–20 minutes, 21-30 minutes, 30–60 minutes, and 1–2 hours), and for the transportation methods, it provides 4 categories. I constructed dummy variables for these variables and their interaction.

For the network coverage map, I use the network coverage map of the G2 mobile phone provided by Econonet, which is the largest mobile money operator in Zimbabwe, with a mobile money market share exceeding 90 percent in Zimbabwe. Using the latitude and longitude information of the households, I construct a dummy variable indicating whether a household is covered by this G2 mobile phone network.

Table 3 shows the summary statistics (mean and standard deviation) of the key variables in my data set. Regarding schooling, about 46 percent of the sampled households stated that they had never experienced financial difficulty in sending their children to school in the last 12 months. About 8 percent of the sampled households stated that they always (more than 10 times a year) experienced difficulty in sending their children to school for a financial reason in the last 12 months.

Regarding the use of mobile money and mobile phone's network coverage, about 51 percent of the sampled households use mobile money, while about 62 percent of the sampled households are covered by the network. Of the sampled households, 85 percent own mobile phones. Regarding saving, 41 percent of the households stated that they have saved in the last 12 months. The average amount of saving is 80 USD. Regarding remittance, about 51 percent of the sampled households receive remittances. The average frequency of receiving remittances is 4.2 times per year.

Concerning borrowing, 51 percent of the households stated that they borrowed in the last 12 months, 45 percent of the households stated that they borrowed from family

Table 3: Summary Statistics of Some Selected Variables

Variables	N	mean	s.d
Mobile Network Coverage			
Mobile Money Dummy	2,621	0.508	0.500
Network Coverage Dummy	2,621	0.624	0.485
Distance to the Network (km)	2,621	-1.885	8.814
Mobile Phone Ownership	2,621	0.849	0.358
Savings			
Having Saved in the last 12 months	2,621	0.421	0.494
Amount of Saving (USD)	2,621	80.0	360.0
Borrowing			
Having Borrowed in the last 12 months	2,621	0.510	0.500
Borrowed from Relatives or Friends	2,621	0.548	0.498
Borrowed from Mobile Money Companies	2,621	0.198	0.399
Borrowed from Savings Club	2,620	0.0927	0.290
Negative Shocks			
Negative Shock Dummy	2,621	0.423	0.494
Death of the Main Earner	2,621	0.0607	0.239
Family Illness	2,621	0.105	0.306
Low Harvest Volumes	2,621	0.265	0.441
Low Price on Output	2,621	0.227	0.419
Remittance			
Receipt of Remittance	2,621	0.510	0.500
Frequency of Receiving Remittance	2,621	4.178	6.389
Frequency of having difficulty in sending to school			
always (more than 10 times in a year)	2,621	0.0839	0.277
1 or 2 times a year	2,621	0.149	0.356
Never	2,621	0.465	0.499
Demographic Characteristics			
Age of the Head of the Household	2,621	44.64	14.36
Gender of the Head of the Household	2,621	0.758	0.428
Household Size	2,621	4.858	1.820
Number of Children	2,621	2.381	1.491

Notes: The number of observations for the Distance to School variable is smaller than the number of observations of the other variables due to the limited response rate to this questionnaire.

or relatives, 20 percent of the households stated that they borrowed from mobile money companies, and 9 percent of the households stated that they borrowed from a savings club.

Concerning negative shocks, 40 percent of the households experienced some kind of negative shocks in the last 12 months, 16 percent of the households experienced death or illness of family members, 26 percent of the households experienced lower harvest volumes, and 26 percent of the households experienced a low price on the output.

4.2 Empirical Strategy

4.2.1 Analysis using Finscope Data

I consider the following Model, based on previous studies (Jack and Suri, 2014; Munyegera and Matsumoto, 2016),

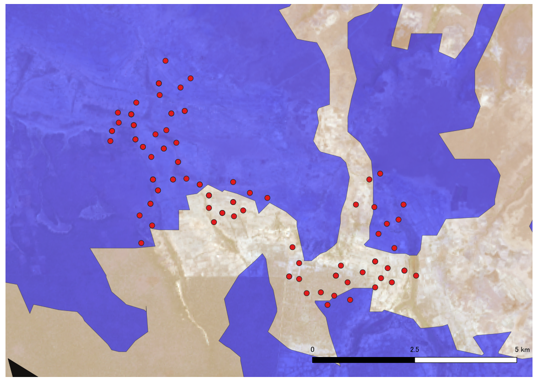
$$\mathrm{Y}_i = \beta_0 + \beta_1 \mathrm{Mobile}_i + \beta_2 x_i + \epsilon_{2i} \tag{1}$$

where Y_i is a dummy variable indicating having saved in the last 12 months. This dummy variable is equal to 1 if a household states that it has saved in the last 12 months, and 0 otherwise. Mobile_i is a dummy variable that is equal to 1 if household i uses mobile money. x_i is a vector of household characteristics and geographical variables, such as ward and enumeration area dummies, distance to market and school, and transportation methods, and their interactions. Additionally, x_i includes a mobile phone ownership dummy, following the specification used in Jack and Suri (2014) and Munyegera and Matsumoto (2016).[8] My parameter of interest is β_1.

There are several reasons why applying OLS to equation (1) would generate an inconsistent estimate of β_1. First, having mobile money is a choice variable. Thus, a household that wants to save (higher value of ϵ_{2i}) might decide to have a mobile money account. In such a case, the mobile money dummy and the error term ϵ_{2i} are positively correlated, and estimating (1) by OLS does not generate a consistent estimate of β_1. In such a case, the estimate of the effect of mobile money on saving is biased upward. Alternatively, a household that is very poor might decide to have a mobile money account to receive remittances. Such poor households might have difficulty in saving

[8] Although the mobile phone ownership dummy is included as a control variable in previous studies on the effect of the use of mobile money on consumption (Jack and Suri, 2014; Munyegera and Matsumoto, 2016), I recognize that the mobile phone ownership dummy is also an endogenous variable and including it as a control variable would introduce bias in the estimated coefficient of β_1 even when mobile money use is instrumented. I discuss the effect of including mobile phone ownership dummy in the estimating equation on the estimation of β_1, later in this subsection.

Figure 1: The Zoomed Network Coverage Area of One Area in Zimbabwe



Notes: The purple-coloured area is the area covered by the G2 mobile phone network of the Econet. Red points are the location of the households. Background is the landsat satellite image of the location in 2015

even if they received remittances. In such a case, the estimate of the effect of mobile money on saving has a downward bias.

Second, a household that uses mobile money can be different from a household that does not use mobile money in terms of other characteristics. When all household characteristics that influence schooling and mobile money are not observed, estimation (1) by OLS generates an inconsistent estimate of β_1

To solve the endogeneity bias and omitted variable bias that occur as a result of applying OLS to the equation (1), I estimate (1) by the 2SLS estimation, by using the G2 mobile phone network coverage as an instrumental variable while using the observed covariates, enumeration area dummy and mobile phone ownership as control variables. Figure 3 shows the relationship between the average use rate of mobile money and the distance from the border of the network area. If the distance is negative, it implies that the location is inside the network area. As Figure 2 shows, there is a clear relationship between the coverage by the mobile phone network and mobile money use rate.

To apply the 2SLS estimation, I estimate the following first-stage equation:

$$\text{Mobile}_i = \alpha_0 + \alpha_1 \text{Network}_i + \alpha_2 x_i + \epsilon_{1i} \tag{2}$$

where Network_i is a dummy variable indicating whether a household location is covered by the G2 mobile phone network of Econet. x_i is the same as that used in (1) and includes demographic characteristics, ward or enumeration area dummies, the mobile phone ownership, the source of income, distance to market and school, transportation methods to those locations, and their interaction.

The basic idea of using the G2 mobile phone network coverage as an instrumental variable while including other covariates as control variables is that the mobile money coverage affects easing financial difficulty in sending to school only through the usage of mobile money once I control demographic characteristics, enumeration area and experience of negative shocks. With this exclusion restriction assumption, in my 2SLS, I compare households whose locations are covered by the mobile phone network with households that live in the same enumeration area and that have the same characteristics but whose locations are not covered by the mobile phone network.

There are several reasons why coverage by mobile phone network is likely to be exogenous once I control demographic characteristics, enumeration area and experience of negative shocks. First, Figure 1 shows the zoomed map of the mobile phone network coverage. Figure 1 shows that among households who live very closely, there are households that are covered by the network and households that are not covered by the network. Since they live very closely, whether a household is covered by the network or not is more likely to be exogenous once I control demographic and economic characteristics, enumeration area, experience of negative shocks and distance to school and markets.

Second, the enumeration area is the first unit that is selected in the first stage in the two-stage stratified sampling design; each enumeration area in Zimbabwe has 150 households in the national census sampling frame, and it is designed to ensure that households are homogeneous as much as possible. Thus, once I control enumeration areas, the observed household characteristics and the experience of the negative shock, it is reasonable to assume that the network coverage is uncorrelated with financial difficulty in sending children to school except through a channel of using mobile money.

Third, the mobile money was officially introduced in 2011, and the survey was conducted in 2014. The mobile phone network was established much before 2011. Thus, it is very unlikely that mobile phone company, which is also a mobile money operator, designed the mobile phone network to provide radio access to particular households that might be interested in using mobile money. Certainly, it is possible that the demand for voice and tex (demand for mobile phone) is correlated with experience of financial difficulty and the network coverage is positively correlated with the demand for mobile phone. In this case, the experience of financial difficulty is positively correlated with the network coverage. But, if this is true, then when I control the mobile phone ownership, the estimated coefficient of the use of mobile should change. On the contrary, when I includes ownership of the mobile phone as a control variable, I found that the estimated coefficient of the use of mobile money in the 2SLS estimation is not sensitive to the inclusion of the mobile phone ownership. This suggest that such a channel is not likely.

Fourth, due to the short gap after the introduction of mobile money, it is very unlikely that a household would have moved its location to the network area for using mobile money within 3 years. Additionally, when I restrict the sample to homeowners or farmers, which have less mobility due to their attachment to own land, I observe a similarity between the estimated coefficients and the estimated coefficient obtained from the unrestricted sample. This suggests that a household's relocation is not likely to be driven by a need for using mobile money, and the network coverage is likely to be exogenous.

However, one might argue that there are still unobserved difference between areas covered by the network and areas not covered by the network. Although I include many variables in the control variables, still it is possible that unobserved characteristics are both correlated with the financial difficulty and the network coverage. To answer such a concern, I conduct two additional analyses.

First, I conduct the coefficient stability test which was initially proposed by Altonji, Elder and Taber (2005) and later refined by Oster (2019) and obtain the robust region of the coefficient of the network dummy in the reduced form. This calculation is based on the observation that it is reasonable to assume that at maximum unobservable factor is correlated with the network dummy when many control variables are already included. In Supplemental material section, I explain how we obtain the robust region of the network dummy. whether unobservable factors are big enough to cancel the size of the coefficient of the network dummy. I find that even if there is unobserved factors which are correlated with the network coverage and financial difficulty in sending children to school, the effect of such unobservable factors is not big enough to cancel the size of my estimated coefficient.

Since the estimated coefficient of 2SLS is the estimated coefficient of the reduced form divided by the estimated coefficient of the first stage. Thus, consider the reduced form regression which regress the outcome variable on the network coverage and control variables. The reduced form regression is represented as

$$\mathrm{Y}_i = \gamma_1 z_i + \phi_1 x_{1i} + \phi_2 x_{2i} + w_i + \epsilon_i \tag{3}$$

where z_i is the network coverage dummy and x_2 is a minimum set of control variables such as enumeration area dummies which is used in any specification. x_3 are control variables such as demographic characteristics, distance to market, experience of negative shock. w_i is an unobserved factor that influences the outcome.

The proportional selection assumption by Altonji, Elder and Taber (2005) and Oster (2019) states that

$$\delta \frac{\mathrm{COV}(z, \phi_2 x_2)}{\mathrm{Var}(\phi_2 x_2)} = \frac{\mathrm{COV}(z, w)}{\mathrm{Var}(w)} \tag{4}$$

δ is the degree of proportionality. It represent to what extent the unobservable factor is correlated with the instrumental variable, z_i, compared with $\phi_2 x_{2i}$. Altonji, Elder and Taber (2005) state that δ =1 at the maximum is reasonable in a situation where a large number of observable control variables are already chosen.

To see the relationship between δ and the degree of bias, let R_l be the R-square with a long list of control variables, x_{1i} and x_{2i} and R_s be the R-square with a short list of control variable with only x_{1i}. Let $\mathrm{R}_{\max}$ be the maximum R-square with x_{1i}, x_{2i} and w_i. Similarly, let γ_{1l} be the estimated coefficient of a long list of control variable, x_{1i} and x_{2i} and let γ_{1s} be the estimated coefficient with a short list of control variables, x_{1i}. Oster show that the bias due to unobservable w_i is approximately equal to

$$\text{bias} = \delta \frac{R_{\max} - R_l}{R_l - R_s} \times (\gamma_{1l} - \gamma_{1s}) \tag{5}$$

Note that $(\gamma_{1l} - \gamma_{1s})$ and $R_l - R_s$ are the change of the estimated coefficient of the key explanatory variable and R-square as the set of explanatory variable is expanded. δ is defined in equation (4). Thus, the above equation shows that the bias becomes smaller as the change of R-square become larger and the change of the estimated coefficient of the key explanatory variable become smaller as the set of control variables is expanded. Altonji, Elder and Taber (2005) and Oster (2019) argue that it is reasonable to assume that the maximum value of δ is close many observable control variables are included, which is true in our case. Oster (2019) argues that $R_{\max} = R_1 \times 1.3$ is reasonable from surveying top economic journals. Thus, assuming that $\delta = 1$, we can calculate the bound of the estimated coefficient of Z_i as $[\gamma_1 + \text{bias}, \gamma_1]$ if bias is negative and $[\gamma, \gamma_1 + \text{bias}]$ if bias is positive. Alternatively, we can calculate δ that is needed to have zero coefficient of the network dummy. In the Result section, I estimate the bound of the coefficient of the network coverage dummy assuming different value of $R_{\max}$.[9]If the sign of the bounds do not change, it shows that my estimated coefficient is robust by the effect of unobserved characteristics.

Endogeneity of Mobile Phone Ownership

In my 2SLS estimation, I include the mobile phone ownership dummy as a control variable in x_i or x_{tci}. Although the inclusion of this mobile phone ownership dummy follows the specification of the previous literature (Jack and Suri, 2014; Munyegera and Matsumoto, 2016), the inclusion of the mobile phone ownership variable can bias the estimate of β_1. This is because mobile phone ownership is the outcome variable, and controlling it introduces bias in estimating the causal effect (Angrist and Pischke, 2008). To examine in which direction the inclusion of the mobile phone ownership bias, observe that the asymptotic bias of 2SLS can be written as follows (Hahn and Hausman (2005), equation 3.1):

$$\text{plim } \tilde{\beta}_1 - \beta_1 = \frac{\alpha_1 \sigma_{\tilde{z}\epsilon_2}}{R^2 \sigma_{\tilde{y}_2 \tilde{y}_2}} \tag{6}$$

where $\tilde{\beta}_1$ is 2SLS estimator of β_1, the coefficient of the use of the mobile money dummy in the second stage equation. $\tilde{y}_2$ is the residual from regressing endogenous variable, y_2, on the control variables. $\tilde{z}$ is the residual from regressing instrumental variable, z, on control variables. R^2 is R-square when $\tilde{y}_2$ is regressed on $\tilde{z}$, which shows the explanatory power of the instrumental variable after partial out the effect of control

[9] Note that the equation (5) holds only in approximation. To calculate the bound precisely, we need to solve polynomial equation.

variables. $\sigma_{\tilde{y}_2\tilde{y}_2}$ is the variance of $\tilde{y}_2$, the use of mobile money dummy after controlling the effect of control variables. α_1 is the coefficient of the instrumental variable in the first stage equation and it is positive. $\sigma_{\tilde{z}\epsilon_2}$ is the covariance between $\tilde{z}$ and the second stage error term, ϵ_2. $\sigma_{\tilde{z}\epsilon_2}$ shows the partial covariance between the instrumental variable and the second stage error term, ϵ_2 while holding the control variables constant.

In SI2, I show that 2SLS estimate of β_1 is biased downward and I examine how β_1 is sensitive to the inclusion and exclusion of mobile phone ownership. Regression results show that it is not sensitive to the inclusion of mobile phone ownership dummy.

5 Results

OLS and 2SLS Estimates

Table 4 shows the estimated coefficients of the mobile money use dummy and the mobile phone ownership dummy when I use the saving dummy as the dependent variable in the OLS estimation of equation (1).

In all the specifications (1)–(5), the dependent variable is a dummy variable, indicating that the household had saved in the last 12 months. The control variables in all the specifications include the enumeration dummies. In column (2), I include the mobile phone ownership as an additional control variable. In columns (3),I add household head characteristics such as the age, education and gender of the household head and household characteristics such as the number of household members. In (4), I add the distance to nearest market and transportation method to the market and their interaction as control variables. In (5), I add the income sources as control variables. Column (5) of Table 4, using mobile money increases the probiblity of having saved in the last 12 month by about 10 percentage points.

It must be noted that, as discussed in section 3, due to an endogeneity, we cannot interpret the coefficient of mobile money as the causal effect of the use of mobile money on experiencing difficulty in sending children to school, and I use the 2SLS to estimate its causal effect.

Figure 2 shows the graphical relationship of the distance from the border of the mobile phone network and the rate of the use of mobile money. Note that both Table 5 and Figure 2 show the unconditional difference of the use of mobile between the

Table 4: The Effect of Mobile Money Use on the Probability of Having Saved in the Last 12 months in OLS Estimation

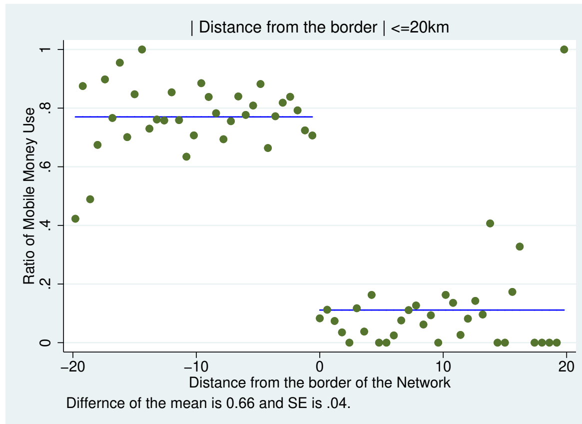
Dependent variable	Having Saved in the Last 12 months				
Variables	(1)	(2)	(3)	(4)	(5)
Mobile Money Dummy	0.145***	0.146***	0.116***	0.116***	0.108***
	(0.0201)	(0.0201)	(0.0210)	(0.0210)	(0.0209)
Mobile Phone Ownership	0.0965***	0.0954***	0.0747***	0.0747***	0.0743***
	(0.0271)	(0.0271)	(0.0272)	(0.0272)	(0.0272)
Negative Shock		0.0392*	0.0499**	0.0499**	0.0540***
		(0.0205)	(0.0207)	(0.0207)	(0.0206)
Control Variables					
Enumeration Areas	yes	yes	yes	yes	yes
Mobile phone ownership		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes
R-squared	0.031	0.031	0.058	0.058	0.066
N	2,621	2,621	2,621	2,621	2,621

Notes: Robust standard errors are in parentheses. All specifications have enumeation fixed effects. The distance to market is the time distance (five categories), transportaton methods (four categories), and their interaction. Demographic variables include the age and gender of the head of the household; age, gender, education, and the head of the household dummy of the respondent; the number of children; the household size; and income source dummies. Income source dummies are dummy variables indicating the source of income (eight categories). Specification (5) has a smaller sample size due to the limited response rate to the question about the distance to school. *** p<0.01, ** p<0.05, and * p<0.1

household who live in the network covered areas and those who live under the network non-covered areas. For example, Figure 2 maps households' average distance and its rate of the use of mobile money regardless of enumeration areas and demographic characteristics[10]. However, from the point of causal inference, we are interested in the conditional difference of the use of mobile money between the households who live in the covered area and households who live uncovered area because the area that is covered the area that is covered in the network and the area that is not covered can

[10]Figure 2 might lead the readers to suggest the use of the (geographical) regression discontinuity design because the regression discontinuity is considered the most credible identification strategy in the evaluation literature (Lee and Lemieux, 2010). However, the data requirement of conducting the geographical regression discontinuity design is quite stringent. It requires that, at all relevant points of the border, I need to find a sequence of household locations that converge to a corresponding border point; subsequently, it entails a comparison between the right limit and left limit of the sequence of households at each point of the border(Dell, 2010). In the data used in this study, for each enumeration area, I have only about 15 households. Thus, it is not feasible to find a sequence of households at the both sides of each point of the border.

Figure 2: The Use of Mobile Money and Distance from the Border of the Network Area

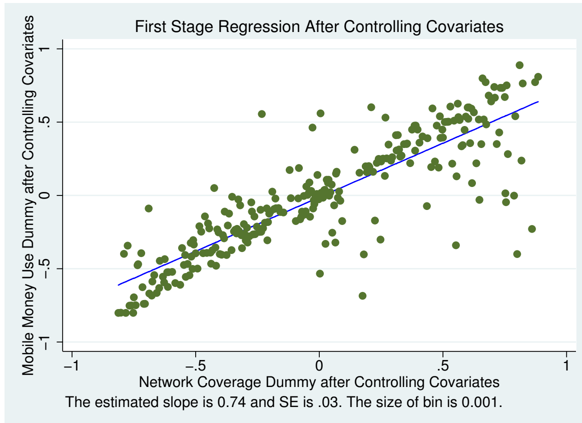


Notes: Each dot shows the average mobile money use rate at each distance from the border of the network area. The difference in the mean of not experiencing financial difficulty in sending children to school between covered and uncovered areas is 0.66, and the standard error is 0.04.

be very different in other dimension. For example, it is possible that the covered area is mainly urban area and uncovered area is mainly rural area.

Table 5 shows the result of the first- and second stages of the 2SLS estimation. Panel A shows the first stage estimation results and Panel B shows the second stage estimation results. Panel C shows the list of control variables that apply to both the first- and second stage estimations, which regress the mobile money use dummy on the mobile phone network coverage dummy with other covariates. In all specifications, I include enumeration area dummy and mobile phone ownership dummy. Inclusion of enumeration area dummy implies that we compare the household who live in the network covered area and the household who live in the uncovered area in the same enumeration area. Column (1) of Panel A of Table 5 shows that when a household is covered by the mobile phone network, the probability of using mobile money increases by 76 percentage points. Kleibeg-Papp-Wald Statistics (Kleibergen and Paap, 2006), which is also equal to the robust version of the first-stage F-statistic (Baum, Schaffer and Stillman, 2007) in our case, is greater than 10 and shows that our instrumental variable, mobile money network dummy, is not a weak instrumental variable. This suggests that there is a substantial variation in the network coverage dummy within

Figure 3: The Network Coverage and Mobile Money Usage While Controlling Covariates



Notes: Horizontal axis is the residual from regressing the network coverage dummy on enumeration area dummy, mobile phone ownership dummy, demographic characteristics, income sources and distance to market and school and their interaction to the transportation mode. Vertical axis is the residual regressing the mobile money use dummy on the same covariates. Then, for each bin of the first residual, the average value of the second residual is plotted on the graph. The size of bin is 0.001.

each enumeration area, and this network coverage affects the use of mobile money strongly within each enumeration.

In column (2), I add the experience of negative shock dummy as additional control variable. Column (2) shows that the estimated coefficient in column (2) is almost identical to the estimated coefficient in column (1). In columns (3), I include demographic characteristics such as age, gender and education of the respondents as control variables. In addition, I also include the distance to market and transportation method to market and its interaction as control variables in column (3). In column (4), I include the income source dummy (6 categories) as additional control variables. In column (5), I include the distance to school dummies, mode to school dummies and their interaction as additional control variables, respectively. Since the response rate to the question about the distance to school is lower than that to other variables, the sample size of column (5) is smaller than the other columns. In summary, Panel A of Table 6 shows that when a household's location is covered by the mobile phone network, the mobile money usage increases about 73 percentage points.

Table 5: The Effect of Mobile Money Use on the Probability of Having Saved in the Last 12 months in 2SLS Estimation

A. First Stage Estimation					
Dependent variable	Mobile Money Dummy				
Variables	(1)	(2)	(3)	(4)	(5)
Network Coverage Dummy	0.759***	0.759***	0.723***	0.723***	0.719***
	(0.0181)	(0.0180)	(0.0185)	(0.0185)	(0.0188)
Mobile phone ownership	0.165***	0.166***	0.133***	0.133***	0.136***
	(0.0212)	(0.0212)	(0.0203)	(0.0203)	(0.0202)
Negative Shock Dummy		-0.0286*	-0.0202	-0.0202	-0.0195
		(0.0153)	(0.0148)	(0.0148)	(0.0148)
R-squared	0.402	0.417	0.460	0.460	0.463
Kleibergen-Paap rk Wald	1302	1307	1100	1100	1053

B. Second Stage Estimatoin					
Dependent variable	Having Saved in the Last 12 months				
Variables	(1)	(2)	(3)	(4)	(5)
Mobile Money Dummy	0.191***	0.191***	0.170***	0.170***	0.154***
	(0.0314)	(0.0314)	(0.0337)	(0.0337)	(0.0339)
Mobile Phone Ownership	0.0837***	0.0829***	0.0627**	0.0627**	0.0642**
	(0.0278)	(0.0278)	(0.0277)	(0.0277)	(0.0277)
negative_shock		0.0405**	0.0509**	0.0509**	0.0547***
		(0.0205)	(0.0207)	(0.0207)	(0.0207)
R-squared	0.028	0.029	0.056	0.056	0.064
Control Variables					
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes
N	2,621	2,621	2,621	2,621	2,621

Notes: Robust standard errors are in parentheses. Network Coverage Dummy is equal to 1 if a household's location is covered by the G2 mobile phone network. The specification of control variables in each column is the same as that in Table 4. Kleibergen-Paap Rank Wald statistics shows the Kleibergen-Paap rank Wald statistics of the weak identification test. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

Figure 3 show the graphical relationship between the mobile phone network coverage and the use of mobile money while controlling the effect of enumeration areas, demographic characteristic and experience of negative shocks. Figure 4 show that there is a clear linear relationship between the network coverage dummy and the mobile money use dummy even after controlling all covariates.

Panel B of Table 5 shows the results of the second stage estimation of 2SLS. The specifications of the control variables are the same as those of Panel A of Table 5 (first-stage). Column (1) shows that the use of mobile money increases the probability of not experiencing financial difficulty in sending children to school by 12.4 percentage points while controlling mobile phone ownership. In column (2), I add negative shock dummy as an additional control variable. The estimated coefficient of column (2) is identical to the estimated coefficient of column (1). In column (3), I include demographic characteristics and distance to school as additional control variables. In this case, the coefficient changes from 12.4 percentage points to 12.9 percentage points. Column (4) shows that when the information on the source of income are included, the use of mobile money increases the probability of not experiencing financial difficulty in sending children to school by 12.0 percentage points. In column (5), I include the distance to school dummies, transportation methods to school, and their interaction as additional control variables. Column (5) shows that the use of mobile money increases the probability of not experiencing financial difficulty in sending children to school by 14.3 percentage points.

Overall, Panel B of Table 5 shows that the estimated coefficients of mobile money usage are quite stable with the inclusion of various control variables. Panel B of Table 5 shows that the use of mobile money increases the probability of not experiencing financial difficulty in sending children to school by 15–19 percentage points.

It is worth noticing that the estimated coefficient of OLS is downward-biased. This implies that, in the OLS estimation, a household which uses mobile money is a household that is experiencing financial difficulty in sending children to school and that a household which does not use mobile money is a household that does not experience financial difficulty in sending children to school.

Table 6 shows the reduced-form regression, which regresses a dummy variable of not experiencing financial difficulty in sending children to school dummy, on a dummy variable of mobile phone network coverage with other covariates. The specifications of the control variables are the same as those of Tables 4 and 5. Table 6 shows that being covered by the mobile phone network increases the probability of having saved in the last 12 months by 11–15 percentage points. Again, Table 6 shows that the relationship between the network coverage dummy and a dummy variable indicating having saved in the last 12 months is quite stable, regardless of control variables. This indicates that those control variables do not change the relationship between the mobile phone

Table 6: Reduced Form Regression
The Effect of Mobile Network Coverage on the Probability of Having Saved in the Last 12 months in OLS Estimation

Dependent variable	Having Saved in the Last 12 months				
Variables	(1)	(2)	(3)	(4)	(5)
Network Coverage Dummy	0.145***	0.145***	0.123***	0.123***	0.111***
	(0.0240)	(0.0240)	(0.0244)	(0.0244)	(0.0244)
Mobile Phone Ownership	0.115***	0.115***	0.0853***	0.0853***	0.0851***
	(0.0270)	(0.0270)	(0.0272)	(0.0272)	(0.0272)
Negative Shock Dummy		0.0350*	0.0474**	0.0474**	0.0517**
		(0.0204)	(0.0206)	(0.0206)	(0.0206)
R-squared	0.023	0.025	0.056	0.056	0.064
Control Variables					
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes
N	2,621	2,621	2,621	2,621	2,621

Notes: Robust standard errors are in parentheses. Network Coverage Dummy is equal to 1 if a household's location is covered by the G2 mobile phone network. The specification of control variables in each column is the same as that in Table 4. Kleibergen-Paap Rank Wald statistics shows the Kleibergen-Paap rank Wald statistics of the weak identification test. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

network coverage and having saved in the last 12 months.

Figure 4 show the graphical relationship between the network coverage dummy and the dummy that indicates that a household did not experience financial difficulty sending children in school. The Figure shows that the relationship between the network coverage and not experiencing financial difficulty sending in children to school is not driven by the outlier.

The Effect of the Use of Mobile Money in Different Types of Savings

In Table 5 and Table 6, we have shown that the use of mobile money increases the probability of saving in the last 12 months. A natural question would be in what form of saving households increases when they use mobile money. Table 7 examine such a relationship. In Table 7, the dependent variable is a dummy variable indicating that a household has saved in a mobile money account or that a household has saved in a bank count. The result of Table 7 shows that a household who used the mobile money increases the probability of having saved in a mobile money account. However, Table

Figure 4: The Network Coverage and Having Saved in the Last 12 Months

Notes: Horizontal axis is the residual from regressing the network coverage dummy on enumeration area dummy, mobile phone ownership dummy, demographic characteristics, income sources and distance to market and their interaction to the transportation mode. Vertical axis is the residual from regressing having saved dummy on the same covariates.

7 shows that the use of mobile money does not increase the probability of saving in a bank account.

Do Unobservable Factors Generate the Result of 2SLS Estimates ?

In my estimation, I have included enumeration area dummies in addition to observable covariates. In other words, I am comparing the outcome of the household in the same enumeration area who live within the network covered area and the household who live outside the network covered area while controlling demographic characteristics and experience of the negative shocks.

However, one might still argue that, even after controlling for observed characteristics enumeration areas and experience of negative shocks and enumeration area, there might be unobserved characteristics that might be correlated with the network coverage and not experiencing financial difficulty in sending children to school. In this case, my 2SLS coefficient of the use of mobile money captures not only the effect of mobile money but also the effect of the unobserved difference in the household characteristics correlated with the network coverage. To address this concern, I show three evidences that my results are robust to unobserved difference of the characteristics of

Table 7: The Effect of Mobile Money Use on
Different Types of Saving Form in 2SLS Estimation

A. Having Saved in Mobile Money Account					
Dependent variable	Having Saved in the Mobile Money Account				
Variables	(1)	(2)	(3)	(4)	(5)
Network Coverage Dummy	0.0971***	0.0973***	0.0841***	0.0841***	0.0833***
	(0.0146)	(0.0146)	(0.0151)	(0.0151)	(0.0151)
Mobile Phone Ownership	-0.0119	-0.0117	-0.0144	-0.0144	-0.0122
	(0.0123)	(0.0123)	(0.0120)	(0.0120)	(0.0119)
Negative Shock Dummy		-0.0132	-0.0109	-0.0109	-0.0118
		(0.0103)	(0.0103)	(0.0103)	(0.0102)
R-squared	0.033	0.034	0.069	0.069	0.074

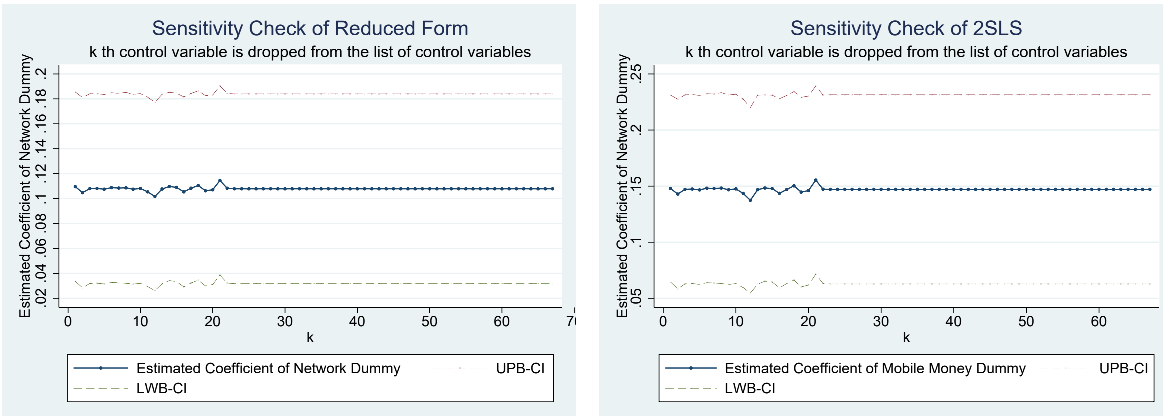
B. Having Saved in a Bank Account					
Dependent variable	Having Saved in a Bank Account				
Variables	(1)	(2)	(3)	(4)	(5)
Network Coverage Dummy	0.0899***	0.0898***	0.0459**	0.0459**	0.0305
	(0.0188)	(0.0188)	(0.0192)	(0.0192)	(0.0189)
Mobile Phone Ownership	0.0351**	0.0350**	0.0238*	0.0238*	0.0195
	(0.0151)	(0.0151)	(0.0144)	(0.0144)	(0.0139)
Negative Shock Dummy		0.00626	0.00652	0.00652	0.0179
		(0.0135)	(0.0130)	(0.0130)	(0.0125)
R-squared	0.023	0.023	0.129	0.129	0.163
Control Variables					
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes
N	2,621	2,621	2,621	2,621	2,621

Notes: Robust standard errors are in parentheses. Network Coverage Dummy is equal to 1 if a household's location is covered by the G2 mobile phone network. The specification of control variables in each column is the same as that in Table 4. Kleibergen-Paap Rank Wald statistics shows the Kleibergen-Paap rank Wald statistics of the weak identification test. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

the households between in the network covered area and network uncovered area.

First, I estimate the reduced form equation and 2SLS equation by dropping one control variable and repeat this excercise for all control variables. This exercise shows how much my reduced form estimates and 2SLS are sensitive the omission of one control variable. Figure 5 show the estimated coefficient of the network coverage dummy in

Figure 5: The Effect of Omission of kth Control Variable from the list of Control Variables in Reduced Form and 2SLS Regression



(a) Reduced Form

(b) Second Stage of 2SLS

Notes: The vertical axis shows the estimated coefficient of the network coverage dummy in the reduced form regression (Figure (a)) and the estimated coefficient of the mobile money use dummy in 2SLS regression (Figure (b)) when k-th control variable except enumeration area dummies is omitted from the full list of control variables in the reduced form and 2SLS, respectively. The horizontal axis shows the index of k-th variable. For example, the vertical height at k=12 show the estimated coefficient when 12th control variable is dropped from the list of control variable. Each graph shows that estimated coefficients of the network coverage dummy in the reduced form regression and the use of mobile money dummy in 2SLS are quite robust regarding the omission of different control variables.

the reduced form and the estimated coefficient of the mobile money dummy when k-th control variable is omitted from the full list of control variable except enumeration dummies. The Figure 5 shows that the estimated coefficients are not sensitive to the omission of one control variables. Also comparison of column (1) and column (5) of both Table 7 and Table 8 shows that when all control variables omitted, the estimated coefficients of the network coverage dummy and the use of mobile money dummy do not change. This suggest that the estimated coefficient of the mobile money use dummy is not sensitive to omission of observable control variables. Given that we have already 62 control variables, it is very likely that omission of the unobservable control variable is not likely to affect the estimated coefficient of the network coverage dummy and the use of mobile money dummy.

Second, I conduct the coefficient stability test proposed by Altonji, Elder and Taber

(2005) and later refined by Oster (2019) using the reduced form regression.

Table 8: Coefficient Robustness to Unobservable Factors

Dependent variable	Having Saved in the last 12 months				
	(1)	(2)	(3)	(4)	(5)
Variable	Baseline Effect (Std. Err), [R2]	Controlled Effect (Std Err),[R2]	R-max	δ for β =0	Identified Set of β
A					
Specification	R-max=1.3 ×R-square of the regression with full control Control Variables in the baseline estimation: Limited Control Variable				
Mobile Money Dummy	0 .096 *** (0.0261),[0.0009]	0.116 ** (0.0426), [0.51]	0.667	4.39	[0.116, 0.156]
B					
Specificatoin	R-max=1.5 ×R-square of the regression with full control Control Variables in the baseline estimation: Limited Control Variables				
Mobile Money Dummy	0 .096 *** (0.0261),[0.0009]	0.116 ** (0.0426), [0.51]	0.77	2.67	[0.116, 0.243]
C					
Specificatoin	R-max=1.3 ×R-square of the regression with full control Control Variable in the baseline estimation: no control variable				
Mobile Money Dummy	0.100 *** (0.0257),[0.0001]	0.116 ** (0.0426), [0.51]	0.667	2.28	[0.116, 0.145]

Notes: The table shows coefficient robustness to unobsrvable factors based on Oster (2019) using the reduced form equation. The column (1) show the estimated coefficient of Network dummy, its standard error and R-square in the baseline model. In Panel A and B, the baseline model includes province dummies, rural area dummy, distance to market dummies interacted with transportaton meothds. In Panel C, there is no control variable in the baseline model. Column (2) shows the estimated coefficient of the netowrk dummy, its standard error and R-square when all control variables are used. Column (3) shows the R-max value, the maximum R-square when all unobservable are hypothetically included in the control variables. Oster (2019) argue that 1.3 times the R-square when all observable control variables are used is appropriate. Column (4) shows the degree in which uonbservable factors need to be important to zero out the estimated coefficient of the Network Dummy (δ). Column (5) shows the potential region of the estimated coefficient of the network dummy when uonbservable is correlated with the network dummy as

More specifically, I estimate the reduced form equation and identify a possible region of the coefficient using Oster's test by assuming that unobservable error term can be correlated with the Network dummy as the same degree as observable. Table 7 show the results of this exercise. The column (1) shows the estimated coefficient of the network coverage dummy in the baseline equation where the control variables are minimized. In Panel A and B of Table 7, I include as the control the province dummy, rural dummy, variables related with distance to market and distance to school. In Panel C of Table 7, I do not include any control variable. Column (2) shows the estimated coefficient of the Network dummy, its standard error and R-square when all control variables are included. Column (3) show the R-max, which is the hypothetical value of R-square when not only observable but also all unobservable covariates are included. Following Oster, I use R-max as R-square in column (3) times 1.3 in Panel A and Panel C. In Panel B, I use R-square times 1.5 to examine the robustness of the result of Panel A. Column 5 calculates the robust region of the coefficient of the network dummy assuming that unobservable is correlated with the network dummy in the same as in the degree as the observable is correlated with network coverage dummy. In Panel A, column (5) show that the estimated robust region of the coefficient of the network dummy is [0.116, 0.156] , which is away from zero and it is economically significant. Column (4) conducts another thought experiment. The column calculates the degree that unobservable need to be correlated for making the true coefficient of the network work dummy zero. The column (4) of Panel A shows that it is more than 2. Altonji and Oster argue that the reasonable maximum number is one. Therefore, it suggests that it is very unlikely that our results are driven by unobservable factors.

In Panel B, I calculate delta and the robust region of the coefficient when the R-max is 1.5 times R-square of the regression when all control variables are included. Again, the delta is 2.67, which is higher than one. In Panel C, I use a different specification of the baseline estimation.

In Panel C, I do not put any control variable in the baseline estimation and check whether my test is sensitive to the specification in the baseline estimation. The estimated identified set is [0.116, 0.145]. Thus, Table 8 shows that my estimation results is robust to possible correlation between network dummy and unobservable factors.

Restricting the Sample to Households close to the Border of the Network Area and Over-Identification Test

In my 2SLS estimation of equation (1) with equation (2), in Table 6, I have included enumeration area dummies (or ward dummies) in addition to observable covariates. The reason behind having enumeration area dummies is attributed to the similarities found between households within each enumeration area that are covered by the network area and not covered by the network, after controlling for the observed covariates. This facilitated comparison between the two types of households when examing the use of mobile money and the rate of not experiencing financial difficulty in sending children to school after controlling for observed characteristics.

Table 9: Robustness Checks (2): Controlling Migration Problem
Restricting the Sample to Households living within 10km
but not within 5km from the Border in 2SLS

Dependent variable	Having Saved in the last 12 months				
	(1)	(2)	(3)	(4)	(5)
Mobile Money Dummy	0.264***	0.263***	0.246***	0.246***	0.196***
	(0.0587)	(0.0587)	(0.0637)	(0.0637)	(0.0633)
N	851	851	851	851	851
Kleibergen-Paap Rank Wald	240.7	238.6	173.7	173.7	167.5
R-squared	0.042	0.042	0.118	0.118	0.149
Control Variables					
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes

Notes: Robust standard errors are in parentheses. A negative distance implies that the location is inside the network area. The specification of control variables are the same as the specifications in Table 4. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

However, one might still argue that, even after controlling for observed characteristics and enumeration areas, there might be unobserved characteristics that might be correlated with the network coverage and not experiencing financial difficulty in sending children to school. In this case, it must be noted that my 2SLS coefficient of the use of mobile money captures not only the effect of mobile money but also the effect of the unobserved difference in the household characteristics correlated with the network coverage. To address such a criticism, in Panels A, B, and C of Table 8, I restrict my sample to households that live within a certain km (10km, 8km, or 6km) from the border of the mobile phone network area, regardless of a household's location within or outside the network area.

In Table 8, a negative distance implies that a household lives within the network area and a positive distance implies that a household live outside of the network area. The specification of control variables is the same as the control variables in Table 6. Columns (1)–(4) use the main sample, and the column (5) uses the subsample of households that have information on the distance to school. Panel A shows the estimated coefficient of the use of mobile money when the sample is restricted to households within 10 km from the border of the network area. It shows that when a household uses mobile money, the probability of not experiencing financial difficulty in sending children to school increases by 24 percentage point. Column (2) controls demographic characteristics, column (3) includes ward area dummies, and column(4) includes enumeration area dummies. Column (4) shows that when demographic characteristics and enumeration areas are controlled and when a household uses mobile money, the probability of not experiencing financial difficulty in sending children to school increases by 15 percentage points. Panel B shows the estimated coefficient when the sample is restricted to households that live within an 8-km area from the network area. The Panel B shows that the estimated coefficient is very similar to the estimated coefficient in Table 6. Panel C restricts the sample to households that live within 6km from the border of the network area. Panels A, B, and C of Table 8 show that the unobserved characteristics do not change significantly when the sample is restricted to households who live close to the border of the network. In Table 6, if the unobserved characteristics cause the bias, then the estimated coefficients would change accordingly as we restrict the sample on account of the similarities among the households that live close to the border of the network. This suggests that our identification assumption that the network coverage is exogenous, once we control observed characteristics and enumeration areas, is likely to be valid.

Does Migration within 6km from the Border Cause Bias?

In Table 8, I have shown that even if I restrict the sample to household who live within 6km from the border of the mobile phone network area, the estimated coefficients of the mobile money dummy are similar to the coefficients obtained from unrestricted sample and argue that it is unlikely that the 2SLS results is generated by the difference of unobserved household characteristics who live in the network area and who live outside the network area. However, one might argue that a household who is initially located just outside of the border of the network and who has a strong demand of using mobile money might move into the area where the mobile phone network is available. In this case, the estimated coefficient might be biased. [11]

Table 10: Robustness Checks (2): Controlling Migration Problem
Restricting the Sample to Households living within 10km from the Border
but not within 5km from the Border in 2SLS

Dependent variable	Having Saved in the last 12 months				
	(1)	(2)	(3)	(4)	(5)
Mobile Money Dummy	0.264***	0.263***	0.246***	0.246***	0.196***
	(0.0587)	(0.0587)	(0.0637)	(0.0637)	(0.0633)
N	851	851	851	851	851
Kleibergen-Paap Rank Wald	240.7	238.6	173.7	173.7	167.5
R-squared	0.042	0.042	0.118	0.118	0.149
Control Variables					
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes

Notes: Robust standard errors are in parentheses. A negative distance implies that the location is inside the network area. The specification of control variables are the same as the specifications in Table 4. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

To examine whether endogenous migration might affect our estimates, I rerstrict the sample to households living within 10km from the Border but not within 5km from the Border. Table 9 shows the estimated coefficients of 2SLS estimation using this sample. The estimated coefficients do not change from Table 5 suggesting that migration is not likely to be the issue.

Summary on the Effect of Mobile Money Use on Saving Decision

In section 4.1, I examined the effect of using mobile money on not experiencing financial difficulty in sending children to school by using different data sets through the application of the 2SLS estimation method. Irrespective of whether I restrict the sample to households that live close to the border of the network area, exclude households that live close to the border of the network area, restrict the sample to a homeowners'

[11]The direction of the bias depends on the amount of remittance that a household receives. If the amount of sufficient, then the estimated coefficient of the network coverage dummy is underestimated. If the amount of sufficiently large, the estimated coefficient is upward biased.

sample or rural household, the estimated coefficients of the use of mobile money remain quite similar. Those robustness check suggests that the effect of mobile money use on not experiencing financial difficulty in sending children to school is quite robust.

5.1 Mechanism

As I discussed in the Introduction, from a theoretical point of view, there are four channels through which the use of mobile money affects a saving decision (new method channel, substitution channel, connection channel, insurance channel, remittance precautionary channel, remittance channel) [12] Among the six channels, the first four channels involve remittance and/or borrowing. Thus, we estimate the following equation by 2SLS:

$$\mathrm{Y}_i = \beta_0 + \beta_1 \mathrm{Mobile}_i + \beta_2 x_i + \epsilon_{5i} \tag{7}$$

where Y_i = $\mathrm{Remittance}_i$ or Y_i = $\mathrm{Borrowing}_i$. $\mathrm{Remittance}_i$ is a dummy variable indicating that a household received remittance in the past 12 months, and $\mathrm{Borrowing}_i$ is a dummy variable indicating that the household borrowed the money in the last 12 months. The above equation examines whether the use of mobile money increases remittance and borrowing.

One of the key issues regarding an increase in receiving remittance or borrowing is whether an increase in remittance or borrowing is related to an intrinsic negative shock to recipient householders. If this is true, then it would suggest that the use of mobile money will affect not experiencing financial difficulty through informal risk sharing or buffer channel through borrowing. If it is not true, then it would suggest that other channels are likely to be working. Let N_i be a dummy variable indicating whether a household experienced at least one negative shock in the past 12 months. I make a

[12] These six channels are not mutually exclusive. For example, the use of mobile money may provide a banking opportunity to the households that do not have access to formal financial institutions, provide a method of safe saving, and, simultaneously, promote a form of informal insurance network through a lower cost of remittance. Additionally, the differences in some channels are quite subtle. For example, the difference between insurance channel and borrowing channel is the obligation to return the money in the case of the latter. In the case of borrowing, a recipient household has an obligation to return the borrowed money, while, in the case of informal insurance, a recipient household has an obligation to help other households when other households are hit by negative shocks.

negative shock dummy if a household experiences one of the following in the past 12 months: (i) the death of the main income earner, (ii) illness of a family member that would lead to a substantial medical expenditure, (iii) a lower level of harvest volume, or (iv) a lower price on the agricultural output. Subsequently, I estimate the following equation in 2SLS:

$$\mathrm{Y}_i = \beta_0 + \beta_1 \mathrm{Mobile}_i + \beta_2 x_i + \beta_3 \mathrm{N}_i + \beta_4 \mathrm{N}_i \times \mathrm{Mobile}_i + \epsilon_{5i} \tag{8}$$

where Y_i is the outcome variable, such as the receipt of remittance, borrowing, or not experiencing financial difficulty in sending children to school. In the above equation, I treat Mobile and $\mathrm{N}_i \times \mathrm{Mobile}_i$ as endogenous variables and use $\mathrm{Network}_i$ and $\mathrm{Network}_i \times N_i$ as instrumental variables.[13]

Effect on Remittance and Borrowing

Panel A of Table 10 shows the estimated coefficients of the effect of the use of mobile money on receiving remittances. It shows that the use of mobile money increases the probability of receiving remittances by 45 percentage points. Panel B of Table 11 shows the estimated coefficients of the effect of the use of mobile money on the frequency of receiving remittances in the past 12 months. The result shows that the frequency of the remittance receipt by a household that uses mobile money increases by 4.3 times than a household that does not use mobile money.

Table 11 presents 2SLS estimates of the effect of the use of mobile money on borrowing. In Panel A of Table 12, the dependent variable is a dummy variable indicating borrowing that is equal to one if a household has borrowed money in the last 12 months. Panel A shows that having a mobile money account increases the probability of borrowing money in the last 12 months by 12 percentage points. In Panels B, C, and D of Table 12, I look at the source of borrowing. In Panel B of Table 12, the dependent variable is a dummy variable that indicates whether a household borrowed money from friends or relatives in the last 12 months. In Panel C of Table 12, the dependent variable is a dummy variable indicating whether a household borrowed money

[13]In Table A2, I examine the orthogonality of negative shock dummy to the network coverage dummy.

Table 11 : The Effect of Mobile Money on Remittance in 2SLS

	(1)	(2)	(3)	(4)	(5)
A. The Effect of Mobile Money on Receiving Remittance					
Dependent variable	Remittance Receipt Dummy				
Mobile Money Dummy	0.481***	0.462***	0.415***	0.422***	0.446***
	(0.0294)	(0.0311)	(0.0325)	(0.0323)	(0.0391)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.212	0.245	0.430	0.450	0.530
B. The Effect of Mobile Money on Frequency of Receiving Remittances					
Dependent variable	Frequency of Receiving Remittances				
Mobile Money Dummy	4.164***	4.095***	3.815***	3.918***	4.327***
	(0.349)	(0.370)	(0.393)	(0.391)	(0.491)
N	2,621	2,621	2,621	2,621	1,789
R-squared	0.109	0.124	0.303	0.333	0.443
C. Control Variables in Panel A and B					
Enumeration Areas	yes	yes	yes	yes	yes
Mobile phone ownership		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes
R-squared	0.031	0.031	0.058	0.058	0.066
N	2,621	2,621	2,621	2,621	2,621

Notes: Robust standard errors are in parentheses. In Panel A, the remittance receipt dummy is equal to 1 if a household has received a remittance in the last 12 months, and 0 otherwise. In Panel B, the frequency of receiving remittance is the number of remittances received in the past 12 months. The specification of control variables in each column is the same as that in Table 4. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

from mobile money companies in the last 12 months. In Panel D of Table 12, the dependent variable is a dummy variable that indicates whether a household borrowed money from savings clubs in the last 12 months. In Panel B of Table 12, the use of mobile money increases the probability of borrowing money from friends or relatives in the last 12 months by 7 percentage points, and it is significant marginally at the 10-percent significance level. Panel C shows that the use of mobile money increases the probability of borrowing money from mobile money companies by 10 percentage points at a 1-percent significance level in all specifications. Panel D of Table 12 shows that the use of mobile money does not affect the probability of borrowing money from

Table 12 : The Effect of Mobile Money on borrwoing in 2SLS

	(1)	(2)	(3)	(4)	(5)
A. The Effect of Mobile Money on Borrowing					
Dependent variable	Borrowed Money				
Mobile Money Dummy	0.0547*	0.0545	0.0774**	0.0940***	0.121***
	(0.0320)	(0.0339)	(0.0351)	(0.0352)	(0.0437)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.050	0.074	0.116	0.305	0.380
B. The Effect of Mobile Money on Borrowing from Friends or Relatives					
Dependent variable	Borrowed from Friends or Relatives				
Mobile Money Dummy	-0.0191	-0.00172	0.0538	0.0570*	0.0704*
	(0.0309)	(0.0332)	(0.0332)	(0.0335)	(0.0402)
N	2,621	2,621	2,621	2,621	2,620
R-squared	0.093	0.108	0.197	0.389	0.469
C. The Effect of Mobile Money on Borrowing from Mobile Money Companies					
Dependent variable	Borrowed from Mobile Money Companies				
Mobile Money Dummy	0.108***	0.0980***	0.114***	0.0816***	0.0950***
	(0.0248)	(0.0263)	(0.0277)	(0.0274)	(0.0325)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.060	0.083	0.141	0.343	0.436
D. The Effect of Mobile Money on Borrowing from a Savings Club					
Dependent variable	Borrowed from a Savings Club				
Mobile Money Dummy	0.0285	0.0200	0.0208	0.0189	0.0313
	(0.0192)	(0.0200)	(0.0208)	(0.0212)	(0.0261)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.018	0.032	0.076	0.280	0.392

Notes: Robust standard errors are in parentheses. The borrowing dummy is 1 if the respondent borrowed the money in the last 12 months, and 0 otherwise. The specification of control variables in each column is the same as that in each column in Table 11. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

a savings club.[14]. In summary, tables 11 and 12 show that the use of mobile money increases the probability of receiving remittance and borrowing money.

Interaction of Mobile Money and Negative Shock

Among the six channels through which the use of mobile money affects schooling, four channels are related to remittance or borrowing. Among the four channels, two channels are related to following the negative shocks: the insurance channel and buffer

[14] I also examined the effect of the use of mobile money on borrowing from employers. The 2SLS regression shows that the use of mobile money does not affect the probability of borrowing from employers. The estimation results are available from the author upon request.

through the borrowing channel. In tables 12 and 13, I estimate the equation (8) in 2SLS and examine whether the use of mobile money affects receiving remittance or borrowing when a household experiences a negative shock such as the death of the main earner or lower harvest volumes.

Table 13 : The Effect of a Negative Shock on Receiving Remittance in 2SLS

	(1)	(2)	(3)	(4)	(5)
A. The Effect on Receiving Remittances					
Dependent variable	Remittance Receipt Dummy				
Mobile Money Dummy	0.427***	0.422***	0.381***	0.387***	0.425***
	(0.0455)	(0.0456)	(0.0471)	(0.0468)	(0.0609)
Mobile Money Dummy	0.0790	0.0576	0.0455	0.0466	0.0193
×Negative Shock Dummy	(0.0537)	(0.0530)	(0.0528)	(0.0528)	(0.0667)
Negative Shock Dummy	0.0123	0.0160	0.0351	0.0319	0.0480
	(0.0330)	(0.0328)	(0.0321)	(0.0321)	(0.0396)
N	2,621	2,621	2,621	2,621	2,621
Kleibergen-Paap Rank Wald	895.6	766.7	667.6	548	360.1
R-squared	0.214	0.246	0.432	0.451	0.531
B. The Effect on Frequency of Receiving Remittances					
Dependent variable	Frequency of Receiving Remittances				
Mobile Money Dummy	3.556***	3.526***	3.155***	3.176***	3.795***
	(0.582)	(0.585)	(0.626)	(0.623)	(0.745)
Mobile Money Dummy	0.903	0.829	0.915	1.032	0.665
×Negative Shock Dummy	(0.676)	(0.671)	(0.749)	(0.752)	(0.831)
Negative Shock Dummy	0.106	0.0892	0.228	0.191	0.216
	(0.349)	(0.351)	(0.389)	(0.390)	(0.409)
N	2,621	2,621	2,621	2,621	2,621
Kleibergen-Paap Rank Wald	895.6	766.7	667.6	548	360.1
R-squared	0.111	0.126	0.305	0.335	0.444

Notes: Robust standard errors are in parentheses. Endogenous variables are mobile money use dummy and mobile money use dummy × negative shock dummy. The instrumental variables are network coverage dummy and network coverage dummy ×negative shock dummy. The specification of control variables in each column is the same as that in Table 11. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

In Table 12, the dependent variable is a variable related to receiving remittance. In Table 12, I examine the coefficient of the interaction term of the mobile money dummy and the negative shocks dummy. The estimated coefficients of the interaction term in Table 12 show that the effects of experiencing negative shocks on on receiving remittances are the same between the mobile money users and non-users.

In Table 13, I estimate the equation (8) when the dependent variable is a dummy variable, indicating that a household borrowed money in the last 12 months. Table 13 shows that the estimated coefficient of the interaction term of the use of mobile money and negative shock dummy is very small and statistically insignificant.

One concern in Tables 12–13 is the orthogonality of negative shocks. One might argue that negative shocks are endogenous. In such a case, it is possible that they are highly correlated with the instrumental variables and, as a result, the interaction term is not estimated precisely. To check such a possibility, in Table A1, with other covariates, I regress the negative shocks dummy on the instrumental variable, the network coverage dummy. Table A1 shows that the negative shock dummy is orthogonal to the network dummy.

Previous studies emphasize the role of the use of mobile money as a method to buffer the negative shocks (Jack and Suri, 2014; Riley, 2018). More specifically, previous studies in Kenya and Uganda showed that the use of mobile mobile money increases the probability and frequency of receiving remittance when household received negative shocks. In contrast, in our paper, we did not find such a pattern. Table 13 shows that the effect of the negative shock on receiving remittance does not depends on the use of the mobile money. Also, it also show that

In summary, tables 12–14 show that the effects of the use of mobile money on receiving remittance and borrowing money are not different between mobile money users and non-users.

6 Discussion and Conclusion

In this study, I have examined the effect of the use of mobile money on saving behavior. My 2SLS estimation results show that the use of mobile money increases the probability of receiving remittances in the last 12 months by 45 percentage points and the frequency with which households receive remittances in the last 12 months increases by 4.3 times when compared to a household that does not use mobile money. I also find that the

Table 14: The Effect of Negative Shock and Mobile Money on Borrowing in 2SLS

	(1)	(2)	(3)	(4)	(5)
A. The Effect on Borrowing					
Dependent variable	Borrowed Money				
Mobile Money Dummy	0.0631	0.0561	0.0689	0.0861**	0.105*
	(0.0408)	(0.0418)	(0.0423)	(0.0418)	(0.0555)
Mobile Money Dummy	-0.0143	-0.00373	0.0358	0.0158	0.0196
×Negative Shock Dummy	(0.0583)	(0.0579)	(0.0588)	(0.0581)	(0.0726)
Negative Shock Dummy	0.0670*	0.0802**	0.0686*	0.0722**	0.0884**
	(0.0348)	(0.0347)	(0.0353)	(0.0352)	(0.0433)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.054	0.079	0.285	0.309	0.385
B. The Effect on Borrowing from Relatives or Friends					
Dependent variable	Borrowed Money from Relatives or Friends				
Mobile Money Dummy	0.0154	0.0256	0.0578	0.0677*	0.0657
	(0.0395)	(0.0409)	(0.0399)	(0.0395)	(0.0507)
Mobile Money Dummy	-0.0709	-0.0598	-0.0191	-0.0275	-0.00626
×Negative Shock Dummy	(0.0566)	(0.0564)	(0.0553)	(0.0546)	(0.0676)
Negative Shock Dummy	0.102***	0.105***	0.100***	0.100***	0.119***
	(0.0336)	(0.0335)	(0.0334)	(0.0333)	(0.0400)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.061	0.084	0.320	0.343	0.436
C. The Effect on Borrowing from Mobile Money Companies					
Dependent variable	Borrowed Money from Mobile Money Companies				
Mobile Money Dummy	0.118***	0.102***	0.0704**	0.0722**	0.0883**
	(0.0309)	(0.0319)	(0.0327)	(0.0324)	(0.0409)
Mobile Money Dummy	-0.0197	-0.00787	0.0271	0.0214	0.0167
×Negative Shock Dummy	(0.0442)	(0.0438)	(0.0444)	(0.0440)	(0.0524)
Negative Shock Dummy	0.0265	0.0360	-0.00276	-0.00268	-0.0293
	(0.0236)	(0.0238)	(0.0250)	(0.0250)	(0.0285)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.020	0.033	0.267	0.283	0.396

Notes: Robust standard errors are in parentheses. The specification of control variables in each column is the same as that in each column of Table 11. Notes in Table 4 apply. Kleibergen-Paap Rank Wald statistics is the same as Table 13 because the endogenous and instrumental variables are the same as the ones used in Table 13 *** p<0.01, ** p<0.05, and * p<0.1

use of mobile money increases the probability of borrowing money and saving by 11 and 14 percentage points, respectively. On the other hand, I find that the effects

Table 15 : The Effect of Network Dummy on Negative Shock (OLS)

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Negative shock dummy				
Network Coverage Dummy	-0.0205	0.00342	0.0125	0.0125	0.0531
	(0.0209)	(0.0212)	(0.0272)	(0.0275)	(0.0387)
N	2,621	2,621	2,621	2,621	2,621
R-squared	0.125	0.153	0.373	0.392	0.457
Enumeration Dummies	yes	yes	yes	yes	yes
Mobile phone ownership	yes	yes	yes	yes	yes
Negative shocks		yes	yes	yes	yes
HH Characteristics			yes	yes	yes
Distance to Markets				yes	yes
Income Sources					yes

Notes: Robust standard errors are in parentheses. The specification of control variables in each column is the same as that in Table 4. Notes in Table 4 apply. *** p<0.01, ** p<0.05, and * p<0.1

of experiencing negative shocks on receiving remittance and borrowing are the same between mobile money users and mobile money non-users.

Previous studies emphasize the role of the use of mobile money as a method to smooth consumption (Jack and Suri, 2014; Riley, 2018). However, we did not find such a role. Instead, we found that the effect of experiencing negative shock on receiving remittance and borrowing money does not depend on the use of mobile money. Also, we find that once we control the use of mobile money, experience of negative shock does not affect receiving remittance while the experience of negative shock certainly increases the probability of borrowing.

This would suggests that the effect of the use of mobile money on easing financial constraints and smoothing consumption is not operating in our data set. The fact that the use of mobile money increases savings might suggest a possibility that mobile money helps households to be engaged in various financial activities and to accumulate wealth, which decrease the need of receiving remittance when a household experience a negative shock.

My empirical results have several implications. First, having more mobile network increases the probability of using mobile money and increasing saving, borrowing and receiving remittance. Second, this increase of the use of mobile money is not for buffering negative shocks. Third,my empirical results have an implication for the regulation of mobile money. As the amount of money transferred through mobile money becomes almost the same as that of money in the traditional banking system, regulatory authorities of the governments of developing countries started taking interest in imposing strict regulations on mobile money providers. Any regulatory policy needs to be balanced between the costs and benefits of regulations. Previous studies identified the benefits of using mobile money, such as the benefits of consumption smoothing (Jack and Suri, 2014; Riley, 2018) and enhancing the efficiency of implementing a welfare system (Aker et al., 2016; Muralidharan et al., 2016) and a payment system (Blumenstock et al., 2015). My results show that the use of mobile money will provide an additional benefit for easing financial constraints in schooling. This factor needs to be taken into consideration in designing a policy for mobile money providers.

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