

Seeing Is Believing?

Evidence from an Extension Network Experiment

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August 2014

Abstract

Extension services are a keystone of information diffusion in agriculture. This paper exploits a large randomized controlled trial to track diffusion of a new technique in the classic Training and Visit (T&V) extension model, relative to a more direct training model. In both control and treatment communities, contact farmers (CFs) serve as points-of-contacts between agents and other farmers. The intervention (Treatment) aims to address two pitfalls of the T&V model: i) infrequent extension agent visits, and ii) poor quality

information. Treatment CFs receive a direct, centralized training. Control communities are exposed to the classic T&V model. Information diffusion was tracked through two nodes: from agents to CFs, and from CFs to others. Directly training CFs leads to large gains in information diffusion and adoption, and CFs learn by doing. Diffusion to others is limited: other males adopt the technique perceived as labor saving, with an effect size of 75 percent.

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August 04, 2014

JEL Classifications: O12, O13, O30, D80.

Keywords: information failures; technology diffusion; agriculture; Africa.

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Research discussed in this publication has been funded by the International Initiative for Impact Evaluation, Inc. (3ie) through the Global Development Network (GDN), the Mozambique office of the United States Agency for International Development, the Trust Fund for Environmentally and Socially Sustainable Development, the Belgian Poverty Reduction Partnership and the Gender Action Plan, and the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI) and financed by the CGIAR Fund Donors. The authors benefited from comments provided by Jenny Aker, Madhur Gautam, Markus Goldstein, and David Spielman and during presentations at the CSAE (Oxford), the Mid-Western Economic Development Conference, the Development Impact Evaluation Seminar Series at the World Bank, and the IFPRI Seminar Series. The views expressed in this article do not reflect those of the World Bank, 3ie or its members. The authors would like to thank Pedro Arlindo, Jose Caravela, Destino Chiar, Isabel Cossa, Beatriz Massuanguanhe, and Patrick Verissimo for their collaboration and support throughout the project. John Bunge, Ricardo da Costa, and Cheney Wells provided excellent field coordination; Siobhan Murray impressive research assistance.

1 Introduction

Agricultural innovation is a necessary condition to accelerate productivity and achieve food security in Africa (Hazell, 2013). Recent efforts focus on designing mechanisms to overcome constraints on farmers’ adoption, such as underdeveloped input delivery systems (Shiferaw, Kebede, and You, 2008), high acquisition costs (Suri, 2009), and time inconsistency (Duflo, Kremer, and Robinson, 2011). A growing literature recognizes the role of information failures in the agricultural technological diffusion process, focusing on conditions for effective communication between peers (Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Magnan et al., 2012; McNiven and Gilligan, 2012; BenYishay and Mobarak, 2013). Despite its formative effect on diffusion (Feder, Just, and Zilberman, 1985; Davis, 2008), evidence on the efficacy of extension to help farmers overcome information failures is mixed (Bindlish and Evenson, 1997; Purcell and Anderson, 1997; Gautam, 2000; Anderson and Feder, 2007; Benin et al., 2007; Davis et al., 2010; Waddington and White, 2014). Recent experiments show potential in improving learning and adoption through participatory approaches in extension, e.g., field trials, farmer field schools, and innovation platforms (Agyei-Holmes et al., 2011; Duflo, Kremer, and Robinson, 2011; Pamuk, Bulte, and Adekunle, 2013; Duflo, Keniston, and Suri, 2014). We focus on the effectiveness of the Training and Visit (T&V) system, applied in several developing countries, to encourage the adoption of sustainable land management (SLM) practices (Gautam, 2000; BenYishay and Mobarak, 2013).

Garden variety T&V models try to expand the geographic coverage of extension by engaging extension agents with a village point-of-contact (contact farmer). The model relies on extension agents (EAs) to transmit information about new technologies to contact farmers (CFs). In central Mozambique, the government randomly assigned 50 communities to the classic T&V model and 150 communities to a modified T&V model to disseminate information on SLM. The modified T&V model offers CFs a direct, centralized training on SLM practices, with similar content and breadth to the EA training. By centralizing and standardizing the training, the intervention addresses two pitfalls in the classic T&V system: i) low transmission of information due to infrequent EA visits, and ii) receipt of poor quality information, e.g., through EA filters on information. There were no other changes in the infrastructure or composition of extension services across treatment and control groups. Comparing CFs’ SLM knowledge and adoption across treatment arms provides a

direct test of the assumption that a T&V model is conducive to EA-to-CF knowledge transfers, as measured against a direct, central CF training.

We next measure how exogenous variations in CF training quality affect other farmers' SLM learning and adoption. Both models ignore constraints on CF outreach¹ and demand-side constraints on adoption in the context of social learning.² Given these limitations, we anticipate farmers to be affected by the revised T&V model in two ways. First, farmers may be exposed to information on additional SLM practices with enhanced frequencies of exposure, if trained CFs alter their demonstration activities and investment portfolio. Second, the direct training may both enlighten the CF and improve the quality of information available. Under those circumstances, risk-averse farmers may be inclined to adopt given reduced uncertainty of the benefits of SLM (Rosenzweig and Binswanger, 1993; Rosenzweig and Wolpin, 1993; Ghadim, Pannell, and Burton, 2005; Dercon and Christaensen, 2011).

The conservation agriculture technologies examined in this study are not akin to the input and crop adoption trials most commonly depicted in the literature (Munshi, 2004; Bandeira and Rasul, 2006; Conley and Udry, 2010; McNiven and Gilligan, 2012). The time and labor allocation required to implement the techniques often do not yield benefits in terms of labor savings from weeding or improvements in soil quality until two or more years post implementation (FAO, 2008). This may be less desirable to subsistence farmers facing high discount rates. Yet, some techniques are considered beneficial to farmers facing tough agronomic conditions. For example, water saving technologies, such as contour farming and micro-catchments, render farmers on sloped or arid land more resilient to losses from erosion and drought. Given high levels of risk aversion with regard to their cultivation decision, the intervention may change the behavior of some farmers by reducing the uncertainty of a technology's benefits in the short term. Furthermore, by introducing multiple SLM techniques

¹First, the original criticism of the T&V model of a lack of accountability and incentive structures to encourage outreach remains in both models (Gautam, 2000). Second, transaction costs associated with communicating to households in remote areas or outside of their social network may continue to limit the diffusion process.

²Common demand-side constraints may inhibit the intervention's success. First, farmers may be inclined to free ride on the learning of others and delay the adoption until profitable (Foster and Rosenzweig, 1995). Second, within a community, farmers may be heterogeneous along dimensions of crop choice, soil conditions, and management style, which can affect the diffusion process (Munshi, 2004; Conley and Udry, 2010). Third, the characteristics of the primary adopter (CF) are likely to affect how other farmers internalize the information. For instance, farmers may be more inclined to learn from others' with similar characteristics (Feder and Savastano, 2006; Bandiera and Rasul, 2006; BenYishay and Mobarak, 2013), while CFs may be quite dissimilar than their communal peers. Social influence may be more relevant to a community of passive learners, requiring interventions that improve the ties and visibility of previous adopters (Hogset and Barrett, 2010).

(mulching, strip tillage, micro-catchments, contour farming, crop rotation, improved fallowing, and row planting), we are likely increase the likelihood of exposure to at least one relevant technique to a group of heterogeneous farmers.

Demonstration activities as well as CFs' private adoption were much higher in communities where the CFs had been centrally trained 15 months after the training. This increase in adoption augmented knowledge of the techniques adopted 27 months after the initial training. Taken together, our results suggest that this wedge in CF knowledge likely corresponds to learning-by-doing in this treatment arm, as the actual benefits of the techniques are exposed through increased practice.

Exploiting this exogenous information shock at the village level to measure the impact of boosting CFs' demonstration, knowledge, and adoption activities on practices within the community provides mixed results. While CFs' activities and knowledge in the revised T&V model successfully increased others' adoption of one of the techniques adopted by the CFs, this is not the case for all demonstrated techniques and all farmers. Only men increased their micro-catchments' adoption by 3 percentage points (an effect size of 75%) 15 months after the intervention. Of the additional techniques adopted by the trained CFs (strip tillage, micro-catchments, and contour farming) in response to the intervention, the adoption of micro-catchments is more likely to achieve positive net short-term benefits as it does not require major investments in tools and labor in its implementation (Liniger et al., 2011). In our study, other farmers exposed to the intervention only perceived micro-catchments as a labor-saving technique and CFs spent less time on agricultural tasks. The indirect evidence suggests that farmers are likely to act on the information they received, when the technology requires little up-front investment and short-term cost savings are expected.

In what follows, we summarize the limitations of the agricultural extension network in Mozambique and improvements provided by the intervention (Section 2). We then describe the evaluation design and empirical strategies used to identify the impact of the modalities used to deliver information to the contact and other farmers (Section 3). Section 4 presents estimates of the impact of the intervention on the contact and other farmers' knowledge and adoption of SLM practices. Section 5 discusses the implications of this study for future adoption studies.

2 Agricultural Extension Constraints in Mozambique and Intervention

Mozambique’s agricultural extension network was created in 1987 and began to operate in 1992 after the peace agreement. During the past two decades, the Ministry of Agriculture (MINAG) promoted the development of extension networks (Eicher, 2002). This expansion is set to continue moving forward (Gêmo, Eicher, and Teclemariam, 2005). Extension agents (EAs) are employed by the District Services for Economic Activities (Serviços Distritais de Actividades Económicas) and operated at the sub-district level to disseminate information and new techniques. The system assumes that information flows are a linear process: agricultural innovations are created by researchers, then distributed by extension workers, and lastly adopted by producers (Pamuk, Bulte, and Adekunle, 2013).

Country-wide, coverage is as low as 1.3 EAs per 10,000 rural people (Coughlin, 2006). Given this shortage, EAs are inclined to visit the same villages every year based on their achievements and potentials (Coughlin, 2006). Only 15 percent of farmers report receiving extension services (Cunguara and Moder, 2011). To address these supply-side bottlenecks, the World Bank promoted the T&V model of extension. In practice, a communal representative, the CF, is designated to receive information on improved techniques from the EA and disseminate it to his community through village-level demonstration activities. Under this model, increased frequencies in training and visits would be made by the EAs to a select group of CFs (Feder and Anderson, 2004).

The present National Plan for Agricultural Extension (PRONEA 2007-2014) and Extension Master Plan (2007-2016) aim to develop the decentralization of services at the district level and expand the T&V model, increase participation of targeted groups (women and marginal farmers), and enhance partnerships with other actors, such as the private sector and NGOs (Callina and Childiamassamba, 2010). Despite the importance placed on extension services and, particularly, the T&V model by the national government, there are no rigorous studies that validate this policy action. The literature that evaluates the T&V system is conducted using non-experimental methods (Gautam, 2000). Recent work attempts to correct for the non-random assignment of extension services (Cunguara and Moder, 2011) and finds a positive impact of extension on farm income in

Mozambique. In what follows, we describe the details of the extension network and the T&V model present at baseline.

2.1 Extension Network in Mozambique’s Zambezi Valley

Our experiment is set in five districts of central Mozambique, Mutarara (Tete province), Maríngue and Chemba (Sofala province), Mopeia and Morrumbala (Zambézia province). This area receives support from a large, World Bank-Government of Mozambique (GoM) investment that aims to support the development of the extension network. The project provides three levels of agricultural technical assistance: each district has a facilitator, an environmental specialist, and eight EAs. A district is sub-divided into four administrative posts (*posto administrativo*) that include about 8-10 communities (*aldeia*). Each community has a designated CF who receives direct assistance from the two EAs placed in his administrative post,³ who in turn receive direct assistance from the district-level technical staff. CFs are expected to provide advice to their peers within the community through demonstration activities, as well as being responsive to farmers’ demands for technical assistance.

We examine whether the T&V model is as effective in getting CFs to demonstrate and learn new technologies as a direct training program. The classic T&V model was adapted from the historical comprehensive model, since monthly EA trainings were difficult to sustain financially (Gautam, 2000). Instead, EAs periodically received an extensive training (2010 and 2012). Moreover, in the classic T&V model, the majority of CFs receive visits from EAs monthly rather than twice a month (as planned under the historical, comprehensive T&V model) (Anderson and Feder, 2004).

The conditions underlying most extension networks raise concerns about the efficacy of the classic T&V model. If EAs are challenged to reach communities in the first place, designating CFs in these communities may not adequately address the supply issue of extension services. Moreover, information may get diluted from the central level to the CFs. EAs may not sufficiently train the CFs to ensure know-how is transmitted. There is also no guarantee that EAs transmit a clear to-do list to CFs to conduct dissemination activities in the communities. By comparing the T&V model to

³EAs can choose which CFs to work with, and do not necessarily split responsibilities. Hence, a given CF may interact with both EAs in his administrative post. CFs are typically chosen by the community. In 2010, CFs were on average in their position 3 years with a standard deviation of 3. This indicates the majority of CFs were already commissioned by the system prior to the intervention.

a central training of the CFs, keeping the extension system and infrastructure constant, we provide a direct test of the first modality of the T&V model, which assumes EAs will successfully train all CFs (with no information filters).

2.2 External Validity

As mentioned above, our study area is limited to five districts of Mozambique’s Zambezi valley. While this is a large-scale program, it is not immediately clear that our results would hold in other contexts. Our study likely provides an upper-bound estimate of the T&V model relative to the impact of central training. Even though the ratio of EAs per administrative post is on par with the national average of 1.89 (Gêmo and Chilonda, 2013),⁴ our study districts are receiving enhanced support from the local Services for Economic Activities office. Hence, it is unclear that EAs in our sample face a smaller set of demands on their time, leading them to be more available to train CFs. A competing assumption is that as EAs receive more attention from the district services in our study area, they may be exposed to more trainings and, therefore, too busy to provide assistance to their communities. We provisionally rule this out, as we did not hear of additional trainings to EAs over our study period.

3 Experimental Design, Data and Identification

At baseline, CFs and EAs were operating in all communities of our five study districts. From these districts, we randomly selected 200 communities (with 200 CFs) in 16 administrative posts, to which 30 EAs are assigned. All EAs received SLM training. We randomly assigned CFs in 150 (“Treatment”) communities to a similar, centrally-administered training on SLM, which we describe in more detail in the next sub-section. CFs in the remaining 50 (“Control”) communities were supposed to receive SLM training from their EAs, which corresponds to the “*status quo*” T&V

⁴This ratio is calculated using the 2010 figures from the Direção Nacional de Extensão Agrária (DNEA), available at the following URL: <http://www.worldwide-extension.org/africa/mozambique/s-mozambique>.

modality.⁵ The randomization was stratified at the district level.

To test for effective knowledge diffusion in the T&V model and isolate the additional effect of a central training of CFs, we hold constant all other typical T&V interventions across treatment and control communities. Specifically, and in line with the *status quo* modality, all CFs in the experimental sample are supposed to receive assistance from their EAs as well as a toolkit to create a demonstration plot within the community (*aldeia*). These demonstration plots are then used by (1) EAs to teach and assist each CF in implementing at least one of the agricultural practices of the CF’s choice, and (2) the CF to demonstrate the elected new techniques to farmers in their community.

It is important to note that all CFs in treatment and control communities are encouraged to maintain demonstration plots within the project areas.⁶ Usage is quite high and not statistically different across treatment and control communities: 82 (83) percent of the CFs in treated (control) communities maintained a demonstration plot in 2012. By 2013, the use of demonstration plots increased to 90 (93) percent. Our experiment allows us to compare information diffusion across two modalities: direct, centrally administered training, vs. second-hand, EA-led training. The extent of information diffusion across the two modalities can then be measured through observed variations in the technique-mix learned and adopted across treatment status, not at the extensive margin of CFs’ demonstration activities.

Our design implies that each EA will work with both “Treatment” and “Control” CFs in his administrative post.⁷ A threat to our identification stems from the fact that CFs may request different levels of attention from their EAs across treatment assignments, displacing EA’s time away from the other treatment status. For instance, “Treatment” CFs may be more engaged with

⁵The full design consists of multiple treatment arms. A second treatment arm was overlaid to our central training that randomly assigned 75 of the 150 treated communities to have an additional trained female. This second treatment is the subject of a separate study. In the present study, we pool the two treatments together, to examine the impact of having at least 1 CF trained on SLM in the community on farmer outcomes. A third treatment arm was overlaid to the first two that attempted to provide different performance-based incentives for the CFs to reach farmers. Although we do not measure this effect explicitly, the third treatment arm is controlled for in the regression analysis.

⁶There is no instruction, however, as to what type of plot should be used for demonstration. CFs can elect to use their own, private plot or use a communal land. Hence, we present the adoption results for any plot (own or demonstration).

⁷A limitation of working with an existing extension network is that we could not withhold information from a random group of CFs by shutting down their interactions with their assigned EAs. Given the small number of extension workers (30), reasonable levels of statistical power cannot be reached by assigning the intervention at the EA level. We do verify that extension agent characteristics are balanced across treatment and control communities at midline (Table A.2). We further include EA-team indicators in our regression analysis (noting that each CF is assisted by two EAs (not one EA) within the administrative post).

the techniques they have learned and request more follow-up visits from their EAs. Reassuringly, we find that “Control” and “Treatment” CFs received equal amounts of attention from their EAs in the year after the training, both at the extensive and intensive margins.⁸ We account for unobserved heterogeneity across EAs using EA fixed effects.

3.1 SLM Trainings

Our training intervention encompasses seven⁹ SLM techniques: Mulching, Crop Rotation, Strip Tillage, Micro-catchments, Contour Farming, Row Planting, and Improved Fallowing. Mulching covers the soil with organic residues to maintain soil humidity, suppress weeds, reduce erosion, and enriches the quality of the soil cover. Crop rotation rotates crops on a given plot to improve soil fertility and reduce the proliferation of plagues. Strip tillage prevents opening the soil, such as through plowing, harrowing, or digging on land surrounding the seed row. Micro-catchments (approximately 15-cm deep permanent holes) are constructed around the base of a plant, such as maize, to aid water and nutrient accumulation. Contour farming is the use of crop rows along contour lines fortified by stones (or vegetation) to reduce water loss and erosion on sloped land. Row planting can improve productivity by improving access to sunlight and facilitates weeding and other cultivation practices (e.g., mulching and intercropping) by providing space between rows. Improved fallowing reduces the productivity losses from fallowing land by targeted planting of species that enrich soil in a shorter time frame than traditional fallowing.

Table 1 summarizes the functionality of each of these techniques (Liniger et al., 2011).¹⁰ In

⁸While access to EAs was also surveyed at endline, the statistics are contaminated by the fact that EAs visited “Treatment” CFs to advertise the second SLM training. Hence, reported access to EAs mechanically goes up in the treatment at endline. Thus, Table A.2 focuses on midline observations only to prove balance across extension agent characteristics. It is also important to note the fact that there were no EA differences across groups at midline has implications on the interpretation of the intervention’s impacts. One interpretation is that EAs were diligent about visiting all CFs irrespective of the intervention which would imply that the main advantage of the treatment is improving the quality of the information delivered. An alternative interpretation is that EAs might be irresponsive to the increase in the demand for services that a centralized training might have produced. This would motivate the centralized training at increasing frequency to address the low transmission of information due to infrequent EA visits.

⁹Intercropping was included in the curriculum, which allows for the cultivation of several crops at once. We exclude this technique from the analysis as it was already widely adopted at the time of the intervention by CFs (98 percent) and other farmers (76 and 81 percent of women and men, respectively). Including the technique bears little consequence on our point estimates (Tables A.3-A.4).

¹⁰As row planting is often used to reinforce some of the above practices (e.g., mulching and strip tillage), the independent number of advantages of row planting are undocumented.

Sub-Saharan Africa, mulching and crop rotation offer the greatest number of advantages in terms of water efficiency, soil fertility, and improving plant material. They were also the most common techniques applied by farmers in the Zambezi Valley at baseline, though adoption rates were far from universal (Tables A.5-A.6). Use of strip tillage, micro-catchments, and contour farming is also deemed effective at improving water efficiency and soil fertility.

For each SLM technique, we asked the CFs in our study whether they believed the practice affected productivity, the land preparation effort, the planting seed effort, and harvesting effort in our midline survey. The greatest percentages of CFs (in the control group) report mulching and crop rotation techniques increase productivity (60% and 36%) and reduce land preparation efforts (45% and 26%). As mentioned, these techniques were also the most popular at baseline. The percentage of CFs (in the control group) that perceive strip tillage and micro-catchments to be productive only slightly lags behind the percentage reported for crop rotation (29% and 24%, respectively). This suggests that some (but not all) SLM technologies pose as reasonable instruments to test knowledge diffusion under the T&V model in the Zambezi valley.

We worked with technical staff from the Ministry of Agriculture (MINAG) to develop an educational agenda for the EAs and CFs on these SLM practices. The EAs were given two three-day training courses in SLM techniques in October 2010 and November 2012 (prior to the main planting season), delivered by their district technical staff with support from the central MINAG project team. Half of the training sessions were devoted to in-class lectures, and the other half consisted of hands-on plot demonstrations. The syllabus included a thorough review of the advantages of each technique over less-environmentally desirable ones. The weeks that followed those two trainings, “Treatment” CFs were invited to attend the same course, delivered by the same district-level technical staff¹¹ with support from MINAG staff¹².

After the first training, all CFs (“Control” and “Treatment”) received a new toolkit¹³ (bicycle, tools to plow the land, and smaller articles) and the mandate to disseminate the techniques most

¹¹In some districts, district staff relied on their EAs to help during the hands-on sessions. This could contaminate our results by lowering the amount of on-farm attention “Treatment” CFs subsequently received from their EAs. If anything, this implies that we will underestimate information flow in the centrally-ran training arm, and overestimate it in the T&V model.

¹²Given the low literacy of farmers, a film covering all techniques substituted the initial lecture format in the second training of the CFs.

¹³The toolkit distribution was planned, regardless of our intervention, by the project staff, as the previous distribution had been done in 2007 and the items were deemed too old to function in 2010.

pertinent to their local area on their demonstration plots.¹⁴ A second toolkit with similar items (including a bicycle) was provided to all CFs again in July 2012 before the second training. The only difference between our “Treatment” and “Control” CFs is the modality through which they received training on the selected seven SLM techniques.¹⁵ EAs were told to transfer their knowledge to “Control” CFs and assist both “Treatment” and “Control” CFs in setting up demonstration activities.

Inviting “Treatment” CFs to the district-level trainings was left to each EA team, at the administrative post level. EAs were given the list of randomly chosen “Treatment” CFs, and the district staff explained the physical impossibility of training all CFs at once and that a lottery had been used to select the participating CFs. An attendance sheet was taken at training by the district staff. In 2010, only four “Treatment” CFs did not attend the training, and all are in the Mopeia district.¹⁶ Since district staffs may have an incentive to misreport attendance, we performed independent audits. First, we verified that the attendance list reflected the (randomly assigned) eligibility, and found no contamination of the control group. Second, we showed up unannounced at the trainings in all five districts. Finally, attendance lists were back-checked: a random set of listed participants were visited in November and December of 2010 and asked whether they attended the SLM training. Our back-checks indicate that attendance was genuine.

Similar checks were performed on the 2012 training. While the attendance list fully lines up with our back-checks, participation was not universal, and contamination was quite substantial. Sixty-three (sixteen) percent of the treated (control) communities had at least one CF attend the training.¹⁷ As these figures signal significant exposure of “Control” CFs to the treatment in 2012, they foreshadow our weakened ability to statistically differentiate the two training models in the 2013 (second follow-up) survey round.

¹⁴The project had started to disseminate mulching, strip tillage, row planting, and crop rotation as early as 2008. However, the formal practice was sparse at the time of the intervention and most EAs and CFs had not received a formal training on SLM techniques or been instructed to transfer their knowledge to their peers.

¹⁵It is possible that in attending the centralized training, CFs might “feel special”. Our treatment effect may incorporate how this feeling may empower CFs to implement their lessons in practice. Although this was beyond the scope of the evaluation, we did ask CFs to report their state of happiness. We found 91 percent of the CFs (in the control group) and 85 percent of the CFs (in the treatment group) were happy and there is not statistically significant difference in those proportions (Table A.1).

¹⁶These CFs were trained by the EA on an individual basis, and the follow-up training was verified.

¹⁷The contamination likely was caused by a combination of EA and self-selection. CFs in the control group could have easily learned about the trainings from peers located elsewhere. Clearly, the EAs were involved in organizing the training. A politically connected CF might have been admitted by the EA or district officer as the project fostering the evaluation was ending.

3.2 Data

We conducted two follow-up surveys, a 2012 (midline) round, and a 2013 (endline), which form a panel of households and CFs in the study area.¹⁸ A baseline census survey was administered to all CFs in August 2010, before the district-level randomization. Figure 1 illustrates the timing of the surveys and CF trainings over the course of four years.

Midline and endline surveys collected household demographics, individual and plot-level SLM adoption, and household production information for approximately 4,000 non-CF households in 200 communities (*aldeias*, that mostly overlap with Mozambique’s enumeration areas) (Figure 2). A listing of households residing in each community was performed, from which we drew a random sample of 18 non CF-households per community. Our field work included five survey instruments: a household questionnaire; a household agricultural production questionnaire; a CF questionnaire; an extension agent questionnaire; and a community questionnaire. The household survey was also administered to CF households, in addition to the specific CF survey. The present analysis exploits the information from the household and CF surveys.

Both midline and endline surveys were conducted during the primary planting season. In each survey round, households were visited twice: pre- and post-harvest. This is because SLM practices are most visible just after planting (pre-harvest, from February to April), while production data can only be obtained after harvest (May-June). Hence, all household surveys were administered during February–April, with the exception of the agricultural production module. The agricultural production (and CF, community, and extension agent) surveys were administered post-harvest during May and June in 2012 and June through August in 2013.

3.3 Balance

We use data from the baseline CF survey and retrospective information collected in the 2012 household survey to check for balance across treatments. Table 2 indicates minor differences between CFs in the treatment and control communities. “Treatment” CFs spent almost four more hours a

¹⁸Following McKenzie (2012), we optimize our probability of detecting a significant impact under a budget constraint by conducting two follow-up data collections rather than a baseline and a follow-up.

week working as a CF (pre-intervention) with slightly more recent training when we condition on being formally trained. “Control” CFs were exposed to a greater number of techniques prior to the intervention.¹⁹ In spite of these differences, (recalled) pre-intervention adoption rates among CFs in control and treated communities are similar.²⁰ Farmers’ (recalled) baseline SLM learning and adoption rates are also similar across treatments (Table 3).²¹

Taken together, these results suggest that we will provide a conservative measure of the relative impact of directly training CFs. Our estimates might understate the impact of direct training, and overestimate the impact of T&V model. In addition, the fact that CFs are more knowledgeable in SLM than the average farmer at baseline further suggests that the impact estimates of the training program are likely not generalizable to the average farmer.

3.4 Measuring Information Diffusion and Behavioral Change

Central to identifying variations in information diffusion is measuring changes in agricultural practices. Our study rests on the reliability of our markers of individual SLM knowledge and adoption outcomes. We focus on three outcomes: a knowledge score (see Kondylis, Mueller, and Zhu (2014) for details of the exam), the number of techniques the respondent identified by name, and the number of techniques the respondent claims to adopt on any plot.²² Objective adoption measures were also collected for two plots per household and largely corroborate the self-reported outcomes (see Kondylis, Mueller, and Zhu (2014) for a detailed comparison).²³

¹⁹Given CFs in treatment villages spend more hours a week working as a CF at baseline, we will include the variable as a control in the regression analysis.

²⁰Balance tests for the CF and other farmers’ knowledge and adoption of individual SLM techniques at baseline are reported in Tables A.5-A.6. Because these values are based on recall data, the tests should be interpreted with caution.

²¹Even though mean comparisons indicate there are no statistically significant differences, recall bias may be present. We therefore do not exploit the recalled information beyond balance checks.

²²For CFs, the majority of the analysis rests on their adoption of techniques on any plot which includes their own and demonstration plots. There are slight differences between adoption measures which include and exclude the demonstration plot for a minority of CFs who’s demonstration plots rest on communal land (29%). We verify the results are not driven by communal propriety of the demonstration plot and report those robustness checks in some but not all of our CF tables of results.

²³Our decision to focus on the knowledge score and self-reported adoption outcomes is motivated by the conclusions of Kondylis, Mueller, and Zhu (2014). Using the Smallholders’ midline survey data, we find that learning outcomes based on knowledge exams provide more precision when compared to know-by-name questions, as they reveal the true knowledge of those individuals less familiar with the name of the technique yet more familiar with its purpose and usage. In our triangulation of the self-reported vs. observed adoption, we find that false reporting is negligible. Since objective measures of adoption are only collected for a subset of plots in the sample (one per respondent), we

Since the CFs were encouraged to choose the most relevant techniques to their local conditions, we focus on aggregate measures of knowledge and adoption for our main results. However, restricting the analysis to aggregate measures of knowledge and adoption may lead us to overlook patterns of substitution across techniques attributable to the intervention. For example, we may underestimate the impact of the intervention if CFs substitute away from already-disseminated technologies to the benefit of some “newer” techniques within the proposed package. We therefore also present how knowledge and adoption of specific techniques indicators are affected by the intervention. Technique-specific knowledge is captured by whether the respondent answers correctly at least 1 of 3 knowledge questions pertaining to the practice.

Knowledge, adoption and perception of the SLM techniques were collected at the individual level from the household questionnaire. Two respondents were interviewed: the household head and his/her partner or spouse. If a polygamous household was encountered, the main spouse was interviewed.²⁴ Thus, our sample of CFs and other farmers consists of those who reported their personal information, participated in an agricultural knowledge exam with questions related to each specific SLM practice, and self-reported their SLM adoption rates. Specifically, 179 and 172 villages were interviewed for the contact farmer survey in 2012 and 2013, respectively; 2,536 male and 3,716 female non-CFs were surveyed in 2012, and 3,115 female and 2,175 male non-CFs in 2013.²⁵ Selective sample attrition is of definite concern, and we detail below how selective attrition is addressed in our specifications.

3.5 Empirical Strategy

We measure information diffusion through a direct training model relative to the traditional, T&V extension network: from EA to CF, and CF to others. A particularly attractive feature of our design is that we track information diffusion through an existing network. We first measure to what extent

instead focus on a more inclusive measure of adoption provided by self-reports of men and women surveyed in the sample.

²⁴A polygamous household is characterized by the household head having more than one spouse or partner. Only 2.7 percent of the households in our sample are polygamous.

²⁵For analysis, we restrict the sample to farmers with complete information on household and individual characteristics. We have 179 and 168 CFs in 2012 and 2013, respectively; 2,475 male and 3,592 female non-CFs in 2012, and 3,098 female and 2,141 male non-CFs in 2013.

directly training CFs affects CFs' and others' knowledge and adoption.²⁶ We causally estimate the *intent-to-treat effects (ITT)* of a community being assigned to a central CF training (relative to a *status quo* T&V information diffusion modality) on the SLM knowledge and adoption of CFs²⁷ and others in the community, Y , using a simple reduced-form specification:

$$Y_{i,h,j} = \beta_0 + \beta_1 T_j + \beta_2 X_{i,h,j} + \epsilon_{i,h,j} \quad (1)$$

T takes the value 1 for each community j with a centrally trained CF. Individual i , household h , and administrative post indicator variables are included in the vector $\mathbf{X}$ to improve the precision of the estimated coefficients.²⁸ Since CFs were exposed to a team of two EAs within each administrative post, we identify the ITT from within-EA-team variations, by including administrative post fixed effects in all regressions. We also use the Huber-White heteroskedasticity-robust estimator to calculate the standard errors when using the sample of CFs. For the other farmer regressions, we cluster the standard errors at the community level to allow for arbitrary correlation of treatment effects within the community. Gender-differentiated effects are presented throughout to allow for different functional form, as women cultivate their own plots separate from their husbands' and may face varying constraints on their time, input use, crop choice, and plot characteristics (Table A.7).

We separate specifications by round for a few reasons. First, nine percent of households attrited between 2012 and 2013. We find evidence of selective attrition across household survey rounds, as individuals present in both midline and endline rounds appear statistically different than individuals only present during the midline and endline surveys (Table A.8).²⁹ Second, in spite of attrition being uncorrelated with the treatment (Table A.10), evolution in the realities of the program on the ground

²⁶CFs have the flexibility to decide which SLM techniques to adopt on the demonstration plot. As the marginal value of adopting a technique will vary with the predominant crops grown, soil quality, topography, and other local conditions, demonstrated technique-mix is unlikely to be uniform across communities.

²⁷CF-level regressions are run using community-level CF outcomes and characteristics. In those communities where we (randomly) assigned a second woman CF, we measure increased village-level exposure by regressing the maximum (mean) value of binary (continuous) outcomes of CFs within the village on the maximum (mean) value of binary (continuous) covariates.

²⁸We address omitted variable bias by including variables that reflect CF (or other farmers') demographic characteristics, the number of hours worked by the CF at baseline, administrative post indicators, and indicators for treatment arms not analyzed in the present study.

²⁹Attrition rates at the household and CF level are not statistically different nor correlated across treatment groups (Tables A.9-A.10). The characteristics of CFs do not vary on average over time (Table A.11). Household attrition rates appear consistent with other studies in the same region (de Brauw, 2014). A probit regression in which reflects the probability of the household attriting indicates the percent of household members that were away in 2012 increases the probability of moving out of the sample (Table A.10). Age and the number of children of the household head reduces the probability of moving out of the sample.

compels us to split the sample by survey year. For instance, as mentioned above, contamination was quite large in 2012, while absent in 2010. Hence, results from the 2013 survey will likely underestimate the impact of the intervention, and our inferences draw heavily on the estimates provided by the 2012 survey.

We perform two robustness checks to examine the sensitivity of our results to attrition. The first diagnostic estimates (1) using the balanced panel. We show that the inclusion of individuals only present in one round affects the precision of our point estimates rather than their magnitude and sign. The second check bounds the treatment effect for selective attrition using a method proposed by Lee (2009). Upper (lower) bounds of the treatment effect are produced non-parametrically by trimming the tail of the distribution of the outcome variable in the treatment group below quantile p (and above quantile $1-p$), where p is the difference in the proportions of non-missing observations between the treatment and control groups divided by the total number of observations in the treatment group.

The technologies we disseminate are somewhat novel in the sense that baseline adoption is low. However, awareness of the techniques is quite high (Tables A.5-A.6). While there are large potential gains in knowledge and adoption as a result of the SLM training, farmers' responses are less likely to be driven by the "freshness" of the material. A caveat to the low novelty content of SLM training is that, should adoption prove low both at the CF and farmer levels, we will not be able to rule out demand-side from supply-side constraints without further investigation. We first provide information on the potential costs savings associated with others' technological adoption (both in terms of changes in perceptions and realized labor savings). We additionally assess whether CF profile and CF similarity in production habits with others' influenced the impact of the intervention, differentiating ITT estimates by variants in CF and farmer characteristics.

3.6 Summary Statistics

To understand the socioeconomic conditions in the project area, we briefly describe the characteristics of the average farmer in our sample (drawing from statistics in Table A.12). The majority of individuals are women, due to the high prevalence of female headship (approximately 30 percent)

in the region (TIA, 2008) . The average plot owner was 38 years old with only 2 years of schooling. Most plot owners were married with 3 children, living in a single-room house made of mud and sticks, with palm or bamboo roofs (not reported). They possess 2 hectares of land on average with a standard deviation of 1.8.

CFs are more knowledgeable (Tables 2 and 3), educated and wealthier (Table 4) than the average farmer. Communicator profile has been shown to affect the diffusion process in ambiguous ways (Munshi, 2004; Bandiera Rasul, 2006; Feder and Savastano, 2006; Conley and Udry, 2010; BenYishay and Mobarak, 2013). While CFs are positively selected in attributes, they are also well-known in their communities: 81 and 90 percent of male and female farmers in the control group declare knowing them personally. However, only 79 and 67 percent of males and females report knowing that these individuals assume a role as CF in their community. Thus, barriers to knowledge diffusion may stem from a lack of transparency in the roles of CFs rather than their dissimilarities with those they intend to serve. We explore the latter possibility explicitly by estimating heterogeneous effects of the treatment.

4 Results

4.1 CF Adoption and Learning-by-doing

Table 5 provides the ITT estimates of aggregate measures of knowledge and adoption. Despite the variety of techniques adopted among control CFs at midline, we detect that CFs adopt an additional technique in response to the training. These effects are not driven by differential access to extension agents (row 1, Table 5).

We further disaggregate ITT estimates by the adoption of specific techniques (Table 6). Directly trained CFs are more likely to adopt techniques that were most uncommon at baseline, and perceived productive as outlined in Section 3.1. Effect sizes range from 24 to 41 percent. Adoption significantly trended downward in both treatment and control villages. In fact, at endline, the impact of the intervention on adoption is insignificant for all techniques.³⁰

³⁰The maintenance costs offer one explanation for the disadoption in the subsequent year of the study. For example,

We next examine changes in CF knowledge scores to test whether direct training corrected for any loss in EA-to-CF information diffusion associated with a pure T&V approach. By additionally comparing the adoption and knowledge gains, we can observe whether increased training helped lift a genuine information constraint to adoption, or whether the gains are purely achieved through increased salience of the techniques. Figure 3 graphs the effect sizes of the treatment on the knowledge and adoption of each SLM technique.³¹ The left panels of Figure 3 indicate that directly training CFs did little to increase CFs’ knowledge scores on the techniques relative to a pure T&V regimen at midline. Hence, the gains in adoption observed under the direct training modality at midline are attributable to increased salience of information rather than an actual learning effect. This is not surprising since CFs were sufficiently aware of the techniques from the outset.

Tracking adoption and knowledge scores across years allows us to document CFs’ learning-by-doing. In contrast to the adoption decay in control and treatment communities, CF knowledge of SLM significantly expands in treatment areas (see Table A.13 for knowledge score point estimates). Treated CFs’ knowledge scores associated with the adopted techniques go up one year after we detect a significant increase in adoption. Moreover, the order of magnitude of these gains is remarkably similar to those achieved on adoption: the largest gains are experienced for contour farming, with slightly lower gains in strip tillage and micro-catchments. Taken together, the profile of this one-year lag from demonstration to learning suggests that CFs acquired knowledge through a learning-by-doing process.

We show direct training has the potential to increase adoption of innovative practices both at the intensive and extensive margins. Although formal training on its own did not appear to lift any knowledge constraint among relatively skilled CFs, it increased adoption through added salience. This intimates a weakness of the T&V model, where EAs are not as effective in getting farmers to devote time to adopting new activities as a direct training.

Liniger et al. (2011) indicate for micro-catchments the long-term benefits appear less positive than the short-term benefits.

³¹The probability of detecting statistical significance due to the intervention increases with the number of outcomes used. Our results are not robust according to the Šidák (p-value=0.015) and Bonferonni (p-value=0.014) adjustments (Abdi, 2007). However, micro-catchment adoption at midline and contour farming knowledge at endline are robust to the adjusted p-values in a regression model that substitutes district indicators for the administrative post indicators.

4.2 CF Substitution of Techniques

We next try to formalize whether the training caused CFs to modify their practices towards newer techniques brought to their attention by the direct training. To gauge the potential substitution effects, we exploit the (recall) baseline adoption measures to estimate the following regression, suppressing all subscripts in (1) but those that reflect time:³²

$$Y_t = \beta_0 + \beta_1 T + \beta_2 Y_{t-1} T + \beta_3 Y_{t-1} + \beta_4 X + \epsilon \quad (2)$$

where t signifies the midline and $t-1$ baseline. The results in Table 7 are suggestive that the training might have encouraged but not substituted techniques (e.g., improved fallowing). Although the signs of the parameter of the variables interacting the treatment and previous adoption (β_3) are negative for mulching and crop rotation, their magnitudes are similar to the ITT estimate. We err on the cautious side in the interpretation of these results, as clearly there appears to be a greater, though statistically insignificant, recall bias among treatment farmers for some techniques.

4.3 Others' Knowledge and Adoption

We now turn to CFs' ability to diffuse knowledge to others. We exploit the random, positive shock introduced by the intervention in CF activity to measure the extent of CF-to-others knowledge transmission. Table 8 provides the mean aggregate knowledge and adoption rates of other farmers in the control communities, as well as the ITT estimates of changes in knowledge and adoption outcomes attributable to our intervention. Even though the margin for gains from receiving the information was larger than that of CFs, other farmers' aggregate SLM knowledge and adoption remained the same. This is in spite of farmers' reporting learning techniques, such as contour farming, explicitly from CFs (Table A.15). The absence of adoption is robust to balancing the panel at midline and accounting for selective attrition at endline (Table 9). These qualitative results indicate that demand-side constraints may continue to hinder farmers' adoption.

³²Note that we focus on the adoption practices on CFs' own plots here, since information on the demonstration plots were not collected for baseline through recall.

4.4 Farmers' Perceptions of Cost Savings

Our midline survey asked farmers whether they perceived each technique to require more labor effort, equivalent labor effort, or less labor effort than the use of traditional cultivation practices. Farmers in the control group perceive all techniques to be labor intensive, with a range of less than 1 percent to 18 percent of farmers declaring the techniques decrease the amount of labor required (Table A.16). We find that increasing exposure to SLM information through the trained CF affected farmers' perceptions of the adoption costs for micro-catchments only. The intervention significantly increased the proportion of farmers who perceive micro-catchments to be labor-saving by 2 percentage points for men, amounting to a 100-percent increase relative to the control for male farmers.

The changes in farmers' perceptions are complementary to the ITT estimates for others' adoption by technique. We observe male farmers exposed to the intervention were more likely to adopt micro-catchments by 3 percentage points (an effect size of 75% according to Table A.14).³³ Women do not act on the information they receive. Though complementary, the above inferences are not indicative of a causal relationship between perceptions and adoption.

We lastly explore whether farmers were motivated by the demonstrated, short-term cost savings of the technology. In particular, we examine whether farmers' adoption rates coincide with CF labor savings in terms of the number of hours spent last week devoted to different agricultural tasks and the total number of weeks devoted to farming in the last year. Noting that our measure of labor efforts is inclusive of all techniques adopted by the CF (not exclusive to micro-catchments), we provide ITT estimates of the CF labor efforts for various agricultural tasks (Table A.18). The results in the Appendix indicate trained, CFs spent four fewer hours preparing land last week, and saved a total of one week spent on farming in the last year at midline.

Thus, male farmers may be particularly motivated to adopt micro-catchments by the immediate gains in labor savings. Although we cannot make claims definitively using cost data, benefit-cost assessments of other SLM studies in Africa suggest micro-catchments offer an additional cost-advantage. Unlike strip tillage and contour farming, additional tools are not required to create

³³The results are not robust to adjustments in the familywise error rates. However, the micro-catchment adoption of male farmers at midline is robust to the Sidak and Bonferonni p-value adjustments in a regression that substitutes district for administrative post indicators.

micro-catchments (Liniger et al., 2011).³⁴

4.5 CF and Others' Heterogeneity

We lastly explore whether CFs' characteristics provoke heterogeneous responses among farmers. Working with an existing network of CFs, we could not exogenously vary their education, age, wealth, or cropping patterns. The results that follow cannot be interpreted as causal linkages but as descriptive evidence. Specifically, it must be noted that, as CFs are, on average, of higher status than other farmers we do not have a counterfactual where average farmers are placed in a communicator role. We simply interact the treatment variable with CF characteristics, while controlling for both CFs and farmers' characteristics, following (1).

Table 10 displays the results from regressions using farmers' adoption of micro-catchments as outcomes, since the adoption for other techniques remained unchanged by the treatment (Table A.14). Estimates of the treatment effect as well as the combined effect of the treatment and the treatment interacted with whether the CF completed his secondary education, was older than the median age, had above median landholdings, or produced the same two primary crops as the farmer are provided. We assume having similar primary crops to the CF is an exogenous variable, i.e. cropping decisions are fixed before adoption decisions and cropping decisions are independent of the treatment.³⁵ For male farmers, exposure to increased CF activity yields larger point estimates when CFs are older and more educated. Only when we distinguish the female sample by whether they have similar crop portfolios as their CF do we observe a positive association between their adoption and treatment. This is somewhat consistent with the idea that social learning is more prevalent in homogeneous farming conditions (Munshi, 2004). Delays in women's adoption may stem from gendered differences in production technologies and an inability to extrapolate demonstrated activities to their own plot.

³⁴Farmers may adopt micro-catchments in order to increase their resilience. We however do not witness any significant changes in the ITT estimates when stratifying the sample by below and above median 30-year cumulative rainfall averages.

³⁵Although not shown here, whether the farmer grew the same primary two crops as the CF is not affected by the treatment at midline. Male farmers exposed to the intervention are more likely to grow the same primary two crops as the CF at endline. The intervention has no effect on the crop decisions of women, however.

5 Discussion

Our study aims to reveal which mechanisms implementable within an existing extension network can improve the limited knowledge and adoption of novel agricultural practices in Mozambican rural communities. We examine innovation diffusion through two nodes of an existing extension network: EA-to-CF and CF-to-others interactions. We find that both modalities come short of effectively propagating innovative SLM techniques. Directly training CFs on SLM dominates a pure T&V approach to extension, as it is conducive to more demonstration, private adoption and learning-by-doing among CFs. This demonstrates that SLM techniques were in fact valued by sophisticated farmers, and that in-depth knowledge, not awareness, of the techniques constituted a barrier to adoption among CFs. Although the point estimates on the learning and adoption gains from direct training are small, the effect sizes are large. Running small-scale, low-cost trainings of designated communicators can provide a more efficient solution to enhance agricultural knowledge and practices than relying on extension workers to provide *ad hoc* training.

Training a few “seed adopters” in a community may not be enough to boost adoption of a new technique. Studying the impact of an exogenous increase in CFs’ activities shows that demonstration is not sufficient to create learning within a community and to get others to adopt on a large scale. Male farmers choose to adopt one of three SLM techniques that the trained, CFs adopted. Looking at the multiplier effect of CFs’ demonstration activities, these results imply that a one percentage point increase in CF demonstration of micro-catchments induces other male farmers to increase their adoption by 0.1 percentage points.

Farmers’ perceived costs of SLM techniques pose one obvious demand-side constraint to adoption. Adoption of micro-catchments increased 3 percentage points among male farmers exposed to the intervention with no changes in adoption for the other two techniques covered by the trained CFs. The average male farmer exposed to the intervention in our study is more likely to perceive micro-catchments as labor saving. Their CFs realized labor savings in the form of a 4-hour reduction in land preparation the week prior to the interview and a 1-week savings of working on the farm over the last year (although these are inclusive of all techniques CFs adopted). The descriptive evidence is consistent with farmers’ beliefs updating in response to the intervention following their adoption of micro-catchments or after observing the CF’s demonstration activities.

The profile of the “seed adopters” influences whether women act on the information they receive. When focusing on the women who have similar cropping patterns as the CF, we observe social learning is more prevalent within this demographic. Women are more likely to act on the information they receive: their micro-catchments’ adoption increases by 3 percentage points at midline and 9 percentage points at endline. Providing messengers with amenable farming conditions may improve the targeting of female farmers in the provision of extension services.

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Figures and Tables

Figure 1: Timeline of Trainings and Contact Farmer and Household Surveys

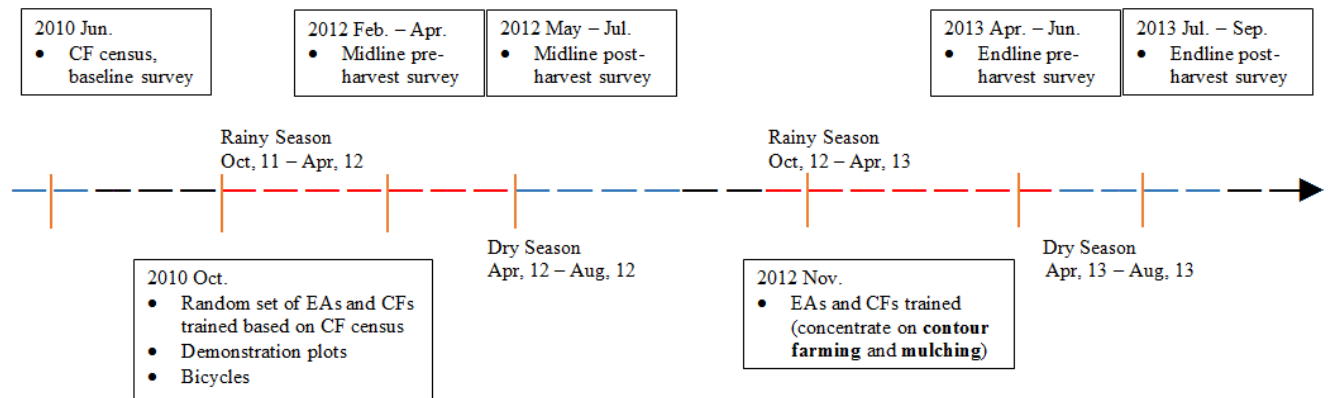


Figure 2: Geographical Distribution of (Non-CF) Households

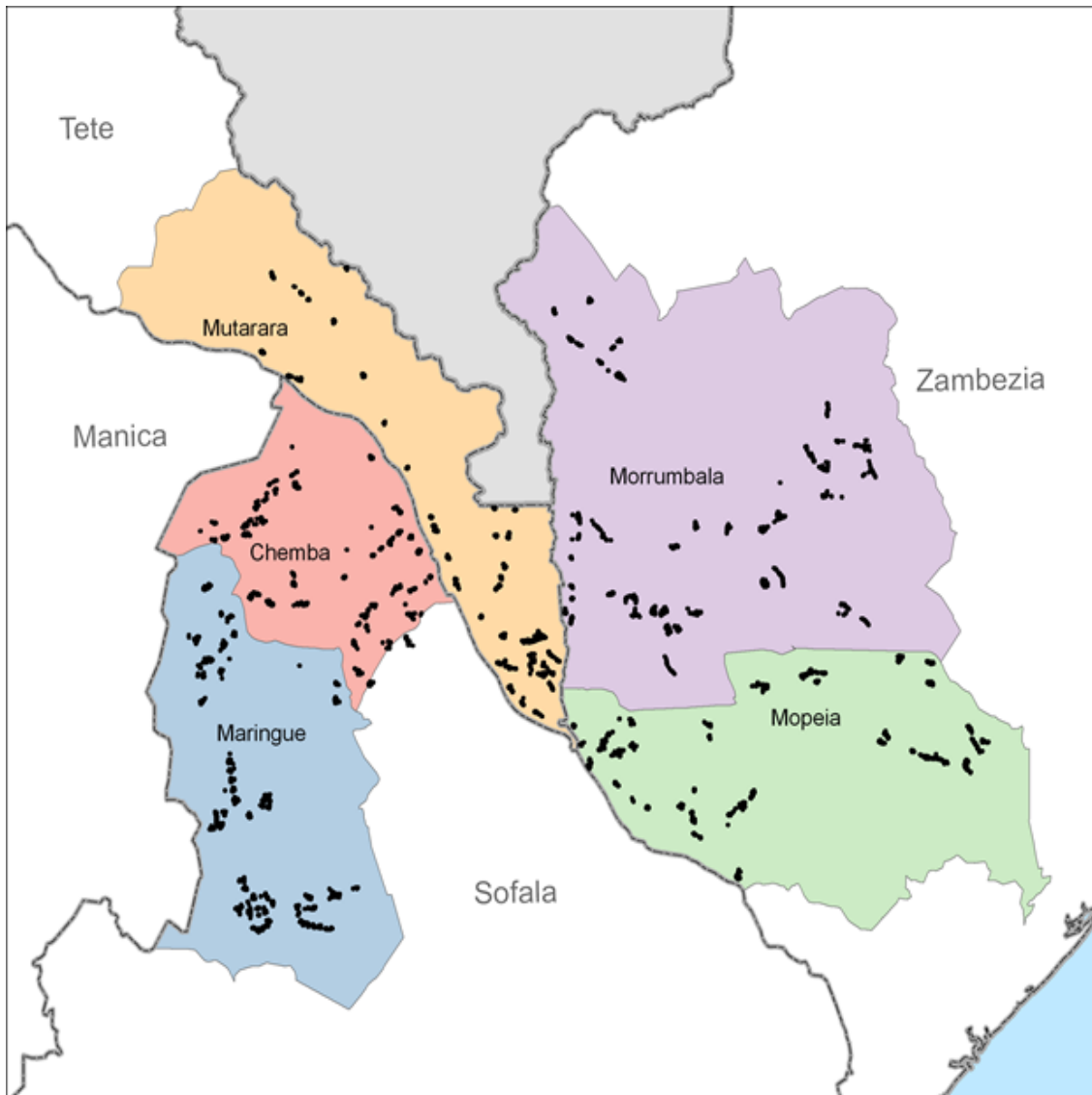


Figure 3: Effect of SLM Training Intervention on Contact Farmers

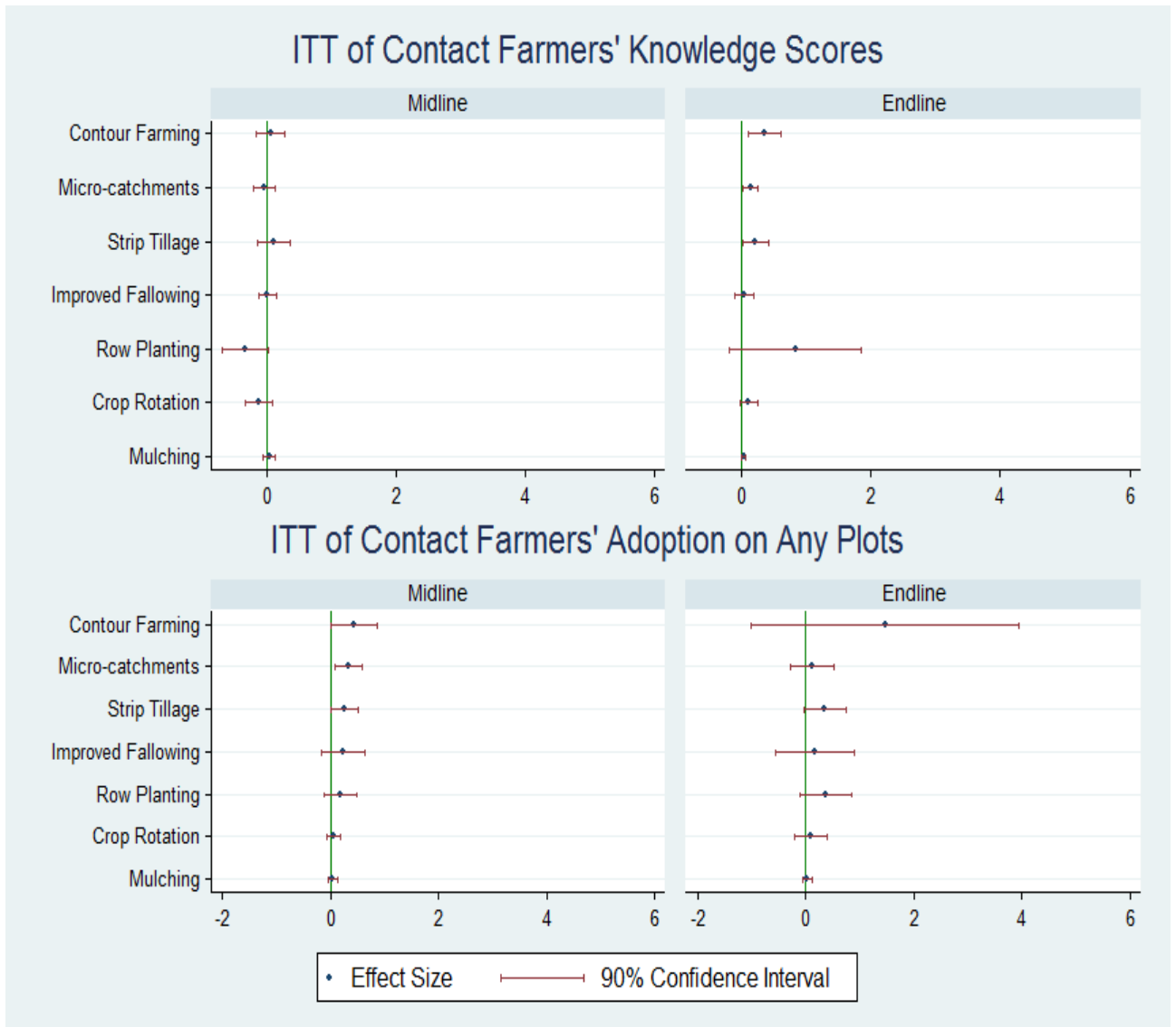


Table 1: Advantages of SLM Techniques

Technique	Water Efficiency	Soil Fertility	Improve Plant Material	Improve Micro-Climate
Mulching	X	X	X	X
Strip tillage	X	X		
Micro-catchments	X	X		
Contour farming	X	X		
Crop rotation	X	X	X	
Improved fallowing		X		
Row planting	-	-	-	-

Source: Sustainable Land Management in Practice, 2011.

Table 2: Contact Farmers' Characteristics in Treated and Control Communities

Variables	Treated		Control		Diff. N of Mean		
	Mean	SD	N	Mean		SD	
<i>Baseline Survey</i>							
CF age	38.858	9.348	148	40.160	10.559	50	-1.302
Ever being formally trained	0.350	0.479	140	0.447	0.503	47	-0.097
Number of years since formal training	2.157	2.239	51	3.409	3.202	22	-1.252*
Experience as CF in years	2.243	2.401	144	2.653	2.570	49	-0.410
# of farmers assisted in last 7 days	18.034	16.095	147	19.100	14.333	50	-1.066
# of male farmers assisted in last 7 days	10.871	9.659	147	10.860	9.064	50	0.011
# of farmers assisted in last 30 days	37.060	28.320	133	38.370	26.441	46	-1.309
# of male farmers assisted in last 30 days	22.480	15.145	148	22.240	17.203	50	0.240
Hours worked as CF in last 7 days	14.813	12.726	144	12.340	11.573	50	2.473
Hours normally working as CF per week	16.322	12.498	143	12.960	12.034	50	3.362
Total acreage of cultivated land	3.184	1.619	144	3.070	1.542	50	0.114
# of households in the community	284.421	267.037	126	244.548	265.410	42	39.873
# of plots in the community	459.269	430.130	108	436.063	426.578	32	23.206
<i>Midline Survey (recall)</i>							
Number of techniques learned before 2010	2.839	2.362	137	3.286	2.255	42	-0.446
Number of techniques adopted before 2010	1.409	1.210	137	1.167	0.935	42	0.242
Number of observations	137			42			179

Source: Contact Farmer Baseline Survey, 2010; Household Survey, 2012.

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 3: Other Farmers' Characteristics in Treated and Control Communities

Variables	Treated		Control		Difference of Mean
	Mean	SD	Mean	SD	
<i>Midline Survey</i>					
Is the head of household	0.585	0.493	0.588	0.493	-0.003
Male	0.420	0.493	0.414	0.493	0.005
Age	37.764	19.980	37.843	20.093	-0.079
Years of schooling completed	2.057	4.866	1.844	4.905	0.213
Single	0.063	0.504	0.058	0.509	0.005
Married	0.844	0.546	0.855	0.550	-0.011
Divorced, separated, or widowed	0.091	0.366	0.085	0.368	0.006
Number of children (ages < 15 years)	2.756	3.406	2.843	3.432	-0.087
Landholdings (hectares)	2.004	3.995	1.880	4.033	0.124
Number of rooms in the house	1.427	2.116	1.444	2.138	-0.017
Housing walls made of brick	0.100	0.777	0.096	0.785	0.004
Housing roof made of tinplate	0.079	0.718	0.079	0.725	0.000
<i>Midline Survey (recall)</i>					
Number of techniques learned before 2010	1.236	4.514	1.303	4.563	-0.066
Number of techniques adopted before 2010	0.509	2.024	0.554	2.045	-0.045
Number of observations	4,385		1,499		5,884

Source: Household Survey, 2012.

Note: T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 4: Characteristics Comparison between Contact Farmers and Other Farmers

Variables	Midline			Endline		
	CFs Mean	Others Mean	Difference of Mean	CFs Mean	Others Mean	Difference of Mean
<i>Household Characteristics</i>						
Is the head of household	1.000	0.586	0.414***	0.988	0.594	0.394***
Age	41.425	37.784	3.640**	43.341	38.775	4.566***
Years of schooling completed	5.469	2.003	3.467***	5.494	2.114	3.380***
Single	0.017	0.062	-0.045	0.006	0.048	-0.042**
Married	0.978	0.847	0.131***	0.971	0.851	0.120***
Divorced, separated, or widowed	0.045	0.089	-0.044	0.07	0.101	-0.031
Number of children (ages < 15 years)	3.779	2.778	1.001***	3.706	2.89	0.816***
Landholdings (hectares)	3.233	1.972	1.261***	3.654	2.401	1.253***
Number of rooms in the house	1.777	1.432	0.345**	1.748	1.412	0.336**
Housing walls made of brick	0.168	0.099	0.068			
Housing roof made of tinplate	0.207	0.079	0.128**			
<i>Production</i>						
Grew maize	0.699	0.636	0.064	0.738	0.642	0.096
Grew sorghum	0.139	0.240	-0.101	0.157	0.274	-0.117
Grew cotton	0.202	0.097	0.105**	0.064	0.052	0.012
Grew sesame	0.243	0.161	0.082	0.337	0.148	0.189***
Grew cassava	0.069	0.171	-0.102	0.041	0.143	-0.102
Grew cowpea	0.225	0.354	-0.128	0.331	0.349	-0.018
Grew pigeon pea	0.202	0.189	0.013	0.186	0.216	-0.030
<i>Farm Characteristics</i>						
Plot size (hectares)	1.151	0.951	0.201*	1.301	1.166	0.135
Plot was flat	0.807	0.639	0.167**	0.640	0.594	0.046
Plot was burnt	0.063	0.240	-0.178**	0.064	0.249	-0.185**
Used herbicides/pesticides/fungicides	0.156	0.062	0.094**	0.087	0.021	0.067***
Used natural fertilizer	0.358	0.269	0.090	0.622	0.438	0.184
Used chemical fertilizer	0.127	0.008	0.119***	0.052	0.005	0.047***
Number of observations	179	5,884	6,063	172	5,076	5,248

Sources: Household Survey, 2012, 2013.

Note: T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 5: Effect of SLM Training Intervention on Contact Farmers

	Control	Midline			Control	Endline		
	Mean(SD)	ITT	N	Adjusted	Mean(SD)	ITT	N	Adjusted
				R2				R2
<i>Access to EAs</i>								
EA visited CF	0.595	-0.079	179	-0.083				
at least 1/month		(0.093)						
EA visited CF	0.738	-0.088	179	-0.129				
at least 1/half year		(0.098)						
EA visited CF	0.786	0.021	179	-0.127				
at least 1/year		(0.093)						
<i>Performance</i>								
Knowledge Score	0.625	-0.002	179	-0.096	0.641	0.093***	168	0.022
	(0.201)	(0.040)			(0.142)	(0.027)		
# of techniques	4.214	0.524	179	-0.079	4.048	1.320***	168	0.040
known by name	(1.601)	(0.369)			(1.667)	(0.387)		
# of techniques	1.214	0.788***	179	0.117	2.357	0.654**	168	0.032
adopted on own plot	(1.001)	(0.247)			(1.340)	(0.308)		
# of techniques	4.452	0.817*	179	-0.072	3.024	0.551	168	-0.029
adopted on any plot	(1.928)	(0.415)			(1.569)	(0.360)		

Source: Household Survey and Contact Farmer Survey, 2012, 2013.

Note: Regressions include the following variables: a constant, age, completed at least primary school dummy, single dummy, number of children, total landholdings, the number of rooms in the household, baseline CF's number of years since formal training, missing dummy, posto indicators, and incentive treatment. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 6: Effect of SLM Training Intervention on Contact Farmers' SLM Adoption

Adoption on Any Plot	Midline				Endline			
	Control Mean	ITT	N	Adjusted R2	Control Mean	ITT	N	Adjusted R2
Mulching	0.929	0.032 (0.051)	179	-0.130	0.929	0.031 (0.053)	168	-0.048
Strip Tillage	0.619	0.152† (0.094)	179	-0.061	0.476	0.172 (0.114)	168	-0.060
Micro-catchments	0.643	0.216** (0.099)	179	-0.087	0.476	0.057 (0.114)	168	-0.129
Contour Farming	0.405	0.171^ (0.105)	179	-0.109	0.048	0.070 (0.071)	168	-0.133
Crop Rotation	0.905	0.050 (0.062)	179	-0.073	0.548	0.049 (0.100)	168	-0.037
Row Planting	0.524	0.097 (0.098)	179	-0.073	0.357	0.138 (0.103)	168	-0.091
Improved Fallowing	0.429	0.097 (0.103)	179	-0.044	0.190	0.034 (0.084)	168	-0.100

Source: Household Survey and Contact Farmer Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 5.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

†: P-value is 0.106. ^: P-value is 0.104.

Table 7: Effect of SLM Training Intervention on Contact Farmers' Adoption Controlling for Previous Adoption

Adoption on Own Plot	Midline				N	Adjusted R2	Treatment Effect (PV)
	Control Mean	ITT	Adopted Before	ITT * Adopt Bef.			
Mulching	0.405	0.254** (0.105)	0.537*** (0.131)	-0.235 (0.143)	179	0.141	0.103
Strip Tillage	0.286	-0.035 (0.060)	0.769*** (0.104)	0.159 (0.114)	179	0.656	0.165
Micro-catchments	0.119	0.162** (0.068)	0.662*** (0.131)	-0.061 (0.146)	179	0.346	0.674
Contour Farming	0.000	0.022 (0.017)	0.981*** (0.081)	0.000 .	179	0.428	.
Crop Rotation	0.262	0.196** (0.089)	0.812*** (0.138)	-0.243 (0.153)	179	0.398	0.115
Row Planting	0.119	0.077 (0.050)	0.810*** (0.121)	-0.157 (0.134)	179	0.488	0.242
Improved Fallowing	0.024	-0.011 (0.042)	0.022 (0.205)	0.484** (0.225)	179	0.161	0.033

Source: Household Survey, 2012.

Note: Regressions include the same explanatory variables as models in Table 5.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 8: Effect of SLM Training Intervention on Other Farmers

		Control	Midline			Control	Endline		
		Mean(SD)	ITT	N	Adj. R2	Mean(SD)	ITT	N	Adj. R2
<i>Access to CF</i>									
Has access to any	Female	0.080	0.028	3423	0.012	0.214	0.028	2951	0.004
contact farmer			(0.025)				(0.033)		
in the last half year	Male	0.135	0.048	2461	0.016	0.301	0.001	2120	0.001
			(0.037)				(0.042)		
<i>Performance</i>									
Knowledge score	Female	0.290	0.004	3423	0.006	0.369	-0.019	2951	0.009
		(0.157)	(0.016)			(0.236)	(0.026)		
	Male	0.316	0.006	2461	0.016	0.416	-0.019	2120	0.013
		(0.161)	(0.016)			(0.221)	(0.024)		
# of techniques	Female	1.457	0.079	3423	0.025	1.581	0.016	2951	0.007
known by name		(1.485)	(0.135)			(1.457)	(0.195)		
	Male	1.709	0.018	2461	0.014	2.025	-0.171	2120	0.010
		(1.588)	(0.144)			(1.610)	(0.196)		
# of techniques	Female	0.659	-0.055	3423	0.005	0.912	0.111	2951	0.003
adopted		(0.765)	(0.072)			(0.932)	(0.109)		
	Male	0.749	-0.034	2461	0.011	1.175	-0.009	2120	-0.001
		(0.820)	(0.080)			(1.002)	(0.118)		

Source: Household Survey, 2012, 2013.

Note: Regressions include the following variables: a constant, age, completed at least primary school dummy, single dummy, widow dummy, number of children, total landholdings, the number of rooms in the household, baseline CF's number of years since formal training, missing dummy, posto indicators, and incentive treatment.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 9: Selective Attrition, Balanced Sample & Lee's Bounds

	Midline (Balanced Sample) [†]				Endline (Lee's Bounds)				Trimming Proportion		
	Control Mean(SD)	ITT	N	Adjusted R2	Treatment Bound Lower	Treatment Bound Upper	Con. Interval Lower	# of Sel. Obs. # of Obs.			
<i>Access to CFs</i>											
Has access to any contact farmer in the last half year	Female	0.083	0.018 (0.026)	2706	0.010	0.027 (0.019)	0.042* (0.024)	-0.006	0.084	2706	0.015
	Male	0.135	0.047 (0.041)	1873	0.017	-0.013 (0.031)	0.007 (0.026)	-0.067	0.053	1874	0.019
<i>Performance</i>											
Knowledge score	Female	0.297 (0.160)	0.002 (0.018)	2706	0.005	-0.005 (0.012)	0.008 (0.014)	-0.025	0.031	2706	0.015
	Male	0.314 (0.162)	0.006 (0.017)	1873	0.018	-0.020 (0.015)	-0.008 (0.015)	-0.046	0.018	1874	0.019
# of techniques known by name	Female	1.524 (1.505)	0.087 (0.145)	2706	0.025	-0.024 (0.073)	0.068 (0.110)	-0.148	0.255	2706	0.015
	Male	1.783 (1.609)	-0.052 (0.157)	1873	0.020	-0.268** (0.120)	-0.149 (0.100)	-0.470	0.019	1874	0.019
# of techniques adopted	Female	0.681 (0.776)	-0.036 (0.077)	2706	0.006	-0.020 (0.045)	0.029 (0.059)	-0.096	0.129	2706	0.015
	Male	0.785 (0.830)	-0.062 (0.084)	1873	0.017	-0.130* (0.074)	-0.058 (0.062)	-0.255	0.046	1874	0.019

Source: *Houshold Survey, 2012, 2013.*

Note: †Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table 10: Heterogeneity of ITT on Other Farmers' Adoption of Micro-Catchments

Adoption of Micro-catchments	Midline						N	Adj. R2
	Ctrl. Mean	ITT	T+T* Ed>7years	T+T* Age≥41	T+T* Land≥2.75	T+T* Same Crop		
Female	0.039	-0.012 (0.014)	0.024 (0.017)				3239	0.002
Male	0.039	0.017 (0.020)	0.056†† (0.025)				2348	0.008
Female	0.039	0.007 (0.017)		-0.004 (0.014)			3239	0.000
Male	0.039	0.036 (0.023)		0.038† (0.021)			2348	0.007
Female	0.039	0.000 (0.016)			0.006 (0.015)		3239	0.000
Male	0.039	0.039* (0.021)			0.027 (0.024)		2348	0.006
Female	0.039	0.002 (0.013)				0.029† (0.017)	3237	-0.001
Male	0.039	0.041** (0.018)				-0.001 (0.039)	2342	0.009
Adoption of Micro-catchments	Endline						N	Adj. R2
	Ctrl. Mean	ITT	T+T* Ed>7years	T+T* Age≥43	T+T* Land≥3.5	T+T* Same Crop		
Female	0.082	0.019 (0.031)	0.004 (0.033)				2474	-0.002
Male	0.137	-0.016 (0.038)	-0.044 (0.048)				1775	-0.001
Female	0.082	0.047 (0.035)		-0.019 (0.028)			2474	0.003
Male	0.137	0.001 (0.048)		-0.053 (0.035)			1775	0.001
Female	0.082	-0.006 (0.028)			0.038 (0.036)		2474	0.000
Male	0.137	-0.029 (0.038)			-0.016 (0.045)		1775	0.001
Female	0.082	0.001 (0.025)				0.089† (0.048)	2546	0.002
Male	0.137	-0.038 (0.033)				-0.007 (0.068)	1843	0.001

Source: *Household Surveys, 2012, 2013.*

Note: Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics. Interaction columns reflect the combined values of the treatment and treatment interacted with the CF characteristics coefficients. †††, ††, and † indicate values are significant based on the treatment and the treatment interacted with the CF characteristics variable at the 1, 5, and 10 percent critical levels.

Appendix A: Additional Tables

Table A.1: Advantages of Being a Contact Farmer in Treated and Control Communities

Variables	Midline		Endline	
	Treated Mean	Control Mean	Treated Mean	Control Mean
CF felted happy	0.854	0.905	0.868	0.884
Being CF: to help community	0.905	0.810	0.984	0.977
Being CF: to learn new techniques	0.562	0.452	0.736	0.767
Being CF: prestige of the position	0.285	0.238	0.171	0.186
Being CF: curiosity for farming techniques	0.190	0.167	0.302	0.302
CF used the demo plot in the past 12 months	0.796	0.857	0.837	0.837
CF owned the demo plot	0.686	0.786	0.713	0.721
EAs gave CF agriculture inputs	0.540	0.524	0.566	0.512
EAs gave CF natural fertilizers	0.146	0.119	0.171	0.163
EAs gave CF chemical fertilizers	0.380	0.381	0.357	0.302
EAs gave CF farming tools	0.175	0.119	0.372	0.419
EAs gave CF any non-technical support	0.577	0.548	0.628	0.535
CF received conservation agriculture trainings			0.961	0.907
Number of CA trainings CF received			2.535	2.488
Training was easy to attend			0.775	0.721
Paid for transportation to attend the training			0.178	0.093
Number of observations	137	42	129	43

Source: *Contact Farmer Survey, 2012, 2013.*

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.2: Extension Agents' Characteristics in Treated and Control Communities at Midline

Variables	Treated		Control		Diff. of Mean
	Mean	SD	Mean	SD	
EA age	35.415	4.646	34.925	4.962	0.489
EA years of schooling completed	7.192	0.534	7.263	0.601	-0.071
# of years worked as EA	6.388	5.919	5.355	4.329	1.033
# of years worked in agricultural section, before became an EA	4.451	2.893	4.412	2.994	0.038
# of training received over the past 5 years	9.624	5.265	9.645	5.563	-0.021
Received training from MINAG (government)	0.344	0.477	0.289	0.460	0.055
Received training from Smallholder project	0.752	0.434	0.816	0.393	-0.064
# of weeks in training during the last 12 months	1.244	0.601	1.276	0.601	-0.032
One of the main topic of trainings was conservation agriculture	0.944	0.231	0.974	0.162	-0.030
Number of observations	125		38		163

Source: Extension Agent Survey, 2012; Contact Farmer Survey, 2012.

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.3: Effect of SLM Training Intervention on Contact Farmers (Includes Intercropping)

	Midline				Endline			
	Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Knowledge Score	0.642 (0.152)	-0.007 (0.033)	179	-0.111	0.661 (0.121)	0.067*** (0.023)	168	-0.014
# of techniques known by name	5.214 (1.601)	0.487 (0.370)	179	-0.086	5.024 (1.689)	1.343*** (0.389)	168	0.042
# of techniques adopted on own plot	2.048 (1.125)	0.799*** (0.269)	179	0.080	3.310 (1.352)	0.653** (0.315)	168	0.038
# of techniques adopted on any plot	5.429 (1.965)	0.824* (0.421)	179	-0.078	4.000 (1.562)	0.532 (0.366)	168	-0.021

Source: Household Survey and Contact Farmer Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 5.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.4: Effect of SLM Training Intervention on Other Farmers (Includes Intercropping)

		Midline				Endline			
		Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Knowledge score	Female	0.339 (0.143)	0.005 (0.013)	3423	0.010	0.410 (0.178)	-0.012 (0.018)	2951	0.012
	Male	0.358 (0.148)	0.008 (0.014)	2461	0.022	0.449 (0.162)	-0.012 (0.016)	2120	0.013
# of techniques known by name	Female	2.377 (1.525)	0.083 (0.138)	3423	0.022	2.486 (1.533)	0.006 (0.186)	2951	0.003
	Male	2.652 (1.622)	0.025 (0.141)	2461	0.015	2.941 (1.666)	-0.159 (0.191)	2120	0.009
# of techniques adopted	Female	1.415 (0.879)	-0.045 (0.086)	3423	0.005	1.757 (1.052)	0.096 (0.107)	2951	0.002
	Male	1.560 (0.924)	-0.045 (0.087)	2461	0.012	2.044 (1.100)	-0.006 (0.114)	2120	-0.001

Source: Household Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.5: SLM Learning before 2010 in Treated and Control Communities (Recall)

Variables	Treated Mean	Control Mean	Difference of Mean
<i>Contact Farmers</i>			
Learned mulching	0.620	0.762	-0.141*
Learned strip tillage	0.321	0.429	-0.107
Learned micro-catchments	0.504	0.524	-0.020
Learned contour farming	0.307	0.381	-0.074
Learned crop rotation	0.591	0.690	-0.099
Learned row planting	0.285	0.238	0.047
Learned improved fallowing	0.212	0.262	-0.050
Number of observations	137	42	179
<i>Other Farmers†</i>			
Learned mulching	0.306	0.337	-0.031
Learned strip tillage	0.182	0.227	-0.045
Learned micro-catchments	0.145	0.113	0.032
Learned contour farming	0.039	0.048	-0.009
Learned crop rotation	0.360	0.360	0.000
Learned row planting	0.104	0.114	-0.010
Learned improved fallowing	0.101	0.104	-0.003
Number of observations	4,385	1,499	5,884

Sources: Household Survey, 2012.

Note: †T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.6: SLM Adoption before 2010 in Treated and Control Communities (Recall)

Variables	Treated Mean	Control Mean	Difference of Mean
<i>Contact Farmers</i>			
Adopted mulching	0.489	0.405	0.084
Adopted strip tillage	0.248	0.214	0.034
Adopted micro-catchments	0.190	0.167	0.023
Adopted contour farming	0.007	0.000	0.007
Adopted crop rotation	0.314	0.262	0.052
Adopted row planting	0.124	0.095	0.029
Adopted improved fallowing	0.036	0.024	0.013
Number of observations	137	42	179
<i>Other Farmers†</i>			
Adopted mulching	0.181	0.203	-0.022
Adopted strip tillage	0.087	0.118	-0.031
Adopted micro-catchments	0.059	0.036	0.023
Adopted contour farming	0.002	0.000	0.002
Adopted crop rotation	0.121	0.132	-0.011
Adopted row planting	0.055	0.059	-0.005
Adopted improved fallowing	0.005	0.005	0.000
Number of observations	4,385	1,499	5,884

Sources: Household Survey, 2012.

Note: †T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.7: Gender Barriers to Adoption (Mean Differences within the Control Group)

Variables	Midline			Endline		
	Male Mean	Female Mean	Difference of Mean	Male Mean	Female Mean	Difference of Mean
<i>Production</i>						
Grew maize	0.650	0.601	0.048	0.753	0.583	0.170***
Grew sorghum	0.122	0.305	-0.183***	0.179	0.332	-0.153**
Grew cotton	0.188	0.024	0.164***	0.096	0.014	0.082***
Grew sesame	0.248	0.092	0.156***	0.181	0.093	0.088**
Grew cassava	0.198	0.154	0.044	0.166	0.128	0.038
Grew cowpea	0.265	0.394	-0.129	0.351	0.347	0.004
Grew pigeon pea	0.204	0.167	0.036	0.233	0.180	0.053
<i>Farm Characteristics</i>						
Plot size (hectares)	1.015	0.821	0.194***	1.292	0.983	0.309***
Plot was flat	0.606	0.633	-0.027	0.570	0.551	0.019
Plot was burnt	0.243	0.268	-0.025	0.249	0.253	-0.003
Used herbicides/pesticides/fungicides	0.124	0.018	0.106***	0.048	0.002	0.046***
Used natural fertilizer	0.278	0.296	-0.018	0.51	0.42	0.09
Used chemical fertilizer	0.009	0.001	0.007	0.01	0.00	0.01
Number of observations	565	675	1,240	481	657	1,138

Sources: Household Survey, 2012, 2013.

Note: T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.8: Other Farmers' Characteristics between Attrition Groups

Variables	Both Rounds	Midline Only	Endline Only	Mean Diff. B-ML	Mean Diff. B-EL	Mean Diff. ML-EL
Is household head	0.609	0.506	0.460	0.102 ***	0.149 ***	0.046 *
Age	38.321	35.898	36.287	2.423 ***	2.034 **	-0.389
Years of schooling completed	1.934	2.242	2.559	-0.308 **	-0.624 ***	-0.316
Single	0.059	0.071	0.113	-0.012	-0.054 **	-0.042 **
Married	0.843	0.861	0.792	-0.019	0.050 *	0.069 ***
Divorced, widow, or separated	0.097	0.060	0.095	0.038 ***	0.003	-0.035 **
Total number of children	2.776	2.788	2.784	-0.012	-0.009	0.003
Total number of rooms	1.414	1.493	1.395	-0.079	0.019	0.098
Total landholdings	1.999	1.879	2.292	0.120	-0.294 *	-0.414 ***
Number of observations	4580	1304	496			

Sources: Household Survey, 2012, 2013.

Note: T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.9: Attrition of CFs and Households

Variables	Treated		Control		Diff. of Mean
	Mean	SD	Mean	SD	
CFs attrited from Midline	0.109	0.313	0.048	0.216	0.062
# of Obs.	137		42		179
Household attrited from Midline†	0.090	0.372	0.087	0.374	0.003
# of Obs.	2750		935		3685

Source: Household Survey and Contact Farmer Survey, 2012, 2013.

Note: †T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.10: Probability of CF and Household Attrition

	CF Village		Household
Treatment 1	0.074 (0.069)	Treatment 1	0.013 (0.014)
Treatment 3	0.003 (0.056)	Treatment 3	-0.011 (0.012)
Age	-0.006** (0.003)	Age	-0.001** (0.000)
Completed at least primary school	0.052 (0.064)	HH head completed at least primary school	-0.004 (0.012)
Single	-0.097 (0.199)	HH head Single	0.023 (0.021)
		HH head divorced, widow, or separated	0.043** (0.017)
Total number of children	-0.010 (0.013)	Total number of children	-0.006** (0.003)
Total landholding (hectares)	0.004 (0.012)	Total landholding (hectares)	-0.004 (0.003)
Total number of rooms	-0.022 (0.035)	Total number of rooms	-0.002 (0.008)
Number of years since formal training	-0.040* (0.024)	Number of years since formal training	0.005 (0.004)
Missing dummy	-0.138 (0.112)	Missing dummy	0.027 (0.020)
Household head was female	-0.033 (0.096)	Household head was female	0.000 (0.013)
% of household members was away	-0.394 (0.368)	% of household members was away	0.131** (0.066)
HH has non-own farming work	0.033 (0.080)	HH has non-own farming work	-0.013 (0.012)
HH has outside employment	-0.017 (0.078)	HH has outside employment	0.003 (0.017)
2012 precipitation shock	0.000 (0.002)	2012 precipitation shock	-0.001 (0.000)
Constant	0.352 (0.436)	Constant	0.030 (0.081)
N	178	N	3656
Adj. R-sq	(0.078)	Adj. R-sq	0.004

Source: Household Survey and Contact Farmer Survey, 2012, 2013.

Note: Regressions include posto fixed effect.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.11: Descriptive Statistics of Contact Farmers' Characteristics

Variables	Pooled		Men	Women	Difference of Mean
	Mean	SD	Mean	Mean	
<i>Midline</i>					
Is the head of household	0.970	0.171	1.000	0.727	0.273***
Age	41.080	10.362	41.599	36.909	4.690**
Years of schooling completed	5.487	2.872	5.672	4.000	1.672***
Single	0.015	0.122	0.011	0.045	-0.034
Married	0.945	0.229	0.972	0.727	0.244***
Divorced, separated, or widowed	0.040	0.197	0.017	0.227	-0.210***
Number of children (ages < 15 years)	3.759	2.151	3.847	3.045	0.802*
Landholdings	3.218	2.284	3.248	2.984	0.264
Number of rooms in the house	1.769	0.919	1.780	1.682	0.098
Number of observations	199		177	22	
<i>Endline</i>					
Is the head of household	0.938	0.242	1.000	0.690	0.310***
Age	43.311	10.703	43.515	42.500	1.015
Years of schooling completed	5.431	2.824	5.754	4.143	1.612***
Single	0.005	0.069	0.006	0.000	0.006
Married	0.938	0.242	0.982	0.762	0.220***
Divorced, separated, or widowed	0.057	0.233	0.012	0.238	-0.226***
Number of children (ages < 15 years)	3.646	2.177	3.772	3.143	0.630*
Landholdings	3.680	2.296	3.772	3.314	0.459
Number of rooms in the house	1.760	0.935	1.744	1.857	-0.113
Number of observations	209		167	42	

Source: Household Survey, 2012, 2013.

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.12: Descriptive Statistics of Other Farmers' Characteristics

Variables	Pooled		Men	Women	Difference
	Mean	SD	Mean	Mean	of Mean
<i>Midline</i>					
Is the head of household	0.586	0.493	0.944	0.329	0.615***
Age	37.784	14.507	40.312	35.967	4.345***
Years of schooling completed	2.003	2.802	3.351	1.033	2.319***
Single	0.062	0.241	0.074	0.054	0.020
Married	0.847	0.360	0.904	0.806	0.098***
Divorced, separated, or widowed	0.089	0.285	0.021	0.138	-0.117***
Number of children (ages < 15 years)	2.778	2.014	2.920	2.677	0.243***
Landholdings	1.972	1.772	2.110	1.873	0.236**
Number of rooms in the house	1.432	0.730	1.491	1.389	0.102*
Number of observations	5,884		2,461	3,423	
<i>Endline</i>					
Is the head of household	0.594	0.491	0.919	0.360	0.559***
Age	38.775	14.322	41.193	37.038	4.155***
Years of schooling completed	2.114	2.793	3.608	1.041	2.567***
Single	0.048	0.214	0.056	0.042	0.014*
Married	0.851	0.356	0.916	0.804	0.112***
Divorced, separated, or widowed	0.101	0.301	0.028	0.153	-0.125***
Number of children (ages < 15 years)	2.890	2.071	3.072	2.760	0.312***
Landholdings	2.401	2.336	2.602	2.257	0.346***
Number of rooms in the house	1.412	0.718	1.461	1.377	0.083
Number of observations	5,076		2,122	2,954	

Source: Household Survey, 2012, 2013.

Note: T test inferences are based on standard errors clustered at the community level.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.13: Effect of SLM Training Intervention on Contact Farmers' SLM Knowledge

Knowledge Score	Midline				Endline			
	Control Mean(SD)	ITT	N	Adjusted R2	Control Mean(SD)	ITT	N	Adjusted R2
Mulching	0.833 (0.258)	0.038 (0.047)	179	-0.099	0.952 (0.139)	0.030 (0.022)	168	-0.126
Strip Tillage	0.460 (0.345)	0.051 (0.072)	179	-0.102	0.563 (0.270)	0.122* (0.066)	168	-0.076
Micro-catchments	0.798 (0.399)	-0.031 (0.082)	179	-0.068	0.798 (0.332)	0.111* (0.057)	168	-0.001
Contour Farming	0.524 (0.369)	0.030 (0.073)	179	-0.094	0.516 (0.405)	0.181** (0.077)	168	-0.039
Crop Rotation	0.540 (0.329)	-0.063 (0.070)	179	-0.102	0.595 (0.271)	0.067 (0.049)	168	-0.076
Row Planting	0.476 (0.505)	-0.155 (0.103)	179	-0.039	0.143 (0.354)	0.118 (0.088)	168	-0.102
Improved Fallowing	0.738 (0.276)	0.008 (0.060)	179	-0.124	0.643 (0.229)	0.024 (0.054)	168	-0.148

Source: Household Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 5.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.14: Effect of SLM Training Intervention on Other Farmers' SLM Adoption

Adoption		Midline				Endline			
		Ctrl. Mean	ITT	N	Adj. R2	Ctrl. Mean	ITT	N	Adj. R2
Mulching	Female	0.248	-0.051 (0.044)	3423	0.009	0.390	0.056 (0.049)	2951	0.009
	Male	0.248	-0.022 (0.041)	2461	0.004	0.512	0.005 (0.051)	2120	0.000
Strip Tillage	Female	0.153	-0.008 (0.039)	3423	0.029	0.200	-0.004 (0.038)	2951	0.002
	Male	0.161	-0.007 (0.040)	2461	0.023	0.225	-0.003 (0.044)	2120	0.006
Micro-catchments	Female	0.041	0.000 (0.013)	3423	-0.001	0.084	0.022 (0.024)	2951	0.002
	Male	0.039	0.033* (0.017)	2461	0.006	0.139	-0.020 (0.029)	2120	-0.001
Contour Farming	Female	0.000	0.002 (0.001)	3423	0.000	0.007	-0.006 (0.005)	2951	0.010
	Male	0.000	0.002 (0.002)	2461	-0.001	0.017	-0.014 (0.010)	2120	0.016
Crop Rotation	Female	0.131	0.005 (0.020)	3423	0.002	0.151	0.039 (0.028)	2951	0.003
	Male	0.182	-0.013 (0.024)	2461	0.004	0.160	0.035 (0.033)	2120	-0.002
Row Planting	Female	0.073	0.012 (0.020)	3423	0.010	0.061	0.002 (0.021)	2951	0.001
	Male	0.093	-0.008 (0.023)	2461	0.011	0.095	-0.023 (0.026)	2120	0.003
Improved Fallowing	Female	0.014	-0.014* (0.008)	3423	0.019	0.019	0.002 (0.006)	2951	0.005
	Male	0.026	-0.020* (0.011)	2461	0.018	0.027	0.012 (0.013)	2120	0.002

Source: Household Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.15: From Whom Other Farmers Claim to Learn SLM Techniques

		Midline				Endline			
		Ctrl. Mean	ITT	N	Adj. R2	Ctrl. Mean	ITT	N	Adj. R2
Mulching	extension	0.041	-0.007	5884	0.017	0.034	-0.012	5071	0.009
	agent		(0.011)				(0.011)		
	contact	0.091	0.008	5884	0.009	0.232	-0.011	5071	0.012
	farmer		(0.022)				(0.034)		
	other	0.296	-0.023	5884	0.021	0.301	-0.003	5071	0.003
Strip Tillage	farmer		(0.041)				(0.039)		
	extension	0.007	0.004	5884	0.005	0.003	0.005	5071	0.002
	agent		(0.006)				(0.004)		
	contact	0.023	0.003	5884	0.003	0.056	-0.010	5071	0.001
	farmer		(0.009)				(0.019)		
Micro- catchments	other	0.166	-0.014	5884	0.036	0.162	0.024	5071	0.004
	farmer		(0.031)				(0.036)		
	extension	0.007	0.013**	5884	0.011	0.005	0.001	5071	-0.001
	agent		(0.005)				(0.003)		
	contact	0.041	0.020	5884	0.006	0.089	-0.011	5071	0.012
Contour Farming	farmer		(0.018)				(0.022)		
	other	0.095	0.021	5884	0.004	0.078	0.012	5071	0.005
	farmer		(0.018)				(0.023)		
	extension	0.002	0.002	5884	0.006	0.003	-0.002	5071	0.000
	agent		(0.002)				(0.002)		
Crop Rotation	contact	0.005	0.010**	5884	0.002	0.015	0.001	5071	0.007
	farmer		(0.005)				(0.007)		
	other	0.037	0.003	5884	0.013	0.013	-0.008	5071	0.004
	farmer		(0.011)				(0.006)		
	extension	0.021	0.004	5884	0.011	0.012	-0.004	5071	0.002
Row Planting	agent		(0.010)				(0.005)		
	contact	0.030	0.012	5884	0.006	0.115	-0.021	5071	0.011
	farmer		(0.011)				(0.028)		
	other	0.302	-0.004	5884	0.006	0.253	0.035	5071	0.002
	farmer		(0.025)				(0.035)		
Improved Fallowing	extension	0.004	0.002	5884	0.001	0.003	0.000	5071	0.000
	agent		(0.003)				(0.003)		
	contact	0.010	0.000	5884	0.000	0.030	0.001	5071	0.000
	farmer		(0.004)				(0.014)		
	other	0.099	0.018	5884	0.007	0.048	0.003	5071	0.002
	farmer		(0.025)				(0.018)		
	extension	0.007	0.001	5884	0.002	0.005	-0.004	5071	0.001
	agent		(0.006)				(0.003)		
	contact	0.011	-0.002	5884	0.001	0.025	-0.003	5071	0.004
	farmer		(0.005)				(0.009)		
	other	0.073	-0.020	5884	0.007	0.083	-0.007	5071	0.004
	farmer		(0.019)				(0.022)		

Source: Household Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.16: Other Farmers' Perceptions of Technique's Labor Savings Compared to Traditional Method

Technique Saves		Control Mean	ITT	Midline	
Labor Time				N	Adjusted R2
Mulching	Female	0.133	-0.025 (0.035)	3423	0.008
	Male	0.142	-0.015 (0.034)	2461	0.018
Strip Tillage	Female	0.156	-0.003 (0.036)	3423	0.018
	Male	0.177	-0.030 (0.040)	2461	0.006
Micro-catchments	Female	0.008	0.006 (0.005)	3423	0.002
	Male	0.008	0.019** (0.009)	2461	0.001
Contour Farming	Female	0.005	0.009 (0.006)	3423	0.005
	Male	0.008	-0.006 (0.005)	2461	0.002
Crop Rotation	Female	0.063	0.007 (0.017)	3423	0.000
	Male	0.090	0.011 (0.021)	2461	0.005
Row Planting	Female	0.041	0.010 (0.014)	3423	0.003
	Male	0.055	0.009 (0.018)	2461	0.009
Improved Fallowing	Female	0.034	-0.010 (0.014)	3421	0.009
	Male	0.043	-0.011 (0.016)	2461	0.008

Source: Household Survey, 2012.

Note: Regressions include the same explanatory variables as models in Table 8.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.17: Contact Farmers' Perceptions of SLM Techniques

Variables		Increase productivity	Reduce land preparation effort	Reduce planting seed effort	Reduce harvesting effort	N
Mulching	Treated	0.569	0.423	0.307	0.234	137
	Control	0.595	0.452	0.310	0.238	42
Strip tillage	Treated	0.314	0.270	0.321	0.139	137
	Control	0.286	0.238	0.286	0.190	42
Micro-catchments	Treated	0.212	0.088	0.124	0.073	137
	Control	0.238	0.143	0.119	0.071	42
Contour farming	Treated	0.095	0.022	0.044	0.036	137
	Control	0.071	0.048	0.071	0.071	42
Crop rotation	Treated	0.401	0.255	0.190	0.182	137
	Control	0.357	0.262	0.214	0.190	42
Row planting	Treated	0.182	0.117	0.168	0.073	137
	Control	0.167	0.095	0.095	0.071	42
Improved fallowing	Treated	0.124	0.036	0.036	0.044	137
	Control	0.095	0.071	0.048	0.048	42

Source: Household Survey, 2012.

Note: ***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.

Table A.18: Effect of SLM Training Intervention on Contact Farmers' Labor Time

	Control	Midline			Control	Endline		
	Mean(SD)	ITT	N	Adj. R2	Mean(SD)	ITT	N	Adj. R2
Hours spent on preparation of land	5.762 (13.879)	-4.124** (1.977)	178	-0.064	6.429 (15.353)	-2.167 (2.857)	168	-0.070
Hours spent on seeding	6.071 (13.767)	-1.183 (2.717)	178	-0.036	10.357 (17.862)	-6.386** (3.081)	168	-0.083
Hours spent on transplantation	3.476 (9.094)	-2.105 (1.613)	178	0.020	1.738 (6.666)	-0.751 (1.516)	168	-0.082
Hours spent on irrigation	0.000 (0.000)	-0.214 (0.380)	178	-0.130				
Hours spent on sacha	15.333 (15.550)	0.258 (3.176)	178	-0.050	5.833 (14.252)	-0.093 (2.539)	168	-0.082
Hours spent on protection	0.000 (0.000)	1.061 (0.805)	178	-0.131	0.000 (0.000)	0.656 (0.658)	168	-0.027
Hours spent on harvesting	6.214 (15.645)	-0.988 (2.391)	178	-0.132	15.810 (19.573)	-3.314 (3.711)	168	-0.011
Total weeks spent on farming in last year	26.143 (17.512)	-1.233 (3.615)	178	-0.114	30.381 (19.196)	-9.298** (3.720)	168	-0.056

Source: Household Survey, 2012, 2013.

Note: Regressions include the same explanatory variables as models in Table 5.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level for t statistics.