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Mozambique Cell Phone Savings Pilot Project

Endline Report

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE IFPRI

Mozambique Cell Phone Savings Pilot Project: Endline Report

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Executive Summary

BACKGROUND

Nampula province in northern Mozambique is a predominantly rural area characterized by high levels of poverty. Most farms are on small plots tended by smallholder farmers, with low levels of agricultural productivity relative to neighboring countries. A major barrier to improved productivity is the low levels of input usage, which, according to the formative research, is explained by: (1) lack of knowledge about when and how to use inputs and their benefits, (2) transaction costs related to market access including distance to input markets and high transport costs, and (3) liquidity constraints during the point of the agricultural cycle when input purchase is optimal. In 2011 4 percent of farmers in the province used inorganic fertilizer, with the average farmer living 34km from the nearest source of fertilizer (Mouzinho, Cunguara, Cavane, & Donovan, 2011).

INTERVENTION DESIGN

The pilot project sought to combine two interventions: one targeted at facilitating access to the formal financial system using mobile money technology, and the other at increasing input usage through localized marketing. Fifty-one smallholder farmer associations were included in the study. Leaders from these associations received their own initial training in Nampula city, which was followed by a group-level training carried out locally for each association. In collaboration with local provider Vodacom, members received SIM cards with mobile money accounts and were trained in how to use the system. The goal was to provide farmers with a simple decentralized technology which could be used for savings.

For the input marketing component, the study followed a randomized control design. Half of the associations were assigned to a treatment arm in which a local NGO provided direct marketing of inputs to farmer associations at the village level, with a rebate available to farmers who purchased inputs using mobile money. For those in the control arm, the local partner carried out their usual input marketing activities in more centralized local producer forums. The aim of this portion of the intervention was to lower the transaction costs associated with input purchases, while providing an incentive to use mobile money technology.

Throughout the duration of the study, the original design was adjusted to account for inaccuracies in the initial reports about the local input market activity, cell phone signal reception, and the mobile money agent network. Additional challenges to the implementation of the project activities included internal organization problems of the FOSC implementing partner, which is a major input and output trader in the area, deactivation of inactive cell phone accounts which the research team had to work with Vodacom to correct, and the discontinuation of USAID's agribusiness support project (AgriFUTURO) in Nampula. These challenges affected the implementation of the pilot project, and affected the effectiveness of its implementation.

CELL PHONE AVAILABILITY

In line with recent global trends, cell phone ownership has increased exponentially in Mozambique, from 3.5 percent of the population in 2004 to 69.7 percent in 2014 (World Development Indicators 2016). Despite high levels of poverty, 62 percent of households in the study reported owning cell phones in 2015.

Despite low levels of education and limited access to electricity, these households are active users, making and receiving 16-17 calls and sending or receiving 8-9 text messages per week on average.

MOBILE MONEY USAGE

To evaluate the effect of the mobile money trainings on association members, we compare outcomes between association members who attended the group-level training and other association members who were not present. We control for observable differences between these groups by including additional socioeconomic explanatory variables in our regression analysis.

Table 1. Impact estimates of mobile money training (2014)

	Knows of Mobile Money	Uses Mobile Money	Has Mobile Money balance	Knows name of a Mobile Money agent
Received Mobile Money Training	0.33***	0.44***	30.13**	0.05***
	(0.04)	(0.03)	(12.76)	(0.02)

Those receiving group-level training in mobile money were statistically significantly more likely to be familiar with mobile money: trainees were 33 percent more likely to know of mobile money than non-trainees, and 5 percent more likely to know the name of their local mobile money agent. Trainees also reported higher levels of usage: they were 44 percent more likely to report using mobile money, and 30 percent more likely to report currently having a positive balance in their mobile money accounts following the training.

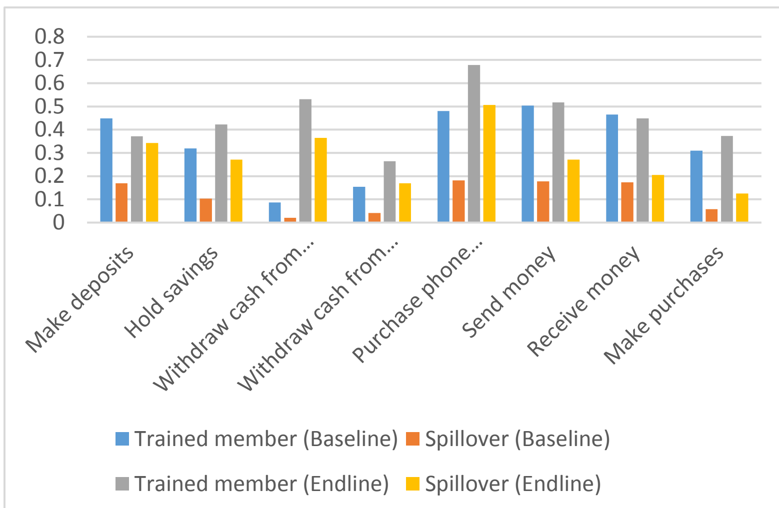

Figure 1. Familiarity with mobile money features

Trained respondents were more likely to report using a mobile money or conventional savings account, and less likely to report using a cashbox to save money immediately following the training, though this effect was reduced over time. Attendees were also better able to report features of the mobile money system, including saving money, making and receiving transfers, and making purchases electronically—knowledge which had increasingly passed on to the spillover group by the time of the endline.

AGRICULTURAL INPUT USAGE

At baseline, levels of input use in the study area were very low. Of households surveyed: 11 percent report use of improved seeds; 13 percent report using pesticides or insecticides; 2 percent report using inorganic fertilizer; and less than 1 percent report using herbicides. Households relied heavily upon family labor, with only 7 percent of those surveyed reporting using hired labor. Access to input markets was limited, with travel times of 1-2 hours to purchase inputs from local markets. Gender appears to play an important role in input access, with female-headed households reporting lower levels of usage across all categories of agricultural inputs, relative to male-headed households.

In evaluating the effect of the training program, we find an overall exogenous increase in input usage, which we are unable to attribute to the treatment assignment. While administrative records do suggest a modest increase in purchases of inputs amongst treated households, this cannot account fully for the large increase in input usage which we observe between periods across the treatment and control group. As a result, we are unable to statistically attribute any increase in input usage to the marketing treatment.

EFFECTS OF INPUTS ON AGRICULTURAL PRODUCTIVITY

While we are unable to detect an effect of the input marketing intervention on input usage, the observed increased take-up of inputs allows us to explore the question of the effect of increased use of inputs for farmers in our sample. Rather than simply estimate the effect of input take-up for the average individual in the sample, we utilize a quantile regression framework to explore the effect of input use at different points in the outcome distribution. This allows us to explore how the effects of taking up a given input vary for farmers who produce relatively more or less of a given crop relative to the median household.

Table 2. Correlates of input use on maize production (2014/2015)

	Production Quantity (Kg)			**Crop value (MZN)**		
Percentile	**25th**	**50th**	**75th**	**25th**	**50th**	**75th**
Paid labor	7.95	18.89**	10.23	110.95**	241.73***	309.18
	(5.10)	(8.19)	(13.94)	(53.58)	(92.48)	(191.85)
Improved seeds	6.47	15.44	15.40	59.95	145.99	161.52
	(6.03)	(11.22)	(18.91)	(48.90)	(107.37)	(177.28)
Chemical fertilizer	45.39	193.63	397.71**	240.63	1,317.71	3,507.13**
	(72.78)	(154.01)	(166.77)	(501.37)	(1,718.13)	(1,581.16)
Pesticide	20.13***	32.75**	49.39*	264.49***	226.45*	608.62**
	(6.72)	(13.81)	(28.82)	(64.09)	(131.63)	(259.08)
Herbicide	35.67	13.74	83.22	283.98	31.72	619.13
	(451.59)	(594.66)	(780.60)	(4,199.03)	(5,713.42)	(11,351.83)

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Looking at the maize, the local staple crop, we find statistically significant benefits of pesticide use to both the quantity produced and the aggregate value of the crop, across the distribution with benefits increasing at higher percentiles. For fertilizer, however, while the coefficients are positive throughout, they are only statistically significant for farmers in the top production/value quartiles—suggesting that the benefits to fertilizer use may be concentrated amongst farmers with high initial productivity levels.

CONCLUSIONS

While we do observe some modest input purchases using mobile money, we are unable to detect a statistically significant increase in input usage or expenditures due to the input marketing treatment. Given the design changes and implementation challenges the project faced, we cannot conclude whether the lack of a response to the treatment is due to the treatment being implemented ineffectively or to the treatment itself being ineffective; it could be with a much-improved implementation that treatment effects would have existed. We therefore do not have enough evidence to conclude that the combination of mobile money incentives and direct marketing, as implemented in this study, represents a cost-effective means to increase agricultural productivity. We do however find evidence that gains to production from increased input use are not homogenous among households—an important finding which should be considered in designing equitable interventions around inputs in this context.

In terms of mobile money, we find that a subset of farmers continue to use mobile money services over a year after the initial training, and are willing to travel to local agents to make transactions—a group that would likely grow in the presence of a larger agent network. While cell phone use is widespread in the area despite the lack of electricity in many villages, we observe that farmers are more likely to make relatively expensive phone calls rather than use SMS technology; we believe this observation may be due to low literacy levels. Thus, while the infrastructure may be present to allow for a variety of ICT related development projects using cell phones, the effectiveness of interventions using text messages may be limited in the study area relative to some otherwise comparable development contexts.

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Section 1. Project Background

While smallholders in Mozambique are often connected to output markets, the adoption of agricultural inputs, such as improved seed and synthetic fertilizer, remains persistently low in Mozambique. As a result, crop yields and thus farmer profits are much lower than their potential. Neighboring countries have achieved significantly higher crop yields relative to Mozambique. For example, in Tanzania the average grain yield is 1,418 kg/ha and in Malawi the average is 2,069 kg/ha, which is significantly higher than the 818 kg/ha grain yield for Mozambique (World Bank 2016). This yield gap, which still falls well below potential, can largely be attributed to low input use in Mozambique.

One explanation for low investment in inputs is that smallholder farmers commonly lack access to formal mechanisms for saving harvest profits, constraining their ability to make crucial investments in the next crop cycle. Another reason for low input adoption is that rural smallholder farmers have limited access to markets where they can purchase inputs. The 2008 *Trabalho de Inquerito Agricola* (TIA), a nationally-representative, agriculturally-focused survey conducted by the Ministry of Agriculture with support from Michigan State University, reports that the average farmer lives 34 kilometers away from the nearest source of fertilizer. Not surprisingly, a recent report showed only 4 percent of farmers in Nampula province used inorganic fertilizer in 2011 and only 2.3 percent of farmers used improved maize seed (Mouzinho, Cunguara, Cavane, & Donovan, 2011). Similarly, according to the 2014 *Inqueríto Agrário Integrado* survey, only 0.3 percent of farmers in Nampula used fertilizer and 4.5 percent of farmers used pesticides

The Mozambique Cell Phone Savings Pilot Project was a study designed and implemented by the International Food Policy Research (IFPRI) with support from the United States Agency for International Development Bureau of Food Security (USAID BFS) aimed at improving farmer take-up of inputs. The research team conducted a feasibility study in 2013 and used secondary data sources, particularly the 2012 TIA, to identify barriers to input take-up among farmers in the study districts of Namialo and Nacololo in Nampula province. The three main barriers that were identified through the formative research included: 1) lack of knowledge about when and how to use inputs and their benefits, 2) transaction costs related to market access including distance to input markets and high transport costs, and 3) liquidity constraints during the point of the agricultural cycle when input purchase is optimal.

The feasibility study confirmed that input use among smallholder famers is extremely low. Input suppliers are based in large towns, making them inaccessible to rural farmers. Some farmer owned service clusters (FOSCs) did offer inputs directly to farmers, but this was not common due to low demand for inputs and because sales must be arranged in advance through the forum (a cluster of FOSCs).

Access to financial services is also low with only four banks in Nampula province as of 2011 and no mobile banking system, although *Banco Oportunidade* does offer mobile banking in other provinces of Mozambique. The background research revealed that most households still resort to informal savings mechanisms. For example, farmers reported burying their money, if they saved at all, or using rudimentary savings groups.

The study uses a randomized controlled trial with an encouragement design to assess the impact of an intervention aimed at reducing the transaction costs faced by farmers, such as distances required to travel to find inputs, when purchasing inputs and increasing investment in productive agricultural inputs with the goal of improving crop production and ultimately household income. The encouragement intervention is designed to address the three key bottlenecks for input adoption identified through the feasibility study. The study is designed with two overlapping treatments. The first is designed to conduct direct input marketing visits with farmers' associations as a mechanism for providing information on different types of inputs, their use, and potential benefits, and as a means of reducing transaction costs by offering inputs for sale directly in farmers' villages. The second offered a rebate for purchasing inputs through a mobile phone technology called Mobile Money. Mobile Money is a mobile phone-based service that allows users to store, send, and receive money. By encouraging the use of and familiarity with this technology, the second treatment had the secondary goal of enabling farmers to safely save profits gained from harvest sales at the end of one season to be invested in input purchases at the beginning of the next season by providing them with a virtual savings device through their mobile money accounts.[1] Payments for inputs made through Mobile Money transfers can also reduce transaction costs commonly incurred by both farmers and traders, by reducing the need to travel to access financial services. Combined with more direct input distribution channels and increased farmer knowledge about the benefits associated with sufficient input use, Mobile Money could potentially increase demand for inputs and ultimately, improve agricultural productivity and farmer incomes.

The original design and implementation of these interventions assumed certain level of inputs availability and output marketing activity, reliability of cell phone services, and a moderately active mobile money agent network based on information provided by the project's local collaborators: 1) AgriFUTURO, a USAID agribusiness project that was run by Abt Associates; 2) IKURU, a collective of farmer cooperatives partially owned by those cooperatives, headquartered in Nampula; 3) mCel, a cell phone service provider, partially owned by the state and running the mKesh mobile money platform; and 4) Vodacom, an international cell phone service provider running the m-Pesa platform since late 2013 in Mozambique. In this context, lowering farmers' transaction costs through more direct input distribution channels and the introduction of mobile money technology to substitute for formal and accessible banking services to rural households offered an excellent opportunity to increase farmers' access to inputs and, in turn, their crop yields. The primary objective of the intervention was to improve agricultural productivity through the increase in input access and use and decrease in the use of informal savings strategies. The secondary objective of the project was to increase mobile money adoption and saving rates among rural households in Nampula. Throughout the duration of the study, the original design was adjusted to account for the inaccuracies in the initial reports of the local context. Input commercialization between input suppliers and forums, FOSCs or farmers rarely took place, cell phone signal reception within areas considered as covered was still spotty (but this improved after switching partners from mCel to Vodacom), and mobile money agent network outside Nampula city was virtually non-existent.

In practice, the assumption that input availability would occur as designed was in fact more challenging to attain than initially expected. While IKURU's managing director was quite knowledgeable about input use, the extension staff were only two people, split regionally in coverage (north and south), and not as

[1] Initially a third, cross-randomized treatment incentivizing the use of mobile money accounts as savings devices was considered to address the liquidity constraint hypothesis. The final sample size of associations within cell coverage was insufficient to support three treatment arms. The research team decided to drop this treatment option due to feasibility concerns (local regulatory constraints (mobile money accounts are not considered to be banking accounts and therefore cannot generate interest gains)) and to USAID preferences to concentrate on treatments that addressed the constraints to input access rather than savings.

knowledgeable about input use. Moreover, the entire organization had difficulty with scheduling issues. According to the original intervention design, IKURU was scheduled to make two visits to each of the treatment associations, one right after the previous season's harvest to capture income from crop sales before it was spent, and one right before planting when farmers would be more immediately concerned with next season's crops. The first input sale visit was designed to address the farmers' liquidity constraints, but also relied on farmers choosing to spend the harvest income on investments for higher future returns, rather than to satisfy immediate necessities. On the other hand, the second input sale visit targeted less patient farmers (in terms of inter-temporal consumption and investment decisions), but not so affected by liquidity constraint issues.[2] Despite the research team's best efforts to catalyze input visits as scheduled, IKURU still missed the first visit at harvest time, and visits with two of the 27 treatment associations at planting time. Moreover, they did not always send extensionists on those visits, but rather marketing specialists, and so extension messages about using improved inputs were not as strong as they could have been. These issues could potentially have been worked out with a stronger presence through a primary agribusiness project (like AgriFUTURO), however, USAID did not award a new agribusiness project after AgriFUTURO ended in 2014 and there was a gap in project support. The gap in external support, coupled with IKURU's leadership changes and internal restructuring from late 2014 through the spring of 2015, resulted in very little output marketing activity by IKURU[3] in 2015, and as a result offers to purchase crops from farmers on Mobile Money could not be arranged. Due to these implementation problems the issue of liquidity constraints and timing were not addressed through the intervention as implemented, and the main takeaways of the evaluation are about the effect of improved access to inputs and reduction of transaction costs in input marketing, rather than its timing.

To try to ensure the reliability of cell phone services, and the mobile money agent network, prior to the commencement of this study the research team did the following. First, we had originally planned to work with mCel and its mobile money product, mKesh, as in the feasibility study. We were convinced by Vodacom that it made more sense to switch to working with Vodacom because 1) they had better cell coverage than mCel in Nampula province, and 2) because they were already planning a rapid expansion of mPesa, which had not existed in Mozambique yet when the feasibility study took place. Vodacom shared with the research team (and with IKURU) maps of Vodacom cell phone coverage and maps of plans for additional cell tower placement in the next 12 months, and resulting coverage. Given that Vodacom was planning more new cell towers for Nampula than mCel was for the entire country, and that mCel would require us to try to recruit agents ourselves as in the feasibility study, it made sense to run the pilot project in collaboration with Vodacom.

The research team then asked IKURU to attempt to place farmer associations on the Vodacom maps so that we could eliminate any groups that would not have coverage. From this exercise, we eliminated, for

[2] This two-visit input sales schedule was designed to replace the prepaid input treatment from the Feasibility Study, where the protocol was to ask for payment at the time of harvest, and deliver inputs at the time of planting. Although the original plan was to test the advance purchase model, in discussions with farmers before implementation began we found that the two-visit scheme was preferred over the prepaid strategy because it ruled out the presence of a confounding effect due to trust issues between the farmers and IKURU (that could be triggered by the gap between payment and delivery times). Additionally, in the study context there was no gain for IKURU or the farmers from delaying input delivery (which could potentially exist if farmers faced storage costs or IKURU required time to procure inputs).

[3] Our endline data corroborate that IKURU did not purchase much from smallholders in 2015; they suggest very few sample farmers sold crops to IKURU.

example, Murrupula district entirely from the potential sample, since there was almost no coverage in Murrupula. IKURU also was able to identify a few potential associations that should be eliminated from the sample. Despite the attempt to match actual cell phone coverage with farmer groups associated with IKURU for the study, there were still associations with no coverage that had to be dropped during the fieldwork. Additionally, Vodacom found it more difficult to recruit mobile money agents than they had expected, and so the agent network did not reach the size that had been projected by the end of the study.

An additional challenge related to the availability of a mobile network relates to SIM card registration, which officially requires significant paperwork, which is a major constraint for farmers who may lack appropriate documents or may not bring them to a village training. In the feasibility study, we found that a major challenge was in fact signing up farmers in a timely manner (then for mCel coverage, but the issue is the same for all cell phone providers in Mozambique). In the pilot project, we dealt with this constraint by using a more limited form of registration. Within the trainings, this process worked much better, as we were able to register all participants to a SIM card quite rapidly and then conduct the trainings. However, due to miscommunication with Vodacom, we did not realize that they would deactivate those numbers within 3 months if the number went unused. Use, in this context, is considered either mobile money use or phone usage. As we did not know ahead of time that numbers would be deactivated, we had to request that a number of the accounts be reactivated so that they could become potentially eligible for the bonuses. For future projects, an easy fix would be to set up a system to call participants on, for example, a bimonthly basis to ask a simple question with an incentive such as airtime for an answer, so that each SIM card held by a participant fits the definition of "use". Given the challenges with reliability, the agent network, and challenges created by the lack of leadership within IKURU, the Mozambique Cell Phone Savings Pilot Project was therefore discontinued after just one year of the intervention.

This report presents results from the endline analysis of the Mozambique Cell Phone Savings Pilot Project. The report proceeds as follows: the next section details the intervention and provides information on the impact evaluation methodology; Section 3 presents descriptive statistics on the sample at baseline and characteristics of poverty within the sample; Section 4 presents analysis on the impact of the intervention on take-up of inputs; Section 5 analyzes results on mobile money usage; Section 6 concludes and offers recommendations for future interventions utilizing mobile money strategies.

Section 2. Study Design

2.1 Partners

AgriFUTURO: USAID's six-year project to increase local private sector competitiveness and develop and scale agricultural value chains in the area, AgriFUTURO was initially supposed to run from 2009-2013 but was extended through the end of 2014. In the feasibility study, it was originally hoped that AgriFUTURO would provide a linkage between IFPRI and the FOSCs, providing assistance in establishing a communication channel with the FOSC leaders, obtaining basic data such as descriptions of FOSC activities and member rosters, helping to strengthen IKURU institutional capacity to deliver services to its member associations, etc. In practice, the information about and direct contact AgriFUTURO had with the FOSCs was limited, and the role they were willing to play was reduced to supporting IFPRI in identifying the partner that would link the study with the FOSCs.

In the pilot project, the initial plan was to work with the follow-on project to AgriFUTURO, once it was awarded and after AgriFUTURO had closed. However, the project was never awarded.

IKURU: An agricultural commodity and input trading peri-statal company in Nampula, and it is mainly involved with sesame, peanut, cashew nut, bean, and soybean farmers; IKURU was identified as a potential partner through AgriFUTURO. IKURU is nominally a FOSC, organized into fora, which are geographic clusters of farmer groups. The model for IKURU is to act as a service organization for member farmers; helping provide them with technical assistance, assistance with input provision, and as an aggregator of output. In fact, much of what IKURU does is to function as a commodity trader, bulking and purchasing crops from the forums to resale at local, regional, or international markets. While IKURU offers some technical assistance and access to input distribution, our experience and research found that they have very heterogenous contact with the member farmer groups, and this contact is often reduced when there are leadership changes and/or organizational constraints posed from within the organization.

Vodacom: The cell phone and mobile money service provider used for the intervention. While Vodacom's signal coverage in the rural areas surrounding Nampula city is not as strong as the newest entrant to the market, Movitel, Movitel does not offer a mobile money service, and the signal for Vodacom is much better than that of the third company, mCel. Advantages of working with Vodacom include its experience in the mobile money business, with successful experiences in other parts of Africa, particularly Kenya and Tanzania. Vodacom also shared plans for the rapid expansion both of cell tower coverage and mobile money coverage in advance of the intervention, which would improve the coverage along both dimensions as the intervention took place, and only required a partnership agreement to work with IFPRI. While there existed some challenges in working with a profit-oriented private firm, overall Vodacom Mozambique was extremely open to cooperate with the study as it viewed it as a good way to learn how to expand their business to rural areas of the country (as most of its experience is focused in urban and peri-urban areas).

2.2. Study Area

The project was carried out in four districts in the province of Nampula in north-eastern Mozambique (Figure 2.1). The districts are located east of Nampula city and south of the port of Nacala. In collaboration with IKURU, the research team identified local smallholder farmer associations in the area as the delivery point for the intervention. The FOSCs are part of larger producer collectives, referred to as forums. The initial research design targeted sixty associations, representing four forums named for their local geographic area: Angoche, Meconta, Monapo, and Mogovolas. Of these, 57 associations were thought to have good network coverage for the telecom service provider Vodacom based on layover maps with the Vodacom coverage. However, when cell phone and mobile money trainings were held in the 57 villages, it was determined that an additional five of the associations did not have sufficient coverage, so the sample was reduced to 52 associations.

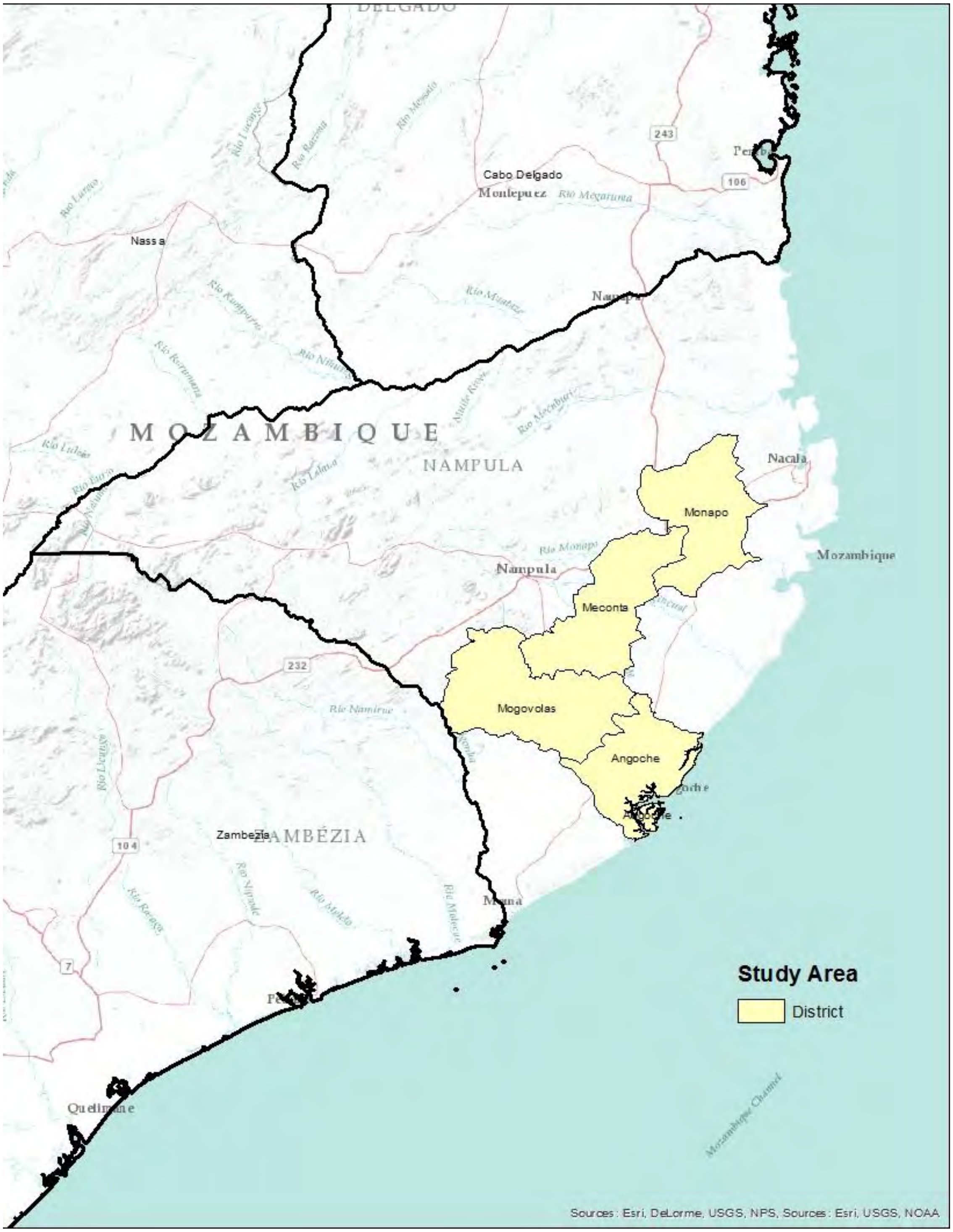


Figure 2.1.1. Administrative Map of Study Area

2.2 Study interventions

To meet the study objectives of increasing input use, the project implemented the following activities: (i) farmer trainings on mobile money technologies; (ii) farmer trainings on benefits associated with the use of agricultural inputs; (iii) input marketing conducted at the association level; and (iv) discounts for inputs that are paid with mobile money. Ideally, with a large sample of associations we would randomize assignment to different and overlapping treatment arms in order to assess the impacts of the mobile money element of the intervention separately and in combination with the input marketing, plus keep a pure control group so we can clearly identify the individual and joint impacts from the interventions. However, given the limited number of associations that met the inclusion criteria within the IKURU member area, the design was limited to a single treatment arm and a control group in order to maintain statistical power to identify an effect. All farmers in the study (treatment or control) were given access to farmer trainings on mobile money technologies. Farmers in treatment associations received direct input marketing visits at the village level, where they received information on input use and were offered a discount (in the form of a 10% rebate) if they made their input purchase using mobile money. Control group associations received marketing visits as normal at the more centralized forum level, where they were also offered a 10 percent rebate if they purchased inputs with mobile money. This design allows us to identify the effect of improved access to inputs in an enabling environment with discounted prices through Mobile Money services and increased farmer knowledge on input use. For both treatment and control groups inputs were available in small quantities (typically 1kg bags) and farmers were presented with an 'input menu' (see example in Appendix A) demonstrating the varieties available, the quantity and purchase price. The menu and availability of inputs did not vary across the treatment and control groups.

Figure 2.2 illustrates the project's prospective impact outcome pathways visually as a theory of change. The Mobile Money component of the farmer training was intended to tackle the barriers to adoption imposed by the introduction of a new technology (Mobile Money), while the input trainings are designed to tackle the knowledge barrier about the importance of inputs and proper input use, to clearly establish the link between adequate input use and higher yields and quality of crops. The input access components of the intervention aimed to tackle the input availability barrier.

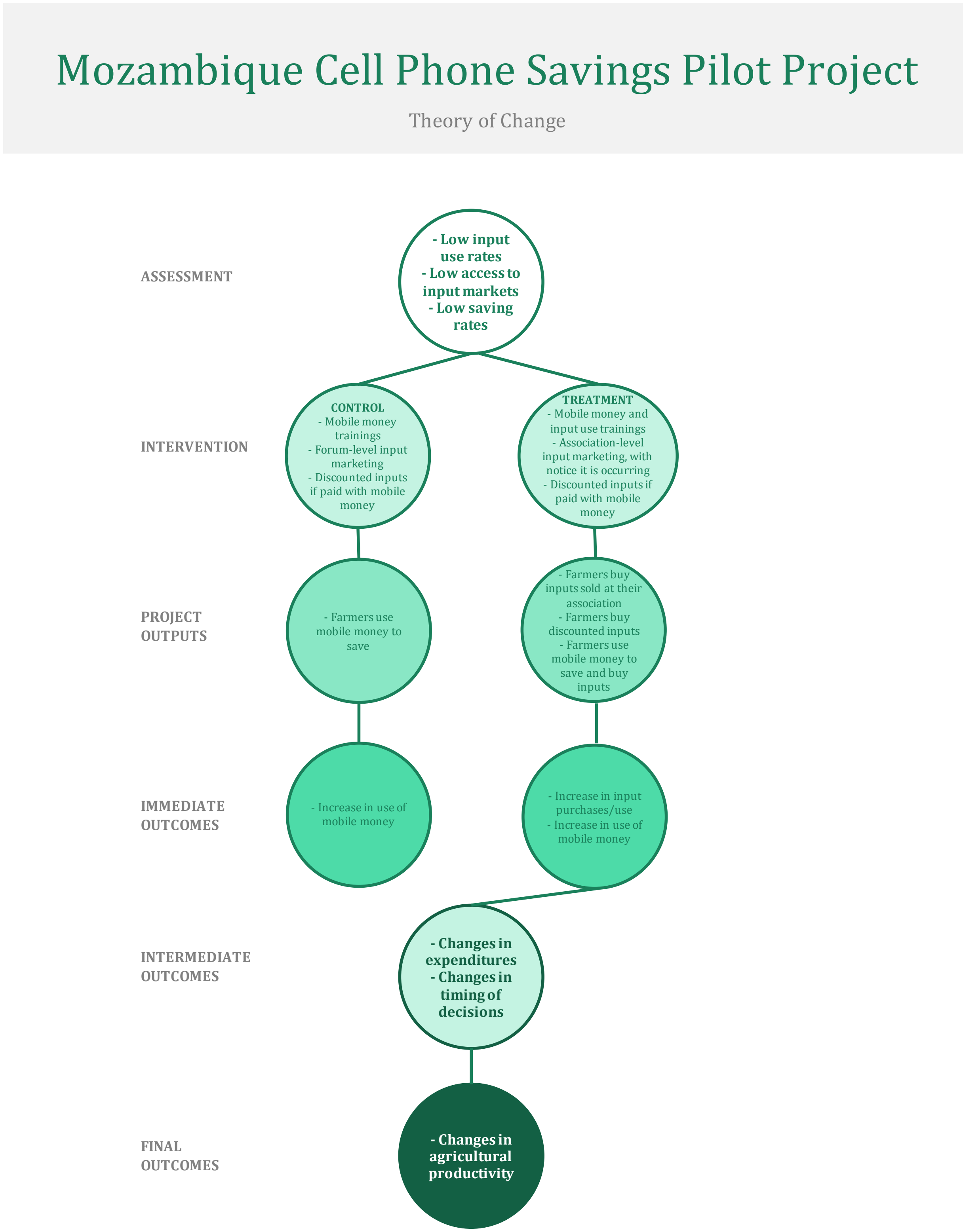


Figure 2.2.1. Theory of Change for Cell Phone Savings Pilot Project

2.3 Mobile Money Trainings

Mobile Money training was offered to all study associations regardless of treatment assignment. In June and July 2014, two levels of Mobile Money training were conducted—leader trainings and association trainings. Based on learning from the 2013 Feasibility Study, the concept for the two-part training was to initially train cell phone "leaders" who could help with the association-level trainings. Giving leaders a more in-depth training would help in mobilizing the rest of their association to participate in the village trainings, create a link between them and the Vodacom staff and agents, as well as allowing the leaders to serve as local providers of basic technical support and troubleshooting to other farmers. Leaders from each association were brought to Nampula city for the training at the Vodacom offices, designed and conducted by Vodacom staff under IFPRI supervision. The association-level trainings followed a few weeks later and were conducted in the gathering places of the associations by Vodacom staff under IFPRI supervision as well. Names, association names, national ID numbers, and mPesa SIM card numbers were collected on all individuals who participated in the trainings.

Leader training sessions were conducted in collaboration with Vodacom. Whereas the plan was to hold full day leader sessions that would last a full day with 60 participants, Vodacom's conference room in Nampula could not hold 60 people, therefore we collaboratively decided to split the training into two half-day sessions with one-half of the 57 participants taking part in a morning session, with the remaining half participating in an afternoon session. Though this would reduce the overall time participants were in training, the smaller group size would allow for greater one-on-one interactions and would help keep participants engaged. Therefore, the decision was made to reduce the trainings to half-a-day.

In these trainings, each leader was given a phone and a new Vodacom SIM card (phone number). After activating the phones and registering their SIM cards on the system, Vodacom gave a presentation on mPesa, Vodacom's Mobile Money service, that included basic information on what Mobile Money is, how it worked, and the benefits of using the service relative to traditional financial institutions. Fifty meticais (just under 2 USD) was loaded onto each phone and participants were broken into small groups to practice using the system. Leaders were told that they would be engaged in the village-level trainings to assist with teaching other farmers to use the system. The leader trainings helped with coordination and mobilization for the association-level group trainings. Leaders helped to ensure that the association members attended the training, which improved attendance at the group trainings.

The association-level trainings took half a day each. A protocol was developed to streamline Vodacom registration for association members. IFPRI and Vodacom staff assisted with the registration process. In addition to providing complementary mPesa-enabled SIM cards, basic cell phone models were provided for sale by Vodacom, to ensure farmers could take advantage of the system even if they did not previously own a phone. However, due to inventory constraints of Vodacom's Nampula office, the cell phone units ran out, and there was more difficulty than expected (by Vodacom, in communication with IFPRI) in replenishing those stocks. Consequently, cell phone units were not available for sale during all of the training sessions, which was part of the original training protocol to allow farmers that wanted to participate but needed to purchase a phone to be able to practice during the trainings. Instead, for communities that could not be trained with cell phones available for sale, we made follow-up visits to ensure that cell phones were made available. While members were able to share phones in the trainings, having more available would have increased the amount of time members were able to practice using the system. The group trainings revealed significant enthusiasm for the Mobile Money system, suggesting that there is latent demand for improved access to financial services, with farmers frequently expressing interest in using the system to send money or make purchases. In some associations, the individual who attended the leader training proved to be very helpful, though this varied by association and appeared to be correlated with leader age (younger leaders on the whole were more familiar with cell phone technology). Association members had time during the trainings to practice using the system, and generally left with a good understanding of how to use Mobile Money. However, success was not uniform, with older and less educated association members frequently struggling with the technology.

2.4 Input Trainings

The input training was implemented according to association treatment assignment.

For associations assigned to the treatment arm, agents from IKURU, the project implementing partner, conducted visits with the study association, meeting in a central area such as a schoolhouse or other meeting area in the village of the association members. These informational visits took place at the association level in the month before the input sales took place (October-November 2014).

The IKURU staff provided informational sessions describing the various inputs, how they should be used on local crops, and the benefits associated with their use. Members of the treatment associations were also given a discount of 10 percent on any input purchased with Mobile Money, in the form of a rebate. The discount was set to be as high as possible to induce farmers' participation, but still commercially viable to allow for the possibility of IKURU adopting it as a business practice. A Vodacom agent accompanied IKURU on visits to the associations and forums to facilitate Mobile Money transactions. Rebates were processed by IFPRI and sent back to farmers after administrative data on input purchases were processed. IKURU implemented visits to each treated association to attempt to sell inputs for purchase with cash or with Mobile Money, offering the discount for purchases by Mobile Money.

For the control associations, IKURU agents conducted input marketing visits at the forum level rather than the association level, at a centralized location where farmer groups typically hold inter-group meetings and related events. These visits were in line with IKURU's description of their typical input marketing activities, with appropriate quantities of various inputs (seeds, fertilizer, and pesticide) available for direct sale and were designed to take place following harvesting and sales, in August when farmers have most cash on hand.

Unfortunately logistical delays resulted in marketing visits being carried out in November. While this delay does not present an obstacle to analysis, it may be the case that ability to purchase inputs may have been dampened by all farmers, including those in the control group, having less money available for inputs at the time of purchase.

Information was also provided to the farmers in advance on the timing of the visit and the types of input available using a visual 'menu' of inputs (Appendix A).

2.5 Data Collection and Description

Data were collected through baseline and endline surveys conducted in collaboration with the *Associação de Nutrição e Segurança Alimentar* (ANSA). Baseline data collection took place shortly before the main growing season in August-September of 2014 to collect data on the 2013-14 production cycle. Endline data collection for 2014-2015 was conducted in October-November 2015, after the harvest (which typically takes place in May-June for most crops, with sales taking place modally in August) and before the following growing season. The initial survey sample started with a list of 60 farmer associations, provided by IKURU. Based on IKURU data, the assumed average size of an association was 19 members: to be conservative our sampling framework assumed a mean size of 15 members. These associations included in the study were selected based on a list of potential groups in the Feed the Future intervention area provided by IKURU and the availability of cell phone service reported on maps by Vodacom, which provided technology and training assistance for the intervention. The farmer associations are organized into four producers' forums for group marketing and other purposes. The forums include Meconta and Monapo in the northern part of the sample area; Angoche and Mogovolas in the southern portion.

Of the 60 associations initially selected, 57 were found to be in the Vodacom coverage area, and all of them agreed to participate in the intervention. Associations were randomly assigned to treatment and control groups, stratified on producers' forum to ensure that treatment associations would not be geographically concentrated. Coordination with IKURU field staff revealed that an additional 5 of the selected associations lacked cell phone service reducing our sample to 52 farmers' associations.

In each association the leader was instructed to promote the mobile money training among association members, so that members would attend the mobile money training; if non-association members came to the training, they were not turned away. While there was some variation in the size of the groups that attended the training, this was largely achieved. In total, 701 individuals attended the group trainings, an average of slightly fewer than 14 members per session. To create the sample, the data collection team was instructed to interview all households in the association where at least one member had attended the group training, along with an additional five households per association, which were selected from association lists among non-participants randomly by the survey supervisors. While the decision to attend the training was likely endogenous, these additional members allow us to explore the diffusion of knowledge about mobile money within farmer groups.[4]

Of the 701 individuals who attended the training, 642 individuals were successfully located by the data collection team and gave their consent to be interviewed, corresponding to 566 households (in 76 cases both the head of household and their spouse attended the training). The field team were generally able to locate additional households where no member had attended the training. In total, they interviewed an additional 243 households (an average of 4.8 per association), bringing the total sample size to 809.

During endline data collection, 689 of the 809 total households were successfully located by the field team and consented to participating in a second interview. At endline, the team interviewed an additional 67 households from the original target sample who were not interviewed in the baseline survey—while we lack baseline covariates for these individuals, the random assignment of treatment status means we can make meaningful comparisons in endline outcomes. For completeness, we include descriptive statistics

[4] The measurement of knowledge diffusion or spillovers was not in the original research design. However, the sample frame was developed from the association list rather than the list of farmers who attended training, so that we could measure an appropriate "intent-to-treat" effect rather than simply a training effect. Households that did not have a member attend the training could have not done so for a number of reasons—they could have been uninterested, but it could also be that information about the training was transmitted poorly within the village, or that household members were unavailable that specific day due to illness or another reason. We split results by those who were trained and those who were not trained to learn something about the effectiveness of the trainings, though we recognize there is likely to be some selection bias in the comparison. These households were referred to as "spillover" households in the baseline report (de Brauw et al. 2015), though they are not truly measured as "spillover" households.

for the full sample for each period (809 households at baseline, 756 at endline) in an Appendix. We focus the remainder of the analysis on the panel of households and individuals for whom we are able to observe outcome measures both at baseline and endline.[5]

Table 2.5.1. Sample Description, by Baseline and Endline, by Assignment to Input Marketing, and by Participation in Mobile Money Training

	Input Marketing Treatment			Mobile Money Training		
	Status	**Total**	***of which trained***	**Status**	**Total**	***of which treated***
Baseline	Control	434	*305*	Training	566	*261*
	Treatment	375	*261*	No training	243	*114*
Endline	Control	408	*285*	Training	531	*246*
	Treatment	348	*246*	No training	225	*102*

2.6 Attrition

Comparing those who were located and agreed to participate in the endline interview to those who left the sample, we find no evidence of differential attrition based on input marketing training status. To make inferences about the effect of the treatment we must be confident that there are no other differential temporal trends which could bias our results. For the input marketing intervention the rate of attrition is very similar across the treatment and control group: 14.8 percent in the control group, and 14.9 percent in the treatment group. One major cause of attrition was household migration—over 5 percent of targeted households were identified by the field team as having migrated. This number likely represents a lower bound on the true rate, as it only includes households which the team was able to explicitly identify as having migrated. A similar proportion of households was recoded as 'Absent' or 'Could Not Locate' despite repeated visits to the location of the household at baseline.

We observe a slight, insignificant, difference between the association members who attended the Mobile Money training compared to the untrained group with a lower rate of attrition (14.0%) among the trained group, compared to 16.9 percent attrition among those in the untrained group, although not large enough to be statistically significant.

Table 2.6.1. Attrition by training/treatment status

	Input marketing treatment		Mobile money training		Sample
	Control	**Treatment**	**Training**	**No Training**	
In endline	370	319	487	202	689
Attrition group	64	56	79	41	120
Attrition rate	***14.75***	***14.93***	***13.96***	***16.87***	***14.83***
Total	434	375	566	243	809

Looking at attrition disaggregated by gendered household type, we see no difference between the endline sample and the attrition group in the proportion of households with only adult females. The proportion of households with only adult males is slightly higher in the attrition group than in the endline sample,

[5] Appendix B presents the descriptive statistics for Section 3 among the full sample.

while the proportion of male and female adult households declines marginally though neither of these differences are statistically significant.

Table 2.6.2. Attrition by gendered household type

	Panel Group			Attrition Group			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
Female adult only	0.07	0.26	689	0.07	0.25	120	
Male adult only	0.06	0.23	689	0.10	0.30	120	
Male and female adult	0.87	0.34	689	0.83	0.37	120	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

One particular concern in any RCT design study is that if attrition is non-random, it may affect the representativeness of the sample, or the comparability of the treatment. If those leaving the sample are distinct in terms of observable (or unobservable) characteristics, one may be concerned that the final sample may not reflect the characteristics of the population originally being studied. To explore this, Table 2.6.3 compares the baseline characteristics of the heads of households that respectively remained in and left the sample.

Table 2.6.3. Attrition by characteristics of household head

	Panel Group			Attrition Group			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
Age	39.47	12.83	683	38.51	13.48	119	
Male	0.91	0.29	689	0.91	0.29	120	
Literate	0.76	0.43	689	0.73	0.44	120	
Primary education or higher	0.89	0.31	689	0.90	0.30	120	
Secondary education or higher	0.17	0.37	689	0.17	0.37	120	
Speaks Portuguese	0.63	0.48	689	0.60	0.49	120	
Owns a cell phone	0.57	0.50	689	0.53	0.50	120	
Does non-farm labor	0.55	0.50	689	0.57	0.50	120	

Reassuringly, heads of households who left the sample look very similar in their baseline characteristics to the heads of those households that remained. Household heads in the attrition sample are very slightly younger, less literate and less likely to speak Portuguese, but slightly more likely to report off-farm labor. However all of these differences are marginal in magnitude and p-values for tests of differences are very large, indicating no statistical significance.

In addition to the representativeness of the sample as a whole, a second concern relating to attrition is whether differential attrition occurs between the treatment and control group. Table 2.6.4 presents a comparison of the means for characteristics of the head of household for treatment and control.

Disaggregating by treatment status, we observe similar trends to the full sample in both treatment and control groups. Households re-interviewed in the endline are slightly older than those leaving the sample, and have slightly higher levels of education. Within group, we do not observe any statistically significant difference between those leaving and those remaining in sample for either treatment. The sole exception is for non-farm labor participation, which is significantly higher in those households who leave the control group. However, since the control group had a slightly higher non-farm labor participation rate at baseline, they remain comparable—55 percent of returning households in the control group report doing non-farm labor, compared to 56 percent in the treatment group.

Table 2.6.4. Baseline Characteristics of Household Head: Control vs. Input Marketing Treatment

	Control Mean			Treatment Mean		
	Panel	**Attrition group**	**Sig.**	**Panel**	**Attrition group**	**Sig.**
Age	38.27	38.02		40.85	39.07	
Male	0.92	0.91		0.88	0.91	
Literate	0.79	0.73		0.74	0.73	
Primary education or higher	0.89	0.91		0.89	0.89	
Secondary education or higher	0.16	0.23		0.17	0.09	
Speaks Portuguese	0.66	0.64		0.6	0.55	
Owns a cell phone	0.58	0.61		0.56	0.45	
Does non-farm labor	0.55	0.69	**	0.56	0.45	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Section 3. Descriptive Statistics

In this section we provide descriptive statistics of the panel households.

3.1 Household Demographics

Households in our sample generally have a traditional monogamous structure, with a couple comprising an adult male and adult female supporting children and other dependents, though some households do report practicing polygamous structures with multiple wives, while others reported having only one adult member.

Table 3.1.1 Gendered household type at baseline (Proportion of households)

	Mean	SD	Min.	Max.	Obs.
Female adult only	0.07	0.26	0.00	1.00	689
Male adult only	0.06	0.23	0.00	1.00	689
Male and female adult	0.87	0.34	0.00	1.00	689

Within the sample, 87 percent of households report at least one male and one female adult member, with the remainder reporting an adult male only (6%) or an adult female only (7%). To explore the potential role of gendered household type we will compare outcomes on selected statistics for the former two categories (male and female adult households and male-only households) to those for the latter (female-only households).

In terms of household composition, the average household size of five people, as measured at baseline, is small relative to some other developing country contexts, though slightly larger than in the USAID Feed the Future Intervention Zone for Mozambique (4.58 on average) and in neighboring countries (e.g., Malawi has an average household size of 4.57 individuals in rural areas according to the 2010 Integrated Household Survey data). Households are approximately evenly balanced in terms of gender composition. Household members are predominantly relatively, young, with 48 percent of household members under the age of 16, and the average age of the entire sample is 19.2 years.

Table 3.1.2. Household composition at baseline

	Mean	SD	Min.	Max.	Obs.
Household size	5.00	2.04	1	11	689
Number male	2.53	1.38	0	8	689
Number female	2.47	1.38	0	7	689
Number adults	2.26	0.75	1	5	689
Number children	2.69	1.77	0	8	689
Proportion aged 0-5	0.21	0.17	0.00	0.67	689
Proportion aged 6-15	0.27	0.20	0.00	0.71	689
Proportion aged 16-64	0.50	0.22	0.00	1.00	689
Proportion aged 65+	0.02	0.10	0.00	1.00	689

Figure 3.1.1 visualizes the distribution of household members' ages within the sample using a kernel density, which is a type of histogram with a smoothed density. In the figure, one can observe a clear concentration of members aged less than twenty, with few members older than 50 years. There is also a

slight concentration around age 40, though this concentration likely represents a bias toward reporting even numbers among adults unable to recall their exact age. Therefore, the figure makes it clear that the households include a lot of young members.

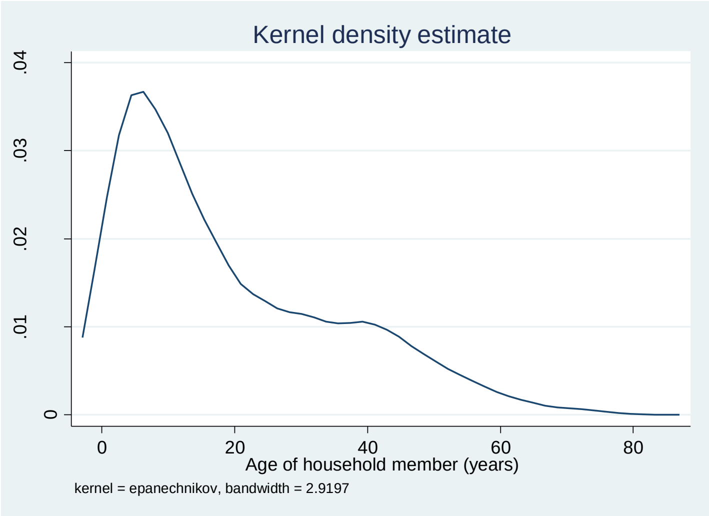


Figure 3.1.1. Density of Household Member Age, in Years

While household members are balanced in terms of gender, those identifying as the household head are almost exclusively male. Of the 689 households in the balanced panel, 624 (91%) report having a male head, compared to only 65 (9%) who report a female head. Of these 65, 51 are households which contain only female members, hence in our sample we see only 14 cases (2%) in which the household contains one or more adult male members, but the person identified as the head of household is female (in analyzing gendered household type, these cases are classified as having both male and female adult household members).

The mean age of household heads is 39.5. The majority of household heads report at least some education, with 89 percent of the sample reporting having received a primary education or higher and 17 percent reporting having received secondary education or better. However, the quality of education is likely to have been poor as 24 percent of household heads report being illiterate and 37 percent report being unable to speak Portuguese, which is an alternative indicator of literacy and crucial to using text messages on cell phones. Given that individuals tend to over-report their level of knowledge, these numbers may represent upper bounds for education and literacy levels among household heads in our sample. Over half of household heads (55%) report working in an additional occupation other than farming, suggesting a need to supplement earnings gained from agricultural production.

Table 3.13 Characteristics of household heads at baseline

	Mean	SD	Min.	Max.	Obs.
Age	39.47	12.83	17.00	84.00	683
Male	0.91	0.29	0.00	1.00	689
Literate	0.76	0.43	0.00	1.00	689
Primary education or higher	0.89	0.31	0.00	1.00	689
Secondary education or higher	0.17	0.37	0.00	1.00	689
Speaks Portuguese	0.63	0.48	0.00	1.00	689
Owns a cell phone	0.57	0.50	0.00	1.00	689
Does non-farm labor	0.55	0.50	0.00	1.00	689

3.2 Poverty and Expenditures

The surveys included an expenditures module, which consisted of a simplified version of the Feed the Future survey food expenditures module and a similar non-food expenditures module. Expenditures are reported in local currency units (Meticais or MZN[6]).

Households in the sample are quite poor with average annual total household expenditure per household member of 6,519 MZN at baseline, equivalent to approximately 18 MZN per person per day. Seventy-two percent of households in the sample are below the poverty threshold based on purchasing power parity of 2005 $1.25 per person per day. Despite an extremely simple food consumption module, this estimate is consistent with data from the rural Nampula sub-sample of the Feed the Future Intervention Zone,[7] which has a reported poverty rate of 75.6 percent, although the impact evaluation survey asked about food expenditures in only two questions rather than breaking up food by type as is common and clearly preferable if trying to estimate poverty (e.g., Beegle et al. 2014).[8] Nonetheless, more than half of household expenditure at baseline (54%) is spent on food.

Table 3.2.1. Expenditures per capita (MZN) and poverty incidence at baseline

	Mean	SD	Min.	Max.	Obs.
Food expenditure per capita	3,358.75	4,625.70	86.67	52,000.00	689
Total expenditure per capita	6,519.34	7,828.32	200.89	78,860.00	689
Food share of expenditures	0.54	0.21	0.01	0.98	689
Poverty rate	0.72	0.45	0.00	1.00	689

We separately analyze expenditures and poverty rates among households with only female adults (Table 3.2.2). These households are notably poorer. Expenditures on food are 18 percent lower for female adult only households but comprise a slightly higher share of total expenditure, constituting 62 percent of expenditures at baseline. Total expenditures are similarly lower, equivalent to 73 percent of total expenditures by all households at baseline. This is reflected in the higher poverty rate for female only

[6] At the time of the baseline report 1USD was equivalent to 33.4 MZN (Source: https://www.oanda.com/currency/historical-rates).

[7] This figure was calculated by the authors using data from the Mozambique Feed the Future baseline (https://www.usaid.gov/data/dataset/75b19d18-202c-45b9-9f49-200a52c785ea).

[8] The goal of the survey was not to estimate poverty incidence but to understand whether input use could be stimulated through mobile money. As such, it was decided not to field a full consumption module, which takes substantial time to administer properly.

households, 82 percent of which report expenditures below the $1.25 per person per day threshold at baseline.

Table 3.2.2. Expenditures per Capita among Female Adult Only Households, Baseline Survey

	Mean	SD	Min.	Max.	Obs.
Food expenditure per capita	2,757.40	2,617.80	260.00	13,000.00	51
Total expenditure per capita	4,753.98	5,458.86	602.67	33,840.00	51
Food share of expenditures	0.62	0.21	0.18	0.98	51
Poverty rate	0.82	0.39	0.00	1.00	51

Finally, in Table 3.2.3, we examine expenditures and poverty incidence disaggregating by treatment and control status, as determined by whether or not the association was chosen randomly for input marketing visits.

Table 3.2.3. Expenditures per Capita at Baseline, by Treatment Status

	Control			Treatment			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Food expenditure per capita	3,505.88	4,848.96	370	3,188.09	4,353.79	319	
Total expenditure per capita	6,913.73	8,558.44	370	6,061.90	6,870.33	319	
Food share of expenditures	0.53	0.21	370	0.54	0.22	319	
Poverty rate	0.70	0.46	370	0.74	0.44	319	

In comparing control and treatment associations, we obtain slightly higher estimated mean values for food expenditure and non-food expenditures (and consequently a lower poverty rate) in the control group relative to the treatment group. None of these differences are statistically significant at conventional levels, nevertheless to ensure that this difference does not influence our results, we include a control for total household expenditures in both the ANCOVA and fixed effects specifications which we estimate in the results section.

3.3 Asset ownership

Statistics on household expenditures suggest low levels of living standards, and as such we might expect low levels of asset ownership as well. Indeed, considering agricultural assets, we find that households typically do not own many rudimentary tools. For example, while all households in the sample report owning at least one hoe at baseline, for each of the other categories of basic agricultural tools listed, fewer than half of all households report owning the item. Hence at baseline 53 percent of households do not own an axe, 71 percent do not own a sickle, 83 percent do not own a shovel, 90 percent do not own a rake, and 94 percent do not own a watering can. Though we see some modest increases at endline, overall ownership levels remain low. At baseline, only 17 percent of households report owning a granary or similar structure to store produce after harvest, while 8 percent report owning some form of transportation equipment, providing suggestive evidence that farmers are likely to face significant constraints to store their products, thus affecting their ability to decide when, where and at what price their products are marketed.

Table 3.3.1. Agricultural asset ownership of sample households, Baseline and Endline

	Baseline			Endline		
Household owns:	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Bucket	0.92	0.27	689	0.97	0.18	689
Watering can	0.06	0.24	689	0.17	0.37	689
Mortar/Pestle	0.87	0.34	689	0.89	0.32	689
Barn/Granary	0.17	0.37	689	0.31	0.46	688
Transport equipment	0.08	0.27	689	0.01	0.08	688
Hoe	1.00	0.00	689	0.99	0.11	689
Axe	0.47	0.50	689	0.63	0.48	689
Machete	0.21	0.41	689	0.91	0.28	689
Shovel	0.17	0.37	689	0.27	0.45	689
Rake	0.10	0.30	689	0.17	0.38	689
Sickle	0.29	0.45	689	0.34	0.47	689

3.4 Landholdings and Agricultural Production

Considering landholdings, the surveys asked about each plot owned as well as the plot size. At baseline each household cultivates an average of 2.3 agricultural plots, with an average reported landholding of 3.9 hectares, equivalent to 1.8 hectares per plot. At endline, we find similar results, which would be expected as land is not easily traded. Households report very slightly more plots and more land than at baseline. Average plot size is virtually the same; none of the differences are statistically significant between samples. It is important to be cautious in interpreting the reported land area, as experience shows that farmers often do not have a good sense of the size of their plots in Africa south of the Sahara, particularly when land is apparently not a constraining factor on agricultural production (Abate et al. 2015).

Table 3.4.1. Average number of plots and reported size of landholdings, Baseline and Endline

	Baseline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	2.34	1.02	1.00	8.00	685
Area owned (hectares)*	3.90	3.21	0.31	22.00	688
Mean plot size (hectares)*	1.82	1.59	0.08	12.00	685
	Endline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	2.57	1.13	1.00	8.00	688
Area owned (hectares)*	4.05	3.38	0.00	20.00	684
Mean plot size (hectares)*	1.74	1.66	0.00	20.00	683

*Note: To reduce the emphasis of extremely small or large reported values, values below the 1st or above the 99th percentile are winsorized (i.e., 2 percent of observations are adjusted).

Female adult, no male adult households cultivate fewer plots than the average household in the data set (Table 3.4.2). At baseline, female adult households cultivate between 1 and 4 plots, with an average of 1.73 cultivated plots. Reported total land area is 2.4 hectares at baseline, which is substantially lower than the sample average of around 4 hectares. Consequently, average plot size is smaller among female adult households than the sample average. These findings are consistent in the endline which is not surprising since the household landholdings are unlikely to vary over short time spans or as a result of the interventions.

Table 3.4.2. Average number of plots and reported size of landholdings among Female Adult Households, Baseline and Endline

	Baseline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	1.73	0.75	1.00	4.00	51
Area owned (hectares)[a]	2.38	1.78	0.42	8.00	51
Mean plot size (hectares)[a]	1.45	1.10	0.42	5.00	51
	Endline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	2.00	1.01	1.00	5.00	56
Area owned (hectares)[a]	2.34	1.57	0.00	8.00	50
Mean plot size (hectares)[a]	1.41	1.09	0.00	6.00	55

[a] To reduce the emphasis of extremely large reported values, values below the 1st or above the 99th percentile are winsorized (i.e., 2 percent of observations are adjusted).

In aggregate, the households in the sample allocate more land to peanuts and cassava than other crops, with an average of about a hectare allocated to each (Table 3.4.3). Cowpeas and maize are the next most common crops, with boer beans and sesame also being close to half a hectare on average across the sample. Note that these averages are subject to the same biases as the aggregate area measure above, as land is not as much of a constraint as labor in much of Mozambique.

Table 3.4.3. Reported Sown Area by Crop, Baseline

	Baseline		
	Mean	**SD**	**Obs.**
Maize	0.86	1.49	689
Rice	0.11	0.39	689
Sorghum	0.20	0.53	689
Cassava	1.11	1.60	689
Peanuts	1.08	1.43	689
Sesame	0.47	1.25	689
Cowpeas	0.92	1.00	689
Boer Beans	0.57	0.87	689
Holoco Beans	0.32	1.00	689

Note: To reduce the emphasis of extremely large reported values, values below the 1st or above the 99th percentile are winsorized (i.e., 2 percent of observations are adjusted).

Table 3.4.4 presents farmers' reported production of major crops, in kilograms. Given the areas listed above, it is not surprising that production is primarily focused on staple cereal crops and legumes, primarily maize, cassava and peanuts.

Table 3.4.4. Production of Major Crops (Kilos), Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Maize	156.70	261.09	689	190.15	340.11	689
Rice	44.82	135.89	689	50.04	111.80	689
Sorghum	24.65	66.65	689	13.77	34.84	689
Cassava	351.35	367.81	689	241.34	366.32	689
Peanuts	417.40	548.90	689	120.20	148.40	689
Sesame	61.54	133.90	689	38.82	80.07	689
Cowpeas	46.52	71.61	689	23.42	47.02	689
Boer Beans	28.62	53.40	689	21.29	45.01	689
Holoco Beans	22.32	62.39	689	25.59	58.21	689

Note: To reduce the emphasis of extremely large reported values, values below the 1st or above the 99th percentile are winsorized (i.e., 2 percent of observations are adjusted).

At baseline, peanuts were the largest crop produced on average by volume, and are an important cash crop in the study region. The average farmer produces 417 kilograms, relative to 351 kilograms for cassava and 157 kilograms for maize at baseline, the second and third most, respectively. From baseline to endline the quantities of most crops produced remain relatively stable, though for a subset of crops—peanuts, sesame, and cowpeas—the mean value produced declines substantially. Declines are particularly evident for peanuts, where 87 percent of farmers reporting production in both periods report a lower value at endline than at baseline, relative to 64 percent of sesame farmers and 61 percent of cowpeas farmers. Among those experiencing a decline in production, the median percentage decrease is substantial—75 percent for peanuts, 67 percent for cowpeas and sesame, which may suggest a general exogenous change affecting these crops. While the survey instrument did not collect detailed information on household shocks, reports from the field team indicate that significant flooding occurred in some areas between baseline and endline data collection. Seeds for replacing peanuts may have then been particularly difficult to obtain for replanting, given that such a high proportion of peanut farmers report declines in production.

3.5 Savings

One of the organizing hypotheses in the study is that households lack access to either savings or credit in order to be able to purchase the optimal level of inputs, or even increased levels of inputs. In addition to overcoming other constraints, a necessary condition to overcome this constraint is that farmers have access to secure savings mechanisms. The problem of under-saving in developing country contexts, and its relationship to agricultural productivity, has been explored extensively in the economics literature (e.g., Deaton 1992; Robinson 2001; Burgess and Pande 2005; Brune et al. 2016). In the baseline survey, rather than asking about the amount of savings held (which is not likely to be accurate due to reporting bias), farmers were asked to specify the amount they would like to save in the coming year. They were then asked to report the amount that they thought they would actually save. Over 95 percent of the sample reported that they believed they would likely save less than they would prefer to in the coming year. They were then asked to cite the reasons why they would save less. Figure 3.5.1 summarizes these responses.

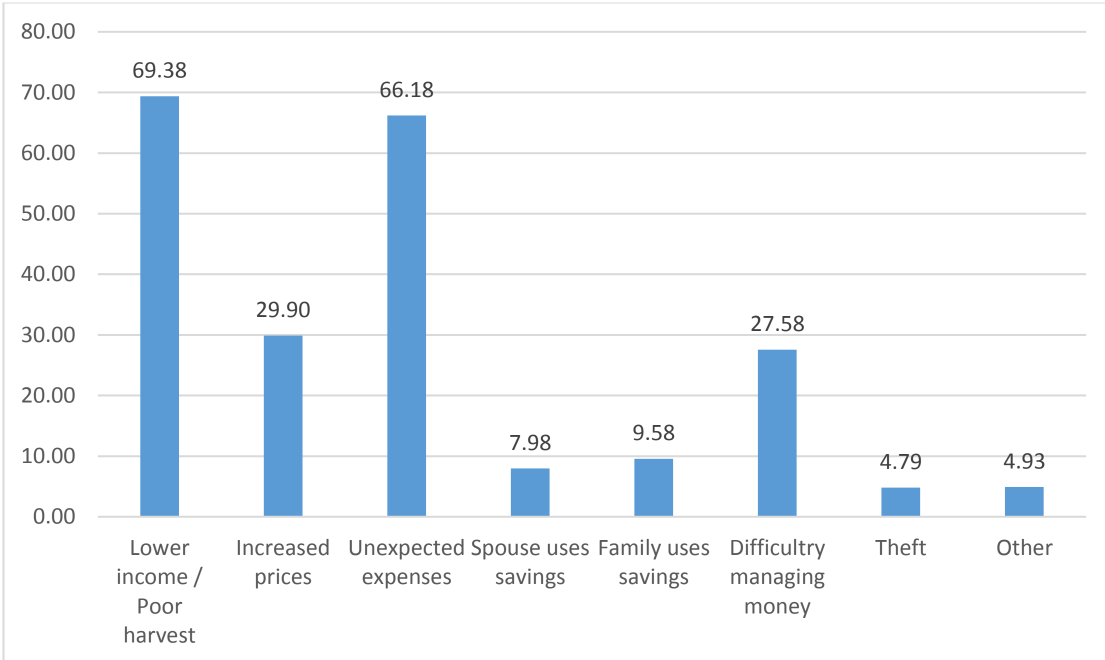


Figure 3.5.1. Reasons Given by Farmers that Savings will be lower than desired, Baseline

For respondents, reasons associated with risk and uncertainty were the most commonly cited reasons for under-saving. Seventy percent of respondents cited a poorer than expected harvest or an unforeseen loss of income, while conversely 66 percent of respondents cited an unforeseen expense. The next most popular reasons were price increases or inflation (30 percent of respondents) and problems in managing money (28%). Concerns about losses to others were also commonly cited, including family members (10%) or spouses (8%).

Respondents were also asked qualitative questions regarding the current status of their savings. Figure 3.5.2 presents these responses. Unsurprisingly, given the level of poverty in the sample, almost no households reported having more than enough savings to cover household consumption and major household expenditures. Sixteen percent reported having sufficient savings to cover consumption needs along with minor expenditures. The remaining 83 percent of the sample reported either having only enough to cover the household's consumption needs (52%) or less than enough to meet consumption needs (31%).

Additionally, farmers were asked about their savings strategies (Table 3.5.1).[9] The most common by far was to use a cash box, which 81 percent of respondents reported using for savings. The next most common was local savings groups such as Rotating Savings or Credit Associations (ROSCAs), which 37 percent of respondents reported using at baseline. The reported use of savings groups was modestly higher in the endline, which may suggest some expansion of such groups during the study. However, it could also be that respondents were confused at baseline about ROSCAs, or that ROSCAs existed and generally had no money in them at baseline; in general, our qualitative work suggested that respondents did not have any savings in general.

[9] Respondents could choose more than one savings strategy.

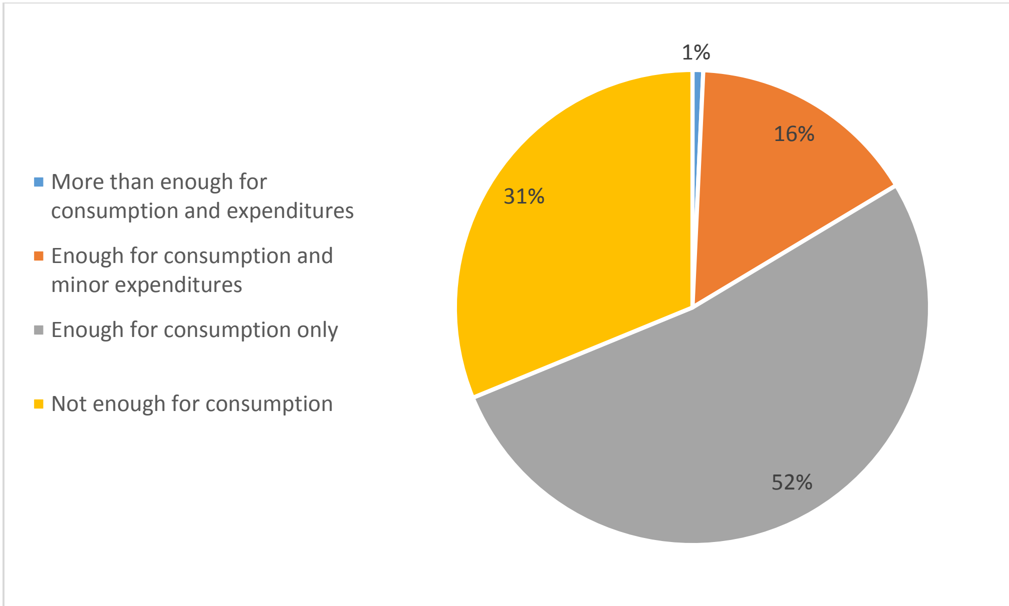


Figure 3.5.2. Reported Current Savings Status, Baseline

The baseline survey followed the Mobile Money training and 27 percent of all respondents reported using Mobile Money as a savings mechanism.[10] The percentage increased to 32 percent of all households in the sample at endline. These statistics indicate that Mobile Money is seen as a potential savings device by households. Among households that were trained in Mobile Money, 38 percent reported using mobile money as a savings strategy at endline, compared to 19 percent among non-trained households. Among households with only adult female members, the gap is similarly pronounced: only 16 percent of non-trained households report using mobile money as a savings device, compared to 27 percent of trained households.

Table 3.5.1. Savings Strategies used by Households, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Cashbox	0.81	0.39	689	0.80	0.40	689
Local savings group	0.37	0.48	689	0.49	0.50	689
Mobile money	0.27	0.44	689	0.32	0.47	689
Microfinance organization	0.10	0.29	689	0.23	0.42	689
Checking account	0.19	0.39	689	0.20	0.40	689
Savings account	0.24	0.43	689	0.10	0.31	689

3.6 Credit

Confirming the assumptions made prior to the study, the survey data reveal that very few households in the survey have access to formal credit sources. The surveys asked respondents about credit at both baseline and endline. At baseline only 39 percent of households had requested loans in the previous 12

[10] While the baseline interviews took place following the training, feedback from field staff suggests that mobile money use prior to trainings was extremely low.

months, while 47 percent had at endline (Table 3.6.1). While a relatively high proportion of the sample report receiving credit, neither the form nor the amount of most of the loans received are comparable to the type of loans available in settings where formal financial institutions are available. The mean size of the primary loan received (conditional on receiving the loan) was 2010 MZN, equivalent to approximately only 6 percent of total annual household expenditures.

Over 60 percent of loans at baseline were used to finance household consumption (41%), pay for healthcare (13%) or pay for a special event such as a wedding or funeral (8%). Among the households requesting a loan from any source, for both rounds very few were requested for agricultural purposes: only 16 percent of loans at baseline, and 11 percent at endline (comprising a smaller share of a greater number of loans requested), were requested for inputs, land purchases, or other farm-related purposes. Furthermore, the majority of loans was from informal social sources in both rounds; 71 percent of loans came from friends or family members in the baseline and 63 percent at endline. Loans from family members are not generally the type of loan that can adequately finance sizable investments in fertilizer or other agricultural inputs as is the case from formal lenders.

Table 3.6.1 Household Credit Activity, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Requested loan	0.39	0.49	689	0.47	0.50	683
Loan for agriculture	0.16	0.37	271	0.11	0.31	318
Loan from family/friend	0.71	0.45	251	0.63	0.48	304
Primary loan amount (MZN)	2,010.88	5,161.04	251	1,736.53	3,980.23	304

3.7 Mobile Phone Ownership

Similar to other countries in Africa south of the Sahara, mobile phone ownership has increased rapidly in Mozambique over the past decade. According to the World Bank, 3.5 percent of Mozambicans paid for mobile phone services in 2004. By 2014, this figure had risen to 69.7 percent. Despite the high level of poverty in our sample, we find rate of cell phone ownership at baseline only slightly lower than that reported by the World Bank. At endline, we find similar statistics for households with working cell phones as found in the baseline (Figure 3.7.1).

More than three-fifths of respondent households (62%) report at least one household member owns a functioning mobile phone. Perhaps surprisingly given that technology usage is typically viewed as being driven by the young, 56 percent of household heads report owning a cell phone. Put differently, in more than 90 percent of households that own a phone the household head personally owns a phone. While mobile phone ownership rates are high at the household level, there is significant gender disparity in ownership at the individual level. While male members of households own phones in 56 percent of sample households at baseline, females own phones in only 26 percent of households. Clearly, in most cases, men own cell phones first in a household and women tend to own secondary phones.

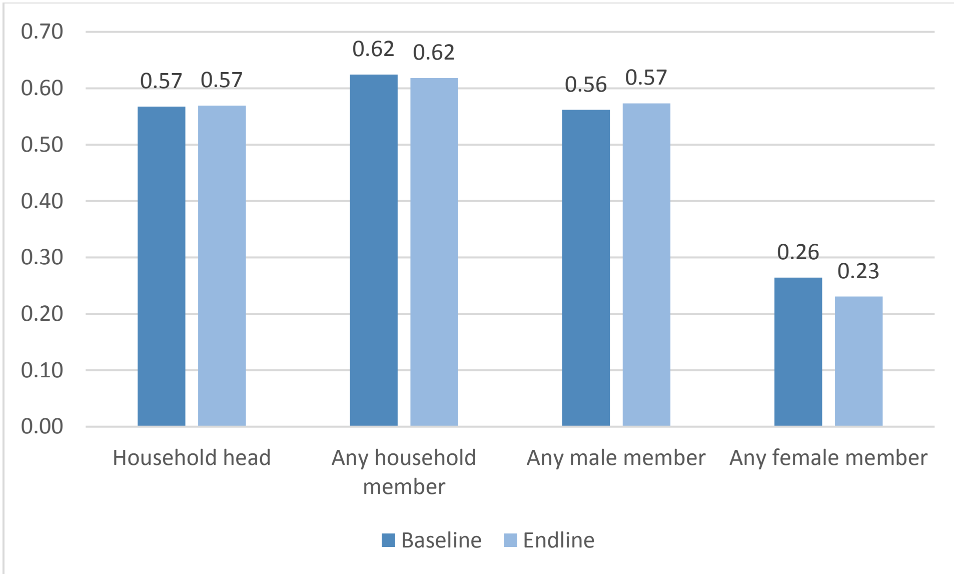


Figure 3.7.1. Proportion of Sample with a Mobile Phone, Baseline and Endline

While ownership rates are comparatively high at the household level, infrastructure constraints in terms of lack of access to electricity to recharge phones and poor network signal quality are constraints that were identified in the study sample, which may dictate the viability of Mobile Money service in this setting, and has implications for the research. The survey instrument was not designed to capture detailed information on access to electricity, in part because electricity service was known not to exist in most of rural Nampula. Only 11 percent of sample households reported some expenditures on electricity bills or vouchers in the month proceeding the interview. In contrast, 32 percent of households reported spending money to charge a cell phone. This observation conforms to anecdotal evidence from the field team, suggesting that while few households have electricity connections, farmers utilize diverse methods to charge cell phones, often taking advantage of neighbors' generators or solar panels, the electricity connection at a local store, or small businesses that are set up to charge cell phones from car batteries.

These strategies, combined with the relatively long battery life of the basic mobile phone models typically used in the area, allow respondents to partially overcome lack of direct access to reliable electricity connections. As a result, farmers typically report having their phone charged (Figure 3.7.2). When asked how frequently their cell phone was charged, 84 percent of respondents replied "Always" (78%) or "Usually" (6%). Less than 10 percent of households reported "Rarely" (4%) or "Never" (5%) having their cell phone charged. Among those who did not own phones, only 3 percent cited lack of access to electricity as the most important reason for not owning a phone suggesting that lack of electricity is not a binding constraint for cell phone use.

Network connectivity presents a potentially more significant impediment to use of mobile services, there is little respondents can do other than move to a different location to try to connect to the cellular network if the signal is poor. While Vodacom and other mobile network providers are making efforts to expand coverage nationally (in particular, the telecom Movitel), many areas still cannot connect to a network, including some zones within the original sample of farmers' associations, as discussed when describing the Mobile Money trainings.

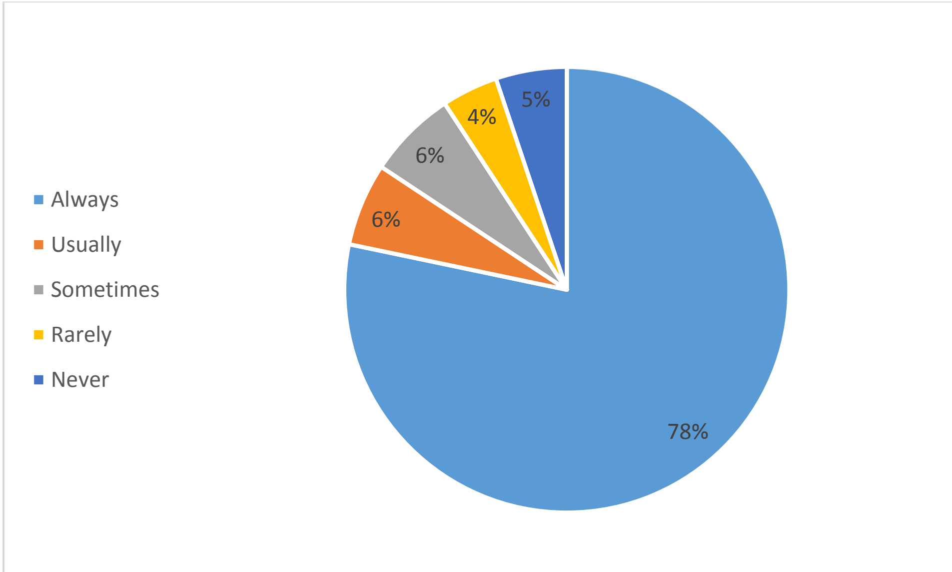


Figure 3.7.2. Frequency cell phone charged, Baseline

Among the associations that were interviewed, survey respondents were asked to rate the quality of the signal in their area (Figure 3.7.3). Over 89 percent of respondents described the quality of the available connection as “OK” or better, with 47 percent rating the signal as “Good” and 25 percent as “Excellent”. Of the remaining 11 percent, 6 percent described the quality of signal as “Poor” while 5 percent reported being unable to get a signal at their home. While this assessment is very positive, it could potentially be overstated, since the question was only asked to households who already owned or could access a cell phone. However, when non-owners were asked for the primary reason why they did not own a cell phone, very few respondents (2%) cited poor network connectivity—in contrast to the 69 percent that cited cost.

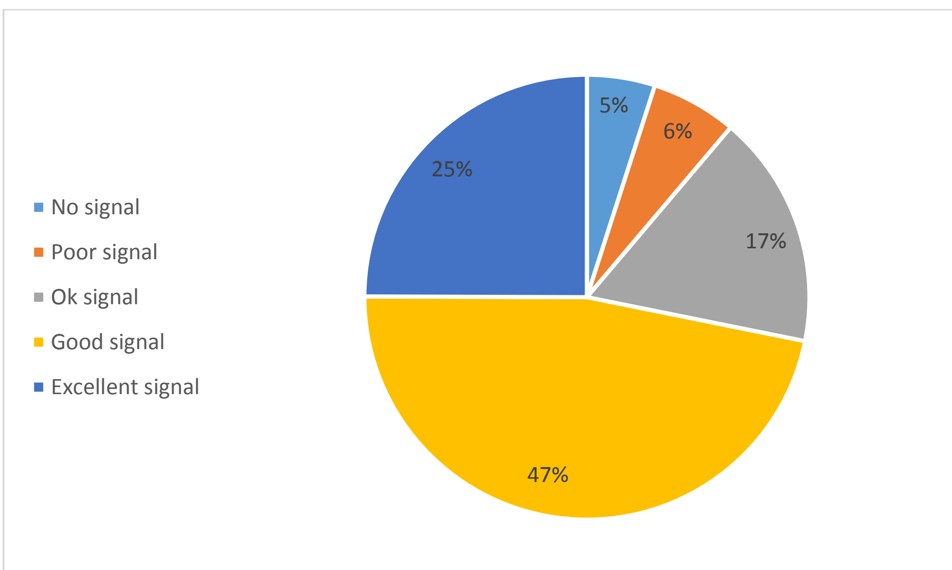


Figure 3.7.3. Reported Signal Quality in the Association, Baseline

Indeed, price constraints appear to be a significant challenge even for those households who do own phones. While 78 percent of those owning cell phones report currently having their phone switched on, only 40 percent reported currently having credit. Of those reporting a non-zero balance, the average credit amount was only 16 MZN at baseline,[11] equivalent to approximately USD 0.54. At endline, a lower proportion of the sample reported having credit on their phones: 27 percent of cell phone owners (Table 3.7.1). Of those reporting credit, the current balance reported is approximately 30 percent higher than at baseline, with the average cell phone owner reporting having a current balance of 21 MZN.

Table 3.7.1. Amount of Cell Phone Credit, Sample Households, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Currently has credit	0.40	0.49	465	0.27	0.44	403
Current credit amount	16.30	19.78	184	21.00	34.02	105
Monthly credit expenditure	163.48	148.03	461	139.84	148.88	410

Monthly credit expenditures are considerably higher than the current credit balance, suggesting respondents top up relatively frequently when they need to make a call. Network providers in Mozambique frequently offer "Jackpot" promotions where purchasers get bonus credit for short term use, which also suggests a demand for ad hoc credit loaded onto phones as needed. Figure 3.7.4 presents a kernel density estimation of monthly credit expenditures at the baseline, which shows that most frequently respondents tend to spend a bit less than the average. The density, which is a type of continuous histogram, demonstrates that there are a few users who spend 300-600 meitcais per month, which certainly pushes up the average; the more common answers are closer to 100 meticais.

[11] While some respondents reported using the 50 MZN received at training to purchase phone credit, there is no significant difference in credit balance among phone owners between trained and untrained respondents at either baseline or endline.

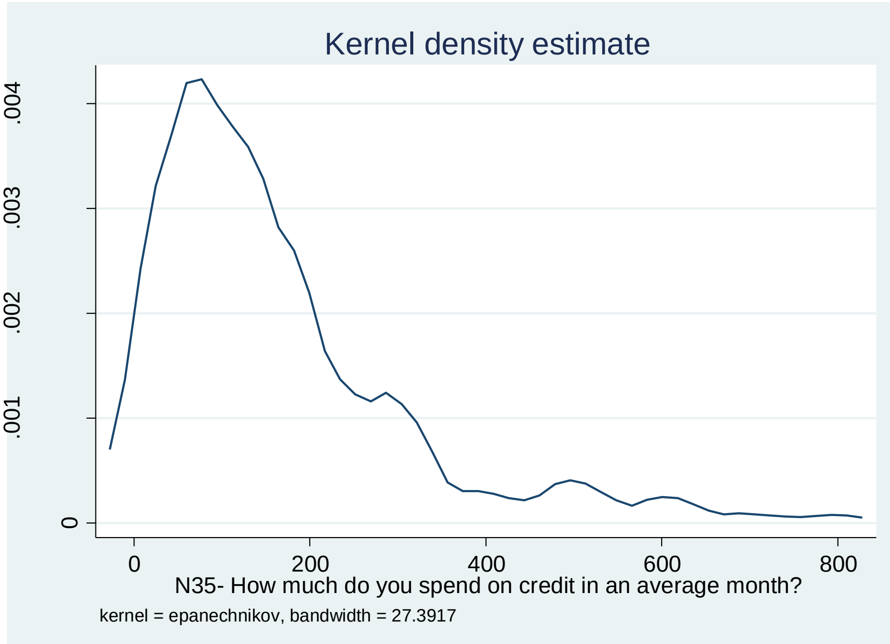


Figure 3.7.4. Mobile Money Credit Use at Baseline, Monthly Basis, Nampula (2014)

Looking at the distribution we are able to see some interesting variation in credit use. The median purchaser spends 100 MZN per month on credit, but users in the top quintile of the distribution spend more than twice that, with the top 10 percent of purchasers reporting monthly expenditures of 300 MZN or higher. This provides some suggestive evidence of heterogeneity among user types, with most phone users making small purchases when required while a small proportion have much larger expenditures. This differentiated usage pattern is also suggested by data on frequency of phone usage, reported in Table 3.7.2.

Table 3.7.2. Calls and Text Messages Sent and Received in the Last Seven Days, Baseline, Sample Households with Access to Cell Phones

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Text messages sent	8.79	15.79	275	10.87	15.21	288
Text messages received	8.85	9.64	275	10.05	11.48	287
Calls made	15.80	15.80	275	13.35	18.96	407
Calls received	16.65	18.98	275	12.86	15.50	406

Note: Figures are conditional on owning phones.

Strikingly, respondents with phones report making and receiving voice calls more often than sending or receiving text messages. Among those reporting having sent or received a text message in the seven days prior to the interview, on average 9 text messages were exchanged compared to an average 13-17 voice calls. This finding may seem surprising since text messages are nearly free to send, while calls are somewhat costly. One possible explanation is that since that the local language (Macua) is primarily oral, respondents prefer making calls in their first language to typing texts in Portuguese. Despite this, there is important variation within the sample, with some individuals reporting sending and receiving dozens of text messages. A similar pattern holds for phone calls, with the median respondent reporting making and receiving 9-10 calls, but respondents in the top 10 percent of the distribution reported making 30 or more calls. We conclude that cell phones use is quite variable within the sample. There is suggestive evidence of a potentially interesting transition in usage from baseline to endline. Cell phone users report slightly higher (though not statistically significant) levels of text message usage at endline, sending an average of 10.9 messages in the week preceding the endline survey compared to 8.8 messages at baseline and receiving an average of 10.1 texts compared to 8.9 at baseline. Conversely, respondents reported making and receiving fewer calls, reporting making 13.4 calls in the previous week compared to 15.8 at baseline, and 12.9 received calls at endline, relative to 16.7 at baseline, a difference which is statistically significant across rounds.

3.8 Mobile Money

Since the Mobile Money trainings took place before the baseline survey, the baseline measures recall soon after the trainings, whereas the endline measures recall more than one year after the training. In the analysis, we use the panel to check if there is a "treatment effect" in the endline; that is, whether offers to sell inputs at a discount via Mobile Money have any differential impact on whether or not households continue to use Mobile Money.

At baseline 59 percent of households reported having heard of Mobile Money. Among those households who owned or reported being able to access a mobile phone, 86 percent reported familiarity with Mobile Money. In the full sample 38 percent of respondents reported using Mobile Money (equivalent to 49 percent of households who owned or could access a mobile phone). This gap between "hearing of" Mobile Money and using Mobile Money could come from a lack of interest in using the product, but there is also potentially a gap in understanding the product or how to use the product. Mobile Money users report a wide range for their current account balance. The mean balance of Mobile Money users was 72 MZN (equivalent to 2.15 USD), but 43 percent of respondents had a current balance of zero and a further 41 percent of respondents report a balance of less than 100 MZN (including 17 percent who report 50 MZN, the initial account credit issued at the Mobile Money training). In contrast, the top decile reported balances in the range 100 to 3,000 MZN, suggesting that among those reporting Mobile Money use, a small number of farmers are considerably more active users than the majority. At endline, almost all households had heard of Mobile Money (85 percent; Table 3.8.1). The use of mobile money had declined from the baseline as time had elapsed since the training, but remained at 20 percent (members were enrolled in the trainings prior to baseline, but no additional trainings were conducted between baseline and endline). In the qualitative work, we found that some farmers were concerned about the distance to agents, and others reported that they could use more training on the system; e.g., that they were not comfortable using the software (conditional on having a phone). Virtually all respondents who used Mobile Money reported using mPesa, though a few also use mKesh (an alternative mobile money service provided by mCel) and others have heard of mobile money services being offered by banks. That said, balances were significantly higher among users compared to baseline. Although a substantial number of users continued to have low balances, the average among users rose to 334.4 MZN and the maximum was over 10,000 MTN, indicating that some Mobile Money users were quite active at endline. Moreover, in the qualitative work farmers reported liking the security offered by mobile money.

Table 3.8.1. Mobile Money usage, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Heard of mobile money	0.59	0.49	689	0.85	0.36	689
Uses mobile money	0.34	0.47	689	0.20	0.40	689
Mobile money balance (users)	72.18	306.25	200	319.92	1,436.94	107

Note: A substantial share of respondents who reported using mobile money did not know the mobile money balance at endline.

Disaggregating between households that received the Mobile Money training and those who were not trained reveals some interesting differences. Training attendees were more likely to report owning at least one mobile phone, as expected, given that phones were available for sale as part of the training (or shortly afterward in the case of some associations). Comparing knowledge of Mobile Money we find that a high proportion of trained households report having heard of Mobile Money (70%), compared to only 32 percent of untrained households. Respondents from households who attended the training were also significantly more likely to report using Mobile Money at baseline: 47 percent of trained households compared to just 1 percent of untrained households. These results suggest that experience actually using Mobile Money is limited in the study area, and virtually no households who were not given direct training were using the service when the baseline occurred (Table 3.8.2).

Table 3.8.2. Statistics Related to Cell Phone Ownership and Mobile Money, by Training Status, Baseline

	Received training			No training			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
Head owns phone	0.61	0.49	487	0.48	0.50	202	***
Household owns phone	0.67	0.47	487	0.51	0.50	202	***
Male member owns phone	0.60	0.49	487	0.47	0.50	202	***
Female member owns phone	0.29	0.46	487	0.19	0.40	202	***
Heard of mobile money	0.70	0.46	487	0.32	0.47	202	***
Uses mobile money	0.47	0.50	487	0.01	0.09	202	***

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We also observe substantial differences between the trained members and the untrained members at endline (Table 3.8.3). Trained households were more likely to own phones, though this is likely a result of purchases of cell phones during trainings. Mobile money use is substantially higher among phone owners in the group that received training, at 25 percent versus 6 percent among those who did not receive training (though the share in the trained group does decline as some of those enrolled at training discontinue use). Although these figures had fallen since the baseline, households that continued to use Mobile Money are clearly more active users. The increase in users among the untrained group, again among phone owners, is at least mildly suggestive that either some spillover took place in the intervening period, or that marketing by Vodacom (e.g., by text message) has led to additional usage.

Table 3.8.3. Statistics Related to Cell Phone Ownership and Mobile Money, by Training Status, Endline

	Received training			No training			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Head owns phone	0.61	0.49	487	0.46	0.50	202	***
Household owns phone	0.67	0.47	487	0.49	0.50	202	***
Male member owns phone	0.62	0.49	487	0.47	0.50	202	***
Female member owns phone	0.25	0.44	487	0.17	0.38	202	**
Heard of mobile money	0.90	0.30	487	0.73	0.45	202	***
Uses mobile money	0.25	0.43	487	0.06	0.24	202	***

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We also asked respondents a set of questions about familiarity with specific features of Mobile Money among those who reported having heard of Mobile Money. We report if individuals know whether they can make specific transactions with Mobile Money, at both baseline and endline (Figure 3.8.1). Two things are apparent from the figure: first, respondents who were trained are much more familiar with features of Mobile Money than respondents from untrained households, and second, we observe that as some people have become substantial users of mobile money, they have become more familiar with the features of mobile money. Perhaps the most substantial change is those with the knowledge that it is possible to withdraw cash from an agent. Among the training attendees, a very low proportion of individuals knew that they could withdraw cash at baseline, but more than half of the respondents who received training stated familiarity with this feature at endline.

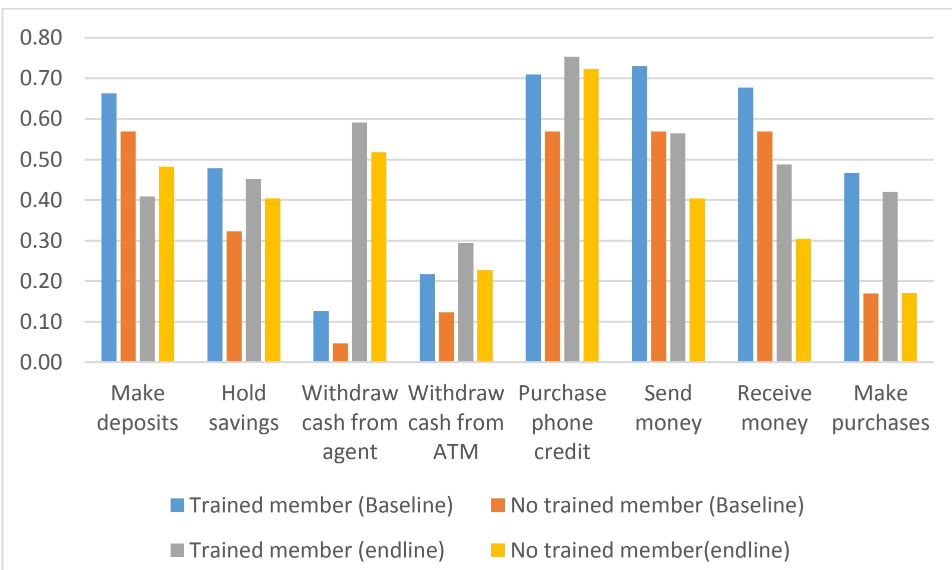


Figure 3.8.1. Familiarity with features of mobile money, by training status, baseline and endline

This finding may reflect that the network of Mobile Money agents was still nascent at the time of the baseline. Vodacom administrative records obtained following the baseline listed six agents in the study area, and closer to the endline our qualitative work identified eleven agents.[12] However, the agent recruitment process was taking place at the time the trainings took place; in fact, one of the motivations from Vodacom's perspective to participate was to attempt to recruit agents. So the six agents that were listed administratively were relatively new and perhaps not yet well known by farmers. The agent network grew over the course of the project, though unevenly. Uneven growth was part of Vodacom's agent recruitment strategy; they stated that their goal initially was to find as many potential agents as possible, and if someone dropped out or did not start doing business they would move to find another agent or agents to fill that area. Another change is that more respondents know it is possible to purchase phone credit using Mobile Money, which we found to be a commonly used feature, at least anecdotally, among Vodacom users.

We asked a set of follow-up questions about Mobile Money agents in both the baseline and endline surveys, again conditional on Mobile Money use. Among users of Mobile Money, respondents had much more familiarity with agents at endline than at baseline (Table 3.8.4). Agents are far from farmers with farmers reporting an average travel time of over two hours to visit their nearest agent at baseline, with only a small reduction at endline. As a result, while cashless transfers can likely facilitate some types of transactions, users still face substantial transaction costs when depositing or withdrawing cash. Among those who had visited an agent, 82 percent reported being able to carry out their transaction successfully at baseline, but that declines slightly at endline to 78 percent. While the transfer system generally functions correctly, meaning that people receive mobile money transferred to them, converting between mobile money and cash remains a challenge to say the least for a very meaningful portion of transactions.

Table 3.8.4 Knowledge of Mobile Money Agents, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Knows agent name	0.13	0.34	232	0.76	0.43	128
Distance to agent (minutes)	129.91	116.42	174	108.18	130.16	116
Agent was able to transact	0.82	0.38	108	0.78	0.42	112

3.9 Input Usage

It is well established that use of modern agricultural inputs is quite low in Mozambique. For example, according to the 2014 *Inqueríto Agrário Integrado* survey, only 0.3 percent of farmers in Nampula used fertilizer and 4.5 percent of farmers used pesticides (Ministry of Agriculture 2015) and baseline survey data are consistent with these findings.[13] The baseline data show that the primary farming inputs are family labor, saved seeds, and exchange labor, the last of which is used by about half the sample. This type of traditional arrangement provides a reciprocal assistance mechanism for farmers when faced with a labor-intensive task, when cash is not available to pay laborers. If cash is available, day laborers are often hired as *ganhu* workers, which also offers a simple means of acquiring cash for day laborers who face liquidity constraints due to the seasonal nature of returns to their own agricultural activities.

[12] Though as discussed in the qualitative report, only 7 of these were active, assuming the same proportion one would infer that four agents or fewer were active in the study area at the time of the baseline trainings.

[13] The report on the TIA 2014 leaves out improved maize seed, which comprised the largest share of improved seed purchases in the impact evaluation data, so we cannot report a comparison.

The use of purchased or chemical inputs were quite low at baseline. Households report very low uses of any chemical inputs (only 15 percent reported using any chemical inputs). They are most likely to have used pesticides (13 percent of households), which largely represents the large proportion of cashew farmers in the Southern areas of the sample relative to a representative sample of the study area. Only 12 percent of households used any improved seeds at baseline, and only 2 percent used any chemical fertilizers. We find that use of herbicides or irrigation technologies are very uncommon as well, with at most 1 percent of the sample reporting usage within the past year.

However, by the 2015 endline, the proportion of households using inputs increased significantly for many inputs (Table 3.9.1). The share of households using any chemical inputs more than doubled, from 14 percent to 31 percent; the use of improved seeds increased from 11 percent of households at baseline to 62 percent of households at endline. Changes in chemical inputs can be derived from increases in the use of organic fertilizer and pesticide.

Despite the intervention design changes and weakened implementation, increases in input use can be partially explained by purchases through the project intervention. We recorded administrative data from sales that took place as part of the treatment, and the bulk of those sales took place among individuals trained on Mobile Money, in the treatment associations (Table 3.9.2). Overall, 69 input transactions took place, of which 86 percent were from individuals who attended the Mobile Money training and thus were able to receive the transaction rebate for paying with mobile money), while the remaining transactions were from untrained households. Approximately two-thirds of the transactions were purchases of seeds (principally maize seeds), while the remainder were for small packets of fertilizer (principally lime). While this demonstrates the existence of demand when the direct input marketing visits were made, the completed transactions represent less than 10 percent of the full sample, clearly showing that other sources are affecting the large increase in input usage that we observe at endline.

Table 3.9.1. Input use, by survey round

	Baseline			Endline			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
Used any seeds	0.97	0.16	689	0.98	0.16	689	
Used any chemical inputs	0.14	0.35	689	0.32	0.47	689	***
Used family labor	0.97	0.18	689	0.99	0.08	689	***
Used paid labor	0.57	0.50	689	0.59	0.49	689	
Used traditional seeds	0.97	0.18	689	0.96	0.19	689	
Used improved seeds	0.12	0.32	689	0.62	0.49	689	***
Used organic fertilizer	0.01	0.10	689	0.11	0.32	689	***
Used chemical fertilizer	0.02	0.13	689	0.02	0.14	689	
Used pesticide	0.12	0.33	689	0.31	0.46	688	***
Used herbicide	0.00	0.04	689	0.01	0.08	689	
Used irrigation (treadle)	0.00	0.04	689	0.01	0.09	688	
Used irrigation (mechanized)	0.02	0.14	689	0.00	0.07	689	*

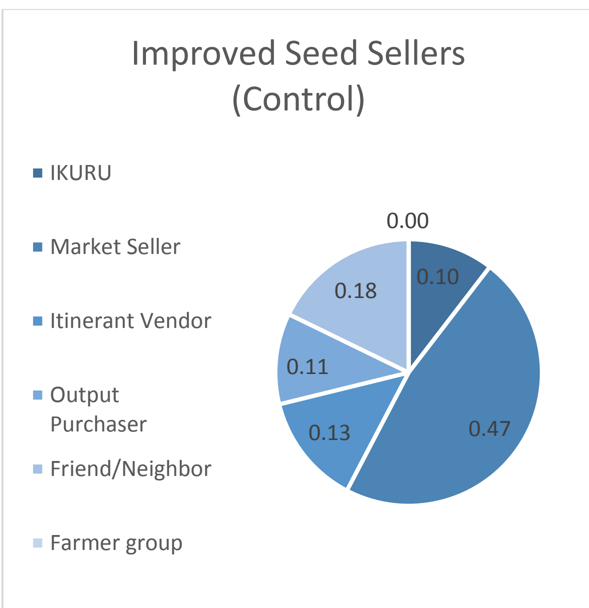
Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

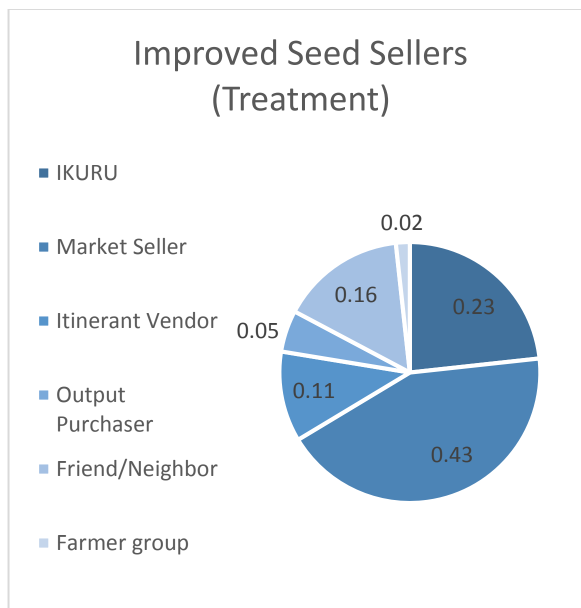
The majority of transactions were made using Mobile Money, both among individuals who received the Mobile Money training (91 percent of purchases) and untrained households (80%) (both groups were eligible for the discount if they transacted using Mobile Money). The mean expenditure on inputs for trained households was 47 MZN, close to the 50 MZN balance that individuals received during the Mobile Money training. However, among those trained, 25 percent of individuals spent over 50MT suggesting that some farmers did not necessarily simply view the input sales as a means of 'cashing out' their mPesa balance.[14]

Table 3.9.2. Administrative Data, Association Visits to Sell Inputs, by Training Status

Variable	Trained	Untrained
Number of transactions with Association Members	59	10
Percentage using mobile money	91%	80%
Mean Expenditure (MZN), conditional on purchase	47.45	34.00
Proportion of individuals spending > 50 MZN	25%	20%

As noted above, the main input used by farmers are improved seeds, and we observe that improved seeds were the most commonly purchased inputs with Mobile Money.[15] In Figure 3.9.1, we illustrate from whom farmers purchased improved seeds, disaggregated by association treatment status. In the treatment associations, almost one-fourth of purchases came from IKURU, but the most common source was actually a market vendor (an additional 2 percent report purchasing from their farmer group, which we conjecture is misattribution as farmers associations do not typically engage in input sales). In contrast, IKURU was the source of purchases for only a tenth of improved seeds in the control group and almost half came from local markets.[16] This clearly demonstrates that there was increased use of improved inputs through market channels other than through the project.





[14] In fact, according to administrative data before input sales took place around one-third of farmers had already used their balances on phone credit.
[15] Some farmers also purchased fertilizer in the association and forum visits that were part of the project.
[16] The difference in proportions purchased from IKURU in treatment and control areas is statistically significant at the 1 percent level.

Figure 3.9.1. Where Improved Seeds were purchased, Endline, by Treatment Status

To better understand where the "market sellers" were located, and whether there was any change from baseline to endline, we next analyze average travel time to purchase inputs (Table 3.9.3). On average, farmers report having to travel almost an hour and a half to make an input purchase at baseline and endline, implying a round trip travel time of approximately three hours. Farmers report average one-way travel times of approximately 80 minutes to purchase traditional seeds or pesticides, 60-90 minutes to purchase chemical fertilizer, and 90-120 minutes to purchase improved seed varieties. Travel times to purchase improved seeds did reduce significantly (at the 5 percent level) between baseline and endline, from nearly 2 hours to closer to 90 minutes.[17] Note that these travel distance is conditioned on respondents who had purchased inputs, thus only represents those who overcame the distance constraint. Those who did not make purchases may be in more remote areas and thus face even higher travel times, which could be a factor in impeding their purchasing behavior. However, the change in input use from baseline to endline suggests that at baseline there were farmers who were not purchasing inputs despite the fact that others with similar travel time would do so.

[17] Given that a relatively low proportion of purchases were made from IKURU, association-level sales are unlikely to account for this entire difference.

Table 3.9.3. Travel time to purchase inputs (minutes)

	Baseline			Endline			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Any input	86.07	92.65	201	86.06	91.06	431	
Traditional seeds	79.86	97.69	96	77.27	94.26	222	
Improved seeds	125.54	110.91	57	92.04	101.03	250	**
Chemical fertilizer	57.86	42.80	7	89.00	47.25	10	
Pesticide	79.15	83.99	68	86.71	83.98	168	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Given changes in the propensity to use inputs, it is not at all surprising that average input expenditures increase substantially between baseline and endline (Table 3.9.4).[18] Average total expenditure on inputs increases from 118 MZN at baseline to 451 MZN at endline (row 1). Expenditures on seeds increased more than expenditures on chemical inputs between baseline and endline; a substantial amount of that investment was in traditional seeds. So although there is some evidence of increased purchase of inputs, not all of the increase in the purchase of inputs implies that farmers are using improved inputs; many of them are using traditional seeds.

Note that even these averages remain small amounts of money in general; the average input expenditure across all inputs at baseline is equivalent to about 4 USD, and at the prevailing exchange rate the average was about 14 USD per household at endline. Meanwhile, a 50-kilogram bag of urea (a nitrogen-fixing fertilizer) would have cost 15 USD at world wholesale market prices at the same time, IKURU was selling them locally for approximately 50 USD (before any discount), and the data suggest a price of 30 USD or more for the same bag, which would not quite cover 1 hectare of land at the South African average fertilizer rate.[19] Clearly, if farmers were to add fertilizers to grow maize, input expenditures would need to substantially increase.

Table 3.9.4. Average Input expenditures at Baseline and Endline (MZN)

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Any inputs	118.30	319.95	689	451.10	931.32	689
Seeds	74.73	231.96	689	356.26	722.45	689
of which traditional seeds	39.76	144.84	689	186.27	523.94	689
of which improved seeds	34.97	188.07	689	169.98	516.47	689
Chemical inputs	42.95	202.02	689	94.69	454.24	689
of which fertilizer	1.85	21.84	689	12.53	181.31	689
of which pesticide	40.81	201.13	689	73.22	217.39	689
of which herbicide	0.29	7.62	689	8.93	163.27	689

Note: Because minor inputs are not included, average for seeds and chemical inputs do not exactly match the averages for "any inputs."

[18] Note, we do not adjust the figures for inflation, since it affected the treatment and control groups similarly. The annual inflation rate between the baseline and endline was about 4 percent, so it cannot account for the difference in expenditures between rounds.

[19] Obviously, farmers would not be able to purchase fertilizer at the wholesale rate, but we provide it as a comparison so that transaction costs plus the mark-up can be highlighted.

There does not appear to be a bimodal distribution of farmers in which some do not invest in inputs at all, while those who do purchase them tend to invest heavily. Rather, it appears that even within the sample of those purchasing inputs, most farmers invest far less of their income than would be optimal, given the potential returns to investment—farmers making input purchases invest on average only 576 MZN, equivalent to 2.64 percent of their total household expenditures on what is their primary source of household earnings. It does not appear to be the case then that smallholders are effectively priced out of local input markets as some have argued (Smart and Hanlon 2014).

In considering reasons that input use could have increased so much over such a short period of time, we see one possibility is that a large program moved into the same area that would impact purchasing behavior; however, neither our qualitative work, our knowledge of projects in the area, nor a web search suggested that any such program exists. A more likely explanation is that some farmers may have lost seed in flooding that occurred in the region in January, 2015. As a consequence, they needed to purchase new seed to reseed their fields once flooding subsided. As floods were localized but widespread around Nampula province, this hypothesis is at least consistent with the fact that we find increased input use spread throughout the four districts.

This exogenous change presents a challenge for our subsequent analysis for several reasons. First, our comparison implicitly assumes a stable trend among treatment and control households for input use. In this case, there is a clear positive shock to input use; we set out to explore the effect of an increase in input supply, whereas apparently, there was also another shock to input supply that could lead farmers to use more purchased inputs. Consequently, it will be difficult to measure a change based on our input supply intervention in the presence of this shock. Second, the additional input use increases the variance of input use, also posing a challenge, as many potential measures of input use would be higher variance than had been accounted for in the sample size calculation.

3.10 Gender Linkages in Input Use

Looking at input usage disaggregated by gendered household type reveals some interesting dynamics. For labor inputs, households with only female adults report similar levels of usage of family labor, and slightly higher levels of use of hired and exchange labor than households with a male adult (Table 3.10.1). For chemical inputs, however, the rate of utilization is much lower for female adult-only households. Households with male adult members report an overall rate of 15 percent utilization of fertilizer, pesticide, or herbicide, compared to only 4 percent for households with only female adults. This is primarily driven by much lower rates of pesticide usage, with female adult-only households 9 percentage points less likely to report use. At endline, the substantial increase in improved seed use is seen across both types of households, though female adult only households continue to have overall lower use rates than households with male adult members (Table 3.10.2). Female adult only households are substantially less likely to use chemical inputs at endline.

Table 3.10.1. Input Use by Gendered Household Category, Baseline Data

	Any Male Households			Female Only Households			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
General Input Categories							
Any inputs	0.97	0.16	638	0.98	0.14	51	
Any seeds	0.97	0.17	638	0.98	0.14	51	
Any chemical inputs	0.15	0.36	638	0.04	0.20	51	**
Specific Input Categories							
Family labor	0.96	0.19	638	0.98	0.14	51	
Paid labor	0.57	0.50	638	0.59	0.50	51	
Traditional seeds	0.97	0.18	638	0.98	0.14	51	
Improved seeds	0.12	0.33	638	0.06	0.24	51	
Organic fertilizer	0.01	0.10	638	0.00	0.00	51	
Chemical fertilizer	0.02	0.13	638	0.00	0.00	51	
Pesticide	0.13	0.34	638	0.04	0.20	51	*
Herbicide	0.00	0.04	638	0.00	0.00	51	
Irrigation (Manual)	0.00	0.04	638	0.00	0.00	51	
Irrigation (Mechanized)	0.02	0.14	638	0.02	0.14	51	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3.10.2. Input Use by Gendered Household Category, Endline Data

	Any Male Households			Female Only Households			
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**	**Sig.**
General Input Categories							
Any inputs	0.98	0.14	633	0.96	0.19	56	
Any seeds	0.98	0.15	633	0.96	0.19	56	
Any chemical inputs	0.33	0.47	633	0.13	0.33	56	***
Specific Input Categories							
Family labor	0.99	0.09	633	1.00	0.00	56	
Paid labor	0.60	0.49	633	0.48	0.50	56	*
Traditional seeds	0.96	0.19	633	0.96	0.19	56	
Improved seeds	0.64	0.48	633	0.48	0.50	56	*
Organic fertilizer	0.11	0.31	633	0.14	0.35	56	
Chemical fertilizer	0.02	0.15	633	0.00	0.00	56	
Pesticide	0.32	0.47	632	0.13	0.33	56	***
Herbicide	0.01	0.09	633	0.00	0.00	56	
Irrigation (Manual)	0.01	0.10	633	0.00	0.00	55	
Irrigation (Mechanized)	0.00	0.07	633	0.00	0.00	56	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Though the intervention was not designed specifically to address gender differences in access to inputs or decision making, any such intervention has the potential to impact the relative role of men and women within the household. The questionnaire included a set of questions to identify which household member made decisions about the use of each type of input, conditional on any input use. Options were to declare that a male made decisions, a female made decisions, or that decisions were made jointly with the aim of providing context on input purchases. Figure 3.10.1 presents the share of these decisions made by each type of decision-maker, within the sample of households with male and female adult members. For all categories with the exception of hired labor and chemical fertilizer, we observe an increase in joint decision-making within households. Decisions concerning the use of improved seeds see the largest increase in joint decision-making, with 53 percent of households reporting joint decisions at endline, relative to 29 percent at baseline.

In line with this we see a general decline in the share of decisions reported as being made exclusively by men in households, again with the exception of decisions concerning hired labor and chemical fertilizer (though in the case of chemical fertilizer the sample size is very small, so care should be taken in trying to discern any trend). While this trend is encouraging, at endline it remains that the case for most input categories decisions about usage are made exclusively by men in approximately one-third to one-half of households. While our input intervention was targeted at the household level, it is clear that there is an important gender dimension to determining input take-up, which might be worth considering in future program design. That said, it is still important to remember that many categories of input use are relatively low, and gendered decision-making was only asked if the input was used. For future survey design, it is worth asking as a hypothetical when households do not grow specific crops.

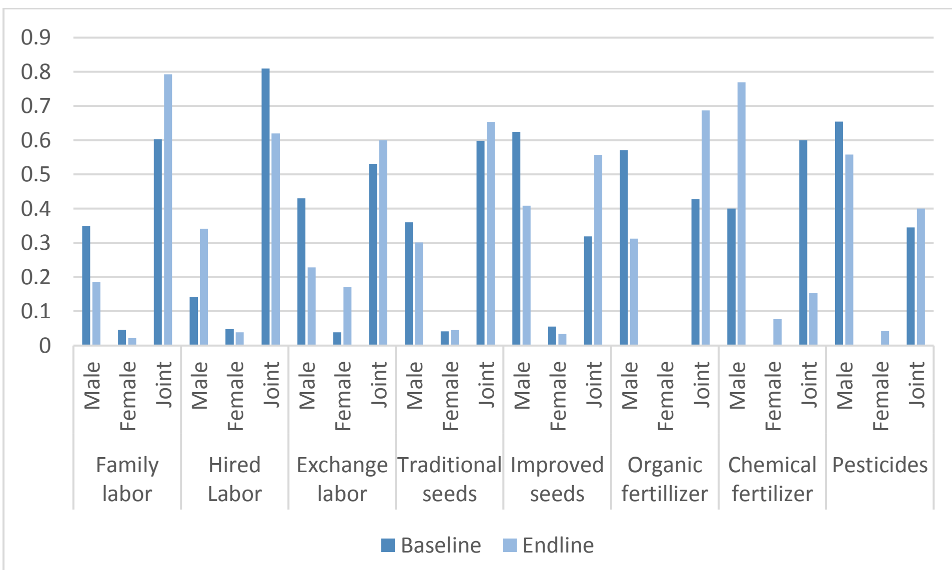


Figure 3.10.1. Gendered decision-making at baseline, by input

Section 4. *Primary Econometric Approach*

To answer the research questions, we largely use a standard difference-in-difference econometric approach. Consider a given outcome, *Y*, for which we would like to understand the impacts of some program, *T*. Ideally, one could observe each individual *i* both in a "treated" and "untreated" state, such that the benefits of the program would be clearly defined as $\delta = Y_T - Y_U$, where subscripts *T* and *U* represent treated and untreated individuals. The average treatment effect on the treated, then would be the average $\bar{\delta}$ over all individuals in the population.[20] Of course, it is not possible to observe individuals who both receive and do not receive some program, so the quantities described above are unobservable.

Instead, we construct a comparison group that matches the treatment group as closely as possible, so that the expected value of outcomes among the control group without treatment is the same as the expected value of outcomes among the treatment group if they had not received treatment. If such a control group can be identified, then the average treatment effect on the treated, which would be computed as $\hat{\delta} = E(Y_t | t \in T) - E(Y_c | c \in C)$ would be the same in expectation as $\bar{\delta}$, the "true" average treatment effect on the treated, where *T* represents the treatment group (and *t* an element in the treatment group), and *C* the control group.

A further consideration in the computation of average treatment effects on the treated is that there may be pre-treatment differences (Figure 4.1), particularly for outcomes of interest. Before we discuss with math, let us give an intuition. If we just measure differences at endline, we may miss the fact that average outcomes differed prior to the intervention. If so, we might attribute simple differences that existed prior to intervention as effects of the intervention. To ensure that we do not do so, we measure outcomes prior to the intervention, and subtract those differences from the difference at endline.

From a mathematical perspective, ignoring pre-treatment differences is that same as using 0 to denote the pre-intervention outcome measure. Then if $Y_t^0 \neq Y_c^0$, the simple difference $Y_t^1 - Y_c^1$ (or B on the diagram) after the program will not represent the treatment effect; it represents both the treatment effect and the pre-treatment difference. The "true" difference-in-difference estimate should be B-A in the diagram, or more formally $\hat{\delta} = B - A = (Y_t^1 - Y_c^1) - (Y_t^0 - Y_c^0)$.

[20] More concretely, this expression gives the average treatment effect on the treated given full compliance or participation in an intervention. We do not assume full compliance, so it can be called the intent to treat effect.

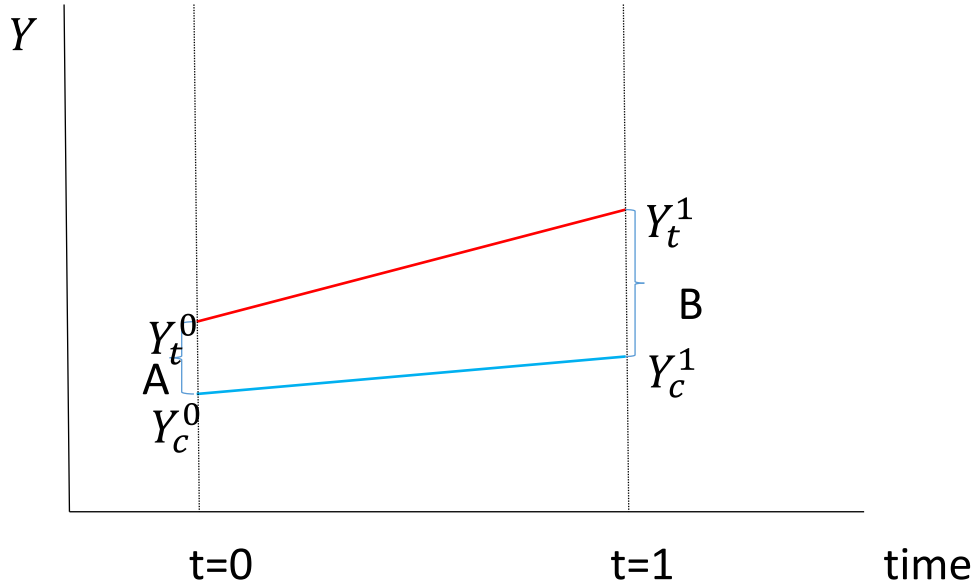


Figure 4.1 Difference-in-difference intuition

To estimate treatment effects using difference-in-difference methodology in a regression framework, we can generally write the equation:

$$Y_{it} = \alpha + \gamma T_i + \theta D_{t=1} + \delta\, D_{t=1} \times T_i + \epsilon_{it} \quad (1)$$

Where: α is a constant term; T_i is a dichotomous variable that takes the value 1 if the household is in the treatment group and 0 otherwise; $D_{t=1}$is a dichotomous variable that takes 1 if the observation is from the endline survey and 0 if from the baseline and ϵ_{it} is a mean zero error term. The coefficient δ on the interaction term $D_{t=1} \times T_i$ represents the treatment effect; e.g., it is the difference in the outcome after the program has been implemented after implementation has occurred.

Note that we have a panel of two observations for each household from baseline and endline. We can then modify equation (1) to include individual-level household fixed effects:

$$Y_{it} = \alpha_i + \gamma T_i + \theta D_{t=1} + \delta\, D_{t=1} \times T_i + \epsilon_{it} \quad (2)$$

and by subtracting the first period, we can instead estimate:

$$\Delta Y_i = \vartheta + \delta\ \ T_i + \Delta\epsilon_{it} \quad (3)$$

For the impact analysis, we actually estimate equation (3) instead of equation (2). The assumption in equation (3) is that the composite error term $\Delta\epsilon_{it}$ is mean zero and asymptotically normally distributed, which differs from the assumptions in equations (1) and (2).

Additionally, we also estimate an additional ANCOVA specification which has the potential to increase our statistical power in estimating the treatment effect. We also consider a vector of household covariates[21] at baseline $Z_{i,t=0}$ which is uncorrelated with the treatment indicator T_i (as a result of the random

[21] Specifically, we include baseline covariates for the demographic characteristics of the household head, household expenditures and a producer forum fixed effect, we find similar results using alternative selections of covariates.

assignment of treatment status) but correlated with Y_{it} and so will reduce the unexplained variation in the regression with the aim of allowing us to estimate the standard error on T_i more precisely:

$$Y_{i,t=1} = \vartheta + \delta T_i + Y_{i,t=0} + \mu Z_{i,t=0} + \epsilon_{i,t} \tag{4}$$

Section 5. Results

5.1 Input Usage

Our first objective is to understand whether the treatment was effective; if the input trainings plus increased access to inputs (sales offered at the association level) increased the use of inputs among treated farmers in the study area relative to the control group.

Note that most farmers use some inputs. At minimum, planting material and labor for planting and cultivation is needed.[22] A minimal input use scenario is that farmers use only saved seeds and family labor, and potentially organic fertilizer, in something akin to a Chayanovian household (Chayanov, 1925). The relevant change is when households decide to use more inputs available through markets—either labor markets, for additional labor for their farm, or input markets, for seeds, fertilizers, or other agro chemicals. Changes may also occur in the allocation of inputs—for example, use of herbicides may act as a substitute for labor hired to perform weeding. We initially report treatment effects on whether or not three categories of inputs were used: any external labor (e.g., hired or exchange labor); any purchased seeds; and any chemicals (e.g., inorganic fertilizer, pesticides, or herbicides). Second, we run regressions on disaggregated indicators of each input use category (e.g., whether or not improved seeds were purchased). For each subset of variables, we report the coefficients and associated standard errors on the following variables: γ (the coefficient on the treatment dummy); θ (the post-treatment period dummy), and δ (the interacted treatment effect, i.e., the difference-in-difference estimator).

Using equation (1) from section 4, we initially estimate the impacts of the treatment on broad categories of external labor and purchased input use in the panel (Table 5.1.1). Overall, we find no statistically significant differences in reported use of any input between the treatment group and control group. The coefficient on the difference-in-difference estimator is small and not statistically different from zero. Looking by input category, we see positive trends in input use across the sample between baseline and endline, which were expected from the descriptive work that is discussed above. Hence, while there is strong evidence of an increase in input usage between the 2014 and 2015 growing seasons, we are unable to attribute this change to the study treatment.

Table 5.1.1. Impact Estimates on Usage of Inputs, Pooling Baseline and Endline Data

	External Labor	Purchased Seeds	Any Chemicals
Treatment Dummy	-0.04	-0.03	-0.03
	(0.05)	(0.03)	(0.04)
Post-Treatment Dummy	0.02	0.52***	0.18***
	(0.03)	(0.03)	(0.03)
Interacted Treatment Effect	0.01	-0.01	0.00
	(0.05)	(0.04)	(0.05)
Observations	1,378	1,378	1,378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

[22] The exception is tree crops, which are grown by some farmers in the data set (especially cashews). In theory, such crops can be grown with almost no inputs once the trees are productive, though with labor and pesticides yields substantially increase.

To explore change in input use in more detail, Table 5.1.2 presents results on inputs used, disaggregated by type, continuing with the difference-in-difference analysis. We disaggregate the purchased seed category into purchase of traditional and improved seeds, respectively, and the chemical use category into use of fertilizer, pesticides, and herbicides. We again find no clear estimated treatment effect. We find that there are some impacts for specific inputs, which mirror the descriptive findings. The inputs for which we do not find statistical impacts (chemical fertilizer and herbicide) are used by very few households in the sample in either year.

Table 5.1.2. Impact Estimates on Usage of Inputs (Disaggregated Categories), Pooling Baseline and Endline Data

	Traditional Seeds	Improved Seeds	Chemical Fertilizer	Pesticide	Herbicide
Treatment Dummy	-0.02	-0.01	-0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.01)	(0.03)	(0.00)
Post-Treatment Dummy	0.19***	0.53***	0.01	0.18***	0.01
	(0.04)	(0.03)	(0.01)	(0.02)	(0.01)
Interacted Treatment Effect	0.02	-0.04	0.00	-0.01	0.00
	(0.05)	(0.05)	(0.01)	(0.05)	(0.01)
Observations	1,378	1,378	1,378	1,378	1,378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We next estimate equations (3) and (4) for the disaggregated input use categories (Table 5.1.3). Again, we find no statistically significant impacts using the household fixed effects model. Using the ANCOVA model, we find a statistically significant negative coefficient on the treatment variable for chemical fertilizer use. Given that the result is only marginally significant in one of our three specifications, it seems likely that this is simply a result of random variation. Further, given that only 13 households in the entire combined data set used any chemical fertilizer, the coefficient does not represent meaningful variation within the study population. We find that there is some correlation in households that purchased improved seeds in both years, but not in traditional seeds, suggesting that some farmers may have moved to purchasing seeds on an annual basis rather than recycling them.[23] Alternatively, households who had seed washed away in floods, as informal interviews indicate occurred, may have had to purchase seed to replace it.

We also find correlation in the pesticide baseline values, which is not surprising, as tree crop yields are highly correlated with pesticide use (cashew, in particular, is an important crop for the sample and is cultivated by 67 percent of farmers). We find significant coefficients in the regressions on the "male household head" variable for all of the dependent variables with the exception of herbicides. The coefficient on traditional seeds is negative, suggesting that female-headed households were more likely to purchase traditional seeds. Conversely, the coefficient is positive for improved seeds, chemical fertilizer and pesticides, suggesting that male-headed households are more likely to use these inputs. We find that the age of the household head is negatively correlated with the probability of using inputs, which suggests that targeting younger households may yield more positive outcomes for future interventions.

[23] We have attempted to confirm with rainfall data. In fact, January 2015 was the third highest rainfall month in Nampula (when germination should have occurred) in the past 15 years.

Table 5.1.3. Impact Estimates on Changes in Household Input Use, Disaggregated Categories (Nampula 2014, 2015)

	Traditional Seeds	Improved Seeds	Chemical Fertilizer	Pesticide	Herbicide
Differenced Model					
Treatment	0.02	-0.04	0.00	-0.01	0.00
	(0.05)	(0.05)	(0.01)	(0.05)	(0.01)
Fixed Effects Model					
Treatment	0.01	-0.05	-0.02*	-0.01	0.00
	(0.04)	(0.05)	(0.01)	(0.04)	(0.01)
Baseline value	0.06	0.13**	0.05	0.25***	-0.01
	(0.05)	(0.05)	(0.09)	(0.06)	(0.01)
Household size	0.01*	0.02	0.01	0.01	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Male	-0.15**	0.20***	0.01**	0.11**	0.00
	(0.06)	(0.06)	(0.01)	(0.05)	(0.00)
Age / 100	-0.64***	-0.29*	0.05	-0.34**	-0.01
	(0.15)	(0.16)	(0.03)	(0.15)	(0.01)
Speaks Portuguese	-0.02	-0.06	-0.02	0.01	0.01*
	(0.03)	(0.05)	(0.01)	(0.04)	(0.00)
Primary education	0.00	0.09	0.03***	0.02	0.00
	(0.07)	(0.07)	(0.01)	(0.06)	(0.00)
Non-farm job	-0.03	-0.05	0.03***	0.05	0.00
	(0.04)	(0.04)	(0.01)	(0.04)	(0.01)
Total expenditures per capita (0000s)	-0.01	0.40*	0.31	27.78	53.56
	(0.03)	(0.20)	(0.54)	(25.19)	(52.28)
Observations	689	689	689	689	689

Notes: 'Differenced model' refers to the regression of treatment status on change in outcome from baseline to endline (i.e., endline value - baseline value); 'Fixed effects model' refers to the regression of treatment status, baseline value of the outcome, characteristics of the household head, and producer forum fixed effects on the endline value of the outcome; standard errors are robust and clustered at the association level; Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01).

The increase in input usage is reflected in increases in mean expenditures on inputs between surveys. Table 5.1.4 presents estimates of equation (1) in section 4 for the mean change in input expenditure for aggregate input categories. We find significant differences between external labor expenditures, expenditures on purchased seeds, and expenditures on chemicals between surveys. However, we do not estimate significant treatment effects between the treatment group and control, consistent with the findings above for the indicator variables.

Table 5.1.4. Impact Estimates on Input Expenditures, Pooling Baseline and Endline Data

	External Labor	Purchased Seeds	Any Chemicals
Treatment Dummy	-113.84	22.43	-3.05
	(167.72)	(22.53)	(17.66)
Post-Treatment Dummy	1737.71**	315.30**	48.19***
	(396.26)	(43.35)	(10.79)
Interacted Treatment Effect	-620.76	-72.94	7.66
	(459.1)	(69.44)	(31.29)
Observations	1,378	1,378	1,378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 5.1.5. Impact Estimates on Changes in Household Input Expenditures

	External Labor	Purchased Seeds	Any Chemicals
Household FE Model			
Treatment	-620.76	-72.94	7.66
	(458.43)	(69.34)	(31.24)
ANCOVA Model			
Treatment	-495.96	-24.82	10.43
	(373.95)	(63.14)	(34.6)
Baseline value	2.11**	0.12	0.41***
	(0.8)	(0.09)	(0.11)
Household size	362.74***	56.06***	24.12
	(127.66)	(14.39)	(15.31)
Male	462.9	8.31	24.24
	(379.92)	(67.36)	(18.49)
Age / 100	-1327.67	-485.45**	-62.27
	(1220.88)	(209.89)	(69.65)
Speaks Portuguese	173.4	-16.94	19.18
	(297.75)	(56.61)	(19.97)
Primary education	-93.82	83.63	0.69
	(248.81)	(66.12)	(29.37)
Non-farm job	560.41**	-16.28	29.17
	(264.53)	(47.41)	(18.31)
Total expenditures per capita (000s)	0.34	0.08*	0.04*
	(0.32)	(0.04)	(0.02)
Observations	689	689	689

Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01.

Next, we estimate equations (3) and (4) for the aggregated measures of household inputs (Table 5.1.5). We again find no significant treatment effects, though we do find some interesting correlations with baseline variables in the second set of regressions. Perhaps surprisingly, we find no correlation between the baseline value and the endline value for purchased seeds (row 3), which suggests that a different set of farmers were purchasing seeds for the 2015 growing season than for the 2014 growing season. We also find that as households get larger, they tend to be more likely to spend on external labor, implying these households may be more diversified in their economic activity as evidenced by the observation that if a member of the household has an off-farm job, the household is more likely to have paid for external labor.

We next look at the disaggregated input use variables in the difference-in-difference framework (Table 5.1.6). Here, we again find no evidence of significant treatment effects, with the exception of improved seeds, where the coefficient is significant, but the sign is negative rather than positive, an unexpected result which we discuss further below. We also find evidence that in the 2015 growing period households purchased more seeds and pesticides.

Table 5.1.6. Impact Estimates on Input Expenditures (Disaggregated Categories), Pooling Baseline and Endline Data

	Traditional Seeds	Improved Seeds	Chemical Fertilizer	Pesticide	Herbicide
Treatment Dummy	9.97	12.46	-1.47	-0.80	-0.78
	(18.58)	(15.12)	(3.17)	(16.53)	(1.63)
Post-Treatment Dummy	138.90*	176.40***	4.89	38.70**	4.59
	(37.60)	(27.64)	(4.16)	(10.16)	(4.61)
Interacted Treatment Effect	16.44	-89.38**	12.51	-13.59	8.74
	(55.99)	(41.13)	(14.86)	(15.81)	(13.25)
Observations	1378	1378	1378	1378	1378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Finally, we examine expenditures on the disaggregated input use variables using equations (3) and (4) (Table 5.1.7). Most of the coefficient estimates are not significant, though the household fixed effects model shows the improved seeds coefficient is negative and significant at the 5 percent level, while it is significant only at the 10 percent level when using the ANCOVA model. This finding is unexpected, since the hypothesized effect was positive. Upon further examination, we find that this negative result is quite sensitive to the specification used. For example, if additional explanatory variables[24] are added to control for land area and crop diversity, the coefficient is no longer statistically significant. Similarly, the outcome is not robust to the introduction of additional economic control variables, such as primary wage from non-agricultural activities.[25] The result is likely driven by outliers in models with or without the covariates. For example, if we run our standard specification where the sample is restricted to farmers spending less than

[24] Since our treatment assignment is randomly assigned, it is hypothesized to be orthogonal to additional covariates. As the primary objective of our model is inferential, our use of covariates is intended to add precision to the estimation of the treatment effect, rather than to predict between-group variation in the dependent variable. As a result we use a simple set of socio-economic controls in estimating equation (4).

[25] We tested the augmented model (including land area and crop diversity) for the other input expenditure categories and similarly find no statistically significant effect for the treatment variable.

1,000 MZN on improved seeds (which is 98 percent of the sample), there is no longer a statistically significant difference between the treatment and control groups.

Table 5.1.7. Impact Estimates on Changes in Household Input Expenditures, Disaggregated Categories (Nampula 2014, 2015)

	Traditional Seeds	Improved Seeds	Chemical Fertilizer	Pesticide	Herbicide
Differenced Model					
Treatment	16.44 (55.9)	-89.38** (41.07)	12.51 (14.84)	-13.59 (15.78)	-72.94 (69.34)
Fixed Effects Model					
Treatment	44.06 (48.46)	-69.13* (37.18)	10.55 (14.89)	-9.09 (15.32)	-24.82 (63.14)
Baseline value	0.14 (0.2)	0.14* (0.08)	-0.09 (0.07)	0.12 (0.1)	0.12 (0.09)
Household size	16.52 (9.99)	39.39*** (12.98)	10.87 (7.76)	8.79** (3.8)	56.06*** (14.39)
Male	-57.14 (52.12)	64.98* (32.95)	7.88 (5.61)	22.25 (16.74)	8.31 (67.36)
Age / 100	-445.62*** (125.84)	-38.54 (164.06)	1.72 (16.71)	-70.59 (73.2)	-485.45** (209.89)
Speaks Portuguese	6.78 (33.02)	-23.97 (42.71)	-1.24 (9.4)	15.53 (10.59)	-16.94 (56.61)
Primary education	30.32 (54.2)	53.43 (44.15)	8.66 (5.63)	-21.42 (29.76)	83.63 (66.12)
Non-farm job	-7.91 (36.2)	-8.81 (36.15)	15.05** (7.35)	14.33 (14.11)	-16.28 (47.41)
Total expenditures per capita (000s)	0.78 (1.83)	6.71** (3.19)	0.80 (0.86)	2.13* (1.27)	7.55* (3.84)
Observations	689	689	689	689	689

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

In sum, we find no evidence of a treatment effect on treated farmers in terms of input use. Given the increase in input use described in Section 3, this finding does not suggest that farmers did not purchase any inputs through the program. There are several potential explanations which may fully or partially explain this finding. Since we did observe sales during the input trainings and follow-up visits, there may have been some positive effects, but due to the smaller number of relative sales these effects could be either too small to discern statistically (particularly since the general increase in input use may violate some of our underlying econometric assumptions) or potential benefits may have been crowded out by this broader trend. That said, we must conclude that the input trainings and targeted discounts through mobile money did not stimulate additional input use among farmers in Nampula.

5.2. Changes in Agricultural Productivity

Our second research question follows from the first research question, asking whether improved access to inputs leads to changes in agricultural productivity, and if so, what factors along the impact pathway drive those changes. We hypothesized such changes could be due to changes in crop diversification, increased use of inputs, changes to the household labor allocation, or some combination of factors. The data present both a challenge and an opportunity in identifying how increased input use might change agricultural productivity. Since we did not find impacts of the treatment on input use, we cannot identify exogenous variation in input use to instrument for any change in productivity, presenting a challenge of attribution. However, we find substantial increases in input use among study households, offering the opportunity to relate input use to productivity, with the understanding that estimates will necessarily lack a causal interpretation.

A second important observation is that we observe some substantial differences in input use across households. In choosing an estimation strategy, we keep first in mind that some households are much more likely to use inputs than others, and that there is likely underlying heterogeneity in the productivity of such farmers; in other words, farmers who are more inherently productive might be both more likely to use inputs and to use inputs more effectively. As a result, we might expect to observe quite a bit of heterogeneity in responses to inputs.

So two obvious approaches to estimating agricultural productivity are perhaps not appropriate. First, we could take an agricultural production function approach, which would estimate a coefficient that averages across the entire sample. However, households are growing different crops (with the exception of maize), and so there is a lot of heterogeneity in production techniques. As a result, this approach might not provide much meaningful information. Moreover, typically production functions are non-linear, and logarithmic transformations of variables (such as the amount of fertilizer used) are common; such a transformation would yield a great deal of missing data in this context.

Similarly, a common approach to understanding agricultural production is to assume that there is a production possibilities frontier, and to estimate impacts of inputs in getting households closer to that frontier. However, establishing a frontier requires a number of farmers to be close to their production potential; given the small number of farmers using fertilizer in this data set, there are not likely to be enough households to establish that frontier. So we instead want to use an approach that allows us to measure heterogenous responses to input use.

An appropriate alternative approach is therefore quantile regression (Koenker, 2005). In our context quantile regression offers two key benefits over using a more typical ordinary least squares approach. First, rather than minimizing the sum of squared deviations from the regression line, as is the method in least squares regression, quantile regression minimizes the sum of the absolute deviations from the regression line. This makes the results much less susceptible to outliers, which, given the presence of heterogeneity, may greatly affect the mean of the outcome variable. Deaton (1997) recommends the use of quantile regression in developing country contexts of studying such heterogeneous relationships.

To motivate the quantile approach a bit more, it is worth understanding the difference between least squares and quantile regression in more detail. Note that in least squares regressions, the regression line always passes through the mean of each variable included in the regression, including the mean outcome. Quantile regression necessarily relaxes this assumption, and only requires the regression line to pass through some percentile of the distribution of the outcome variable. As a result, we can vary the percentile of the distribution around which the regression passes through, so we are able to observe the magnitude of the coefficient at different point in the distribution. We can thus compare the impact of input uptake for a farmer in the top 25 percent of the production distribution with that of a farmer in the lowest quartile. If the coefficients are not statistically different, then heterogeneity does not exist; however, if they test or are obviously statistically different, then we can conclude that heterogeneity exists.

The following equation is used to estimate the productivity effects:

$$Y_{it} = \alpha_t + \beta X_{it} + \theta Z_{it} + u_{it} \quad (5)$$

where Y represents production outcomes; X represents indicators for whether or not specific inputs were used, and Z represents demographic characteristics and asset holdings of the household. As mentioned before, we choose estimates for β and θ that minimize the absolute value of computed errors, rather than the squared error terms, choosing a quantile of *Y* as a reference point. To ensure we have support on either side of the quantile, we use the 25th percentile, the median, and the 75th percentile as the quantiles of interest.

While we cannot place causal interpretations on the coefficients, as described above, the correlations that the regressions measure may be useful in understanding how changes in policy or programming might affect different types of producers in the FTF intervention Zone. The fact that we can pool two years of production data offers a longitudinal view of the underlying relationships that may determine productivity outcomes.

We use three different sets of productivity measures for the dependent variables in our models: 1) quantity and value of maize production, the single most widely produced crop, 2) gross and net value of total agricultural production, and 3) crop diversity.

To determine the measure of productivity, we examine use of improved seeds by crop (Figure 5.2.1). We find that by far the most commonly grown crop for which improved seeds were purchased in 2015 was maize. Thus, we use quantity and value of maize production for the first productivity measure. We note that self-reported measures of land area, a factor in yield calculations, do not correlate very well with actual measures, when measured by GPS, which is why we use overall maize production rather than yield, ensuring that we control for reported land area on the right-hand side of the regression equation.[26]

[26] See Abate et al. (2015) for a graph of measured plot area versus farmer estimates in a survey context.

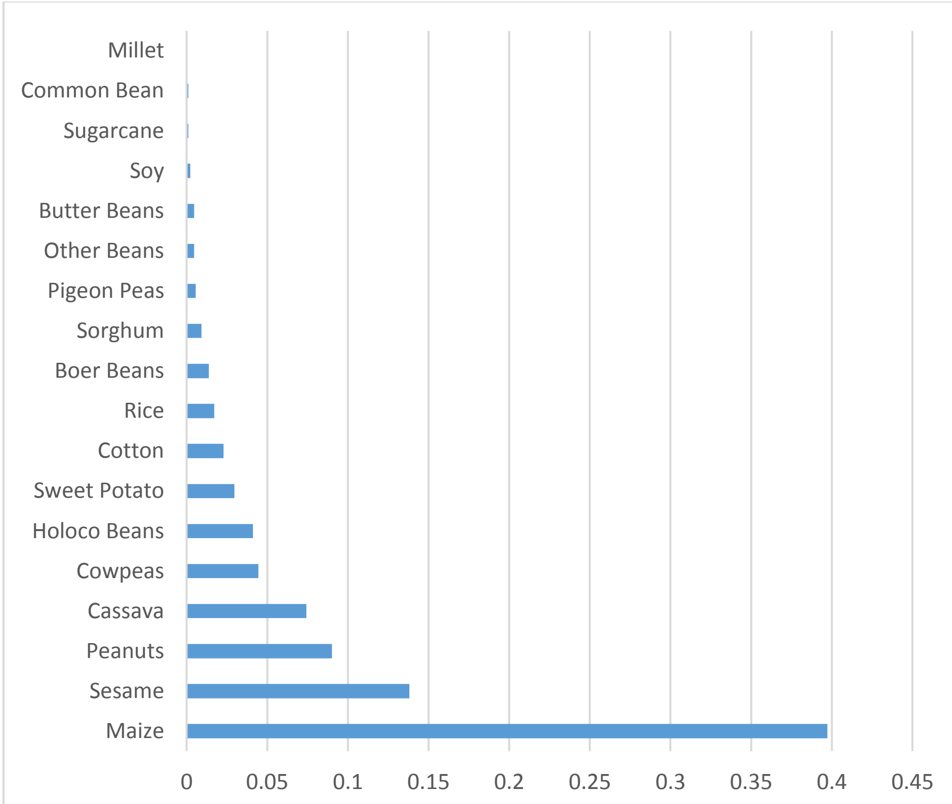


Figure 5.2.1. Improved seeds use, by crop type

We initially use the total quantity of maize produced and the total value of maize produced as dependent variables (Table 5.2.1). Four sets of coefficient estimates stand out as interesting. While we do not find statistically significant results on the family labor use indicator, the coefficient on the indicator for external agricultural labor is positively related to both maize production and the value of the maize crop, providing suggestive evidence that more productive households may use hired labor more efficiently.[27] We find a positive coefficient for chemical fertilizer use, which is significant at the 1 percent level at the 75th percentile, and coefficients are dramatically larger than at the 25th percentile. Recall, only a few households (2%) used any chemical fertilizer, but those that did appear to have production and crop value at the top end of the distribution. Households using pesticides also have higher output and crop value throughout the distribution, but the differential is highest at the 75th percentile of the production distribution (though not statistically significant). The coefficient for pesticide use in the crop production regression is statistically significant for the 25th and 50th percentiles (at the 10 percent level) reflecting the far more widespread pesticide use relative to chemical fertilizer across the distribution. Both chemical fertilizer and pesticide use increases output of maize among those producing greater quantities. Finally, we note that the relationship between self-reported land area and maize production is as expected throughout the distribution, more is correlated with higher production, but the correlation is greater at higher points in the output distribution.

[27] Testing the same specification with other locally important crops such as peanuts and sesame, we find similar positive returns to hiring external labor.

Table 5.2.1. Correlates of input use with Maize Production and Value, Estimated by Quantile Regression, Nampula, Baseline and Endline Data

	Production Quantity (Kg)			Crop value (MZN)		
Percentile	**25th**	**50th**	**75th**	**25th**	**50th**	**75th**
Paid labor	5.80	4.00	14.50	81.66	117.02	299.47
	(9.75)	(11.94)	(19.06)	(80.00)	(111.48)	(220.21)
Improved seeds	5.55	23.72*	13.84	56.37	281.09*	190.98
	(9.55)	(14.39)	(26.08)	(91.87)	(170.31)	(310.49)
Chemical fertilizer	98.83	247.36	457.54**	418.02	1,936.65	4,381.55***
	(98.26)	(192.57)	(185.74)	(1,094.75)	(1,842.17)	(1,560.95)
Pesticide	16.48*	29.61*	52.01	191.34*	266.74	464.81
	(9.53)	(17.06)	(36.52)	(101.29)	(185.33)	(452.85)
Herbicide	34.45	-35.76	25.10	244.76	-409.98	-272.65
	(274.82)	(522.90)	(693.08)	(5,114.31)	(8,781.81)	(11,481.19)
Endline	-18.05**	-29.59**	-1.80	-505.04***	-743.92***	-708.36**
	(9.13)	(13.25)	(28.09)	(84.78)	(164.09)	(352.92)
Area owned (Hectares)	3.92*	7.89**	32.57***	29.87	84.87**	252.55***
	(2.29)	(3.96)	(9.22)	(23.53)	(41.19)	(85.62)
Household size	4.12	10.17***	12.10**	50.54*	89.65***	115.49*
	(2.70)	(3.08)	(5.89)	(26.83)	(32.96)	(64.01)
Is male	11.69	11.81	30.12	188.38*	56.86	304.09
	(10.08)	(14.81)	(24.39)	(106.95)	(152.80)	(264.39)
Age	-0.15	0.07	-0.34	-2.83	-2.74	-1.84
	(0.27)	(0.43)	(0.70)	(2.95)	(4.04)	(7.88)
Speaks Portuguese	16.17	14.43	21.99	167.62**	230.60	344.81
	(10.03)	(13.87)	(25.72)	(84.00)	(152.39)	(292.80)
Primary education	3.71	-12.09	-1.37	-60.79	-115.06	-122.02
	(12.29)	(18.68)	(25.49)	(116.50)	(171.38)	(327.37)
Non-farm employment	-11.35	-21.75*	-31.71*	-192.24***	-278.12**	-140.60
	(10.25)	(11.66)	(17.87)	(73.72)	(132.21)	(206.81)
Total expenditure per capita (000s)	0.41	4.85*	6.56*	9.55	59.92***	86.33*
	(1.61)	(2.89)	(3.93)	(16.01)	(22.45)	(45.36)
Observations	770	770	770	770	770	770

Notes: Simultaneous quantile regression, with producer-forum fixed effects. Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01).

We find only weak positive correlation between maize production and the indicator for purchased improved seed (row 2). As Mozambican farmers tend not to use other inputs for maize production, this result supports the arguments that development of better open pollinated maize varieties could better serve Mozambican farmers than hybrid varieties which typically require the use of chemical fertilizer to attain improved yields.

As a second set of productivity measures, we use the gross and net value of total agricultural production. The gross value of agricultural production is computed as the sum of the price per unit times the quantity produced for all crops produced by each household. When prices are not available in the data, because the crop was used for household consumption, then either association level median sales prices are used to estimate the value, or, if these are unavailable, forum level median sales prices are used. The net value of agricultural output is calculated as the gross value less all purchased inputs; we do not reduce by the amount of family labor used, so this measure can also be thought of as the net return to land and family labor in agriculture.

We observe several interesting relationships in the data (Table 5.2.2). Expanding analysis beyond maize to all crops, we observe a strong relationship between paid labor for both measures of aggregate output. At higher percentiles of the distribution, the coefficient is larger, suggesting that paid labor helps increase output even more at higher levels of the distribution, even when the cost of that labor is deducted from the value of output for net agricultural value (columns 4 through 6). Similarly, we find that pesticide use increases the value of production and coefficient estimates increase at higher percentiles of the distribution, even when the cost of those pesticides is deducted from the value of output. We observe a similar pattern with reported land area where coefficients are positive, significant, and increase as the regression centers around higher percentiles of the distribution. These coefficients are substantially higher compared to those for the value of maize output alone. Thus, there appears to be high returns to growing other crops in addition to maize, and households at the top end of the distribution appear to reap more benefits. We also find a positive and large coefficient for use of improved seeds, but only for households at the 75th percentile of the distributions for both agricultural value indicators. Households with higher levels of output are much more likely to use improved seeds, whether or not one controls for the expense of inputs. If one assumes that improved seeds are effectively hybrids, then one observes that households with higher output are using hybrid seeds more effectively than households with lower productivity.

Finally, we measure crop diversity as another proxy for agricultural production to assess the degree households diversify production beyond maize to include higher value crops. Crop diversity is measured as the number of different crops households grow.

Table 5.2.2. Correlates of input usage with Gross and Net value of Agricultural Output, Estimated by Quantile Regression, Nampula, Baseline and Endline Data

	Agricultural Value (Gross)			Agricultural Value (Net)		
Percentile	**25th**	**50th**	**75th**	**25th**	**50th**	**75th**
Paid labor	2,129***	2,955***	3,747***	2,113***	2,752***	3,698***
	(385)	(409)	(888)	(349)	(487)	(824)
Improved seeds	252	214	1,728**	148	293	1,632*
	(479)	(598)	(867)	(422)	(560)	(901)
Chemical fertilizer	-1,059	4,847	5,705	-1,522	4,728	5,836
	(2,994)	(4,508)	(4,545)	(2,853)	(4,837)	(4,775)
Pesticide	2,256***	3,058***	4,172***	1,851***	2,621***	3,892***
	(498)	(627)	(1,197)	(533)	(679)	(1,471)
Herbicide	1,691	-3,457	18,474	-751	-2,382	18,088
	(122,702)	(239,376)	(530,696)	(122,952)	(171,059)	(533,767)
Endline	-2,849***	-4,199***	-5,808***	-2,811***	-4,567***	-5,848***
	(464)	(585)	(861)	(387)	(578)	(876)
Area owned (Hectares)	464***	761***	1,700***	466***	777***	1,718***
	(102)	(140)	(305)	(105)	(137)	(343)
Household size	396***	532***	798***	364***	481***	757***
	(96)	(142)	(204)	(92)	(130)	(201)
Is male	2,166***	2,502***	2,266**	2,185***	2,471***	2,305**
	(374)	(739)	(988)	(492)	(713)	(1,173)
Age	-22	12	20	-15	11	24
	(18)	(16)	(29)	(15)	(15)	(26)
Speaks Portuguese	-237	1,095**	1,253	-391	1,104*	1,323
	(308)	(509)	(820)	(358)	(642)	(952)
Primary education	-1,005	-1,637*	-2,238**	-865	-1,597*	-2,372**
	(662)	(938)	(1,134)	(606)	(962)	(1,146)
Non-farm employment	-362	-618	-552	-370	-484	-576
	(410)	(509)	(754)	(404)	(511)	(870)
Total expenditure	114*	258***	526***	99*	214**	516***
per capita (000s)	(59)	(87)	(158)	(57)	(89)	(154)
Observations	1,378	1,378	1,378	1,378	1,378	1,378

Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01).

As with the other measures of productivity, we estimate correlations between indicators for input use and crop diversity and find coefficient estimates are far more consistent across quantiles relative to the estimates for value of output, which suggests that the linear relationships for this measure are more stable through the crop diversity distribution (Table 5.2.3). The use of improved seeds appears to be correlated with growing, on average, between 0.5-0.7 additional crops. Pesticides appear to be positively correlated with the number of crops grown, but this correlation may be concentrated among initially less diverse farmers focused on specific cash crops, as the magnitude of the coefficient estimates decline through increasing percentiles of the crop diversity distribution. The use of external labor also appears correlated with greater crop diversity. Among household characteristics, larger households appear to grow a more diverse crop mix. None of these results seem to refute the results from regressions on the gross value of agricultural output, which suggest heterogeneity in the response to inputs by overall production value.

Table 5.2.3. Effects of input usage on crop diversity, Estimated by Quantile Regression, Nampula, Baseline and Endline Data

	Number of crops grown		
Percentile	**25th**	**50th**	**75th**
Paid labor	0.44***	0.38***	0.43**
	(0.16)	(0.13)	(0.17)
Improved seeds	0.57***	0.64***	0.48**
	(0.18)	(0.15)	(0.22)
Chemical fertilizer	-0.66**	-0.98**	-0.91
	(0.33)	(0.43)	(0.98)
Pesticide	0.48**	0.44**	0.19
	(0.21)	(0.17)	(0.16)
Herbicide	0.37	-0.35	-1.04
	(1.15)	(1.24)	(2.18)
Endline	0.49***	1.20***	1.77***
	(0.16)	(0.12)	(0.23)
Area owned (Hectares)	0.04**	0.06***	0.05**
	(0.02)	(0.02)	(0.03)
Household size	0.04	0.05*	0.06
	(0.03)	(0.03)	(0.04)
Is male	0.31	0.29*	0.63***
	(0.21)	(0.16)	(0.21)
Age	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.01)
Speaks Portuguese	-0.00	-0.09	0.07
	(0.14)	(0.10)	(0.18)
Primary education	-0.44**	-0.28*	-0.32
	(0.20)	(0.17)	(0.32)
Non-farm employment	0.13	0.13	0.06
	(0.10)	(0.11)	(0.16)
Total expenditure	-0.02	-0.01	-0.01*
per capita (000s)	(0.01)	(0.01)	(0.01)
Observations	1,378	1,378	1,378

Notes: Simultaneous quantile regression, with producer-forum fixed effects. Stars indicate significance at standard alpha levels (* p<0.1, ** p<0.05, *** p<0.01).

To summarize, in this subsection we study the correlations between input use and measures of agricultural production at the household level, using quantile regression. Putting the results together, there are a few important lessons. Consider the results on purchased inputs, such as seeds, fertilizer, and pesticides. There are gains to using any of these inputs, but the gains are concentrated among relatively more productive farmers. It seems likely that, as described in Carter, Laajaj, and Yang (2013), large input subsidies strongly favor farmers who are already more productive. It is clearly more challenging to reach the median farmer and the farmer at the 25th percentile; programming that targets just improved seeds for higher yields of target crops, for example, appears likely to benefit farmers at the upper end of the production distribution. Moreover, the most commonly used input in the data (improved seeds) do not appear to affect production at the lower end of the distribution at all.

5.3. Cost-Effectiveness

Our third research question follows from the preceding two questions, asking whether the potential benefits of an increase in input demand and input sales for IKURU would be high enough to offset costs associated with a more direct input marketing and distribution strategy. Given that we cannot statistically identify impacts of the intervention on input demand, it is clear that increased costs associated with a more direct input marketing strategy for IKURU are not cost-effective, regardless of whether paired with marketing through Mobile Money, which faced coordination challenges in the implementation. Moreover, those farmers that were using Mobile Money by the endline survey appear to be willing to travel some distance to access the service, as there were only seven established agents in the area at the time of the endline. Consequently, it might be valuable for IKURU to include Mobile Money options to clients within their informal marketing strategy to provide those farmers using the service with an additional mechanism to make input purchases.

An alternative way to change the system would be to require farmers to make these transactions on mobile money. Such a system would only work if IKURU, or whomever purchased crops from farmers, only offered to purchase crops on mobile money. However, unless there was a clear monopsonist buyer in the area for specific crops, it would be unlikely for such a strategy to work well to promote mobile money, as farmers might prefer cash to mobile money. Such a strategy would also raise ethical concerns if agents were not available. Our data make it clear that IKURU is not a monopsonist buyer from these farmer associations.

5.4. Mobile Money Usage

Our final research question asks whether or not the input marketing treatment actually helped increase the use of Mobile Money accounts. All farmer associations in the study had members who were trained in Mobile Money, so we examine whether the randomized intervention of association-level input marketing, farmer trainings, and sales visits had an impact on Mobile Money use among treated associations compared to no-treatment associations.

To examine potential impacts, we use both the administrative data and the endline survey data. We obtained administrative records from Vodacom on whether or not phone numbers in our study had active mPesa accounts and whether they had any available balance in early 2015, after the study treatment had been implemented. We could not obtain individual transaction data by phone number, thus were not able observe specific uses of mobile money accounts. Instead, we were able to capture a ‘snapshot’ of account activity status following the training. We complement this data with our own administrative records of input purchases during the marketing visits. Combining these sources, we consider households as “users” of Mobile Money either if we observe their account number being used to make a purchase during input marketing visits, or if we observe their Mobile Money account as having current or recent activity at the time at which the Vodacom data was captured. We then use this data to determine whether the input trainings and sales appear to have catalyzed additional users of Mobile Money in treatment associations. As of May 2015, we were able to match 397 farmers that had attended the Mobile Money trainings to the administrative data. Within this group 71 percent were either currently using both the SIM card and phone number they received at the training (12%), or had previously transacted on that account (59%) during the intervening period.[28] We only measure the effects of the training in the endline data after the intervention had been implemented using self-reported data. As the endline took place just over a year after the treatment took place, it could be that households had initially used Mobile Money but stopped by the time of the endline survey. Consequently, our analysis primarily uses a version of equation (4) from Section 4 excluding the baseline outcome variable.

As shown in Section 3, a considerable amount of information was collected on the use of Mobile Money by study households. The data include both households including individuals that were trained and households with no trained individuals in the use of Mobile Money. Although participation in the Mobile Money trainings is not an exogenous factor (since members could choose if they would attend the training), we can still use participation as an indicator to see whether people who were trained became Mobile Money users more frequently than those who were not trained. These regressions speak to the effectiveness of the trainings. We examine whether trained households initially perform better with outcomes associated with Mobile Money use, and then more than a year after the training takes place. We also explore whether households that attended the Mobile Money training consider Mobile Money as a potential means for saving.

Treatment Effects on Mobile Money Usage

The administrative data from Vodacom allowed us to look at a snapshot of mPesa usage between the two survey rounds.

Table 5.4.1. Number of active mPesa users (May 2015)

	Users	%
Currently active users	46	11.59
Previous users	235	59.19
Inactive, no use	116	29.22
Total	397	100.00

Disaggregating this data by treatment status, we observe a very similar allocation of user types between treatment and control groups (Table 5.4.2). In line with the findings described above on the main outcomes of interest for the intervention, we fail to reject the null hypothesis of no difference in proportion of user types between the treatment and control groups.

[28] In the cases in which the phone number was listed as "currently active," we know that the individual is currently using the SIM card received from the project. However, Vodacom did not provide the research team with information about those users' mobile money accounts, despite multiple queries and language in a partnership agreement intimating that such information could be made available. Although we believe such users likely fit the definition of Mobile Money users, we have to assume that combining the previous users' category (for which we know that Mobile Money has been used) with the "currently active" category represents an upper bound on the total mobile money users, as we cannot be absolutely sure that the "currently active" users ever used Mobile Money.

Table 5.4.2. Number of active mPesa users, by treatment status (May 2015)

	Control		Treatment	
	Users	**%**	**Users**	**%**
Currently active users	27	11.95	21	11.80
Previous Users	134	59.29	106	59.55
Inactive, no use	65	28.76	51	28.65
Total	226	100.00	178	100.00

Using the endline data, we select four variables to measure Mobile Money use: 1) whether the respondent knows of Mobile Money, 2) whether the respondent has used Mobile Money, 3) whether the respondent's current Mobile Money balance is greater than zero, and 4) whether or not the respondent knows the name of a Mobile Money agent. To preserve balance in the sample between treatment and control groups, we estimate by intent-to-treat, using a value of zero when households do not own or regularly use a cell phone for the latter three variables. We use these outcomes as dependent variables in the modified version of equation (4), and estimate the effect of the treatment variable, simply controlling for forum level fixed effects (Table 5.4.3). We find no evidence of a treatment effect on any of the four explanatory variables. The finding is not surprising, as the actual users of input trainings and discounts were a relatively small share of the sample.[29]

Table 5.4.3. Impact Estimates of Input Marketing Treatment on Mobile Money Use at Endline

	Knows of Mobile Money	**Uses Mobile Money**	**Has Mobile Money balance**	**Knows name of Mobile Money agent**
Treatment	-0.04 (0.03)	0.01 (0.04)	8.95 (44.58)	0.00 (0.04)
Observations	689	689	689	689

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We next include household-level covariates from the baseline survey (Table 5.4.4). The baseline covariates reduce variance, at least theoretically, in the treatment effect estimates, but we still find no significant treatment effects. We do find that household size appears to be positively associated with many of the variables. Similarly, whether the household head speaks Portuguese is positively associated with three of the four Mobile Money use variables, which underscores that literacy is important for the use of mobile money, and may be limited in its reach among older residents due to low literacy levels in rural Mozambique.

[29] We do not remove the nonparticipants or even households that do not own a cell phone at endline because we would be concerned about selection effects; e.g., that households owning phones might differ between the treatment and control groups.

Table 5.4.4. Impact Estimates of Input Marketing Treatment on Mobile Money Use with Baseline Demographic Controls at Endline (Nampula 2015)

	Knows mobile money	Uses mobile money	Mobile money balance	Knows agent name
Treatment	-0.02 (0.03)	0.03 (0.04)	33.63 (40.70)	0.01 (0.03)
Household size	0.03*** (0.01)	0.03*** (0.01)	-0.51 (16.48)	0.03*** (0.01)
Male	0.06 (0.06)	0.03 (0.04)	11.91 (20.14)	0.03 (0.03)
Age / 100	-0.21 (0.14)	-0.15 (0.09)	202.58 (174.28)	-0.11 (0.08)
Speaks Portuguese	0.03 (0.03)	0.14*** (0.03)	49.26* (26.49)	0.11*** (0.03)
Primary education	0.06 (0.05)	0.02 (0.03)	42.27 (39.62)	-0.02 (0.02)
Non-farm job	0.00 (0.03)	-0.04 (0.04)	-10.34 (46.63)	-0.02 (0.03)
Total expenditures per capita (000s)	0.00*** (0.00)	0.01*** (0.00)	7.40 (6.13)	0.00** (0.00)
Observations	689	689	689	689

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We are effectively looking to identify a treatment effect from the input trainings and marketing visits as "intent-to-treat" effects in an intervention that had relatively low measurable participation (the 69 farmers purchasing inputs). Moreover, the input offers took place about three months after the trainings took place. Mobile Money use might have been improved if IKURU had offered farmers the option to pay farmers for their commercialized crops on Mobile Money, which would have induced savings. However, according to the data, IKURU appears to have essentially failed to purchase anything from farmers in the study sample, as only three groundnut farmers and two sesame farmers report selling their crops to IKURU.[30] The descriptive statistics appear to have borne out a story in which a substantial share of mobile phone owners have begun to use Mobile Money in earnest; it seems much more plausible in retrospect that the Mobile Money training catalyzed this use in lieu of the input trainings on top of the Mobile Money training.

In sum, we do not find a significant treatment effect of the input trainings and discounts on Mobile Money usage. However, we note in the descriptive section that there is a substantial share of people who are actually using Mobile Money across both the treatment and control groups.

Association of Training with Mobile Money Usage and Savings

The data set includes households with an individual that attended the Mobile Money and households without any trained individuals. The latter households did not participate in the Mobile Money training,

[30] Both figures represent about 1 percent of sample farmers who sold those crops.

but were picked up in the surveys to more appropriately measure intent to treat effects. We compare Mobile Money use among those who chose to attend the Mobile Money against those who were not. Participation in the mobile money trainings was voluntary–association leaders were instructed to invite all association members who were interested to attend. Since individuals who did not attend the trainings did not attend for some reason, there are clearly potential selection effects if we try to measure the association of the trainings with Mobile Money use. The most obvious bias would be that individual household members who were interviewed but did not participate in the Mobile Money trainings did so because they were not informed of the training by the association leader or because they did not see the value in participating. In this case, we might expect a positive bias for coefficients estimated if such households are used as the control group in a regression.

However, there are at least two ways that such bias could be diluted. First, some households in the data set might have simply not heard about the training, or were not around when it occurred; if so, then it could be effectively random that they did not participate. To explore whether bias appears to occur, Table 5.4.5 compares characteristics between trained households and those who did not receive training.

Table 5.4.5. Baseline characteristics of trained vs. untrained households

	Trained		Untrained		
	Mean	**SD**	**Mean**	**SD**	**p-Value**
Household size	5.05	2.10	4.62	1.95	0.01***
Male	0.91	0.29	0.90	0.30	0.57
Age	39.82	12.98	38.20	12.73	0.11
Speaks Portuguese	0.66	0.48	0.56	0.50	0.01***
Primary education	0.91	0.29	0.86	0.35	0.05**
Non-farm employment	0.54	0.50	0.59	0.49	0.17
Land area owned	4.36	5.91	3.49	3.68	0.03**
Food expenditures per capita	3,478	4,506	3,245	4,706	0.51
Total expenditures per capita	6,960	8,064	6,045	7,538	0.13

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

On average, individuals who did not attend trainings are from smaller households and are more likely to engage in non-farm employment, which is logical since both of these factors might influence the likelihood of a household member being present in the village at the time of the training. We control for both of these variables explicitly in the subsequent regressions which include covariates. Untrained households are similar to trained households in terms of gender and age, though slightly less educated on average—a potentially important consideration in designing future voluntary trainings. In terms of expenditures, untrained households are similar to trained households, suggesting that individuals did not select into the training based on income. While we control for household covariates in subsequent regressions, members of untrained households look similar to those in trained households along observable dimensions.

Second, slightly more subtly, we should think about the comparison to randomized trainings. Had we randomized the trainings at the association level, the control associations may never have heard about Mobile Money, or would not be exposed to word-of-mouth advertising of Mobile Money. In this scenario we would expect very low average knowledge of Mobile Money among the control group. It is much more likely that households in or near the associations could have picked up on the potential use of Mobile

Money as a result of those trainings through word-of-mouth, and consequently either at baseline or endline positive indication of knowing about Mobile Money and potential usage would be higher than it would be otherwise, which would result in a small, positive bias on coefficient estimates.

Note that as the Mobile Money trainings took place before the baseline survey, we can examine either knowledge and/or use of Mobile Money soon after the trainings at baseline, or a longer time after the trainings at endline. We essentially use the following regression framework to do so:

$$Y_i = \alpha + \delta \; Tr_i + \mu Z_i + \epsilon_i \tag{6}$$

where Y is the outcome, Tr represents that the individual or household was trained in Mobile Money use; Z are household control variables, and ϵ_i represents a mean zero error term. We run separate regressions for the baseline and endline surveys. As training participation was not random we do not ascribe a causal interpretation to results.

First, we estimate the association of Mobile Money training with the four Mobile Money use variables described in the previous subsection, measured at baseline (Table 5.4.6). We find a positive and statistically significant association between training participation and all four variables. Specifically, we find that the trained group were 38 percentage points more likely to state they know about Mobile Money; 47 percentage points more likely to state that they use Mobile Money; their balances are on average 30 MZN higher than non-trained individuals; and they are 6 percentage points more likely to know the agent's name. The fact that not everyone in the trained group reports knowing about or using Mobile Money implies that either a few people were really lost during the training as well as some cases where the trained individual was unavailable and a different household member acted as the respondent for the interview. Thirty-two percent of the untrained group reported knowing of Mobile Money but virtually none of them used it at all.

Table 5.4.6. Impact Estimates of Mobile Money Training on Mobile Money Use at Baseline (Nampula 2014)

	Knows of Mobile Money	Uses Mobile Money	Has Mobile Money balance	Knows name of Mobile Money agent
Treatment	0.38***	0.47***	29.64**	0.06***
	(0.04)	(0.03)	(12.01)	(0.02)
Mean, Untrained group	0.32	0.01	0.00	0.00
Observations	689	689	689	689

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We next report the same regressions, with baseline covariates (Table 5.4.7). The training coefficients are all qualitatively similar, which suggests that at least household head characteristics and some of the household demographics do not appear to affect the coefficient estimates. Consequently, at least at first glance it appears that selection is not affecting these estimates much, at least selection on observables.[31] We find that literacy seems to matter towards knowing about and using Mobile Money; the household head's age is negatively correlated with their Mobile Money balance, which suggests that older households may either cashed out their initial balance (both anecdotal and administrative evidence

[31] Selection on unobservables could still affect these estimates.

suggests farmers did so largely to purchase phone credit) or simply been unaware that their balance persisted.

Table 5.4.7. Impact Estimates of Mobile Money Training on Mobile Money Use with Baseline Demographic Controls, at Baseline (Nampula 2014)

	Knows mobile money	Uses mobile money	Mobile money balance	Knows agent name
Treatment	0.32***	0.43***	28.27**	0.05***
	(0.04)	(0.03)	(12.84)	(0.02)
Household size	0.04***	0.02**	0.54	0.01
	(0.01)	(0.01)	(1.10)	(0.01)
Male	0.00	0.05	7.55	-0.02
	(0.07)	(0.06)	(5.97)	(0.02)
Age / 100	-0.11	-0.15	-60.66**	-0.08
	(0.14)	(0.11)	(24.81)	(0.07)
Speaks Portuguese	0.20***	0.16***	16.66**	0.04**
	(0.04)	(0.04)	(7.67)	(0.02)
Primary education	0.15**	0.01	-4.12	0.01
	(0.06)	(0.04)	(3.05)	(0.01)
Non-farm job	-0.01	-0.03	18.35	0.01
	(0.03)	(0.04)	(12.34)	(0.02)
Total expenditures per capita (000s)	0.01***	0.01**	1.59*	0.00
	(0.00)	(0.00)	(0.84)	(0.00)
Observations	689	689	689	689

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

We repeat these regressions with the endline data (Table 5.4.8). After a year, the magnitude of the coefficient estimates for whether or not trained respondents know of or use Mobile Money decrease somewhat relative to the baseline survey, suggesting that there is some depreciation of knowledge among trained respondents. This finding is unsurprising given that we would expect some drop-off in users in the absence of additional trainings or actual use of Mobile Money. However, trained groups were still much more likely to know of or use Mobile Money at endline; notably, they are 19 percentage points more likely to use mobile money than respondents in households that were not trained. We do not find a significant difference on the Mobile Money balance, with a very large standard error relative to the magnitude of the coefficient. This is likely driven by the distribution of mobile money users' balances, where most users report very low balances while a small proportion of active users report much higher amounts. Finally, we find that those who were trained are 16 percentage points more likely to know the nearest agent's name; this figure represents a large increase from the baseline, in part because agents are better established (from 6 new agents in the administrative data at baseline, though we do not know how many were actually functioning, to 7 functioning agents at endline), as noted in the qualitative report (Cunguara, de Brauw, Maruyama, and Munhaua, 2016). However, it is a good indication that the Mobile Money training can be associated with a substantial number of Mobile Money users, as they continue to use the product.

Table 5.4.8. Impact Estimates of Mobile Money Training on Mobile Money Use at Endline (Nampula 2015)

	Knows of Mobile Money	Uses Mobile Money	Mobile Money balance	Knows name of a Mobile Money agent
Training	0.17*** (0.03)	0.19*** (0.03)	17.06 (47.12)	0.16*** (0.02)
Observations	689	689	689	689

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

When we add covariates to the regression described above, measured at baseline, again we find few changes in the measured treatment effects (Table 5.4.9). There is no impact on the Mobile Money balance, but the other findings are of similar size and remain statistically significant. Moreover, we find similar positive coefficient estimates on the "speaks Portuguese" variable, suggesting again that literacy is important to continued use of Mobile Money.

Table 5.4.9. Impact Estimates of Mobile Money Training on Mobile Money Use with Baseline Demographic Controls, at Endline (Nampula 2015)

	Knows mobile money	Uses mobile money	Mobile money balance	Knows agent name
Treatment	0.15*** (0.03)	0.16*** (0.02)	-0.10 (42.43)	0.13*** (0.02)
Household size	0.02*** (0.01)	0.03** (0.01)	-0.40 (16.45)	0.03*** (0.01)
Male	0.07 (0.06)	0.02 (0.04)	7.94 (17.06)	0.03 (0.03)
Age / 100	-0.26* (0.13)	-0.18* (0.09)	215.85 (183.54)	-0.14* (0.08)
Speaks Portuguese	0.02 (0.03)	0.12*** (0.02)	47.20* (25.61)	0.10*** (0.03)
Primary education	0.05 (0.05)	0.01 (0.03)	45.23 (41.24)	-0.02 (0.03)
Non-farm job	0.01 (0.03)	-0.03 (0.03)	-8.91 (49.28)	-0.01 (0.03)
Total expenditures per capita (000s)	0.00*** (0.00)	0.01** (0.00)	7.31 (6.02)	0.00** (0.00)
Observations	689	689	689	689

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Mobile Money Features

We next want to understand if trained individuals know more about the different uses of Mobile Money. We asked an open ended question about what respondents knew what they could do with Mobile Money, and recorded if they answered that they can make deposits, save money, withdraw cash from an agent, withdraw cash from an ATM, purchase credit, send money, receive money, or make purchases with

Mobile Money. Here, we go back to estimating a difference-in-difference model of baseline and endline data to see how many of the features of Mobile Money are recalled a year after the training.

Not surprisingly, all of the features are more often mentioned in the intent-to-treat model at baseline among those who were trained versus those who were not (Table 5.4.10; row 1). Respondents were most likely to mention that they could purchase phone credit, or send or receive money; many of them knew they could make purchases, deposits, or save money as well. Fewer respondents mentioned that they could withdraw cash from an agent or an ATM.

By endline, we find seven of the eight associations remain statistically significant at the 5 percent level or better (row 5). The only one that is no longer significant is the ability to make deposits; it could be that respondents did not mention this point as they felt it was obvious. In Kenya, as mPesa has matured the main three functions of mobile money have been deposits, transfers, and withdrawals; purchases with mobile money are relatively rare (Jack and Suri 2014). Moreover, one of the main things that increases is the ability to withdraw cash from an agent; clearly, the individuals who have begun to use mobile money and know their agent can withdraw their money.

Table 5.4.10. Impact Estimates of Mobile Money Training on Knowledge of Mobile Money Features, Pooling Baseline and Endline Data (Nampula 2014 and 2015)

	Make Deposits	Save Money	Withdraw Cash (Agent)	Withdraw Cash (ATM)	Purchase Credit	Send Money	Receive Money	Make Purchases
Training	0.28***	0.23***	0.07**	0.11***	0.31**	0.33***	0.29**	0.27**
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)
Endline	0.15**	0.18***	0.35***	0.12***	0.32***	0.10**	0.03	0.06*
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.03)
Training*Endline	-0.24**	-0.10*	0.11**	0.00	-0.13**	-0.09*	-0.06	-0.01
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)
Net Training Effect	0.03	0.13	0.18	0.11	0.18	0.23	0.23	0.26
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
p-value (Train+(Train*Endline)=0)	0.41	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00**
Observations	1,378	1,378	1,378	1,378	1,378	1,378	1,378	1,378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Mobile Money and Savings

We finally report on whether the Mobile Money training was associated with use of different savings mechanisms by study households, including a cash box, a local savings group, Mobile Money, a microfinance organizations, a checking account, or a savings account. We again use the difference-in-difference model (Table 5.4.11). At baseline, we find that households are significantly more likely to report that they used Mobile Money for savings, as well as microfinance organizations if they were in the trained group. It could be that households who attended trainings were more likely to be looking for a safer way to save, due to sensitization provided during the training. Still, it is notable that a substantial share of households still state that they save using Mobile Money by endline.

Table 5.4.11. Impact Estimates of Mobile Money Training on Savings Mechanisms Used, Pooling Baseline and Endline Data (Nampula 2014 and 2015)

	Cashbox	Local Savings Group	Mobile Money	Microfinance Organization	Checking Account	Savings Account
Training	-0.04 (0.03)	0.04 (0.04)	0.29*** (0.04)	0.05** (0.02)	0.05 (0.06)	0.05 (0.03)
Endline	-0.05 (0.04)	0.18*** (0.05)	0.12*** (0.04)	0.14*** (0.06)	0.01 (0.05)	-0.11*** (0.02)
Training*Endline	0.05 (0.04)	-0.09* (0.05)	-0.10* (0.06)	0.00 (0.05)	-0.01 (0.06)	-0.03 (0.04)
Net Training Effect	0.01 (0.03)	-0.05 (0.04)	0.19 (0.04)	0.05 (0.03)	0.04 (0.03)	0.02 (0.02)
p-value (Train+(Train*Endline)=0)	0.76	0.21	0.00***	0.18	0.15	0.34
Observations	1,378	1,378	1,378	1,378	1,378	1,378

Notes: Ordinary least squares regression, with forum-level fixed effects. Standard errors are robust and clustered at the association level. Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

At endline we find that households who were trained are 19 percentage points more likely to report Mobile Money as a savings device, and this difference is significant at better than the one percent level. Since the households at baseline could have just been reporting the 50 MZN starter balance, this finding is a strong indication that some savings with Mobile Money were induced by the trainings, without any financial inducement to do so.

The latter finding is in line with some of the literature on the economics of Mobile Money, both within and outside Mozambique. For example, Batista and Vicente (2013) find their experiment on mKesh leads to a 23-25 percentage point change in the willingness to save via mobile money. Jack and Suri (2014) also report that m-Pesa users in Kenya intend to save money using their phones, even if they do not. Using aggregate data, Mbiti and Weil (forthcoming) show that m-Pesa use and growth in Kenya increases the likelihood that individuals become banked, though they do not appear to save using Mobile Money. Given that the agent network is sparse in northern Mozambique relative to Kenya, it is perhaps not surprising that respondents trained in Mobile Money report using it as a savings device, even if we cannot demonstrate an increase in the amount being saved.

Section 6. Discussion and Conclusions

In this report, we describe the results from an impact evaluation using a clustered randomized control trial design, which was conducted to try to induce farmers to use more inputs by offering discounts through the Mobile Money service and increasing access to inputs through association-level input marketing and training. We observe modest levels of input purchases using Mobile Money among participating treatment households. However, during the study period between the 2014 and 2015 growing seasons, input use increased substantially among all farmers in the study area, which could not have been predicted. Consequently, the modest input purchases induced by the IKURU input sales did not lead to a detectable intervention effect on input use among the treatment group. The assumptions underlying our empirical approach are dependent upon a stable trend, which was clearly not present as input use substantially increased between baseline and endline. Since this assumption did not hold, our ability to identify a treatment effect (if one existed) was substantially diminished.

In terms of the impact of the intervention on Mobile Money, we are able to draw more definite conclusions. We find no impacts of the treatment upon Mobile Money usage by late 2015. Given the absence of confounding factors, we can state that trying to induce additional input use through direct marketing of inputs tied to Mobile Money discounts is not a viable cost effective strategy for increasing input use. This conclusion could be interpreted as a result of implementation difficulties, but given the costs of visiting associations relative to forums, and that farmers tended not to purchase more expensive items such as fertilizer, even with improved and more timely implementation, we are confident that such visits would not be cost effective. We do, however, find evidence that some farmers have adopted mobile money and are using mobile money over a year after the trainings took place, and are willing to travel to a local agent to use mobile money. This finding is at least suggestive that the trainings were effective in inducing mobile money use and have provided an additional savings vehicle for a non-trivial proportion of trained farmers.

While we do not find a significant impact of the randomized input trainings and discounts on input use, there are a number of interesting findings from the data that help improve the understanding of cell phone use in northern Mozambique, understanding the way that programming could be designed in the future to try to stimulate input use, and that point to success in training farmers in the use of Mobile Money. We summarize and discuss these three points here.

First, our descriptive results on sample households illuminate how farmers in northern Mozambique are using cell phones, with the caveat that the sample is not representative of farmers in Nampula or even the selected districts. We find that more than half (67%) of households own phones, which implies the proportion is not increasing as fast as it once was (e.g., de Brauw et al. 2014); we find little growth in cell phone use between the 2014 and 2015 surveys. Households with only female adults present are less likely to own phones, and households report using phones primarily as a communication device; men appear more likely to report using cell phones or even considering cell phones as business devices as well. Charging phones does not seem to be an issue, despite the relative lack of electricity. Perhaps most surprisingly, in both surveys respondents report being more likely to use phones through calls rather than through text messages; this finding is surprising as texts are cheap relative to making calls, and we expected these uses to be reversed. However, we note that literacy levels are fairly low in Mozambique, relative to other countries in Africa South of the Sahara, and moreover texts are typically sent in

Portuguese, so reading texts may be difficult for some people.[32] Also, the most common basic cell phones with only a number key pad can be challenging to use for selecting characters to write a text message. This point has important ramifications for programming related to information and communications technology (ICT). While there appears to be a demand, at least among male respondents, for market information (e.g., crop prices) as discussed in the qualitative report (Cunguara et al. 2016), demand for other forms of information by households may be limited. For example, m-Health programs might not be as effective as hoped in northern Mozambique, in part because of literacy challenges, and in part because females may lack access to a phone; females tend to be the target beneficiary group of m-Health programs.

Second, in the quantile regressions we generate to examine the relationship between production and input use, we find that gains to using basic purchased inputs appear concentrated among relatively more productive farmers. An important lesson from this analysis is that interventions might contemplate the heterogeneity of impact response by the type of producer to target beneficial impacts across the productivity distribution, since the benefits of a given intervention may be concentrated amongst already more productive farmers, while other might see few gains. Programming that aims to increase input use should realize that methods for reaching the smaller producing farmers should be considered in the design, otherwise such interventions may only benefit farmers at the upper end of the production distribution, exacerbating inequality. Moreover, to help benefit farmers toward the lower end of the distribution, programming should not focus exclusively on hybrid or improved seeds. We find no gains to production among farmers at the lower end of the distribution, so any programming moving beyond seed is likely to help the upper portion of the productivity distribution. Alternative technologies should be considered when targeting less productive smallholders; for example, open-pollinated seed varieties, in particular, may be worthy of consideration, since these are less reliant on complementarities with other inputs.

Third, we note that the regression analysis suggests that the Mobile Money trainings were successful in developing a base of individuals in these areas who use m-Pesa. The half day centralized leader training provided to farmers, with hands-on practice, created a pre-trained group of "cell phone leaders," which greatly facilitated registering farmers for the trainings relative to procedures followed in the feasibility study. One could probably improve participation by advertising the trainings in advance for anyone interested ahead and targeting trainings in places near established agents, which would imply that more participants would likely come from areas near agents. We cannot make definitve statements about impacts, unfortunately, because we did not randomize access to the Mobile Money trainings. However, we do find that even controlling for some demographic and household head characteristics, there is a fairly sizeable group of trained farmers who continued to use Mobile Money, who knew the closest agent, and clearly used the system to at least receive transfers and purchase credit.

This story has similarities to findings in Jack and Suri (2014) and Mbiti and Weil (Forthcoming), which describe the growth of m-Pesa in Kenya. However, different from the context in Kenya where the number of agents grew rapidly, and the growth was so fast that Jack and Suri (2014) argue that it was close to random in where agents were placed, here, we find much slower growth in the agent network in Mozambique, and it would be very difficult to argue that agent placement was random. While no agents

[32] Note that all pre-written texts in Mozambique are in Portuguese; several languages native in Mozambique are not typically written down, including Macua, spoken in the area of Mozambique covered here.

existed prior to baseline, by endline there were only 7 agents after substantial effort (at least along the Nampula-Nacala road) by Vodacom to sign up agents. Kenya likely differs from Mozambique and other lower resource countries in southern Africa as substantial rural-urban migrant networks were in place before Mobile Money was introduced, and informal institutions to work around the lack of a formal banking sector for remittances were well established (e.g., Luke (2008)).

The agent network in Mozambique is growing, but the present network that is publicly listed is clearly highly urban biased.[33] Where the Mobile Money system has great potential for farmers, as a way to store money between seasons, it requires a strong and growing agent network for success, and that growth appears to likely radiate out of urban areas. In other words, we do not believe the Jack and Suri's suggestion of almost random placement of agents in Kenya is even close to occurring in Mozambique. If left alone to develop on its own, agent networks will probably develop first where strongest rural-urban linkages occur, along major roads and in locations where cell phone service is strong. Also, not all major roads have enough business to support Mobile Money; for example, when setting up the project we considered Murrupula district, which is between Alto Molocué in Zambézia and Nampula; Alto Molocué also had people interested in using m-Pesa or m-Kesh (the mobile money service provided by mCel). However, Murrupula did not have enough farmer groups in areas with cell phone coverage to include in this study.

A final issue related to projects that aim to engage farmers with mobile technology to improve their productivity relates to whether they should be encouraged to use cell phones for transactions or required to do so. One could imagine a design focused on with output sales in which farmers that are trained on Mobile Money, receive a cell phone, and are offered discounts on inputs through Mobile Money are required to receive payment for their crops with Mobile Money if selling through the targeted association.[34] If all farmers within a group have money on cell phones, then there will very likely be a demand for agents. While the model described here might lead to additional demand for Mobile Money and therefore build an agent network, it could also be at risk of falling apart if projects change or end since considerble support would be required, and in particular if part of the agent network refuses to redeem mobile money for cash; even in Kenya, mobile money is typically just transferred once before being cashed out (Jack and Suri 2014). In the latter case, farmers would bear the risk of not being able to receive cash for their output. An alternative model might be to use an encouragement design, meaning paying a premium to farmers for taking crop payments through mobile money, in areas in the urban periphery where liquidity and other constraints are less severe, along with farmer trainings as used in this project, which would then firmly establish a sustainable agent network as well as dedicated Mobile Money users.

Finally, it is worth noting some caution in the set up of this type of project in the future. Whereas we want to encourage piloting and experimentation with delivery ideas, since such experimentation can lead to improved outcomes, in this case the experimentation likely suffered as the research team attempted to ensure that implementation occurred, attempted to coordinate with the local mission and agribusiness project, coordinated with the mobile money provider, attempted to broker negotiations between the mobile money provider and the FOSC, and attempted to conduct the research. With complex pilots such as this one that require several local partners (specifically, a FOSC and the mobile money provider at minimum), a better strategy might have been to ensure the presence, continuity and strong participation

[33] A list of agents can be found at http://www.vm.co.mz/en/Individual/M-Pesa/M-Pesa-Agents.

[34] Technoserve implemented a model along these lines in another part of Mozambique.

in implementation of an agribusiness support project like AgriFUTURO, as they would have been better placed locally to ensure actions at IKURU took place in a timely manner, to monitor pilot implementation both from the perspective of the IKURU and Vodacom (e.g., ensuring account activity on farmer accounts), and to ensure that negotiations between IKURU and Vodacom were both timely and successful. From a programmatic perspective, such active participation would need to be worked into both the project workplan and its relevant performance indicators. It is not clear how much implementation would have actually improved if it had been run by a larger entity such as AgriFUTURO (if any), but it could have had a positive effect on the quality of implementation.

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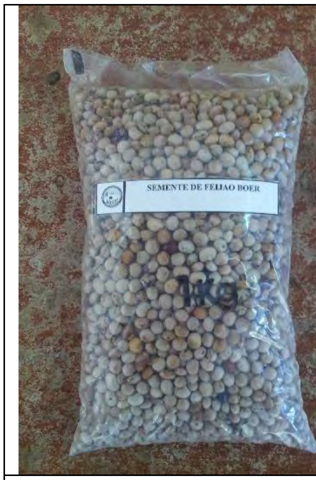
Appendix A: Sample Marketing Input Sales Sheet

Menu of inputs availble from IKURU: Seeds

			
Boer Beans	Holoco Beans	Nyemba Beans	Soy
(1kg – 35.00 MTS)	(1kg – 35.00 MTS)	(1kg – 35.00 MTS)	(1kg – 45.00 MTS)
			

Appendix B: Descriptive Statistics (Repeated Cross-Section)

Table 3.1.1. Gendered household type at baseline (Proportion of households)

	Mean	SD	Min.	Max.	Obs.
Female adult only	0.07	0.26	0	1	809
Male adult only	0.06	0.24	0	1	809
Male and female adult	0.86	0.34	0	1	809

Table 3.1.2. Household composition at baseline

	Mean	SD	Min.	Max.	Obs.
Household size	4.92	2.06	1	11	809
Number male	2.49	1.40	0	8	809
Number female	2.42	1.38	0	7	809
Number adults	2.25	0.76	0	5	809
Number children	2.62	1.79	0	8	809
Proportion aged 0-5	0.21	0.18	0.00	0.67	809
Proportion aged 6-15	0.26	0.20	0.00	0.75	809
Proportion aged 16-64	0.50	0.22	0.00	1.00	809
Proportion aged 65+	0.02	0.11	0.00	1.00	809

Figure 3.1.1. Density of Household Member Age, in Years

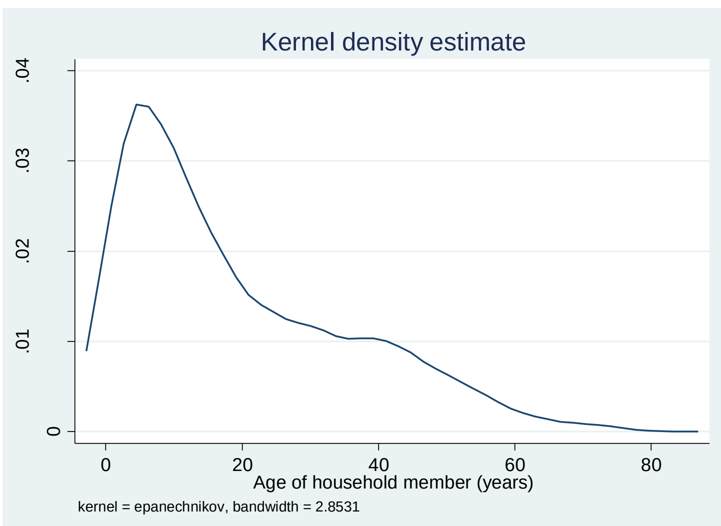


Table 3.1.3. Characteristics of household heads at baseline

	Mean	SD	Min.	Max.	Obs.
Age	39.33	12.92	17	84	802
Male	0.91	0.29	0	1	809
Literate	0.76	0.43	0	1	809
Primary education or higher	0.89	0.31	0	1	809
Secondary education or higher	0.17	0.37	0	1	809
Speaks Portuguese	0.63	0.48	0	1	809
Owns a cell phone	0.56	0.50	0	1	809
Does non-farm labor	0.56	0.50	0	1	809

Table 3.2.1. Expenditures per capita (MZN) and poverty incidence at baseline

	Mean	SD	Min.	Max.	Obs.
Food expenditure per capita	3,407.82	4,564.91	86.67	52,000.00	809
Total expenditure per capita	6,685.31	7,916.31	200.89	78,860.00	809
Food share of expenditures	0.53	0.21	0.01	0.98	809
Poverty rate	0.71	0.45	0	1	809

Table 3.2.2. Expenditures per Capita among Female Only Households, Baseline Survey

	Mean	SD	Min.	Max.	Obs.
Food expenditure per capita	3,041.44	3,235.75	260.00	18,200.00	59
Total expenditure per capita	5,280.83	6,191.61	602.67	33,840.00	59
Food share of expenditures	0.62	0.21	0.18	0.98	59
Poverty rate	0.78	0.42	0	1	59

Table 3.2.3. Expenditures per Capita at Baseline, by Treatment Status

	Control			Treatment			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Food expenditure per capita	3,617.93	4,814.65	434	3,164.65	4,251.07	375	
Total expenditure per capita	7,212.41	8,739.41	434	6,075.27	6,802.06	375	**
Food share of expenditures	0.53	0.21	434	0.54	0.21	375	
Poverty rate	0.68	0.47	434	0.74	0.44	375	*

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3.3.1. Agricultural asset ownership of Sample Households, Baseline and Endline

	Baseline			Endline		
Household owns:	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Bucket	0.93	0.26	809	0.97	0.18	756
Watering can	0.07	0.25	809	0.18	0.38	756
Mortar/Pestle	0.85	0.35	809	0.88	0.33	756
Barn/Granary	0.16	0.36	809	0.31	0.46	755
Transport equipment	0.08	0.28	809	0.01	0.08	755
Hoe	1.00	0.00	809	0.99	0.11	756
Axe	0.47	0.50	809	0.63	0.48	756
Shovel	0.16	0.37	809	0.27	0.44	756
Rake	0.10	0.30	809	0.17	0.38	756
Sickle	0.30	0.46	809	0.34	0.47	756

Table 3.4.1. Average number of plots and reported size of landholdings, Baseline and Endline

	Baseline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	2.36	1.03	1	8	804
Area owned (hectares)*	3.89	3.30	0.31	22.00	808
Mean plot size (hectares) *	1.79	1.55	0.08	12.00	804
	Endline				
Number of plots	2.56	1.13	1	8	754
Area owned (hectares)*	4.04	3.37	0.00	20.00	750
Average plot size (hectares)*	1.75	1.67	0.00	20.00	748

Table 3.4.2. Average number of plots and reported size of landholdings among Female Adult Households, Baseline and Endline

	Baseline				
	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Number of plots	1.71	0.72	1	4	59
Area owned (hectares)*	2.40	1.75	0.42	8.00	59
Mean plot size (hectares)*	1.47	1.07	0.42	5.00	59
	Endline				
Number of plots	2.06	1.01	1	5	64
Area owned (hectares)*	2.64	2.39	0.00	12.00	63
Mean plot size (hectares)*	1.33	1.05	0.00	6.00	63

Table 3.4.3. Reported Sown Area by Crop, Baseline

Area (hectares)	Mean	SD	Obs.
Maize	1.34	1.60	511
Rice	0.73	0.73	116
Sorghum	1.07	0.78	149
Cassava	1.41	1.62	620
Peanuts	1.32	1.41	648
Sesame	1.31	1.72	285
Cowpeas	1.27	0.94	563
Boer beans	1.26	0.94	361
Holoco beans	1.22	1.52	210

Note: To reduce the emphasis of extremely large reported values, values below the 1st or above the 99th percentile are winsorized (i.e., 2 percent of observations are adjusted).

Table 3.4.4. Production of Major Crops (Kilos), Baseline and Endline

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Maize	156.15	257.34	809	186.43	330.54	756
Rice	43.42	135.10	809	50.19	113.21	756
Sorghum	23.86	65.92	809	13.66	35.05	756
Cassava	340.83	364.98	809	239.59	359.46	756
Peanuts	406.20	545.09	809	117.56	144.83	756
Sesame	61.85	137.55	809	38.89	81.76	756
Cowpeas	44.62	69.76	809	22.80	45.96	756
Boer Beans	27.45	51.20	809	21.05	44.74	756
Holoco Beans	23.34	65.20	809	24.16	56.17	756

Figure 3.5.1. Reasons Given by Farmers that Savings will be lower than desired, Baseline

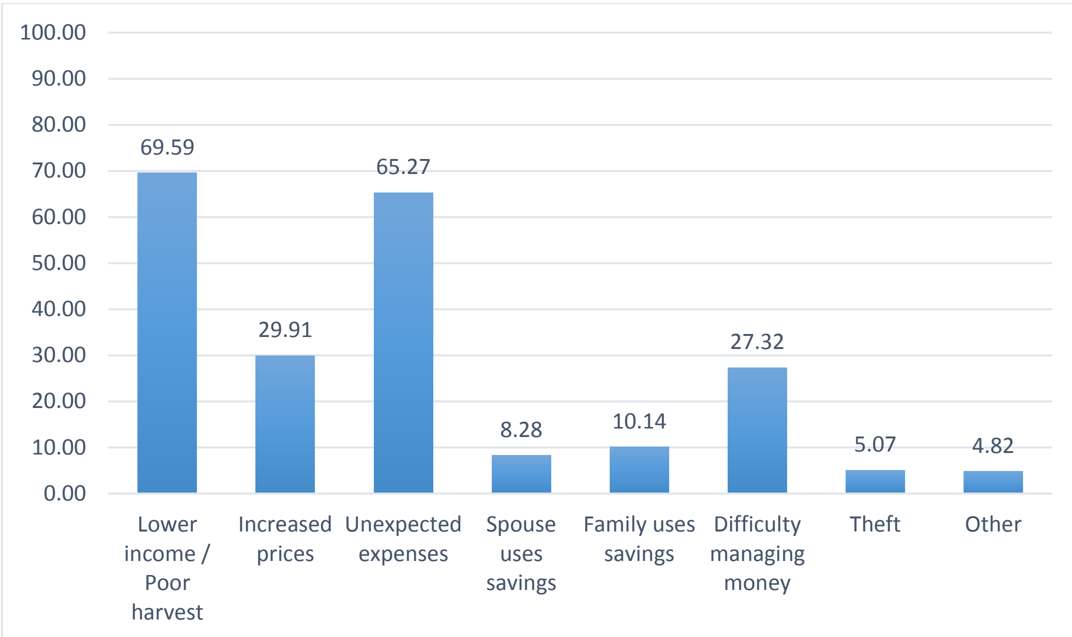


Figure 3.5.2. Reported Current Savings Status, Baseline

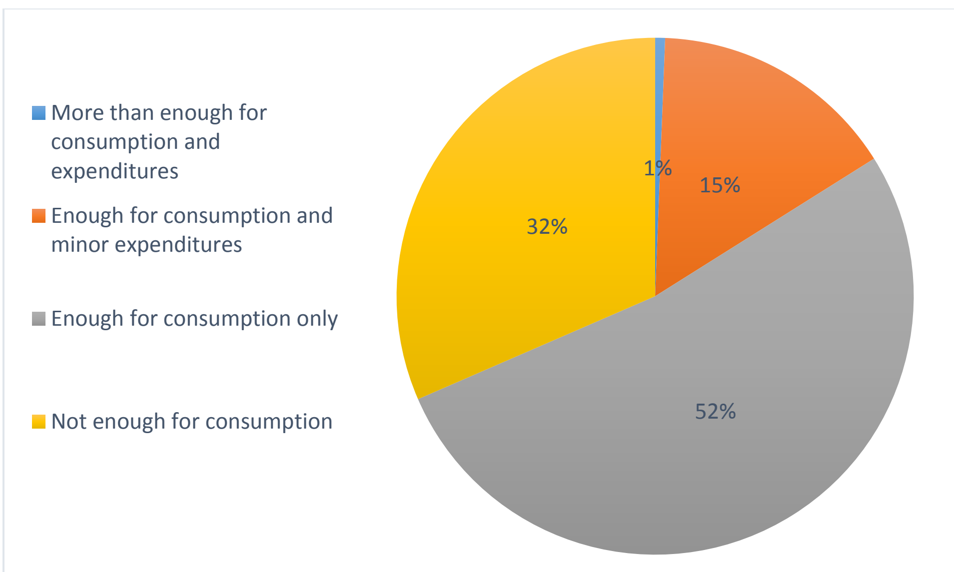


Table 3.5.1. Savings Strategies used by Households, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Cashbox	0.80	0.40	809	0.81	0.39	756
Local savings group	0.35	0.48	809	0.50	0.50	756
Mobile money	0.27	0.44	809	0.33	0.47	756
Microfinance org.	0.10	0.30	809	0.23	0.42	756
Checking account	0.18	0.39	809	0.20	0.40	756
Savings account	0.25	0.43	809	0.10	0.30	756

Table 3.6.1. Household Credit Activity, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Requested loan	0.39	0.49	809	0.47	0.50	749
Primary loan amount (MZN)	1,931.63	5,044.16	297	1,671.81	3,808.82	335
Loan for agriculture	0.16	0.37	319	0.10	0.30	349
Loan from family/friend	0.71	0.46	297	0.63	0.48	335

Figure 3.7.1. Proportion of Sample with a Mobile Phone, Baseline and Endline

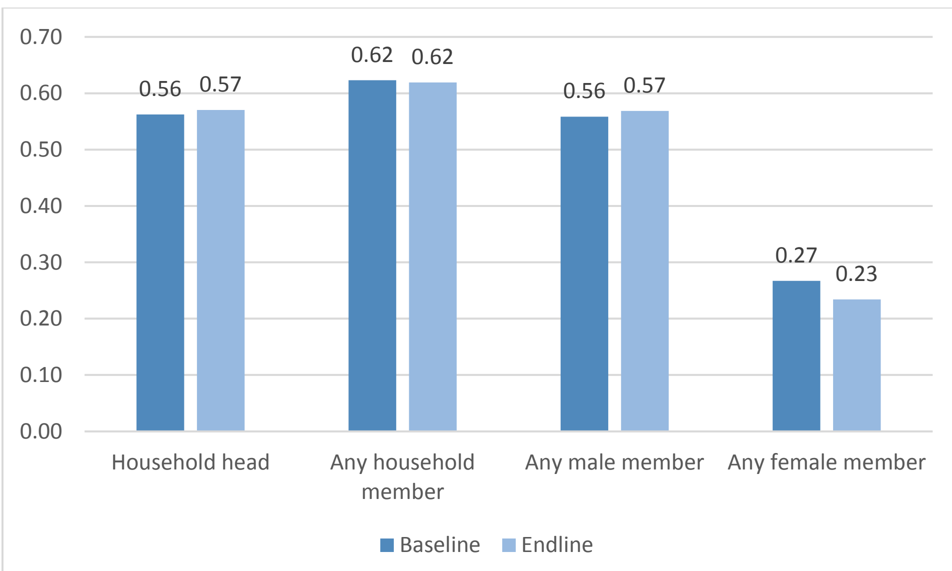


Figure 3.7.2. Frequency cell phone charged, Baseline

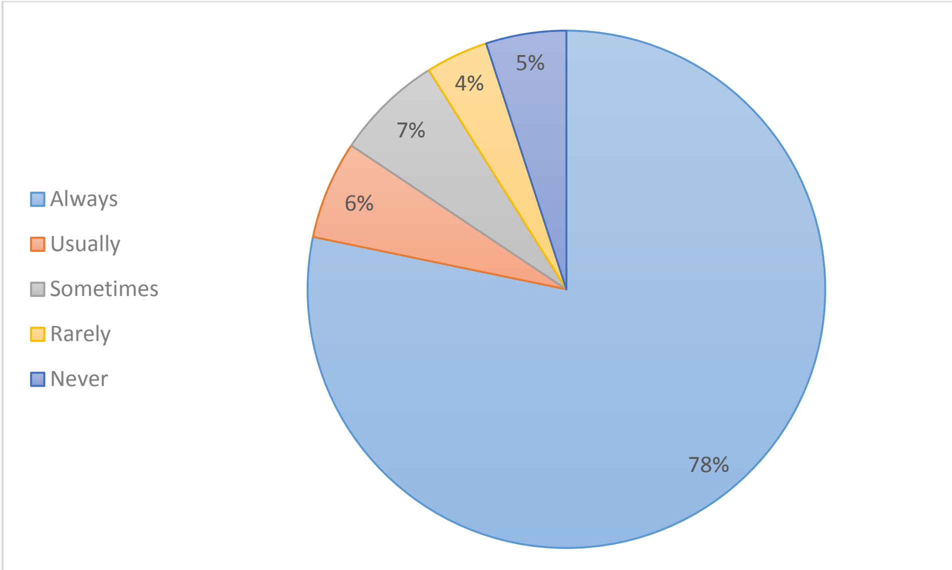


Figure 3.7.3. Reported Signal Quality in the Association, Baseline

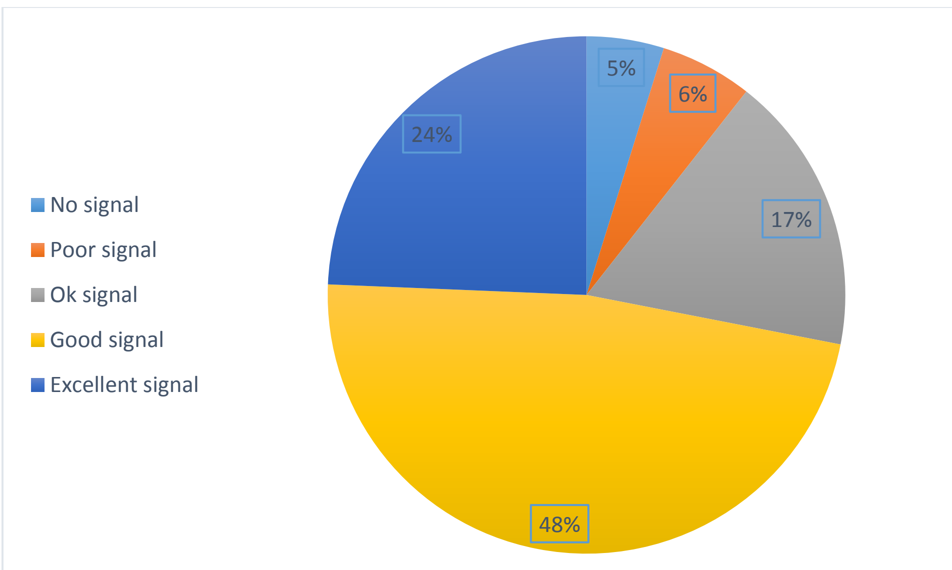


Table 3.7.1. Amount of Cell Phone Credit, Sample Households, Baseline and Endline

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Currently has credit	0.41	0.49	538	0.27	0.44	443
Current credit amount	15.76	18.67	218	20.15	32.51	117
Monthly credit expenditure	163.58	148.94	534	137.95	145.08	450

Figure 3.7.4. Mobile Money Credit Use at Baseline, Monthly Basis, Nampula (2014)

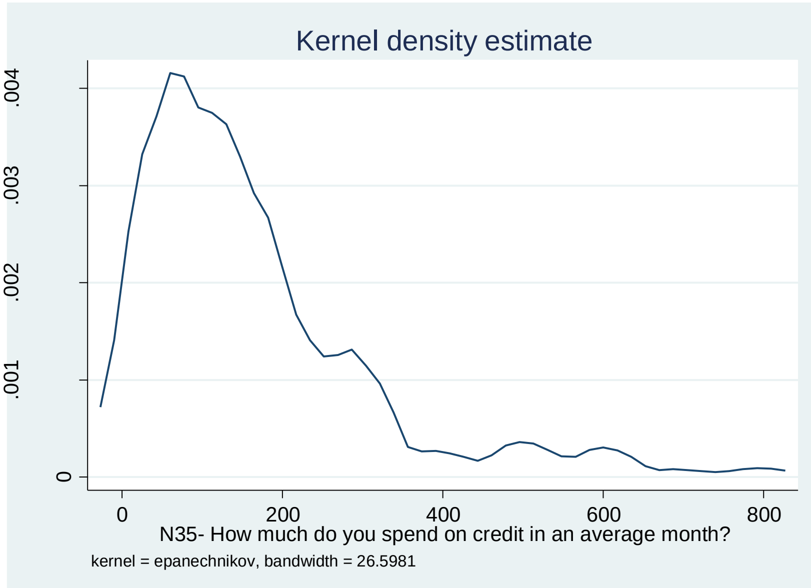


Table 3.7.2. Calls and Text Messages Sent and Received in the Last Seven Days, Baseline, Sample Households with Access to Cell Phones

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Text messages sent	8.84	15.20	325	10.76	15.11	318
Text messages received	9.10	10.02	325	9.85	11.14	317
Calls made	16.39	17.78	326	13.08	18.30	447
Calls received	16.73	18.59	326	12.55	15.09	445

Table 3.8.1. Mobile Money usage, Baseline and Endline

	Baseline			Endline		
	Mean	**SD**	**Obs.**	**Mean**	**SD**	**Obs.**
Heard of mobile money	0.86	0.35	538	0.85	0.36	752
Uses mobile money	0.56	0.50	468	0.31	0.46	463
Mobile money balance	73.06	293.47	230	334.45	1,431.26	113

Table 3.8.2. Statistics Related to Cell Phone Ownership and Mobile Money, by Training Group, Baseline

	Received training			No training			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Head owns phone	0.60	0.49	566	0.48	0.50	243	***
Household owns phone	0.67	0.47	566	0.52	0.50	243	***
Male member owns phone	0.60	0.49	566	0.47	0.50	243	***
Female member owns phone	0.29	0.46	566	0.21	0.41	243	***
Heard of mobile money	0.96	0.19	400	0.55	0.50	138	***
Uses mobile money	0.67	0.47	392	0.03	0.16	76	***

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3.8.3. Statistics Related to Cell Phone Ownership and Mobile Money, by Training Group, Endline

	Received training			No training			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
Head owns phone	0.61	0.49	531	0.47	0.50	225	***
Household owns phone	0.67	0.47	531	0.50	0.50	225	***
Male member owns phone	0.61	0.49	531	0.48	0.50	225	***
Female member owns phone	0.26	0.44	531	0.18	0.39	225	**
Heard of mobile money	0.90	0.30	530	0.73	0.45	222	***
Uses mobile money	0.37	0.48	350	0.14	0.35	113	***

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Figure 3.8.1. Familiarity with features of mobile money, by training status, baseline and endline

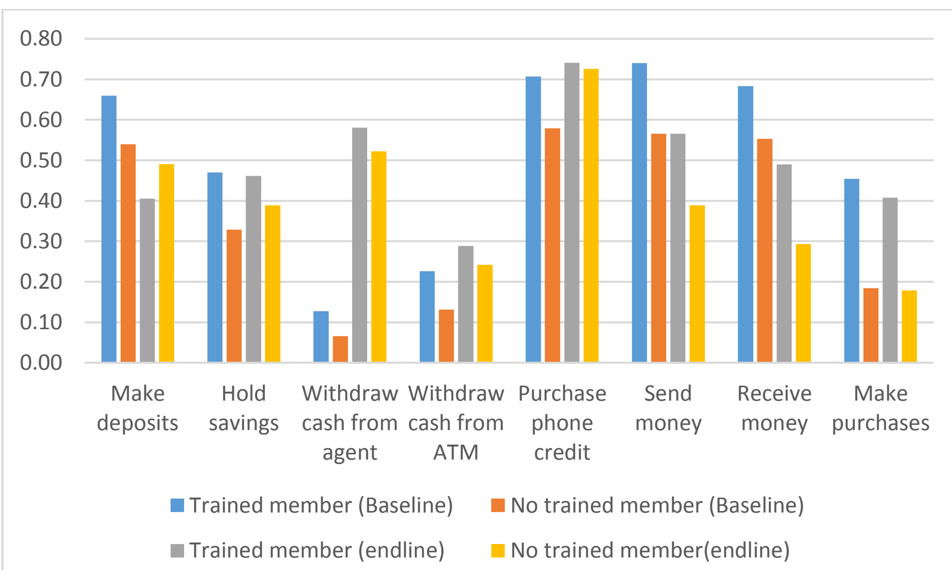


Table 3.8.4. Knowledge of Mobile Money Agents, Baseline and Endline

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Knows agent name	0.14	0.35	264	0.77	0.42	137
Distance to agent (minutes)	131.91	121.74	204	109.35	127.51	125
Agent was able to transact	0.83	0.38	124	0.77	0.42	121

Table 3.9.1. Input use, by Survey Round

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Used any seeds	0.98	0.16	809	0.97	0.16	756
Used any chemical inputs	0.14	0.35	809	0.31	0.46	756
Used family labor	0.96	0.19	809	0.99	0.10	756
Used paid labor	0.57	0.50	809	0.59	0.49	756
Used traditional seeds	0.97	0.17	809	0.96	0.20	756
Used improved seeds	0.11	0.32	809	0.62	0.49	756
Used organic fertilizer	0.01	0.11	809	0.11	0.32	756
Used chemical fertilizer	0.02	0.13	809	0.02	0.14	756
Used pesticide	0.13	0.33	809	0.30	0.46	755
Used herbicide	0.00	0.04	809	0.01	0.09	756
Used irrigation (treadle)	0.00	0.04	809	0.01	0.10	755
Used irrigation (mechanized)	0.02	0.13	809	0.01	0.08	756

Figure 3.9.1. Where Improved Seeds were purchased, Endline, by Treatment Status

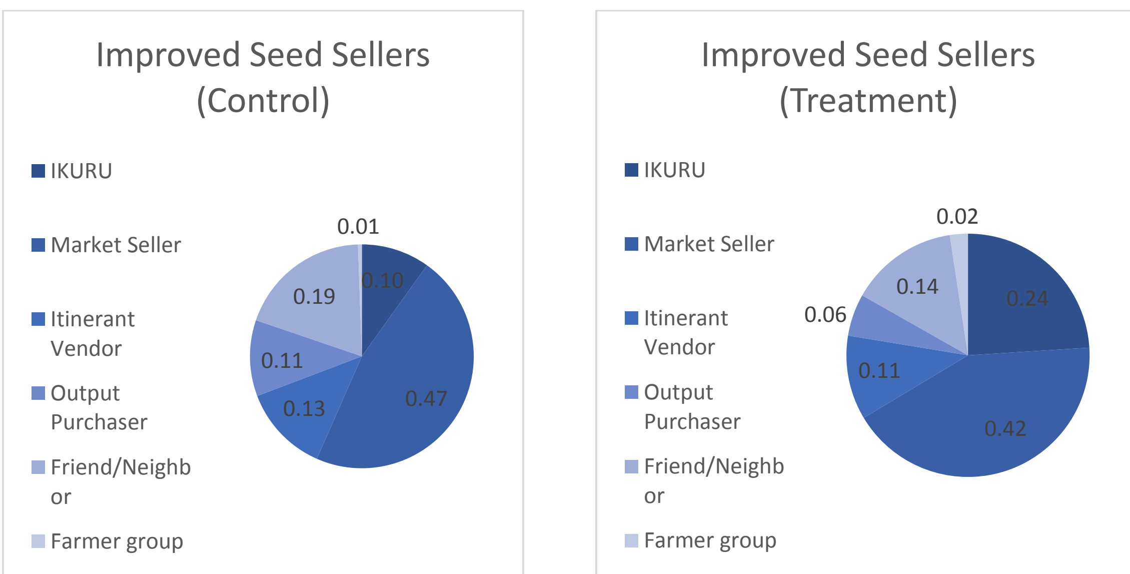


Table 3.9.3. Travel time to purchase inputs (minutes)

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Any input	82.35	89.11	245	85.10	90.50	473
Traditional seeds	74.64	92.87	123	75.95	92.62	247
Improved seeds	116.52	107.22	65	91.93	100.90	276
Chemical fertilizer	65.00	42.43	9	89.00	47.25	10
Pesticide	81.36	83.25	81	88.43	85.70	177

Table 3.9.4. Average Input expenditures at Baseline and Endline (MZN)

	Baseline			Endline		
	Mean	SD	Obs.	Mean	SD	Obs.
Any inputs	125.77	331.56	809	468.81	1,056.79	756
Seeds	83.82	259.68	809	375.37	884.86	756
of which traditional seeds	48.64	181.71	809	202.62	717.66	756
of which improved seeds	35.18	193.69	809	172.76	511.62	756
Chemical inputs	40.87	191.51	809	93.30	436.76	756
of which fertilizer	2.02	22.82	809	11.42	173.12	756
of which pesticide	38.60	190.48	809	73.08	213.44	756
of which herbicide	0.25	7.03	809	8.80	156.90	756

Table 3.10.1. Input Use by Gendered Household Category, Baseline Data

	Any Male Households			Female Only Households			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
General Input Categories							
Any inputs	0.98	0.15	750	0.98	0.13	59	
Any seeds	0.97	0.16	750	0.98	0.13	59	
Any chemical inputs	0.15	0.36	750	0.05	0.22	59	**
Specific Input Categories							
Family labor	0.96	0.19	750	0.98	0.13	59	
Paid labor	0.57	0.50	750	0.54	0.50	59	
Traditional seeds	0.97	0.17	750	0.98	0.13	59	
Improved seeds	0.12	0.32	750	0.05	0.22	59	
Organic fertilizer	0.01	0.11	750	0.00	0.00	59	
Chemical fertilizer	0.02	0.13	750	0.00	0.00	59	
Pesticide	0.13	0.34	750	0.05	0.22	59	*
Herbicide	0.00	0.04	750	0.00	0.00	59	
Irrigation (Manual)	0.00	0.04	750	0.00	0.00	59	
Irrigation (Mechanized)	0.02	0.13	750	0.02	0.13	59	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3.10.2. Input Use by Gendered Household Category, Endline Data

	Any Male Households			Female Only Households			
	Mean	SD	Obs.	Mean	SD	Obs.	Sig.
General Input Categories							
Any inputs	0.98	0.15	692	0.97	0.18	64	
Any seeds	0.97	0.16	692	0.97	0.18	64	
Any chemical inputs	0.33	0.47	692	0.11	0.31	64	***
Specific Input Categories							
Family labor	0.99	0.10	692	1.00	0.00	64	
Paid labor	0.60	0.49	692	0.48	0.50	64	*
Traditional seeds	0.96	0.20	692	0.97	0.18	64	
Improved seeds	0.63	0.48	692	0.52	0.50	64	*
Organic fertilizer	0.11	0.31	692	0.14	0.35	64	
Chemical fertilizer	0.02	0.15	692	0.00	0.00	64	
Pesticide	0.32	0.47	691	0.11	0.31	64	***
Herbicide	0.01	0.09	692	0.00	0.00	64	
Irrigation (Manual)	0.01	0.10	692	0.00	0.00	63	
Irrigation (Mechanized)	0.01	0.08	692	0.00	0.00	64	

Note: Stars indicate significance at standard levels (* p<0.1, ** p<0.05, *** p<0.01).

Figure 3.10.1 Gendered decision making at baseline, by input