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Mobile Money, Agricultural Marketing, and Off-Farm Income in Uganda

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Abstract

Mobile money (MM) services can contribute to welfare gains in smallholder farm households. Previous research showed that one important pathway is through higher remittances received from relatives and friends. Here, the role of other impact pathways is examined, especially focusing on agricultural marketing and off-farm economic activities. The analysis builds on panel data from smallholder coffee farmers in Uganda. Regression models show that the adoption of MM technology has contributed to higher household incomes and consumption levels. Off-farm income gains are identified to be an important pathway, also beyond remittances. Typical off-farm income sources are small businesses in trade, transport, and handicrafts, which benefit from novel savings and money transfer opportunities through MM. In terms of agricultural marketing, MM users sell a larger proportion of their coffee as shelled beans to buyers in high-value markets, instead of selling to local traders immediately after harvest. MM services help reduce cash constraints and facilitate transactions with buyers from outside local regions. In conclusion, MM can contribute to rural development through various important pathways. Analysis of adoption patterns suggests that MM services are socially inclusive.

Keywords: mobile phones; rural banking; smallholder farmers; impact evaluation; Africa

JEL codes: O12; O16; O33; Q12

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Mobile Money, Agricultural Marketing, and Off-Farm Income in Uganda

1. Introduction

The use of mobile phone technologies has rapidly increased in many developing countries since the late-1990s. This has contributed to economic growth and poverty reduction, especially in rural areas where mobile phones have helped households to access better market information and fetch higher prices for their products (Torero and Von Braun, 2005; Jensen, 2007; Muto and Yamano, 2009; Aker, 2010; Aker, 2011; Aker and Mbiti, 2010; Sekabira et al., 2012; Nakasone et al., 2014; Tadesse and Bahiigwa, 2015; Aker and Ksoll, 2016; Blauw and Franses, 2016). In addition to the direct positive effects of mobile phones on people's lives, their widespread use has also facilitated the adoption of other mobile technologies. One important example is mobile money (MM). MM services enable the electronic transfer of money via mobile phones. This reduces transaction costs for the payment of bills, and making remittances; enhancing rural banking and financial inclusion. Recipients of these electronic transfers can either save the money on their mobile account or collect it in cash from a MM service center. MM services are particularly attractive for people with limited access to the traditional banking system. The recent spread of this technology was particularly rapid in sub-Saharan Africa (Suri et al., 2012; Jack et al., 2013).

MM could revolutionize the nature of market transactions and private transfers for the previously unbanked, but so far relatively little is known about the real effects in developing countries (Nakasone et al., 2014). Especially for smallholder farmers, the knowledge about MM effects is thin. A few recent studies have looked at impacts on household welfare in Kenya and Uganda (Kirui et al., 2013; Jack and Suri, 2014; Kikulwe et al., 2014; Murendo and Wollni, 2016; Munyegera and Matsumoto, 2016). These studies confirm that MM has positive effects on income, consumption, and food security. However, the pathways through which MM affects these welfare outcomes remain understudied. One pathway that most studies mention is remittances. More remittances received from relatives and friends increase household incomes directly; indirect effects can occur because remittances also act as a kind of insurance (Jack and Suri, 2014; Munyegera and Matsumoto, 2016). Wider effects for other economic activities of farm households have hardly been studied. One exception is Kikulwe et al. (2014) who showed that MM has increased the use of agricultural inputs and levels of commercialization in the Kenyan small farm sector.

We add to this literature by further analyzing how the adoption of MM technology affects the economic activities of smallholder households, including both farm and off-farm activities. To our knowledge, impacts of MM on off-farm income of smallholder farmers have not been analyzed beyond the question of remittances. We hypothesize that the new options for savings as well as for transferring money between business partners may especially encourage self-employed activities and thus increase off-farm income. Through similar mechanisms, agricultural incomes may increase as well. Here, we are particularly interested to see whether MM allows farmers to access high-value markets where better prices can be obtained. For the empirical analysis, we use panel data collected from coffee farmers in Uganda. Uganda is of interest not only because many of the poor are smallholder farmers, but also because MM technology has been rapidly adopted there in recent years.

2. Conceptual framework

The use of mobile money (MM) services can influence the welfare of farm households in various ways. A simple framework of potential pathways is shown in Figure 1. A first pathway that was confirmed to be relevant in recent empirical work is higher remittances received from relatives and friends (Suri et al., 2012; Jack and Suri, 2014; Munyegera and

Matsumoto, 2016). The main reason for the increase in remittances is that MM has lowered the transaction costs of transferring money even to remote rural locations. As a source of income, remittances can contribute to improved household welfare directly. In addition, the higher availability of cash can facilitate investments into farm and off-farm economic activities. Remittances are often a more reliable source of income than self-employed activities for the rural poor, thus also providing some kind of insurance (Jack et al., 2013).

<<<Figure 1>>>

Use of MM can also affect farm and off-farm economic activities directly. People often use their MM account for savings, which can be used for later cash withdrawals or for paying business partners for goods and services received. Kikulwe et al. (2014) showed that farmers with MM used more fertilizers, pesticides, and hired labor. They also marketed a larger proportion of their output. Especially when the ordering of goods and services, the delivery, and the payment do not occur in one place and at one point in time, MM transfers can be useful to reduce transaction costs. Such conditions are particularly relevant in high-value agricultural markets that often involve contractual ties between buyers and sellers (Blandon et al., 2009; Rao and Qaim, 2011; Reardon and Timmer, 2012).

An important question for farmers is when to sell their crop, in what form, and to whom. Smallholders often sell their produce to local traders immediately after harvest, without any further storage or processing, because they need the cash to pay for urgent consumption needs or outstanding bills (Fafchamps and Hill, 2005). Sometimes, cash-constrained farmers even sell their crop before harvest. Coffee growers in Uganda, for instance, sometimes decide to sell their coffee to middlemen when it is still at the flowering stage in the field. Many other farmers sell the red coffee cherries right after harvest or after some drying, even though more money can usually be earned when selling as shelled green beans (Chiputwa et al., 2015). We hypothesize that the use of MM allows farmers to sell a larger proportion of their coffee as shelled green beans. Related to this, we also hypothesize that MM helps farmers to fetch higher prices for their coffee. This is not only related to higher levels of processing. Even at the same processing level, farmers with MM may find it easier to transact with buyers in different locations, thus being able to benefit from the best price offers.

Off-farm income sources also play an important role for many smallholder farmers, including for coffee growers in Uganda. Beyond salaried employment, many households have their own small non-farm businesses, for instance in food processing, handicrafts, or transport, trade, and repair services. Such off-farm activities can also benefit from mobile money transactions. Off-farm income sources contribute directly to household welfare. In addition, off-farm earnings are sometimes used for investments in farming, especially in situations where rural financial markets fail (Oseni and Winters, 2009).

In the empirical analysis below, we analyze the impact of MM use on household welfare in terms of income and per capita consumption. We also examine some of the impact pathways, concentrating especially on those that have not been studied previously, such as off-farm income and aspects of agricultural marketing and prices.

3. Materials and methods

3.1 Survey of farm households

We use panel data collected in two survey rounds from randomly selected coffee-growing households in Luwero and Masaka (now named Bukomansimbi) Districts, Central Uganda. The first survey round was conducted in 2012, the second round three years later in 2015.

The two districts were chosen, as they are important production regions for Robusta coffee. Farmers in these regions do not grow Arabica coffee, which requires higher altitudes. Within the two districts, we selected specific locations with a high density of coffee farmers. In these locations, we randomly selected farmers based on lists provided by village and coffee cooperatives' leaders. Many of the sample farmers are members of cooperatives, while others are not. The first round of the survey covered 419 coffee-producing households. In the second round, the same households were targeted, however, some sample attrition occurred. We had to replace 25 farmers that we were unable to interview again (6% attrition rate). These replacements were randomly sampled in the same locations. In addition, we somewhat increased the sample size to a total of 455 households in 2015. For the analysis, we use the unbalanced panel with 874 observations from 480 households.

In both survey rounds, we used a structured questionnaire for face-to-face interviews. The questionnaire focused on details of coffee production and marketing, other farm and non-farm economic activities, consumption, as well as socio-demographic and contextual details. One section of the questionnaire also asked for mobile phone and mobile money use. The section about mobile money was only included in the 2015 survey round, but also covering mobile technology use in 2012 through recall questions. With some assistance from the interviewers, such as reminding of important past events as a reference, respondents had no problems in recalling when exactly they had started using mobile money services.

3.2. Modeling mobile money adoption

In a first step, we want to explain what factors influence whether or not farmers use MM services. This is modeled in a probit framework as follows:

$$MM_{jt} = \alpha + \beta \mathbf{X}_{jt} + \gamma T_t + \varepsilon_{jt} \qquad (1)$$

where MM_{jt} is a dummy dependent variable that takes a value of one if household j used MM in year t, and zero otherwise. $\mathbf{X}_{jt}$ is a vector of household, farm, and contextual characteristics, and T_t is a year dummy controlling for time fixed effects and taking a value of one for observations referring to 2015. α, β and γ are parameters to be estimated, and ε_{jt} is a normally distributed error term.

3.3. Modeling mobile money impacts

Beyond explaining MM adoption, we want to evaluate impacts of adoption on household welfare and on intermediate outcomes to explain income pathways. We use panel regression models as follows:

$$Y_{jt} = \theta + \phi MM_{jt} + \chi \mathbf{V}_{jt} + \delta T_t + \mu_{jt} \quad (2)$$

where Y_{jt} is the outcome variable such as income, consumption, or coffee price received by household j in year t. MM_{jt} is the treatment dummy variable of particular interest. A positive estimated treatment effect ϕ would imply that MM use affects income or other outcomes in a positive way. We control for other household, farm, and contextual variables that may affect outcomes through including the vector $\mathbf{V}_{jt}$. In addition, we control for time fixed effects through the year dummy T_t. θ, χ and δ are other parameters to be estimated, and μ_{jt} is the random error term.

The model in equation (2) can be estimated with random effects (RE) panel estimator. However, if there are any unobserved factors that influence MM_{jt} and Y_{jt} simultaneously, then the treatment effect ϕ would be biased. Since farmers decide themselves whether or not to use MM it is well possible that adopters and non-adopters differ in terms of unobserved characteristics. Similarly, it is possible that early MM adopters differ from later adopters. To test and control for unobserved heterogeneity, we use a fixed effects (FE) estimator, which is possible because we have sufficient variation in the treatment variable over time. FE estimators evaluate differences within households, so that any time-invariant heterogeneity between adopters and non-adopters – regardless of observed or unobserved – is cancelled out (Cameron and Trivedi, 2005). For all outcome variables, we compare RE and FE estimates by means of a Hausman test. An insignificant test result implies that unobserved, time-invariant heterogeneity is not an issue. In that case, the RE estimator is reliable and more efficient. A significant Hausman test indicates that the FE model is preferred to reduce bias in the estimated treatment effect, while as well ensures consistency.

3.4. Variables used

The treatment variable in all models is MM use, which is defined as a dummy that takes a value of one if at least one household member had a MM money account and had used MM services in the respective year. In almost all adopting households, the household head is a MM user, even though other household members may have their own MM account as well.

Household welfare is measured in terms of two indicators, namely household income and per capita consumption. Household income is the combined farm and off-farm income obtained over a period of one year. Farm income includes the value of all farm produce – either sold or kept for household consumption – minus production costs. Off-farm income includes salaries, wages, and pensions of all household members, land rents and capital earnings, as well as any net profit (revenue minus cost) from non-agricultural businesses. Remittances are also included as an off-farm income source. The other welfare measure – per capita consumption –

measures the value of all food and non-food goods and services consumed in the household divided by the number of persons living in the household. Food consumption data were collected through a seven-day food recall. For most non-food items, monthly expenditures were recorded. For the analysis, we converted all expenditure data to a daily basis.

Remittances and other off-farm incomes are used as intermediate outcome variables. Remittances refer to money received during the respective year from any relatives or friends not living in the same household. This can be through MM services or through any other mechanism. To differentiate between different types of off-farm income, we calculate off-farm income with and without remittances included.

To evaluate agricultural marketing pathways, we look at the proportion of coffee that is sold as shelled green beans. As explained above, selling shelled coffee requires drying and processing and allows farmers to enter higher-value markets. Furthermore, we use the average coffee price received by farmers in the respective year as another intermediate outcome variable. As farmers sold their coffee in various forms (e.g., red cherries, dried cherries, green beans), the prices reported are not directly comparable. For instance, 5 kg of red cherries or 2 kg of dried cherries will typically result in only 1 kg of shelled green beans. To make prices comparable, we used appropriate weight conversion factors. This does not account for the actual cost of processing, which is mainly the opportunity cost of time. However, during the survey many farmers told us that the cost is less of an issue. The main reasons mentioned for not selling more coffee in higher-value form were pressing consumption needs such as payments for medical care, school fees, food, or fuel.

All monetary values are expressed in Ugandan shillings ((UGX): 1 US$ = 2,690 UGX). To account for inflation and make monetary values comparable for the two survey rounds, 2012 data were adjusted to 2015 using the official consumer price index (UBOS, 2015).

For most of the regression models, the same vector of covariates is used, even though – depending on the particular outcome – individual variables are sometimes added. The vector of covariates includes household characteristics, such as education, age, and gender of the household head, farm characteristics, such as land owned and the value of other productive assets, and spatial characteristics, such as distance to the next tarmac road and a district dummy.

The use of MM is closely correlated with the use of mobile phones. As mobile phones can also affect the welfare of households through channels other than MM, it is important to control for mobile phone use in order not to overestimate the MM treatment effect. Furthermore, cooperative membership and farmer participation in certification schemes for sustainability standards, such as Fairtrade or Organic, can influence farm household welfare (Chiputwa and Qaim, 2016). We include dummies for mobile phone use and sustainability certification into all impact models. Cooperative membership is closely correlated with certification in the study region, so we do not include both to avoid issues of collinearity. Use of mobile phones and participation in certification schemes are time-variant and may proxy for the farmers' openness to technical and institutional innovations more generally. Thus, including these variables will also reduce any possible bias through unobserved time-variant heterogeneity.

4. Results and discussions

Mobile money (MM) services were introduced in Uganda in 2009. The most important MM service providers are Mobile Telephone Network (MTN) and Airtel, which are both foreign-owned private companies. Seventy-one percent of MM adopters in our sample had an MTN account in 2015, 28% had an Airtel account. Table 1 shows how MM use developed in recent years among the sample households. Between 2012 and 2015, the share of households with MM more than doubled from 23% to 62%. This increase was facilitated by the rapid spread of MM service centers. Typically, these service centers are kiosks or small shops where cash can be deposited or withdrawn from mobile accounts. The same shops also provide other mobile phone related products and services. While in 2012 only 17% of the sample households had a MM service center in their village, by 2015 this had increased to 54%. Table 1 also shows the development of mobile phone usage among sample households, which increased from 76% in 2012 to 89% in 2015.

<<<Table 1>>>

Figure 2 shows the most important MM activities used by sample households. In this graph, for each adopting household we only counted the most frequently performed activity, so the numbers add up to 100%. More than two-thirds of the households reported that withdrawing money from their mobile account is the most important activity. Withdrawals can be from previous own cash deposits or from transfers through business partners or private remittances. Usually, small amounts are withdrawn. The mobile accounts are considered relatively secure for savings. Depositing money is free, whereas for withdrawals a small proportional fee is charged. Most households also use their mobile accounts for sending money and for paying goods and services, but in terms of frequency these other activities were reported less often.

<<<Figure 2>>>

4.1 Descriptive statistics

Table 2 presents descriptive statistics of the outcome variables and covariates used in the regression models, differentiating between MM users and non-users in 2012 and 2015. Data for the pooled sample, including both survey rounds, are also shown in the last two table columns. MM users have higher household incomes and per capita consumption levels than non-users. MM users also have higher off-farm incomes, both with and without remittances included. The most important off-farm income source for sample households are small businesses like retail shops, trade in forest products, transport services, or handicrafts, followed by remittances, and salaries from employment as teachers, nurses, or office clerks (Figure 3).

<<<Table 2>>>

<<<Figure 3>>>

As discussed, agriculture-related outcome variables of interest here are the proportion of coffee sold as shelled beans and average coffee prices received by farmers. Table 2 shows that MM users sell a higher proportion of their harvest as shelled coffee, whereas for coffee prices we do not observe significant differences.

The lower part of Table 2 shows the covariates used in the regression models. For many of these covariates, significant differences between MM users and non-user households can be observed. MM users tend to have younger heads that are more likely to be male, have higher levels of education, more land and other productive assets. MM users also spend more money on agricultural inputs and are more likely to be certified under a sustainability standard. Finally, MM users have more neighbors that also have a mobile money account, possibly pointing at social influence in technology adoption at the local level. This neighborhood variable was captured by asking how many of the respondent's 10 nearest neighbors in the village use MM services.

4.2 Determinants of mobile money adoption

Table 3 presents the estimation results from the probit model to explain MM adoption, as described in equation (1). We used a random effects probit estimator. In column (1) of Table 3, we excluded the adoption of mobile phones and sustainability certification as other technical and institutional innovations, whereas in column (2) these variables were included as covariates. Especially for mobile phones the adoption determinants may potentially be very similar as for MM, which could lead to potential issues of multicollinearity. Unsurprisingly, mobile phone adoption influences mobile money adoption in a positive way. But the coefficients of other variables are hardly affected by including or excluding mobile phone use and certification, suggesting that multicollinearity is not an issue.

<<<Table 3>>>

The other results in Table 3 show that larger households are more likely to be MM users. Obviously, when there are more household members the probability that at least one of them uses MM services increases. Male-headed households are significantly less likely to use MM, which is striking because the descriptive statistics above suggested otherwise. The reason for this discrepancy is that females tend to be disadvantaged in terms of other factors, such as education and asset ownership. The probit models, which control for such other factors, imply that females may possibly benefit more from MM services than males. This is plausible given that female farmers are often more time-constrained, so that innovations that help reduce the costs of market and financial transactions are particularly welcome.

Access to MM service centers and neighborhood effects also affect MM adoption in a positive way. Having a MM service center in the village means that cash withdrawals and deposits are not associated with much travel time, which can be an important incentive for adoption. Service centers can also provide technical support. Similarly, having more neighbors using the same technology facilitates access to information and technical advice. Finally, the 2015 year dummy has a highly significant positive coefficient, underlining the rapidly increasing adoption of MM technology over time.

It is worth mentioning that household income, farm size, other productive assets, and distance to roads are all insignificant in the models in Table 3. This suggests that factors related to wealth and infrastructure, which often affect the adoption of other types of technologies, are less relevant for MM adoption. Infrastructure matters in terms of MM service centers, but these centers haven been spreading fast even to more remote rural area. The results suggest that MM could positively affect the lives of even those people that are often more disadvantaged in terms of other innovations.

4.3 Impact of mobile money use on household welfare

Table 4 shows the estimation results of the models that we use to evaluate the impact of MM on household welfare, as described in equation (2). The RE specifications in columns (1) and (2) of Table 4 suggest that MM use affects household income and per capita consumption in a positive and significant way. While the FE specifications in columns (2) and (4) also show positive treatment effects, these are not statistically significant. However, the Hausman test statistics, which are shown at the bottom of Table 4, are not statistically significant, so that the RE models are preferred because of their higher estimation efficiency. The results confirm earlier work that showed positive welfare effects of MM use on rural households in Kenya and Uganda (Kikulwe et al., 2014; Munyegera and Matsumoto, 2016).

<<<Table 4>>>

As we use linear model specifications, the coefficient estimates in Table 4 can also be interpreted as marginal affects. Controlling for other factors, MM use has increased annual household income by 503 thousand UGX on average. Compared to mean income levels of non-adopters in our sample, this is equivalent to an increase of 19%. The MM treatment effect on daily per capita consumption is 227 UGX, equivalent to a 6.5% increase over mean consumption levels of non-adopters.

Covariates that affect household income and per capita consumption in a positive way are education, land owned, and other productive assets. Sustainability certification has a positive effect on consumption levels. And households located in Masaka have higher incomes than those located in Luwero District.

4.4 Impact of mobile money use on remittances and off-farm income

Table 5 shows the estimation results for impacts on remittances and off-farm income. Columns (1) and (2) show RE and FE specifications with remittances received as dependent variable. While in both models MM use produces positive effects, these are not statistically significant. This does not necessarily prove that MM has no impact on remittances. Once we exclude other variables such as asset ownership, distance to road, or use of a mobile phone, the MM effect actually turns significant. However, these results suggest that – even if there is a positive effect on remittances received – this is probably not the main or the only pathway through which MM affects household welfare. We therefore look at other possible pathways in the following.

<<<Table 5>>>

In columns (3) and (4) of Table 5, the effects of MM use on total off-farm income, including remittances are shown. Given the significant Hausman test statistic, the FE model in column (4) is preferred. MM use has increased annual off-farm income by 330 thousand UGX, equivalent to a 45% treatment effect over non-adopters. In columns (5) and (6) of Table 5, the same models are shown but now using off-farm income without remittances included within the dependent variable. Again, the FE specification is preferred. The treatment effect remains large and positive (307 UGX, equivalent to 47% over non-adopters), also underlining that remittances are not the main driver of the MM effect on off-farm incomes. As explained above, small-scale businesses in trade, transportation, and handicrafts may particularly benefit from the new savings and money transfer opportunities through MM technology.

Other covariates that affect off-farm income positively are education, male household heads, and ownership of productive assets. These effects are more pronounced in the RE specifications, which is due to the low data variation over time within households for these variables. Households in Masaka have lower off-farm incomes than households in Luwero, in spite of higher overall income levels. Due to better agricultural production conditions, households in Masaka derive a larger share of their income from farming activities. Similarly, participation in sustainability certification of coffee seems to shift the household focus more towards farming income.

4.5 Impact of mobile money on agricultural marketing

Table 6 shows the model estimates with the proportion of coffee sold as shelled green beans as dependent variable. The proportion of shelled beans is used as proxy for selling in higher-value markets rather than selling immediately after harvest in unprocessed form. Due to the significant Hausman test, we prefer the FE model that is shown in column (2) of Table 6. Our hypothesis that MM has a positive effect on the proportion of coffee sold as shelled beans is confirmed. The treatment effect of 0.19 implies that the proportion is increased by 19 percentage points. Given that non-adopters of MM sold about 23% of their coffee as shelled beans, the 19 percentage point increase implies almost a doubling, which is a substantial effect. This effect may be explained by MM users being less cash-constrained and therefore more willing and able to sell after drying and processing. Additionally, MM users have an advantage in transacting with buyers from outside their location. Local traders, and middlemen buying coffee at farm gate, are primarily interested in red coffee cherries or unshelled beans.

<<<Table 6>>>

Covariates that also affect the proportion of coffee sales as shelled beans that we control for in Table 6 are distance to road and sustainability certification. Especially Fairtrade certified farmers in this region often sell shelled coffee beans directly to exporters in Kampala (Chiputwa et al., 2015). Farmers in Masaka also sell a larger proportion of their coffee in shelled form. The significantly negative year dummy coefficient is due to the fact that rainfalls and yields were lower in 2015 than they were in 2012 (UBOS, 2015). In these models in Table 6, we also control for a few other farm characteristics that may affect coffee output and marketing decisions, such as input use, age of coffee plants, and time needed to reach the coffee plots. Input use has a positive effect in the RE specification. The other variables are not statistically significant.

Effects of MM use on coffee prices received are shown in Table 7. Given the significant Hausman test statistic, we concentrate on the FE model in column (2) for interpreting the treatment effect. MM use has a positive effect. Controlling for other factors, MM adopters have received 320 UGX more per kg of shelled coffee (or weight equivalence of coffee sold in other forms), which translates into a 7% increase over the mean prices received by non-adopters. The higher price can be explained by MM users selling more of their coffee as shelled beans and having better access to buyers in higher-value markets.

<<<Table 7>>>

Other covariates that influence the coffee prices received include productive assets and distance to road (Table 7). Productive assets include vehicles and transport equipment, so the positive effect is unsurprising. Longer distances to the tarmac road lead to higher transportation costs, thus lowering prices for agricultural outputs sold at the farm gate. The positive effect for Masaka is due to better developed market infrastructure in that district. Additionally, we observe a positive coefficient for certified households. This is in line with previous studies showing that Fairtrade and other sustainability standards can be associated with higher coffee prices for participating farmers (Weber, 2011; Chiputwa et al., 2015; van Rijsbergen et al., 2016). Finally, prices in 2015 were significantly lower than in 2012. This reflects international price developments. Also, due to lower rainfalls the average coffee quality was somewhat lower in 2015.

5. Conclusions

Previous studies showed that the rapid spread of mobile money (MM) in Africa can contribute to welfare gains in rural and urban households. One important mechanism that was mentioned in several studies is through higher remittances that MM users receive from relatives and friends. In this article, we have tested the hypothesis that other impact pathways – that were not analyzed previously – can also be important, especially in a smallholder farming context. In particular, we had hypothesized that MM services can help farmers to access higher-value markets and thus receive higher prices for their products. We had also hypothesized that the use of MM can increase off-farm income beyond remittances.

These hypotheses were tested and confirmed with panel data from smallholder coffee farmers in Uganda. Panel regression models have shown that the adoption of MM technology contributes to higher household welfare in terms of income and consumption. Total household income gains through MM were estimated at 19%. Gains in off-farm income were estimated at 45%, regardless of whether or not remittances were included. In fact, the MM treatment effect on remittances alone was found to be insignificant, suggesting that MM services may be more relevant for other off-farm income sources in this particular case. Small businesses in handicrafts and trade and transport services are the most important off-farm income sources for rural households in the sample. These businesses benefit from the new savings and money transfer opportunities through MM technology.

MM users were also found to be more likely to sell coffee in dried and shelled form to buyers in higher-value markets instead of selling to local traders immediately after harvest. Due to higher savings and off-farm incomes, MM users are less cash-constrained, so that the need to sell immediately after harvest is reduced. Moreover, MM services facilitate transactions with buyers from outside their local region, including through contractual agreements where product orders, deliveries, and payments may not occur at the same time and place. Controlling for other factors, MM users fetched 7% higher average prices for their coffee than farmers who were not using this new technology.

We conclude that MM services can contribute to rural development through various important pathways. The rapid spread of MM technology within only a few years is remarkable. By 2015, 89% of the randomly selected households in our sample were using mobile phones, and 62% had a mobile money account. Adoption models showed that factors related to wealth and infrastructure, which typically constrain the adoption of other new technologies, are less relevant for MM technology. And, after controlling for other covariates, female-headed households were found to be more likely using MM than male-headed households. These results suggest that MM services are socially inclusive and can positively affect the lives of even those people that are often disadvantaged in terms of other innovations. It is interesting to note that these are purely private-sector driven developments.

The findings from this study should not be widely generalized, as our sample of small-scale coffee growers in Uganda may not be representative for various other small farm settings. We should also mention that panel data with only two rounds of observations, as used here, and have their limitations. For instance, addressing possible issues of reverse causality would benefit from panel data with more rounds of observations. Finally, we acknowledge that additional impacts and impact pathways – not analyzed here – may also be important. One interesting aspect would be to analyze the gender implications of MM services in greater detail. More research is needed to confirm the findings and further advance the research direction.

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Table 1: Mobile money use and distribution

	2012	2015	Pooled sample
Proportion of households using mobile money	0.23	0.62***	0.44
Proportion of households with mobile money service center in their village	0.17	0.54***	0.36
Proportion of households using mobile phone	0.76	0.89***	0.83

Note: *** differences in proportions between the two years are significantly different at the 1% level.

Table 2: Descriptive statistics by users and non-users of mobile money (MM)

	2012		2015		Pooled sample	
	Users (N=98)	Non-users (N=321)	Users (N=284)	Non-users (N=171)	Users (N=382)	Non-users (N=492)
Outcome variables						
Household income (million UGX per year)	3.754**	2.876	4.186***	2.040	4.075***	2.585
	(3.737)	(3.173)	(3.803)	(2.260)	(3.786)	(2.913)
Per capita consumption (thsd. UGX per day)	3.136	3.332	4.161	3.759	3.898***	3.481
	(1.645)	(1.962)	(2.714)	(2.368)	(2.522)	(2.119)
Remittances (million UGX per year)	0.324	0.405	0.527	0.401	0.502	0.403
	(0.499)	(0.766)	(0.596)	(0.467)	(0.623)	(0.622)
Off-farm income (million UGX per year)	1.013	0.813	1.421***	0.600	1.316***	0.739
	(1.533)	(1.409)	(1.748)	(1.009)	(1.703)	(1.287)
Off-farm income without remittances (million UGX)	0.960	0.750	1.209***	0.466	1.145***	0.651
	(1.496)	(1.389)	(1.694)	(0.932)	(1.647)	(1.256)
Shelled coffee sales (proportion)	0.427	0.295	0.273***	0.099	0.313*	0.227
Coffee price (thsd. UGX per kg of shelled coffee)	4.478	4.446	4.288	4.217	4.350	4.401
	(0.465)	(0.447)	(0.245)	(0.352)	(0.342)	(0.438)
Explanatory variables						
Education of household head (years of schooling)	5.945***	4.851	5.882***	4.469	5.898***	4.718
	(2.946)	(3.388)	(2.920)	(3.199)	(2.923)	(3.325)
Age of household head (years)	54.118*	57.210	56.745***	61.989	56.071***	58.871
	(11.577)	(15.014)	(13.018)	(14.417)	(12.701)	(14.969)
Male head (dummy)	0.806	0.741	0.835***	0.684	0.827***	0.722
Household size (persons)	7.534***	6.373	7.145***	5.448	7.245***	6.051
	(3.145)	(2.992)	(2.907)	(2.923)	(2.970)	(2.997)
Land owned (ha)	1.268*	1.007	1.131***	0.618	1.166***	0.872
	(1.134)	(1.172)	(1.388)	(1.394)	(1.327)	(1.266)
Productive assets (million UGX)	7.975***	7.258	8.028***	6.840	8.014***	7.113
	(1.515)	(1.799)	(1.598)	(1.747)	(1.575)	(1.790)
Distance to tarmac road (km)	17.888	18.322	17.900	17.282	17.897	17.961
	(9.449)	(10.145)	(9.383)	(9.297)	(9.387)	(9.862)
Masaka district (dummy)	0.500	0.495	0.493**	0.398	0.495	0.461
Migrant household (dummy)	0.224	0.215	0.158	0.129	0.175	0.185
Certified (dummy)	0.745**	0.617	0.673*	0.591	0.691**	0.608
Neighbors using MM (number out of 10 nearest neighbors)	2.745***	0.106	5.264***	0.111	4.618***	0.108
	(2.542)	(0.686)	(2.820)	(0.723)	(2.961)	(0.698)
Age of coffee plants (years)	29.522**	33.092	31.223	32.962	30.791***	33.047
	(11.319)	(13.443)	(11.992)	(12.793)	(11.832)	(13.208)
Input use (thsd. UGX per ha)	49.802	44.323	68.123***	52.795	63.423***	47.267
	(31.652)	(34.533)	(31.435)	(34.089)	(32.454)	(34.581)
Walking time to coffee plots (minutes)	1.899	1.349	3.377***	2.465	2.998***	1.737
	(4.436)	(4.444)	(2.423)	(2.104)	(3.118)	(3.832)

Notes: Mean values are shown with standard deviations in parentheses. *, **, *** differences between MM-users and non-users are significant at the 10%, 5%, and 1% level, respectively. 1 US$ = 2,690 UGX

Table 3: Determinants of mobile money adoption (random effects probit models)

	(1)	(2)
Education of household head (years)	0.038	0.031
	(0.076)	(0.079)
Age of household head (years)	-0.020	-0.016
	(0.017)	(0.018)
Male head (dummy)	-1.117**	-1.195**
	(0.550)	(0.608)
Household size (persons)	0.247***	0.221**
	(0.087)	(0.093)
Income (UGX)	-5.8E-08	-6.3E-08
	(7.3E-08)	(7.4E-08)
Land owned (ha)	0.152	0.195
	(0.259)	(0.274)
Square of land owned	-0.077	-0.088
	(0.076)	(0.078)
Productive assets (UGX)	1.4E-07	1.3E-07
	(1.5E-07)	(1.6E-07)
Distance to tarmac road (km)	0.012	0.017
	(0.025)	(0.027)
Masaka district (dummy)	0.438	0.179
	(0.484)	(0.520)
Migrant household (dummy)	0.514	0.483
	(0.488)	(0.506)
MM service center in village (dummy)	5.655***	5.549***
	(0.874)	(1.183)
Neighbors using MM (number out of 10 nearest neighbors)	1.314***	1.276***
	(0.203)	(0.273)
Year 2015	1.182***	1.055**
	(0.418)	(0.461)
Mobile phone use (dummy)		1.832*
		(0.998)
Certified (dummy)		-0.184
		(0.518)
Constant	-5.873***	-7.116***
	(1.684)	(2.297)
No. of observations	874	874
No. of households	480	480
Wald χ^2	65.98***	28.31**
Likelihood-ratio test rho=0	17.18***	15.34***

Notes: Probit coefficients are shown with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of mobile money use on household welfare

	Household income (Thousand UGX per year)		Per capita consumption (UGX per day)	
	(1) RE	(2) FE	(3) RE	(4) FE
Mobile money use (dummy)	502.9**	391.4	227.1**	61.8
	(227.4)	(368.7)	(114.5)	(194.5)
Education of head (years)	108.4 ***	-2.5	32.4*	39.4
	(34.9)	(78.9)	(17.4)	(41.7)
Age of head (years)	-19.1**	-33.7	9.5**	-10.4
	(7.9)	(24.6)	(3.9)	(12.9)
Male head (dummy)	212.3		183.9	
	(256.2)		(127.2)	
Household size (persons)	-55.4	-95.5	-308.0***	-283.7***
	(36.1)	(76.2)	(18.0)	(40.2)
Land owned (ha)	418.9***		78.6*	
	(85.3)		(42.9)	
Productive assets (UGX)	7.3E-04***	5.6E-04***	2.8E-04***	2.6E-04***
	(6.9E-05)	(1.3E-04)	(3.5E-05)	(6.6E-05)
Distance to tarmac road (km)	6.8		9.0	
	(11.1)		(5.5)	
Mobile phone use (dummy)	-75.5	182.1	124.8	342.0
	(290.8)	(430.3)	(147.2)	(227.0)
Certified (dummy)	9.7	582.5	226.8**	-11.6
	(225.3)	(573.8)	(112.2)	(302.7)
Masaka district (dummy)	788.6***		-37.0	
	(232.6)		(115.2)	
Year 2015	112.9	224.4	429.1***	524.7***
	(198.7)	(250.0)	(102.3)	(131.9)
Constant	-2.7E03***	779.2	1.1E05***	1.1E05***
	(708.2)	(1.7E03)	(353.8)	(897.0)
No. of observations	874	874	874	874
No. of households	480	480	480	480
Wald $\chi2$	379.9***		415.1***	
F-value		4.11***		15.14***
Hausman test $\chi2$		9.66		7.63

Notes: Estimation coefficients are shown with standard errors in parentheses. RE, random effects; FE, fixed effects, *** p<0.01, ** p<0.05, * p<0.1; 1 US$ = 2,690 UGX

Table 5: Impact of mobile money use on remittances and off-farm income

	Remittances		Off-farm income including remittances		Off-farm income without remittances	
	(1) RE	(2) FE	(3) RE	(4) FE	(5) RE	(6) FE
Mobile money use (dummy)	34.8 (29.6)	26.8 (54.8)	265.5** (114.8)	330.2* (185.5)	245.1** (111.2)	307.1* (175.5)
Education of head (years)	2.5 (4.4)	-17.0 (11.7)	71.3*** (17.7)	-8.6 (39.8)	69.9*** (17.3)	9.9 (37.6)
Age of head (years)	4.9 *** (0.9)	1.4 (3.6)	-2.8 (4.0)	-3.3 (12.4)	-7.3* (3.9)	-4.2 (11.7)
Male head (dummy)	-39.1 (31.9)		155.5 (129.9)		217.9* (127.7)	
Household size (persons)	4.3 (4.5)	-5.3 (11.3)	-2.8 (18.2)	14.9 (38.7)	-2.9 (17.8)	22.2 (36.6)
Land owned (ha)	20.2* (10.4)		-22.8 (43.1)		-30.6 (41.8)	
Productive assets (UGX)			2.2E-04*** (3.5E-05)	1.8E-04*** (6.3E-05)	1.9E-04*** (3.4E-05)	1.5E-04** (5.9E-05)
Distance to tarmac road (km)	-3.6*** (1.4)		-8.9 (5.6)		-5.5 (5.5)	
Mobile phone use (dummy)	55.9 (38.3)	111.7* (64.0)	19.6 (146.6)	129.5 (216.6)	-28.5 (141.5)	20.9 (205.0)
Certified (dummy)			-155.6 (113.9)	-160.7 (289.9)	-184.6* (111.7)	-215.3 (274.4)
Migrant household (dummy)	18.2 (32.9)	-0.4 (52.6)	65.8 (124.5)	271.6 (178.5)	63.0 (120.1)	275.7 (168.9)
Masaka district (dummy)	19.6 (27.9)		-201.1* (117.9)		-213.4* (116.2)	
Year 2015	93.0*** (28.1)	104.0*** (37.4)	103.4 (100.4)	204.8 (126.9)	12.9 (95.5)	104.6 (120.1)
Constant	-253*** (79.7)	5.9 (225.2)	-759.9** (359.1)	-497.0 (855.9)	-410.9 (350.9)	-350.3 (810.1)
No. of observations	874	874	874	874	874	874
No. of households	480	480	480	480	480	480
Wald χ^2	74.8***		129.57***		118.42***	
F-value		4.19***		3.22***		2.21**
Hausman test χ^2		7.01		33.47***		28.78***

Notes: All dependent variables are measured in thousand UGX per year. Estimation coefficients are shown with standard errors in parentheses. RE, random effects; FE, fixed effects, *** p<0.01, ** p<0.05, * p<0.1; 1 US$ = 2,690 UGX

Table 6: Impact of mobile money use on proportion of coffee sold as shelled beans

	(1) RE	(2) FE
Mobile money use (dummy)	0.092*	0.192**
	(0.050)	(0.085)
Education of head (years)	-0.007	-0.002
	(0.008)	(0.018)
Age of head (years)	-9.9E-05	0.002
	(0.002)	(0.006)
Male head (dummy)	0.068	
	(0.055)	
Household size (persons)	-0.008	0.005
	(0.008)	(0.018)
Land owned (ha)	-0.002	
	(0.019)	
Productive assets (UGX)	1.9E-08	-2.6E-08
	(1.6E-08)	(2.9E-08)
Distance to tarmac road (km)	-0.007***	
	(0.002)	
Mobile phone use (dummy)	-0.028	0.102
	(0.065)	(0.101)
Certified (dummy)	0.335***	0.097
	(0.048)	(0.133)
Age of productive coffee trees (years)	-0.005	-0.012
	(0.022)	(0.037)
Square of age of productive coffee trees	2.6E-04	6.9E-04
	(6.8E-04)	(1.2E-03)
Input use (UGX per ha)	1.7E-06**	6.8E-07
	(6.9E-07)	(1.1E-06)
Walking time to coffee plots (minutes)	-0.006	
	(0.006)	
Masaka district (dummy)	0.513***	
	(0.050)	
Year 2015	-0.155***	-0.207***
	(0.048)	(0.060)
Constant	-0.271	-0.066
	(0.166)	(0.432)
No. of observations	874	874
No. of households	480	480
Wald $\chi2$	224.84***	
F-value		2.47***
Hausman test $\chi2$		18.68**

Notes: Estimation coefficients are shown with standard errors in parentheses. RE, random effects; FE, fixed effects, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Impact of mobile money use on coffee prices received

Model	(1) RE	(2) FE
Mobile money use (dummy)	164.3	319.6*
	(111.6)	(179.7)
Education of head (years)	-16.4	-21.4
	(17.1)	(38.5)
Age of head (years)	0.8	11.8
	(3.9)	(11.9)
Male head (dummy)	160.4	
	(125.6)	
Household size (persons)	-25.4	-17.6
	(17.7)	(37.2)
Land owned (ha)	40.6	
	(41.9)	
Productive assets (UGX)	7.8E-05**	1.0E-04*
	(3.4E-05)	(6.1E-05)
Distance to tarmac road (km)	-21.6***	
	(5.5)	
Mobile phone use (dummy)	-121.1	175.1
	(142.9)	(209.8)
Certified (dummy)	1,094***	312.0
	(110.5)	(279.7)
Masaka district (dummy)	1,908***	
	(114.0)	
Year 2015	-511.9***	-673.4***
	(97.8)	(121.9)
Constant	-492.5	-387.2
	(347.4)	(828.8)
No. of observations	874	874
No. of households	480	480
Wald $\chi2$	477.35***	
F-value		4.89***
Hausman test $\chi2$		40.42***

Notes: Estimation coefficients are shown with standard errors in parentheses. RE, random effects; FE, fixed effects, *** p<0.01, ** p<0.05, * p<0.1; 1 US$ = 2,690 UGX

Figure 1: Impact pathways of mobile money use on household welfare

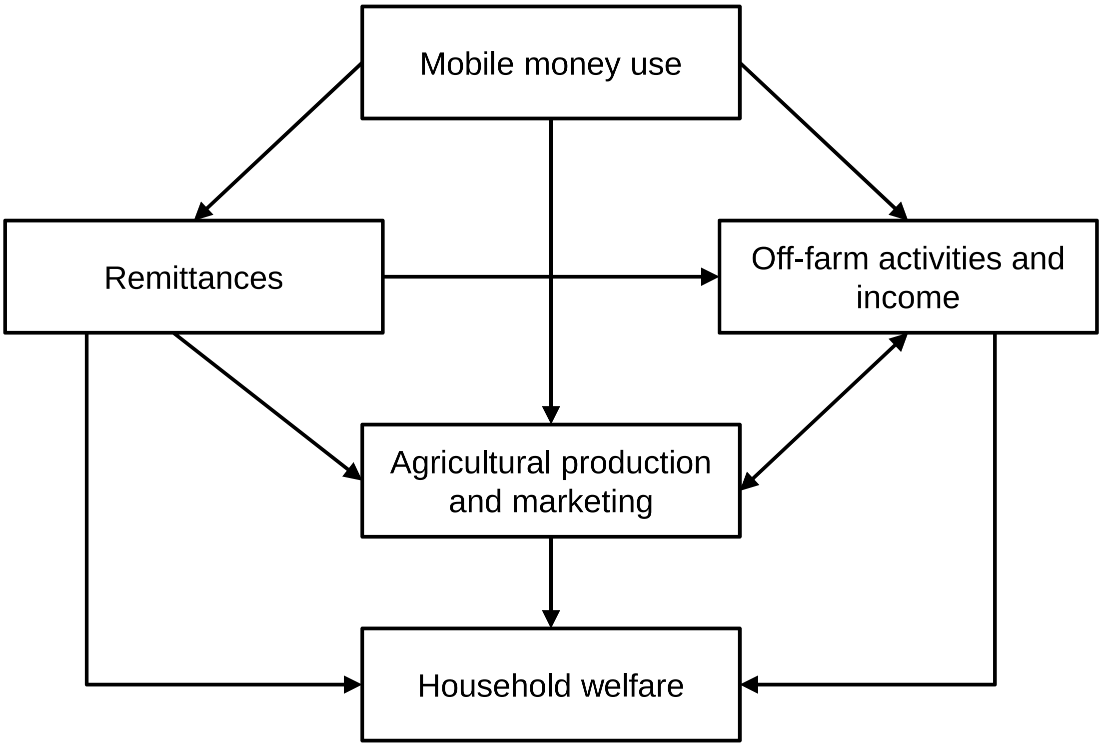

Figure 2: Most important mobile money activity

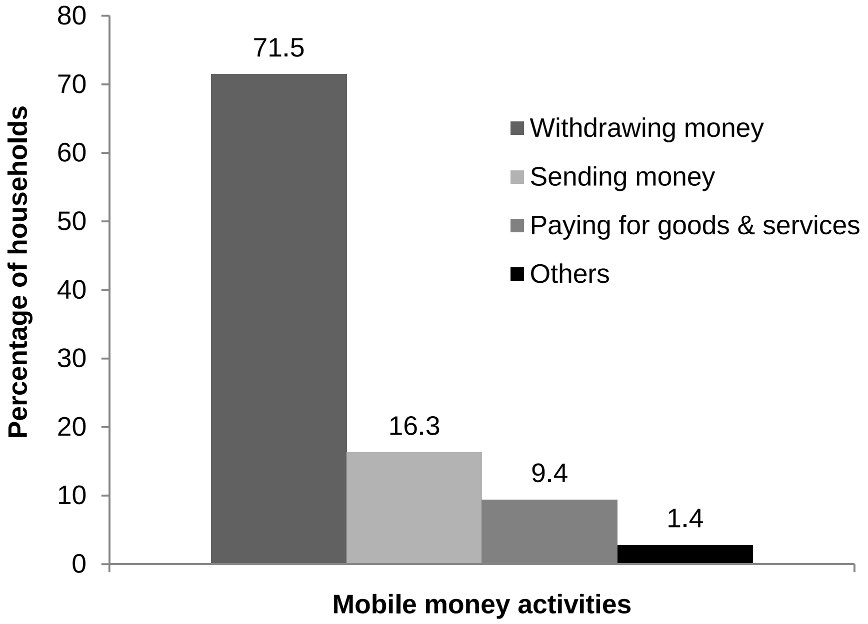

Figure 3: Most important off-farm income source