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The Impact of Mobile Money on Poor Rural Households

Experimental Evidence from Uganda

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Abstract

Mobile money lowers the costs of financial transactions, making it a promising tool for brining financial services to rural areas. This paper studies the effects of rolling out mobile money agents in poor and remote areas in Northern Uganda. The authors randomly assigned 329 areas to receive an agent in 2017, using 329 areas as a control group. Data from a 2018 household survey and administrative transactions data show little effect of the rollout. Mobile money transactions remained low, suggesting policies focused only on opening mobile money agents will not lead to transformative effects in poor and remote areas.

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The Impact of Mobile Money on Poor Rural Households: Experimental Evidence from Uganda*

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1. Introduction

For the past 15 years, mobile money has enabled its users to transfer and save money on their phone via an agent network, lowering transaction costs (Suri et al 2021). In some countries, mobile money has helped households to smooth consumption in the face of shocks, through increased remittances and risk sharing (Blumenstock, Eagle and Fafchamps 2016; Jack, Ray, and Suri 2013; Jack and Suri 2014; Riley 2018). It has also raised consumption and savings, and decreased poverty in the long run (Suri and Jack 2016; Munyegera and Matsumoto 2016).

Given these positive effects of mobile money on households' economic outcomes, the development community has supported increased coverage of mobile money operators. For example, USAID and Citi Foundation (2012) argue that "mobile money can transform the lives of 1.8 billion people who have access to a mobile phone but not a bank" (p. 2). Mobile money could be particularly useful for connecting rural areas in Africa to basic financial services since most households in these areas don't have a bank account (Demirgüç-Kunt et al 2022; Dupas et al 2016). However, although mobile money agent networks have grown quickly in some countries (Andersson-Manjang 2021), agents tend to be concentrated in urban areas (Akinyemi and Mushunje 2020), leaving households in rural areas with limited access to both banks and mobile money agents. Most existing studies on the impact of mobile money are also based on urban or relatively connected households.[1]

To assess the promise of mobile money for rural households, we collaborated with the International Finance Corporation (IFC) and Airtel Uganda to implement a field experiment in rural Northern Uganda covering an area of approximately 125,000km^2. Our setting includes some of the poorest and most remote areas of Uganda. Households in this area are less connected than in previous

[1] Two exceptions are Batista and Vicente (2022) and Lee et al (2021), which we discuss below.

studies. Only 28 percent of households owned a phone, compared to 69 percent in Kenya (Jack and Suri 2014), 73 percent in rural areas throughout Uganda (Munyegera and Matsumoto 2016), and 76 percent of coffee farmers in Central Uganda (Sekabira and Qaim 2017). Similarly, only 15 percent of households in our sample report receiving remittances compared to 40 percent in Jack and Suri (2014) and 65 percent in Munyegera and Matsumoto (2016). Areas in our sample also have low access to financial services, with a median distance to a bank branch of 25km.

We ask whether rolling out mobile money in these poor and remote areas has the transformative effects found in earlier research. In a remote and disconnected context, we might expect large economic effects of rolling out a digital financial service that makes it easier for households to receive remittances and allows them to save in mobile money accounts. Several studies have found that bringing traditional financial services, in particular bank accounts, to rural areas in developing countries can increase savings, business investment and income.[2] On the other hand, households in remote areas may not benefit from financial services if they are too poor to save in formal accounts (Dupas et al 2018). The low baseline rates of mobile phone ownership and remittance receipts in our setting also point to potentially low benefits of mobile money for the average household.

To measure the effects of rolling out mobile money agents, we randomly assigned 658 clusters of enumeration areas (EAs) to a treatment or a control group, stratified by a commercial priority rating provided by Airtel. None of the clusters had Airtel Money agents at baseline. Less than two percent of clusters had mobile money agents from other providers. In early 2017, a professional services firm recruited and activated Airtel Money agents in treatment clusters, spending more time in clusters with high priority rating. On average, 35 percent of treatment

[2] See Burgess and Pande (2005) and Young (2015) for India, Bruhn and Love (2014) for Mexico, Allen et al (2021) and Dupas and Robinson (2013) for Kenya, and Brune et al. (2016) for Malawi.

clusters received at least one agent (46 percent in high priority clusters and 24 percent in low priority clusters).

We use data on about 9,000 households from a 2018 follow-up survey and 2017 administrative data from Airtel Money to measure the effects of the agent rollout on mobile money usage, savings, remittances, self-employment, and food security. In contrast to the studies of mobile money in more connected settings, our results show that the agent rollout did not increase use of mobile money, savings, or remittance transactions. We find weak evidence that the agent rollout decreased transportation costs by 76 percent for those receiving remittances, in high priority areas where more agents were rolled out. Consistent with this result, we also find that the agent rollout increased food security in these areas. Neither of these effects are statistically significant when controlling for multiple hypothesis testing. However, the effects are in line with those in Aker et al (2016), who show that paying government transfers in Niger via mobile money instead of in cash reduced time costs for recipients and led to better household nutrition.

Unlike Sekabira and Qaim (2017), who conclude that mobile money increased nonfarm income in Central Uganda, we find no robust effect on nonfarm self-employment. Overall, our findings suggest that, in poor and remote areas with low mobile phone penetration and low remittances, rolling out mobile money agents has limited effects on the average household.

To our knowledge, our paper is the first to study the effects of rolling out mobile money agents in poor and remote areas, without any additional interventions. In that sense, our results capture the effects of a policy focused only on opening mobile money agents. Our paper is closely related to two other randomized experiments with poor rural households.

First, Lee et al (2021) conducted a field experiment with poor rural households in Bangladesh and their family members who had migrated to the city. Although the study took place in one of the poorest areas of Bangladesh, 99 percent of this sample of households with migrants had access to a mobile phone. The study used an encouragement design, providing training and technical assistance for using mobile money to treatment households. This intervention increased mobile money use and remittances, leading to more rural consumption and less poverty. These results are consistent with our finding that the agent rollout benefitted household receiving remittances via lower transportation costs. While Lee et al (2021) measure the effects of mobile money on households with migrants, we measure the effects of rolling out agents on the average household and find these broader effects to be limited.

Second, Batista and Vicente (2022) study 102 rural areas in Mozambique that did not have mobile money agents at baseline. Randomly selected treatment areas received three combined interventions (i) rollout of a mobile money agent, (ii) a community theater and a meeting demonstrating mobile money services, and (iii) support and incentive payments for opening mobile money accounts for 16 individuals in each area. This combined intervention increased mobile money use, savings, migration, remittances, and expenditures. Together with our results, these findings suggest that rolling out mobile money agents is not enough, but that complementary interventions are needed to increase mobile money usage and its economic effects in rural areas.

The rest of this paper proceeds as follows. Section 2 provides background information on mobile money in Uganda. Section 3 discusses the study design and agent rollout. Section 4 describes the data. Section 5 presents the results. Section 6 examines self-reported reasons for not using mobile money, and section 7 concludes.

2. Mobile Money in Uganda

In 2009, MTN, a mobile network operator (MNO), launched the first mobile money platform in Uganda. Since then, several competitors have entered the market, including three MNOs – Airtel, Africell, and Uganda Telecom through M-Sente – and a few non-MNO mobile payment providers, such as M-Cash, Ezee Money, and Micro-pay.

Via a network of mobile money agents, Uganda's mobile money platforms offer a variety of services including cash withdrawals, cash deposits, purchase of airtime, sending and receiving money, bill payment (such as school fees and utilities), and payment for goods and services.

In 2017, there were 147,146 mobile money agents in Uganda, serving 22.9 million registered customers (56 percent of the population) who made 1,111 million transactions worth 52.8 trillion Ugandan shillings (about 14.6 billion USD) in one year (Bank of Uganda 2017). Less than 3 percent of agents were in Northern Uganda, the majority of which (76 percent) were MTN agents.

For this study, IFC collaborated with Airtel to roll out agents in Northern Uganda in locations not yet served by Airtel Money. Airtel Money was launched in January 2012, and despite its ambition to increase the delivery of financial services to the Ugandan population, growth in Northern Uganda has been slow. Administrative data shows that most existing Airtel Money agents in Northern Uganda had low profitability. IFC has had an interest in increasing Airtel's mobile money market share by improving and strengthening its operations for two reasons: (i) to increase outreach into remote communities and (ii) to foster competition, avoiding a monopolistic environment to improve pricing, sharing of agents and the potential for interoperability of mobile money providers.

3. Study Design and Agent Rollout

3.1 Study Design

The Uganda Bureau of Statistics (UBOS) helped define the study sample. The starting sample included all rural enumeration areas (EAs) in all sub-counties in the

West Nile, Mid-North and Karamoja regions. From this list, sub-counties that had an Airtel Money agent were dropped, based on an agent database provided by the Bill and Melinda Gates Foundation. Moreover, all EAs without Airtel network coverage were removed. A random sample of 1,200 (EAs) was drawn from all rural EAs in the remaining 249 sub-counties using population proportional to size sampling stratified by sub-county.

In September and October 2015, a household listing exercise was conducted in the EAs selected for the study to generate a sampling frame for the baseline survey. At the same time, all businesses in each EA were listed to gain information on potential mobile money agents in the EA.

To minimize potential spillovers of agents to control group EAs, the selected EAs were mapped and grouped into clusters. A 0.5km buffer was drawn around the boundary of each EA and EAs whose buffers overlapped were grouped. Clusters were thus at least 1km apart from each other.

In this process, some EAs were dropped from the sample since either the listing exercise could not be conducted (for logistical or security reasons), the listing did not yield any businesses and thus no potential agents, or the maps were missing from the software to group EAs into clusters. As a result, there were 929 EAs that were grouped into 658 clusters.

Using a computer assisted stratified randomization approach, we assigned 329 clusters to a treatment group and 329 clusters to a control group. The treatment clusters formed the list of EA clusters for Airtel Money agent rollout. No such agents were to be rolled out in control clusters.

The randomization strata were based on three variables, resulting in 16 strata. First, a variable equal to one if the cluster included more than one EA (which was the case for 16 percent of clusters) and equal to zero if the cluster included only one EA. Second, a variable equal to one if the distance to the nearest bank branch was greater than the median distance across all clusters (25.2km) and equal to zero otherwise. These bank branches refer to Airtel partner banks and the distance was calculated as the closest distance from any point on the cluster boundary. The third stratification variable was based on a strategic priority rating based on business potential provided by Airtel, ranging from one to four. In clusters with greater priority, more time was spent rolling out agents than in areas with low priority.

3.2 Agent Rollout

The Airtel Money agent rollout took place in treatment clusters between January and June 2017. A professional services firm assisted with identifying potential agents.[3] This firm also helped agents with the logistics of signing-up to become Airtel Money agents and provided them with the necessary equipment, training, and marketing materials. However, the firm did not provide support in signing up households for Airtel Money services. The research team closely supervised the professional services firm and quality-checked information provided by them.

During the rollout, the professional services firm activated 400 agents who reportedly undertook a successful first transaction. To verify activation, we matched the phone numbers associated with these agents with Airtel Money transactions data. Only 370 of the 400 agents were found in Airtel's data, which could potentially be due to typos in the recorded phone numbers.

Based on the matched 370 phone numbers, panel A of appendix figure A1 shows the number of active agents in the Airtel Money transactions data from January 2017 to November 2017. The number of active agents increased steadily, reaching a high of 285 in August 2017 with a relatively stable number of agents through November 2017. Not all agents transacted each month, which is why the

[3] As a starting point to identify agents, information from the 2015 business listing exercise was used. The following information was collated into an index: (i) number of employees; (ii) type of business (service, retail, others); (iii) annual turnover; (iv) proximity to closest bank branch; (v) business closed when visiting bank branch; and (vi) business used mobile money before. In treatment areas with more than one listed business, the business with the highest index score was selected to be the first business to be approached.

number of active agents per month is below 370. The total number of transactions across all active agents reached over 31,000 transactions in November 2017, corresponding to an average of 76 per active agent.

Although the agent rollout specifically targeted treatment areas, the implementation was not exact. To verify agent location, we used GPS coordinates that are available for 375 agents. About 45 percent of GPS locations are inside a treatment cluster and another 39 percent are within 1km of a treatment area, with a total of 94 percent falling within 2km of a treatment area. Two GPS locations are inside a control area, about 2 percent are within 1km of a control area and 13.6 percent fall within 2km of a control area.

According to data from the Bill and Melinda Gates Foundation, the average distance to the closest agent for the cluster in our sample was 10km in 2015, suggesting that the agent rollout brought agents much closer for treatment clusters that received an Airtel agent during the rollout. Appendix figure A2 shows the Gulu district as an example, illustrating the location of treatment and control clusters, along with pre-existing agents and Airtel agents that were rolled out as part of this study.

Agents were not distributed evenly across EA clusters. Only 35 percent of treatment clusters received at least one agent. This number is higher among treatment clusters with a high priority rating from Airtel (46 percent of clusters) and lower in treatment clusters with a low priority rating (24 percent). Appendix figure A3 shows the clusters in our study by low and high priority rating.

4. Data

4.1 Survey Data

We use data collected in two survey rounds. Based on the household listing exercise conducted in September and October 2015 (see section 3.1), we randomly selected eight households in each EA for a baseline survey implemented in December 2015 and January 2016, giving a total sample of 7,399.

In the follow-up survey, conducted in January and February 2018, we interviewed nine households in each EA, increasing the sample size to a total of 9,037 households.[4] For each EA, field supervisors were provided with a list of the eight households interviewed during the baseline as well as one additional household randomly drawn from the household listing. Households that could not be interviewed at follow-up were replaced with other randomly sampled households in the same EA. We re-interviewed 79 percent of baseline households in the second round (78 percent in the treatment group and 80 percent in the control group).

In both survey rounds, we conducted face-to-face interviews. The questionnaire focused on sociodemographic information, labor outcomes, usage of mobile phones and mobile money, and financial transactions. Survey questions on food security were added in the follow-up survey and are not available at baseline.

Table 1 shows household background characteristics from the baseline survey. Household heads in our sample were on average 42 years old at baseline. Only about 44 percent of households had at least one member with completed primary education. Most households (82 percent) experienced a negative shock, such as a flood, drought, theft, death, or illness, in the last six months. About 42 percent of respondents had access to a phone, although only about 28 percent reported owning a phone, suggesting households share phones.

Table 1 also describes mobile money usage at baseline. About 61 percent of households were aware of mobile money, but only 16 percent reported that they

[4] The baseline survey interviewed households in EAs that were dropped prior to randomization for the reasons described in section 3. Instead of re-interviewing households in the dropped EAs, we increased the sample size in the 929 EAs included in the randomization. According to UBOS, the average number of households per EA in our sample 99, so that our survey covers about 9 percent of households in each EA.

used mobile money in the last three months. Although 80 percent of respondents reported saving some money, only 8 percent saved in a mobile money account.

The surveys included modules on remittances, asking if households had received money from somebody outside the household during the past six months. For the households that reported receiving money, the surveys then asked for details of the transactions with the person they received money from most frequently. At baseline, only 15 percent of respondents reported that they received money via any channel with 7 percent receiving the transfer via mobile money. Almost all other transfers were hand or bus delivered by somebody in the households or a friend. Conditional on receiving money, the average transportation cost for picking up the money was 7,400 shillings. This amount corresponds to about 20 percent of monthly household expenditures per capita (median of 32,859 shillings, mean of 41,995 shillings).

Most households in the sample engage in agriculture. At baseline, only about 11 percent of the sample worked outside farming, with about 5 percent being self-employed.

4.2 Airtel Transactions Data

We obtained monthly data from Airtel on mobile money transactions for June 2016 to November 2017, including seven types of transactions: sending a peer-to-peer (P2P) transfer, receiving a P2P transfer, cash-in, cash-out, bill pay, airtime top-up and data top-up.

To analyze these data, we had to map them to our study clusters, which was not straightforward. We have the phone number associated with each transaction, but we do not have information on who owns the phone number or where the owner is located. The location can be approximated by the location of the cell phone tower the number uses the most. However, the radius of cell phone towers is up to 40km, implying that it covers multiple clusters in our study.

We thus mapped the transaction data to our study locations by using the phone numbers households reported in our baseline and follow-up surveys. That is, we compiled a list of all Airtel phone numbers reported by the households in our follow-up survey. We verified that these numbers are correct by checking that they are present in Airtel's call records. This process yielded 476 correct phone numbers (249 in treatment clusters and 227 in control clusters), which we then merged with the transaction data.

Table 2 displays the average number of monthly transactions for these 476 phone numbers in 2016, before the agent rollout. The average phone number in a treatment cluster performed only 0.7 transactions per month, most of which were airtime or data top ups, followed by cash out and cash in. The average number of transactions in the control group was 2.4. This higher number is driven by outliers performing many more airtime or data top ups in the control than in the treatment group (1.7 vs. 0.3 on average, respectively), although this difference is not statistically significant. The average number of monthly P2P transfers sent was 0.03 in the treatment group and 0.04 in the control group. Average P2P transfer receipts were 0.03 and 0.06, respectively.

The number of monthly transactions looks low, but it is comparable to mobile money usage in rural Mozambique. Batista and Vicente (2022) find that treatment group individuals who received information on and assistance with using mobile money made between 2.5 and 6.5 transactions per year on average (depending on the year), with at least half of these being airtime purchases.

5. Results

We estimate the impact of Airtel Money agents with the following intention-to-treat (ITT) equation

$$y_{i,c,s} = \alpha + \beta Agent_{c,s} + \sum \gamma_s d_s + \delta Age_{i,c,s} + \varepsilon_{i,c,s} \quad (1)$$

where $y_{i,c,s,}$ is a follow-up survey measure of mobile money usage or other outcome of household i, in cluster c and randomization strata s. The variable $Agent_{c,s}$ indicates whether the cluster was randomly selected for the agent rollout and is thus equal to one for the treatment group and equal to zero for the control group. We control for randomization strata dummies d_s, as well as for household head age $Age_{i,c,s}$ since table 1 shows that average household head age is slightly lower in the treatment group than in the control group. Standard errors are clustered at the EA cluster level. To deal with multiple hypothesis testing, we calculate sharpened q-values that hold constant the false discovery rate (Anderson 2008).

In heterogenous treatment effect regressions, we examine whether the effect of the agent rollout varies by Airtel priority rating using the following equation

$$y_{i,c,s} = \alpha + \beta^{High} Agent_{c,s} * High_{c,s} + \beta^{Low} Agent_{c,s} * Low_{c,s} + \sum \gamma_s d_s + \delta Age_{i,c,s} + \varepsilon_{i,c,s} \quad (2)$$

where $High_{c,s}$ is a dummy variable equal to one if the EA cluster had a priority rating of three or four and equal to zero otherwise. Similarly, $Low_{c,s}$ is a dummy variable equal to one if the EA cluster had a priority rating of one or two and equal to zero otherwise.

As described above, we stratified the randomization by priority rating. In clusters with higher priority, the professional services firm spent more time rolling out agents and a larger fraction of these clusters received an agent than clusters with low priority. Appendix Table A1 shows that most household characteristics are similar across high priority and low priority areas. One significant difference is that households in high priority areas are slightly more likely to have heard of mobile money (62 percent vs. 58 percent, respectively). Appendix Table A2 reveals that high priority areas tended to have a greater number of Airtel Money transaction at baseline, although these differences are not statistically significant.

5.1 Impact on Mobile Money Usage and Remittances

Table 3 reports the effects of the rollout on mobile money usage and remittances. The agent rollout had no effects on mobile money awareness or the probability of using mobile money (columns 1 and 2). It also had no effect on savings (column 3 and 4). The agent rollout did not change the probability of receiving money via any channel or via mobile money (columns 5 and 6), but, conditional on receiving money via any channel, it decreased transportation costs, by 45 percent on average (column 7). This effect is driven by clusters with high Airtel priority rating. In these clusters, average transportation costs for receiving money decreased by 76 percent. The agent rollout may have reduced transportation costs since it brought mobile money agents closer to treatment clusters and thus allowed respondents to walk or bike to an agent instead of having to pay for a motorcycle or mini-bus taxi. However, the estimated effects on transportation costs are not statistically significant when controlling for multiple hypothesis testing.

Table 4 displays the effect of the agent rollout on transactions in Airtel's mobile money data. Consistent with the results in table 3, we do not find a significant effect of the agent rollout on the number of Airtel Money transactions. Further, appendix figure A4 illustrates that Airtel Money transactions remained low, both in control and treatment areas, after agents were rolled out in treatment clusters in 2017.

Overall, we thus do not find any evidence that the agent rollout increased use of mobile money, savings, or remittances. For households who were already receiving remittances, we find weak evidence that the agent rollout decreased transportation costs for making these transactions. The results suggest that these households used the newly rolled out agents instead of going to previously existing agents that were located further away. However, the rollout did not lead to more households using mobile money or existing users making more transactions.

5.2 Impact on Self-Employment and Food Security

We now examine the effects of the agent rollout on self-employment and food security. We do not expect to find large effect here since the agent rollout did not increase mobile money usage or remittances. That said, if the rollout led to cost-savings for remittances receivers, as suggested in table 3, households could potentially have used this money to start a non-farm business, purchase more food, or make investments in agriculture that would yield more food. Aker et al (2016) point out that even small savings can have large effects if they occur during the agricultural planting season.

The results in table 5 show no robust effect of the agent rollout on self-employment (column 1). Columns 2 and 3 indicate no effect on food security on average. However, in high priority clusters, the agent rollout lowered the fraction of respondents who reported that they had to reduce the number of meals during the past 7 days by 6.8 percentage points from a control group mean of 48.7 percent. Similarly, the fraction of respondents who had a very low food security index dropped by 7.6 percentage points, compared to a control group mean of 59.8 percent. These effects on food security are not statistically significant at conventional levels after controlling for multiple hypothesis testing.

We conclude that the agent rollout did not affect self-employment. Weak evidence suggests that the rollout increased food security in high priority clusters, which is consistent with the suggestive evidence of increased cost-savings for remittance transactions in table 3.

6. Reasons for not using mobile money

During the follow-up survey, we asked households why they have not used mobile money. This question was posed to 3,116 household who reported that they had never used mobile money. Appendix table A3 shows that the most stated reasons were that (i) respondents don't have enough money (44 percent of households); (ii) they had no need to use mobile money since they don't conduct financial transactions (27 percent); and (iii) they don't have a phone (18 percent). These reasons, combined with the low usage of mobile money agents rolled out during our study, suggest that the areas in our sample may simply be too poor and disconnected to benefit from an agent rollout without additional interventions.

The answers in table A3 further suggest that 8 percent of non-mobile money users intended to register for the service but had not done so yet. Another 7 percent said they did not have enough information about mobile money. These issues can be tackled by complementary interventions, such as the information and registration support provided in the study by Batista and Vicente (2022), which can lead to greater mobile money usage. However, given the responses in table A3, it is unlikely that providing information and registration support would lead to widespread use of mobile money in our sample.

7. Conclusion

This paper studies the impact of rolling out mobile money agents in rural areas of Northern Uganda. Compared to areas included in previous impact evaluations of mobile money agents, the areas here tend to be poorer, have lower access to financial services through bank branches, and have almost no pre-existing mobile money agents. Households are also less likely to own a mobile phone, and few receive remittances.

In this setting, we do not find transformative effects of mobile money. The agent rollout did not increase use of mobile money, savings, or remittances. We find weak evidence that it led to lower transportation costs of those receiving remittances and increased food security. However, overall remittance receipts and other mobile money transactions remained low after the agent rollout.

Low transactions also provide a challenge for agents since the limited commissions earned may not cover their start-up and other fixed costs (Unnikrishnan et al 2019). For this reason, policymakers interested in expanding access to mobile money in rural areas often consider providing subsidies for setting up agents (Hernandez 2019). However, our results suggest that this kind of policy would have limited if any benefits for the average rural household in remote and disconnected areas. Complementary interventions, such as individual level assistance and financial incentives for opening a mobile money account, may be needed to achieve greater mobile money usage and economic effects (Batista and Vicente 2022).

Similarly, MNOs trying to expand mobile money coverage into remote areas may have to adjust their business model to allow agents to make other types of transactions. For example, MNOs could introduce new payment products tailored to rural customers (Unnikrishnan et al 2019). They could also consider selling agricultural insurance (Hernandez 2019). These additional products could help agents to increase their revenue and may lead to greater economic effects on poor rural households.

Finally, our findings suggest that MNO’s commercial interests play a role in determining the impact of mobile money on rural households. The weakly significant effects we find on transportation costs and food security are concentrated in areas that Airtel designated to be of higher commercial priority and where more time was spent rolling out agents. Policy efforts to expand mobile money agent networks thus need to consider MNO's incentives and commercial interests.

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Table 1: Baseline Survey Summary Statistics by Treatment Status

	Number of households	Control group		Treatment group		P-value of difference in means
		Mean	Standard deviation	Mean	Standard deviation	
Background characteristics	(1)	(2)	(3)	(4)	(5)	(6)
Household head is male	7112	0.75		0.77		0.126
Household head's age	7110	42.68	15.13	41.6	14.48	0.015**
No household member completed primary	7373	0.45		0.44		0.575
Experienced negative shock in last 6m	7399	0.82		0.82		0.994
Has access to a phone	7399	0.41		0.42		0.705
Mobile money usage and remittances						
Is aware of mobile money	7399	0.59		0.61		0.51
Used mobile money in last 3 months	7399	0.14		0.16		0.143
Saved money in last 6 months						
Any type of savings	7399	0.79		0.8		0.334
In mobile money account	7399	0.07		0.08		0.439
Received money in the last 6 months						
Via any channel	7399	0.14		0.15		0.203
Via mobile money	7399	0.06		0.07		0.172
Transportation costs (Ugandan Shilling)	1075	6782.39	68194.77	7401.81	85264.84	0.844
Occupation						
Does non-farm work	7379	0.09		0.11		0.054*
Self-employed (non-farm)	7379	0.04		0.05		0.108

Note: The sample size varies from question to question due to nonresponse. Transportation costs are for households who received money via any channel in the last 6 months. Column 6 shows the p-value of the difference in treatment and control group means, clustered at the EA cluster level and conditional on strata dummies.

Table 2: Baseline Airtel Data on Mobile Money Transactions by Treatment Status

Number of monthly transactions (June to December 2016)	Control group		Treatment group		P-value of difference in means
	Mean	Standard deviation	Mean	Standard deviation	
	(1)	(2)	(3)	(4)	(5)
Any transaction	2.383	22.627	0.734	4.075	0.253
Send P2P transfer	0.040	0.367	0.034	0.341	0.788
Receive P2P transfer	0.056	0.379	0.034	0.269	0.333
Cash in	0.221	1.471	0.153	1.217	0.515
Cash out	0.203	0.995	0.160	0.819	0.556
Bill pay	0.077	0.926	0.017	0.215	0.222
Airtime or data top up	1.731	21.708	0.321	2.208	0.307
Observations	1589		1743		3332
Number of months	7		7		7
Number of phone numbers	227		249		476

Notes: This table displays data for 476 Airtel phone numbers reported by our survey respondents. We do not include other phone numbers in the Airtel transactions data since we do not have the necessary information to map these to our study locations. Column 5 shows the p-value of the difference in treatment and control group means, clustered at the EA cluster level and conditional on strata and month dummies.

Table 3: Effects of Agent Rollout on Mobile Money Usage and Remittances (Follow-up Survey)

	Dependent variable:						
	Is aware of mobile money	Used mobile money in last 3 months	Saved money in any type of savings	Saved money in mobile account	Received money via any channel	Received money via mobile money	IHS transport costs for receiving money
Panel A: ITT for all clusters	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agent	0.010	0.002	-0.018	-0.007	0.006	0.007	-0.448*
	(0.023)	(0.013)	(0.022)	(0.009)	(0.011)	(0.010)	(0.248)
R-squared	0.042	0.015	0.021	0.014	0.010	0.011	0.035
Control group mean	0.594	0.183	0.737	0.090	0.135	0.100	1.994
Panel B: ITT by Airtel priority							
Agent*High priority	0.006	0.002	-0.015	-0.010	0.011	0.009	-0.760**
	(0.033)	(0.017)	(0.027)	(0.011)	(0.015)	(0.013)	(0.337)
Agent*Low priority	0.015	0.002	-0.020	-0.004	0.000	0.006	-0.135
	(0.033)	(0.019)	(0.034)	(0.013)	(0.017)	(0.014)	(0.368)
R-squared	0.042	0.015	0.021	0.014	0.010	0.011	0.037
F-test p-value (Agent*High = Agent*Low)	0.857	1.000	0.925	0.717	0.629	0.856	0.212
Control group mean - High priority	0.608	0.180	0.771	0.079	0.131	0.096	2.138
Control group mean - Low priority	0.580	0.186	0.702	0.101	0.140	0.103	1.855
Observations	8844	8844	8844	8844	8844	8844	1212

Note: Panel A shows results from OLS regressions of the dependent variables on a dummy variable that is equal to 1 if the cluster was randomly selected for the agent rollout and equal to zero otherwise. Panel B shows results from similar regressions, where the agent rollout dummy is interacted with two dummy variables indicating Airtel priority rating. In clusters with higher priority, the professional services firm spent more time rolling out agents and a larger fraction of these clusters received an agent than clusters with low priority. The randomization was stratified by priority rating. All regressions include randomization strata dummies and household head age. Control group means are means of the dependent variables. Transport costs are for households who received money via any channel. Standard errors clustered at the cluster level in parenthesis. Statistical significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. To deal with multiple hypothesis testing, we calculated sharpened q-values and indicate statistical significance levels: † $q<0.10$, †† $q<0.05$, ††† $q<0.01$.

Table 4: Effects of Agent Rollout on Airtel Mobile Money Transactions (January to November 2017 Administrative Data)

	Dependent variable: Number of monhtly transactions						
	Any transaction	Send P2P transfer	Receive P2P transfer	Cash in	Cash out	Bill pay	Airtime or data top up
Panel A: ITT for all clusters	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agent	-1.360	-0.000	0.009	-0.132	-0.044	-0.100	-1.047
	(1.107)	(0.015)	(0.022)	(0.130)	(0.061)	(0.083)	(0.989)
R-squared	0.164	0.009	0.014	0.010	0.026	0.149	0.181
Control group mean	2.395	0.032	0.047	0.296	0.196	0.157	1.606
Panel B: ITT by Airtel priority							
Agent*High priority	-2.090	0.013	0.024	-0.201	0.036	-0.187	-1.794
	(2.181)	(0.024)	(0.032)	(0.252)	(0.080)	(0.167)	(1.980)
Agent*Low priority	-0.637	-0.014	-0.006	-0.064	-0.123	-0.013	-0.306
	(0.457)	(0.017)	(0.031)	(0.064)	(0.091)	(0.016)	(0.214)
R-squared	0.165	0.008	0.014	0.009	0.027	0.150	0.181
F-test p-value (Agent*High = Agent*Low)	0.515	0.360	0.496	0.599	0.188	0.302	0.456
Control group mean - High priority	3.641	0.031	0.046	0.427	0.164	0.289	2.670
Control group mean - Low priority	1.116	0.032	0.049	0.161	0.228	0.023	0.514
Observations	5236	5236	5236	5236	5236	5236	5236
Number of months	11	11	11	11	11	11	11
Number of phone numbers	476	476	476	476	476	476	476

Note: Analysis at the phone number level for 476 Airtel phone numbers reported by our survey respondents. We do not include other phone numbers in the Airtel transactions data since we do not have the necessary information to map these to our study locations. Panel A shows results from OLS regressions of the dependent variables on a dummy variable that is equal to 1 if the cluster was randomly selected for the agent rollout and equal to zero otherwise. Panel B shows results from similar regressions, where the agent rollout dummy is interacted with two dummy variables indicating Airtel priority rating. In clusters with higher priority, the professional services firm spent more time rolling out agents and a larger fraction of these clusters received an agent than clusters with low priority. The randomization was stratified by priority rating. All regressions include randomization strata dummies and household head age. Control group means are means of the dependent variables. Standard errors clustered at the cluster level in parenthesis. Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. To deal with multiple hypothesis testing, we calculated sharpened q-values and indicate statistical significance levels: † q<0.10, †† q<0.05, ††† q<0.01.

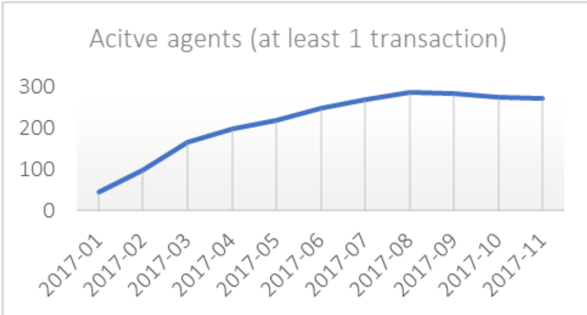
Table 5: Effects of Agent Rollout on Self-Employment and Food Security (Follow-up Survey)

	Self-employed (non-farm)	Had to reduce number of meals in last 7 days	Food security index is very low
Panel A: ITT for all clusters	(1)	(2)	(3)
Agent	0.011*	-0.033	-0.026
	(0.006)	(0.022)	(0.022)
R-squared	0.013	0.041	0.050
Control group mean	0.032	0.480	0.594
Panel B: ITT by Airtel priority			
Agent*High priority	0.014	-0.068**	-0.076**
	(0.009)	(0.033)	(0.033)
Agent*Low priority	0.009	0.003	0.025
	(0.008)	(0.029)	(0.029)
R-squared	0.013	0.042	0.052
F-test p-value (Agent*High = Agent*Low)	0.665	0.108	0.021
Control group mean - High priority	0.040	0.487	0.598
Control group mean - Low priority	0.024	0.474	0.590
Observations	8816	8844	8844

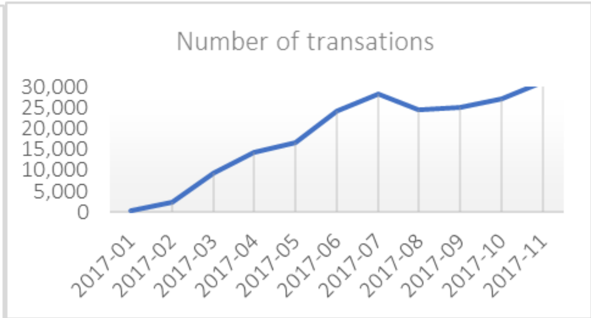
Note: Panel A shows results from OLS regressions of the dependent variables on a dummy variable that is equal to 1 if the cluster was randomly selected for the agent rollout and equal to zero otherwise. Panel B shows results from similar regressions, where the agent rollout dummy is interacted with two dummy variables indicating Airtel priority rating. In clusters with higher priority, the professional services firm spent more time rolling out agents and a larger fraction of these clusters received an agent than clusters with low priority. The randomization was stratified by priority rating. All regressions include randomization strata dummies and household head age. Control group means are means of the dependent variables. Standard errors clustered at the cluster level in parenthesis. Statistical significance levels: * p<0.10, ** p<0.05, *** p<0.01. To deal with multiple hypothesis testing, we calculated sharpened q-values and indicate statistical significance levels: † q<0.10, †† q<0.05, ††† q<0.01.

Appendix Figure A1: Number of Active Agents and Usage

Panel A: Number of Active Agents by month

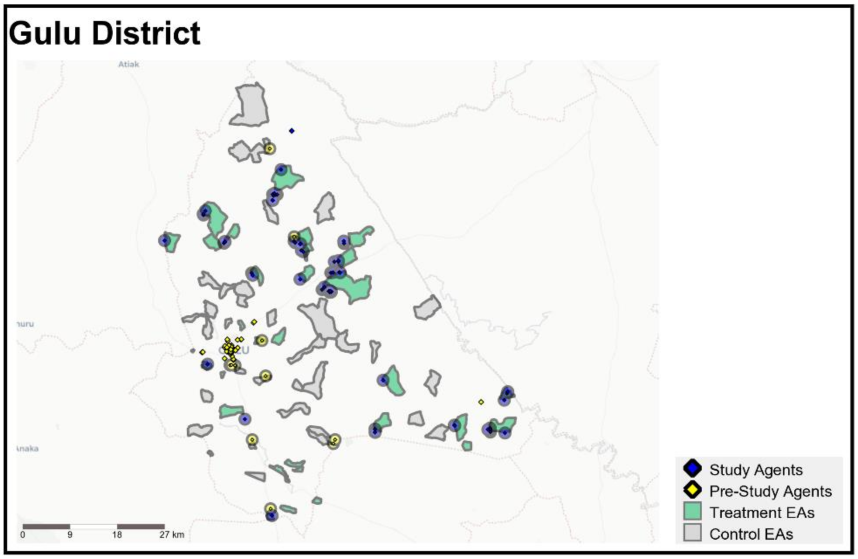


Panel B: Number of Transactions by month



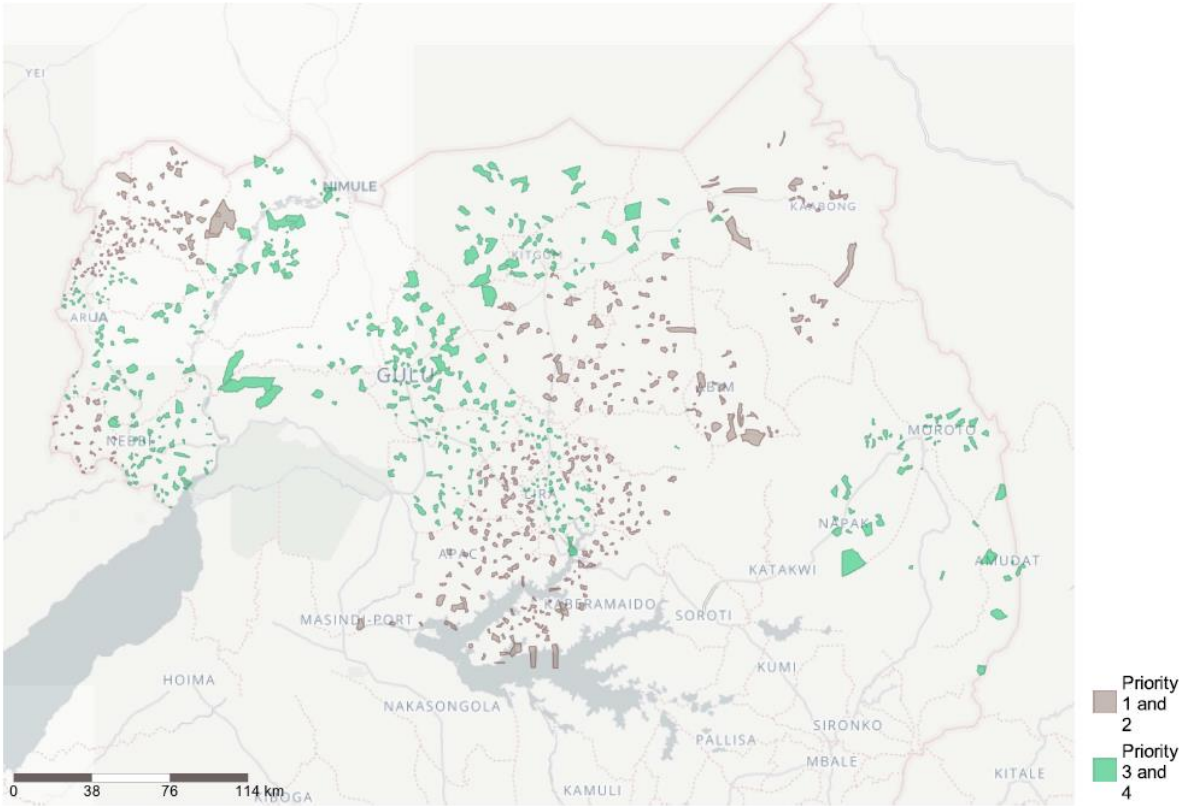
Source: Own calculations based on Airtel Money transaction data.

Appendix Figure A2: Example of Treatment and Control Areas with Agents



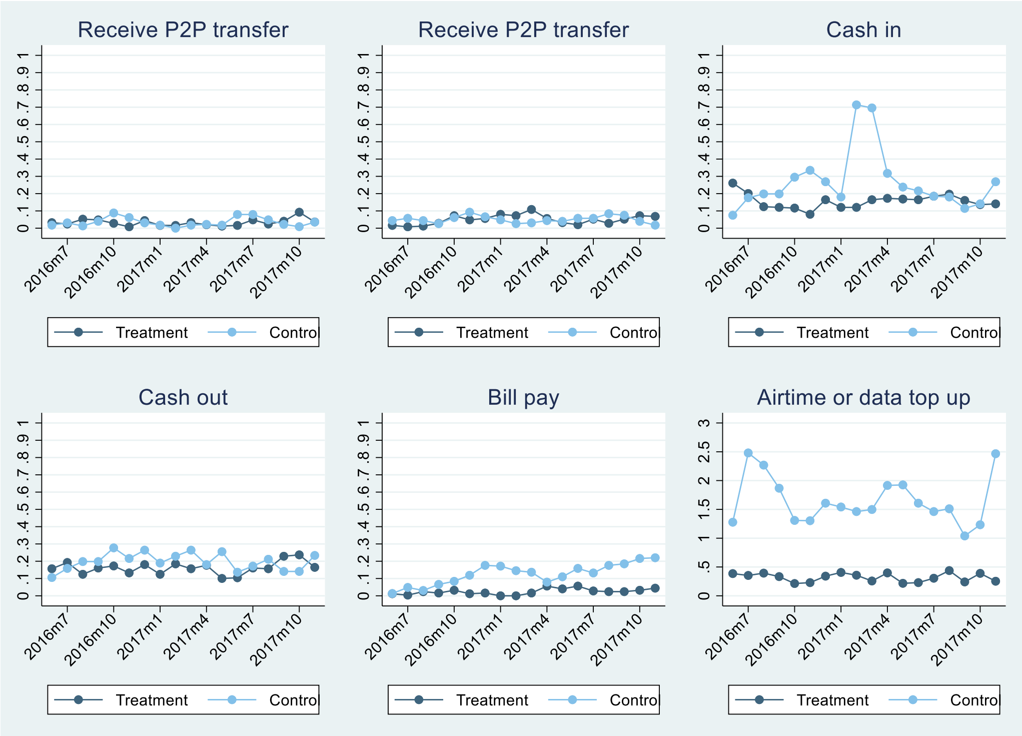
Note: The map shows treatment and control clusters in the Gulu district. Study agents are Airtel agents that were rollout out as part of this study. Pre-study agents are agents from any provider that existed in 2015.

Appendix Figure A3: Areas Included in the Study



Note: The map shows the 658 clusters of enumeration areas in our study. Airtel assigned a strategic priority rating, ranging from 1 to 4. In clusters with greater priority, more time was spent rolling out agents than in areas with low priority.

Appendix Figure A4: Airtel Money Transactions Over Time



Note: The figure shows the average number of monthly transactions for 476 Airtel phone numbers reported by our survey respondents. We do not include other phone numbers in the Airtel transactions data since we do not have the necessary information to map these to our study locations.

Table A1: Baseline Survey Summary Statistics by Airtel Priority Rating

	Number of households	Low priority		High priority		P-value of difference in means
		Mean	Standard deviation	Mean	Standard deviation	
Background characteristics	(1)	(2)	(3)	(4)	(5)	(6)
Household head is male	7112	0.79		0.73		0.998
Household head's age	7110	42.21	15.05	42.08	14.59	0.604
No household member completed primary	7373	0.44		0.45		0.081*
Experienced negative shock in last 6m	7399	0.84		0.8		0.962
Has access to a phone	7399	0.38		0.45		0.727
Mobile money usage and remittances						
Is aware of mobile money	7399	0.58		0.62		0.011**
Used mobile money in last 3 months	7399	0.16		0.14		0.663
Saved money in last 6 months						
Any type of savings	7399	0.81		0.78		0.59
In mobile money account	7399	0.08		0.06		0.764
Received money in the last 6 months						
Via any channel	7399	0.14		0.15		0.133
Via mobile money	7399	0.06		0.07		0.228
Transportation costs (Ugandan Shilling)	1075	10913.74	110585.3	3567.5	15173.15	0.749
Occupation						
Does non-farm work	7379	0.09		0.12		0.444
Self-employed (non-farm)	7379	0.04		0.05		0.942

Note: The sample size varies from question to question due to nonresponse. Transportation costs are for households who received money via any channel in the last 6 months. Column 6 shows the p-value of the difference in treatment and control group means, clustered at the EA cluster level and conditional on strata dummies.

Table A2: Baseline Airtel Data on Mobile Money Transactions by Airtel Priority Rating

Number of monthly transactions (June to December 2016)	Low priority		High priority		P-value of difference in means
	Mean	Standard deviation	Mean	Standard deviation	
	(1)	(2)	(3)	(4)	(5)
Any transaction	0.737	3.829	2.304	22.162	0.297
Send P2P transfer	0.020	0.271	0.054	0.420	0.224
Receive P2P transfer	0.041	0.317	0.049	0.335	0.224
Cash in	0.114	0.588	0.256	1.805	1.000
Cash out	0.149	0.808	0.211	0.997	0.224
Bill pay	0.013	0.191	0.078	0.911	0.484
Airtime or data top up	0.344	1.955	1.643	21.234	0.292
Observations	1589		1743		3332
Number of months	7		7		7
Number of phone numbers	227		249		476

Notes: This table displays data for 476 Airtel phone numbers reported by our survey respondents. We do not include other phone numbers in the Airtel transactions data since we do not have the necessary information to map these to our study locations. Column 5 shows the p-value of the difference in treatment and control group means, clustered at the EA cluster level and conditional on strata and month dummies.

Table A3: Self-reported reasons for never having used mobile money

Fraction of households mentioning this reason (multiple mention)	
I don't have any money	0.443
I have no need to use mobile money/No financial transactions	0.272
I don't have a phone	0.181
It's too expensive (usage charges)	0.143
No agent nearby	0.139
I am using other ways of sending/receiving money	0.086
I have not registered for mobile money	0.079
I don't know enough about mobile money	0.067
I don't trust those services	0.062
Network not reliable	0.034
Services do not exist in my language	0.026
The available functions don't meet my needs	0.010
Other reasons	0.009

Notes: Based on responses to the question "Why have you never used mobile money services?" The sample consists of 3116 households who, during the follow-up survey, stated that they had never used mobile money.