Seeing is Believing? Evidence from an Extension Network Experiment

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April 15, 2014

Abstract

We test knowledge diffusion through an existing network of agricultural extension. We track information transmission through two nodes: from extension agents to contact farmers (CFs), and from CFs to others. We find that knowledge does not propagate efficiently in a classic training and visit (T&V) model. Directly trained CFs are significantly more likely to demonstrate and adopt techniques and learn-by-doing. Subsequent diffusion within the community is limited: only the technique with perceived labor savings is practiced by other males, with an effect size of 150 percent.

JEL Classifications: D83, O13, Q16.
Keywords: technology adoption, agricultural extension service, contact farmer, sustainable land management practices (SLM).

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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. The authors benefited from suggestions and comments during presentations at the CSAE (Oxford), the Mid-Western Economic Development Conference, and the Development Impact Evaluation Seminar Series at the World Bank. 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 Massuanganhe, 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. Usual disclaimers apply.

1 Introduction

Understanding low levels of agricultural technology diffusion among subsistence farmers is an ongoing empirical debate. In Africa, increasing adoption of proven agricultural innovations will be crucial to accelerate the productivity necessary to achieve food security (Hazell, 2013). Supply-side constraints, such as information failures, high acquisition costs and underdeveloped input delivery systems, hinder the use of improved agricultural practices (Shiferaw, Kebede, and You, 2008; Suri, 2009). Demand-driven factors, such as behavioral biases, time inconsistency (Duflo, Kremer, and Robinson, 2011), and risk aversion also preclude agricultural investments (Rosenzweig and Binswanger, 1993; Rosenzweig and Wolpin, 1993; Ghadim, Pannell, Burton, 2005; Dercon and Christaensen, 2011).

While extension networks have shown some potential in delivering information to motivate agricultural development (Feder, Just, and Zilberman, 1985), the evidence is mixed at best (Purcell and Anderson 1997; Gautam, 2000; Anderson and Feder, 2007; Benin et al., 2007; Davis et al., 2010; Waddington et al., 2010; Agyei-Holmes et al., 2011). Compounding the limited impact of extension services is the severe budget constraint agricultural ministries typically face (Bindlish and Evenson, 1997). Yet, agricultural extension systems are rapidly expanding (Davis, 2008; Taye, 2013), and researchers in the field increasingly recognize the need to formally document what modalities can best deliver information to farmers and lead to adoption (Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Magnan et al., 2012, McNiven and Gilligan, 2012; BenYishay and Mobarak, 2013). Understanding the role of supply-side and demand-side information constraints in technological adoption could result in pragmatic solutions to improve existing extension networks.

This study contributes to the literature on learning and adoption of improved technologies by tracking technology diffusion through a large, existing extension network in 200 villages of Mozambique's Zambezi valley. Recent field trials in Africa concentrate on participatory approach models, such as field trials, farmer field schools, and innovation platforms (Howard et al., 1999; Agyei-Holmes et al., 2011; Duflo et al., 2011; Pamuk et al., 2013; Duflo et al., 2014). While these methods have shown some potential in improving learning and adoption, they do not address the key problem of the sustainability of agricultural extension networks.

A popular, low-cost option for diffusing knowledge to the village level is the Training and Visit

(T&V) system. Garden variety T&V models expand the geographic coverage of extension by engaging extension agents with a village point-of-contact (contact farmer). Use of representative communal farmers serves the purpose of increasing access to information at a low cost. Our study builds on previous work (Gautam, 2000; Anderson and Feder, 2007; BenYishay and Mobarak, 2013) to assess the sustainability of the T&V model. Working to disseminate a new technology through an existing network makes our results immune to "novelty bias", where farmers respond to the intervention initially but lose interest over time (Gravetter and Forzano, 2011).

A possible disadvantage of the T&V model is that it may not actually address the constraints faced by extension services. Typically, contact farmers (*Facilitadores Communitarios*, CFs) are not formally trained and do not derive any (explicit) income from their role. The model requires that CFs not only learn from extension agents (EAs), but teach others in their community. By directly testing the extent of knowledge diffusion at these two nodes, we provide new insights on the capacity of an existing T&V extension network to propagate information.

In practice, we work with an existing T&V extension system in the Zambezi valley of Mozambique, and track the diffusion of a somewhat novel technology: sustainable land management practices (SLM). EAs and CFs were established at baseline, and the adoption of SLM practices was low. Given the small number of extension workers in the area, reasonable levels of statistical power cannot be reached by assigning the intervention at the level of the EA. Instead, all EAs are trained on SLM and we randomly assign CFs to two modalities: (i) the garden variety T&V model, where EAs are responsible for training their CFs; and (ii) a revised version of the T&V approach, where direct and structured training was administered to CFs, following the same SLM curriculum as the EAs' training. All else is held equal across CFs. All CFs (with or without central training) were asked to demonstrate techniques they knew for the benefit of the community. We track learning and adoption through two nodes of the network, EA-to-CF and CF-to-others interactions, over the course of three years (2010-2012). Comparing CFs' SLM demonstration activities, knowledge and adoption across treatment arms sheds light on the extent of knowledge diffusion in the T&V model. It 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 exploit the wedge in CFs' knowledge created by these exogenous variations in training quality to explore whether modifying the demonstration, knowledge and adoption of a single farmer in a community (the CF) can lead others to learn. Communication on agricultural technology is typically limited among subsistence farmers (Duflo, Kremer and Robinson, 2006). Targeting influential members of a community can be an attractive way to remedy both supply-side (knowledge and exposure) and demand-side (risk aversion and perception biases) constraints to adoption. We directly test this second hypothesis of the T&V model by measuring differences in information diffusion among farmers exposed to a directly trained CF in their community.

The impact of exposing farmers to a training and demonstration experiment on their adoption behavior is a *priori* ambiguous. Should uncertainty of the technological benefits hinder adoption, then providing access to enhanced knowledge, through a more enlightened CF, would, in principle, have a positive effect on adoption. The presence of elite capture may alternatively reinforce barriers (Bardhan and Mookherjee, 2000; 2005). For example, CFs could intentionally disseminate a subset of known techniques. Recent work shows that elites only nominally increase their access to resources (Alatas et al., 2013). Fear of popular disapproval and electoral mechanisms minimize the capture.

Common 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 proven 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).

The conservation agriculture technology examined in this study is 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). SLM practices are widely encouraged in sub-Saharan Africa, as studies have demonstrated these technologies incur less upfront monetary costs, mitigate the prevalence of soil erosion, improve the efficiency of water use, and increase yields (Liniger et al., 2011). However, the high variable costs in terms of time and labor allocation can be prohibitive. Many of the benefits (such as improvements in soil quality) are realized over a longer time horizon. Reducing the uncertainty of the technology's benefits may serve as one stepping stone to inducing subsistence farmers to adopt, given high levels of risk aversion with regard to their cultivation decision (Eswaran and Kotwal, 1990).

Fifteen months after the initial training, we find that the T&V model instilled similar levels of familiarity with the new technique among CFs as a direct, central training. Yet, demonstration activities as well as CFs' private adoption were much higher in communities where the CFs had been centrally trained. This increase in adoption augmented 30 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' awareness and adoption of one of the techniques adopted by the CFs, this is not the case for all demonstrated techniques. Male and female farmer knowledge of micro-basins increased 6 and 8 percentage points, respectively, (two years after the initial CF training). Men increased their micro-basins' adoption by 6 percentage points (an effect size of 150%) in 2012.

The adoption of techniques post-training fostered learning-by-doing for the CFs, but had little bearing on others' adoption decisions. Indeed, the use of micro-basins among other farmers followed increases in CF adoption of the technique in the communities exposed to the revised T&V model. Of the additional techniques adopted by the trained CFs (strip tillage, micro-basins, and contour farming), the adoption of micro-basins 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-basins as 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 farmer's 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 in a linear process: agricultural innovations are created by researchers, then distributed by extension workers, and lastly adopted by producers (Pamuk et al., 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 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.

Most of the literature evaluates the T&V system through non-experimental methods and provides mixed results (Purcell and Anderson 1997; Gautam, 2000; Anderson and Feder, 2007; Benin et al., 2007; Davis et al., 2010; Waddington et al., 2010; Agyei-Holmes et al., 2011). 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-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,[1] 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 conditions underlying most extension networks raise concerns about the efficacy of the standard 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. Similarly, there is 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 a central training of the CFs, we provide a direct test of the first modality of the T&V model, which assumes EAs will successfully train CFs and emulate demonstration activities in their respective villages.

[1] EAs 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.

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, since our study districts are receiving enhanced support from the local Services for Economic Activities office. Yet, the ratio of EAs per administrative post is on par with the national average of 1.89 (Gêmo and Chilonda, 2013).[2] Hence, it is unclear that EAs in our sample face a smaller set of competing 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 modality.[3] 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

[2] This ratio is calculated using the 2010 figures from the Direçâo Nacional de Extensâ Agraria (DNEA), available at the following URL: http://www.worldwide-extension.org/africa/mozambique/s-mozambique.

[3] The 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.

experimental sample are supposed to receive additional 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.[4] 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.[5] 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 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.[6]

[4] There 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 agnostically present the adoption results on any plot (own or demonstration).

[5] A 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.1).

[6] While access to the EA 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 EA mechanically goes up in the treatment at endline.

3.1 SLM Trainings

Our training intervention encompasses seven[7] SLM techniques: Mulching, Crop Rotation, Strip Tillage, Micro-basins, Contour Farming, Row Planting, and Improved Fallowing.[8] Table 1 summarizes the functionality of each of these techniques (Liniger et al., 2011). Mulching and crop rotation offer the greatest improvements to production. They were also the most common techniques applied by farmers at baseline, though adoption rates were far from universal (Tables A.4-A.5) . Use of strip tillage, micro-basins, and contour farming is deemed effective at improving water efficiency and soil fertility. As row planting is often used to reinforce some of the above practices (e.g., mulching and strip tillage), the independent benefits of row planting are undocumented. Given their advantages, SLM technologies present 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 staff[9] with support from MINAG staff[10].

[7]Intercropping 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.2-A.3).

[8]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-basins (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.

[9]In 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.

[10]Given the low literacy of farmers, a film covering all techniques substituted the initial lecture format in the second

After the first training, all CFs ("Control" and "Treatment") received a new toolkit[11] (bicycle, tools to plow the land, and smaller articles) and the mandate to disseminate the techniques most pertinent to their local area on their demonstration plots.[12] The only difference between our "Treatment"and "Control" CFs is the modality through which they received training on the selected seven SLM techniques. 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.[13] 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. 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.

3.2 Data

We conducted two follow-up surveys, a 2012 (midline) round, and a 2013 (endline), which form

training of the CFs.

[11]The 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.

[12]The 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.

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

a panel of households and CFs in the study area.[14] 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 this region. 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 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. In spite of these differences, (recalled) pre-intervention adoption rates among CFs in control and treated communities are similar.[15] Farmers' (recalled) baseline SLM learning and

[14]Following 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.

[15]Balance tests for the CF and other farmers' knowledge and adoption of individual SLM techniques at baseline

adoption rates are also similar across treatments (Table 3).[16]

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 (2013) 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. Objective adoption measures were also collected for two plots per household and largely corroborate the self-reported outcomes (see Kondylis, Mueller, and Zhu (2013) for a detailed comparison).[17]

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

are reported in Tables A.4-A.5.

[16] Even 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.

[17] Our decision to focus on the knowledge score and self-reported adoption outcomes is motivated by the conclusions of Kondylis, Mueller, and Zhu (2013). 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 instead focus on a more inclusive measure of adoption provided by self-reports of men and women surveyed in the sample.

and his/her partner or spouse. If a polygamous household was encountered, the main spouse was interviewed. 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.[18] Selective sample attrition is of definite concern, and we check for selective attrition in all specifications.

3.5 Empirical Strategy

We measure information diffusion through a direct training model relative to the traditional, T&V extension network. A particularly attractive feature of our design is that we track information diffusion through an existing network: from EA-to-CF, and CF-to-others. We first measure to what extent directly training CFs affects CFs' and others' knowledge and adoption.[19] 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 CFs[20] and others in the community, Y, using a simple reduced-form specification:

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

T takes the value 1 for each community j with a centrally trained CF. Individual i, household h, and district indicator variables are included in the vector $\mathbf{X}$ to improve the precision of the estimated coefficients.[21] 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

[18] For 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.

[19] CFs 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.

[20] CF-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.

[21] We address omitted variable bias by including variables that reflect CF (or other farmers') demographic characteristics, district indicators, and indicators for treatment arms not analyzed in the present study.

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.6).

At times, we report the ITT estimates of the knowledge and adoption of specific techniques to document the learning channels from the training (particularly for the CFs) and methods of transmission from CF to others. Since there are several techniques, the probability of detecting statistical significance due to the intervention because of Type I error increases. We therefore also present the Šidàk and Bonferonni-corrected p-values in which account for a family of t tests (Abdi, 2007) .

We separate specifications by round for a few reasons. First, 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.7). Second, in spite of individual attrition being uncorrelated with the treatment (Table A.8), evolution in the realities of the program on the ground 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.4-A.5). 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.9). 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; BenY-ishay 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), and wane over time.

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 proven to improve water efficiency and soil fertility (strip tillage, micro-basins, and contour farming, as outlined in Table 1). Effect sizes range from 29 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 but one technique (contour farming).

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.[22] 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.10 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

[22]Figure A.1 provides the point estimates of the knowledge and adoption effects of the intervention with the adjustment of the familywise error rate.

similar to those achieved on adoption: the largest gains are experienced for contour farming, with slightly lower gains in strip tillage and micro-basins. 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.

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:

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

where t signifies the midline and *t-1* baseline. The results in Table 7 are suggestive that the training might have reinforced the application of some techniques (strip tillage) and encouraged others (improved fallowing). There appears to be no substitution of techniques. Although the sign of the parameter of the variable interacting the treatment and previous adoption (β_3) is negative for mulching, its magnitude is 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 increased interaction with CFs in the treatment communities (Table 8) and learning techniques explicitly from CFs (Table A.11). 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.

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.12). We find that increasing exposure to SLM information through the trained CF affected farmers' perceptions of the adoption costs for micro-basins only. The intervention significantly increased the proportion of farmers who perceive micro-basins to be labor-saving by 1-2 percentage points, amounting to a 100-percent increase relative to the control for both male and female farmers.

The changes in farmers' perceptions are complementary to the ITT estimates for others' adoption by technique. From Figure 4, we observe male farmers exposed to the intervention were more likely to adopt micro-basins by 6 percentage points (an effect size of 150%). 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. Furthermore, the magnitude of the adoption effect is much larger than the shifts in farmers' perceptions.

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. Noting that our measure of labor efforts is inclusive of all techniques adopted by the CF (not exclusive to micro-basins), we provide ITT estimates of the CF labor efforts for various agricultural tasks (Table A.13). The results in the Appendix indicate trained, CFs spend a nominal increase in time (1-hour) on land protection in a given week in exchange for a four hour-gain in time spent preparing land (midline).

Thus, male farmers may be particularly motivated to adopt micro-basins 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-basins offer an additional cost-advantage. Unlike strip tillage and contour farming, additional tools are not required to create micro-basins (Liniger et al., 2011).

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, or wealth. 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-basins as outcomes. 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, and had above median landholdings are provided. For male farmers, exposure to increased CF activity yields larger point estimates when CFs are older, more educated and wealthier. For female farmers, interacting treatment with CF characteristics increases the precision of our estimates in 2012. We detect 3 and 4 percentage-point increases in adoption when the messenger is above the median age and has above median landholdings. The 2013 estimate suggests that more affluent communicators are most effective in getting women to adopt, with a 6.5 percentage-point increase.

We lastly interact the treatment variable with whether the primary two crops produced by other farmers were similar to those produced by CFs. Social learning has been postulated to be less prevalent among farmers with heterogeneous farming conditions (Munshi, 2004). 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.[23] Similarity in crop profile has the largest effect on women at midline (6 percentage points) and endline (12 percentage points). Similarity in the production profile of the CF achieves a greater response from women than CF wealth. Delays in women's adoption may stem from gendered differences in production technologies and an inability to extrapolate demonstrated activities to their own plot.

5 Discussion

Our study aims to reveal the role of existing extension models to distribute solutions for 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. Farmers choose to adopt one of three SLM techniques that the trained, CFs adopted. For women, we find that awareness improves without actual adoption. Looking at the multiplier effect of CFs' demonstration activities, these results imply that a one percentage point increase in CF

[23] Although 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, however. The intervention has no effect on the crop decisions of women, however.

demonstration of micro-basins induce other male farmers to increase their adoption by 0.3 percentage points.

Farmers' perceived costs of SLM techniques pose one obvious demand-side constraint to adoption. Adoption of micro-basins increased 6 percentage points among male farmers exposed to the intervention with no changes in adoption for the other two techniques covered by the trained CFs. Earlier work suggests the construction of micro-basins predominantly relies on additional labor effort rather than the acquisition of tools for its implementation. The average male and female farmer exposed to the intervention in our study is more likely to perceive micro-basins as labor saving. Their CFs realized labor savings in the form of a 4-hour reduction in land preparation in a given week (although these are inclusive of all three techniques CFs adopted). The descriptive evidence is consistent with farmers' beliefs updating in response to the intervention following their adoption of micro-basins or after observing the CF's demonstration activities.

The profile of the "seed adopters" influences whether woman act on the information they receive. We observe women are more likely to adopt when the messenger is older and wealthier at midline, with CF wealth having a larger, persistent effect over time. Women are also more likely to act on the information they receive when the CF has similar cropping patterns: their micro-basins' adoption increases by 6 percentage points at midline and 12 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

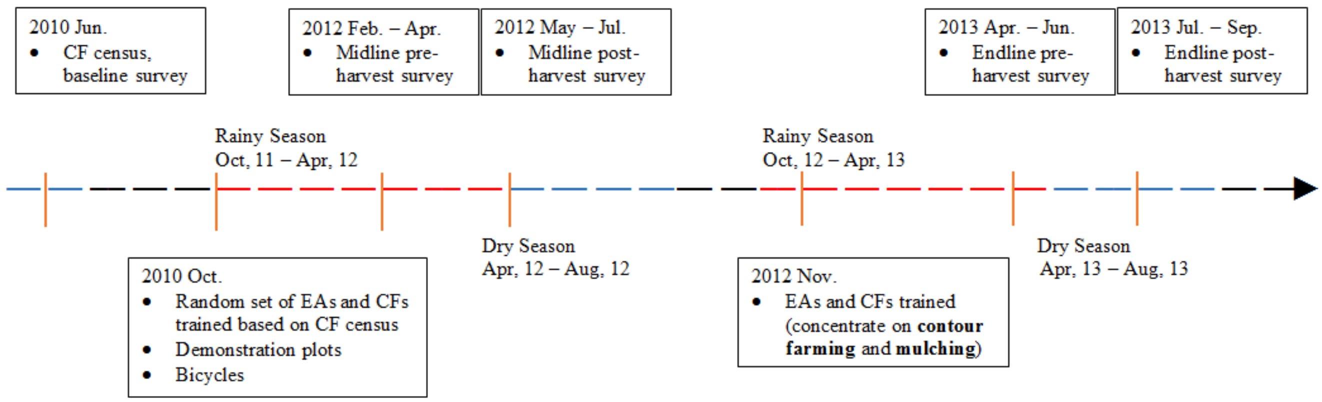

Figure 2: Geographical Distribution of (Non-CF) Households

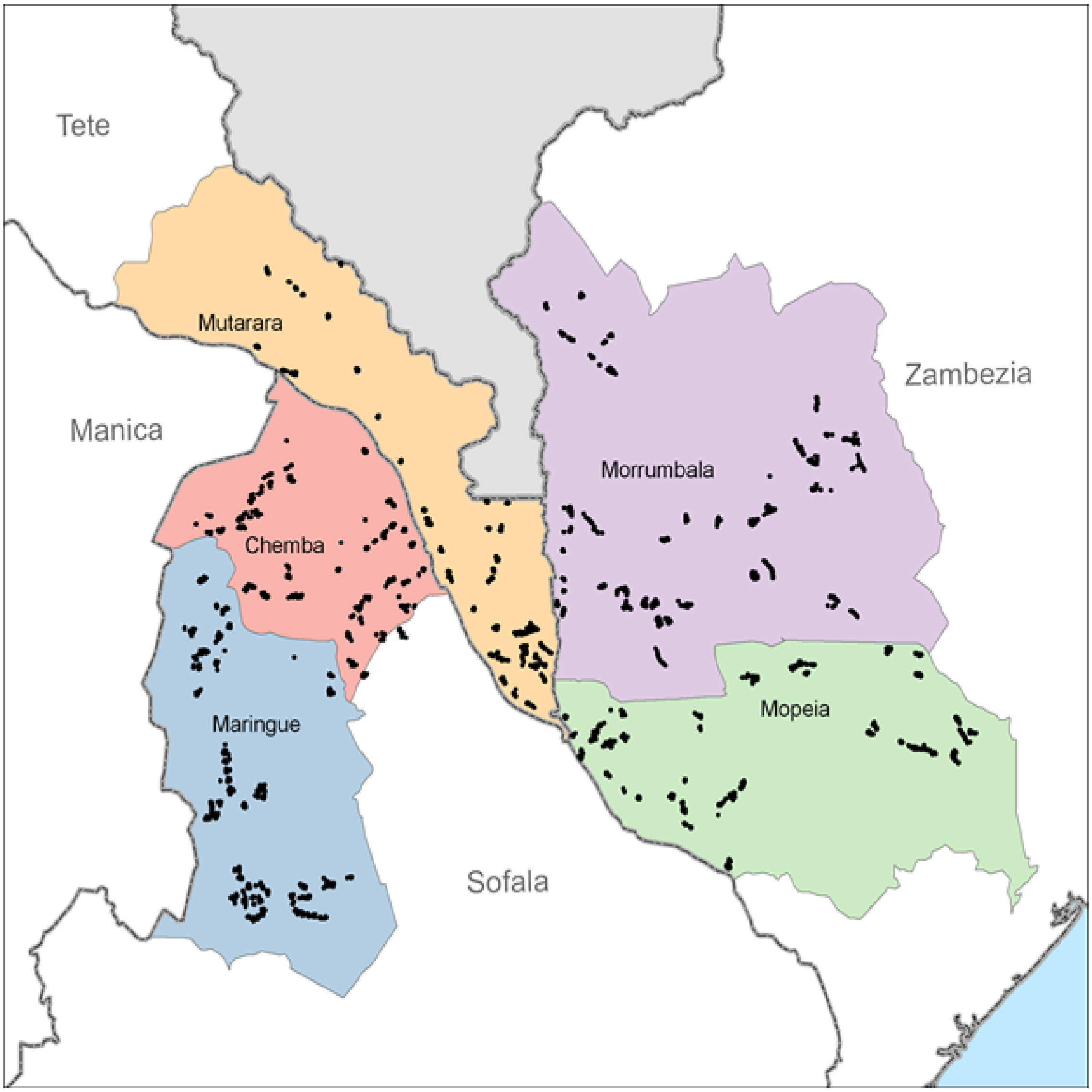

Figure 3: Effect of SLM Training Intervention on Contact Farmers

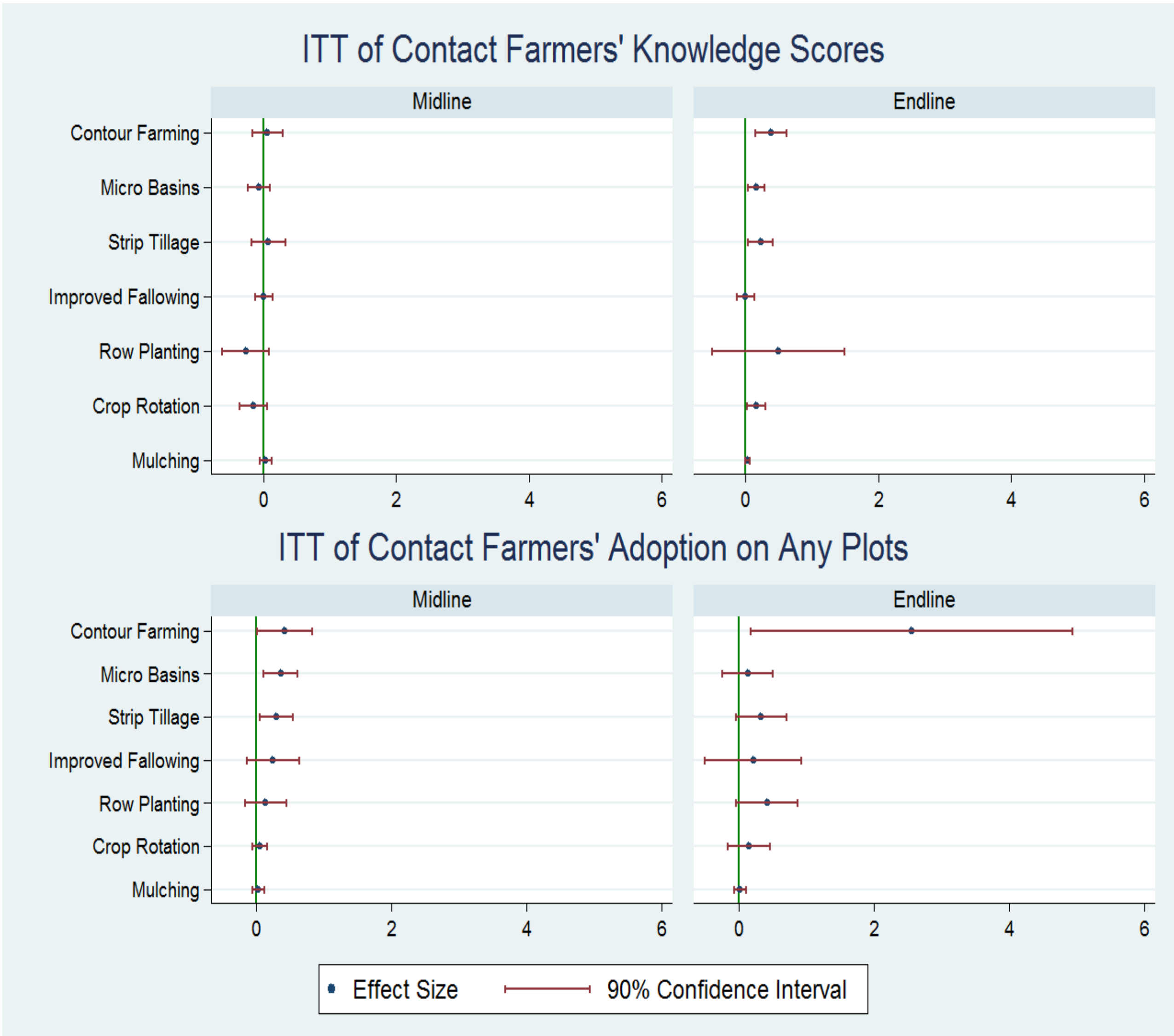

Figure 4: Effect of SLM Training Intervention on Other Farmers' SLM Adoption with Adjustment of Familywise Error Rate

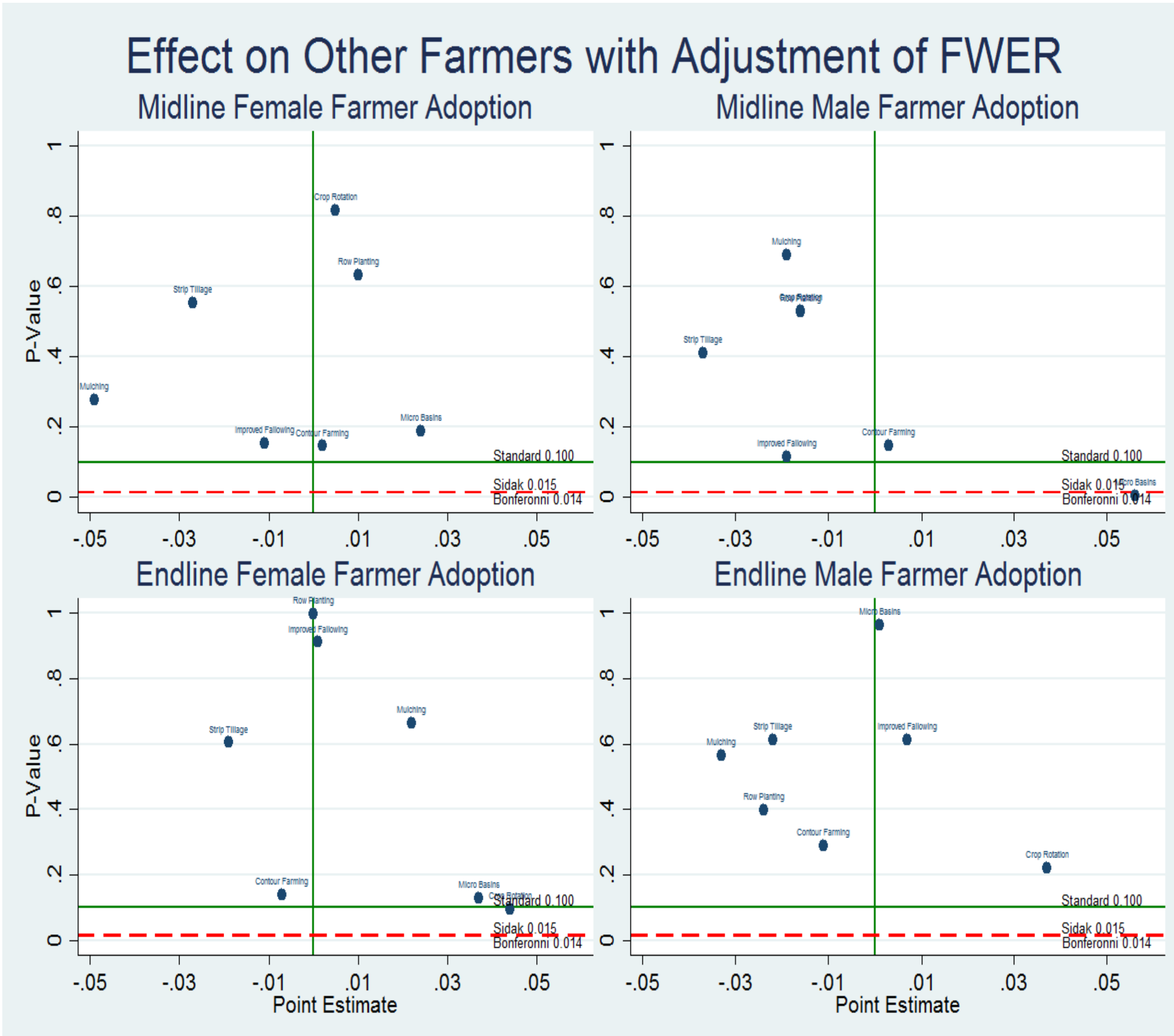

Table 1: Principles of Best SLM Practices

Technique	Water Efficiency	Soil Fertility	Improve Plant Material	Improve Micro-Climate
Mulching	X	X	X	X
Strip tillage	X	X		
Micro-basins	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.
	Mean	SD	Mean	SD	of Mean
Baseline Survey					
CF Age	38.878	9.325	40.100	10.626	-1.222
Ever being formally trained	0.350	0.479	0.447	0.503	-0.097
Number of years since formal training	2.157	2.239	3.409	3.202	-1.252*
Experience as CF in years	2.236	2.406	2.673	2.553	-0.437
Number of farmers assisted last 7 days	17.660	15.385	20.200	16.369	-2.540
Number of male farmers assisted in last 7 days	10.810	9.680	11.040	8.994	-0.230
Number of farmers assisted last 30 days	37.038	28.331	38.435	26.403	-1.397
Number of male farmers assisted in last 30 days	22.507	15.135	22.160	17.228	0.347
Hours worked as CF in last 7 days	14.813	12.726	12.340	11.573	2.473
Hours normally working as CF per week	16.483	12.499	12.500	11.886	3.983*
Total acreage of cultivated land	3.191	1.616	3.050	1.549	0.141
Number of households in community	285.135	266.876	242.405	265.562	42.730
Number of plots in community	465.074	431.141	416.469	421.319	48.605
Number of observations	148		50		198
Midline Survey (recall)					
Number of techniques learned before 2010	2.839	2.362	3.286	2.255	-0.446
Number of techniques adopted before 2010	1.409	1.210	1.167	0.935	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.

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

Variables	Treated		Control		Difference
	Mean	SD	Mean	SD	of Mean
Midline Survey					
Is the head of household	0.568	0.495	0.572	0.495	-0.004
Male	0.410	0.491	0.403	0.491	0.007
Age	37.664	19.895	37.756	19.993	-0.092
Years of schooling completed	2.054	4.953	1.848	4.988	0.206
Single	0.062	0.498	0.056	0.502	0.006
Married	0.848	0.540	0.859	0.543	-0.011
Divorced, separated, or widowed	0.088	0.361	0.082	0.362	0.005
Number of children (ages $<$ 15 years)	2.787	3.455	2.880	3.478	-0.093
Landholdings (hectares)	2.044	3.996	1.915	4.028	0.128
Number of rooms in the house	1.438	2.161	1.452	2.180	-0.014
Housing walls made of brick	0.102	0.803	0.099	0.810	0.003
Housing roof made of tinplate	0.082	0.749	0.084	0.756	-0.002
Midline Survey (recall)					
Number of techniques learned before 2010	1.236	4.521	1.305	4.563	-0.069
Number of techniques adopted before 2010	0.518	2.051	0.559	2.069	-0.041
Number of observations	4,525		1,542		6,067

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.

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
Household Characteristics						
Is the head of household	1.000	0.569	0.431 ***	0.988	0.577	0.412 ***
Age	41.425	37.687	3.737 **	43.341	38.700	4.641 ***
Years of schooling completed	5.469	2.002	3.468 ***	5.494	2.125	3.369 ***
Single	0.017	0.061	-0.044	0.006	0.047	-0.042 **
Married	0.978	0.851	0.127 ***	0.971	0.855	0.116 ***
Divorced, separated, or widowed	0.045	0.086	-0.042	0.070	0.097	-0.028
Number of children (ages $<$ 15 years)	3.779	2.811	0.968 ***	3.706	2.916	0.790 ***
Landholdings (hectares)	3.233	2.011	1.222 ***	3.654	2.439	1.215 ***
Number of rooms in the house	1.777	1.441	0.335 **	1.748	1.419	0.329 *
Housing walls made of brick	0.168	0.102	0.066			
Housing roof made of tinplate	0.207	0.083	0.124 **			
Production						
Grew maize	0.699	0.635	0.064	0.750	0.640	0.110
Grew sorghum	0.139	0.243	-0.105	0.151	0.270	-0.119
Grew cotton	0.202	0.095	0.107 **	0.064	0.051	0.013
Grew sesame	0.243	0.161	0.082	0.320	0.151	0.168 ***
Grew cassava	0.069	0.168	-0.099	0.058	0.139	-0.081
Grew cowpea	0.225	0.349	-0.124	0.320	0.346	-0.027
Grew pigeon pea	0.202	0.189	0.013	0.186	0.213	-0.027
Farm Characteristics						
Plot size (hectares)	1.151	0.955	0.196 *	1.314	1.167	0.147
Plot was flat	0.807	0.642	0.164 **	0.599	0.591	0.008
Plot was burnt	0.063	0.236	-0.174 **	0.076	0.246	-0.170 **
Used herbicides/pesticides/fungicides	0.156	0.061	0.095 **	0.110	0.020	0.091 ***
Used natural fertilizer	0.358	0.268	0.090	0.616	0.441	0.176
Used chemical fertilizer	0.127	0.009	0.118 ***	0.058	0.006	0.052 ***
Number of observations	179	6,067	6,246	172	5,254	5,426

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.

Table 5: Effect of SLM Training Intervention on Contact Farmers

	Midline				Endline			
	Control Mean(SD)	ITT	N	Adjusted R2	Control Mean(SD)	ITT	N	Adjusted R2
Access to EAs								
EA visited CF	0.595	-0.086	179	0.008				
at least 1/month		(0.094)						
EA visited CF	0.738	-0.092	179	-0.031				
at least 1/half year		(0.094)						
EA visited CF	0.786	0.013	179	-0.048				
at least 1/year		(0.088)						
Performance								
Knowledge Score	0.625	-0.007	179	-0.031	0.641	0.099***	168	0.076
	(0.201)	(0.041)			(0.142)	(0.028)		
# of techniques	4.214	0.323	179	-0.008	4.048	1.096***	168	0.095
known by name	(1.601)	(0.359)			(1.667)	(0.364)		
# of techniques	1.214	0.791***	179	0.115	2.357	0.501*	168	0.089
adopted on own plot	(1.001)	(0.254)			(1.340)	(0.292)		
# of techniques	4.452	0.848**	179	-0.003	3.024	0.635*	168	0.050
adopted on any plot	(1.928)	(0.391)			(1.569)	(0.347)		

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, district 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 Control Mean	Midline ITT	Midline N	Midline Adjusted R2	Endline Control Mean	Endline ITT	Endline N	Endline Adjusted R2
Mulching	0.929	0.030 (0.049)	179	-0.041	0.929	0.017 (0.050)	168	0.023
Strip Tillage	0.619	0.183** (0.091)	179	0.007	0.476	0.159 (0.106)	168	0.026
Micro-Basins	0.643	0.233** (0.096)	179	-0.006	0.476	0.063 (0.108)	168	-0.049
Contour Farming	0.405	0.171* (0.101)	179	-0.022	0.048	0.122* (0.068)	168	-0.029
Crop Rotation	0.905	0.052 (0.060)	179	-0.036	0.548	0.083 (0.105)	168	0.011
Row Planting	0.524	0.072 (0.096)	179	-0.016	0.357	0.150 (0.098)	168	-0.029
Improved Fallowing	0.429	0.107 (0.100)	179	0.024	0.190	0.041 (0.082)	168	0.000

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

Adoption on Own Plot	Midline						
	Control Mean	ITT	Adopted Before	ITT * Adopt Bef.	N	Adjusted R2	Treatment Effect (PV)
Mulching	0.405	0.276**	0.644***	-0.262*	179	0.275	0.077
		(0.109)	(0.132)	(0.148)			
Strip Tillage	0.286	-0.019	0.722***	0.202*	179	0.664	0.084
		(0.061)	(0.103)	(0.116)			
Micro-Basins	0.119	0.165**	0.697***	-0.060	179	0.429	0.667
		(0.066)	(0.124)	(0.139)			
Contour Farming	0.000	0.021	0.980***	0.000	179	0.469	.
		(0.016)	(0.078)	.			
Crop Rotation	0.262	0.175**	0.808***	-0.217	179	0.446	0.140
		(0.087)	(0.133)	(0.147)			
Row Planting	0.119	0.065	0.892***	-0.152	179	0.525	0.264
		(0.050)	(0.122)	(0.136)			
Improved Fallowing	0.024	0.009	-0.050	0.538**	179	0.179	0.013
		(0.041)	(0.198)	(0.214)			

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

		Midline				Endline			
		Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Access to CF									
Has access to any contact farmer	Female	0.106	0.045*	3592	0.023	0.247	0.025	3098	0.007
			(0.027)				(0.032)		
in the last half year	Male	0.135	0.062*	2475	0.018	0.301	0.009	2141	0.001
			(0.037)				(0.042)		
Performance									
Knowledge score	Female	0.294	0.012	3592	0.011	0.374	-0.013	3098	0.005
		(0.158)	(0.016)			(0.235)	(0.024)		
	Male	0.316	0.017	2475	0.020	0.416	-0.021	2141	0.012
		(0.161)	(0.017)			(0.221)	(0.023)		
# of techniques known by name	Female	1.479	0.126	3592	0.027	1.612	-0.010	3098	0.000
		(1.497)	(0.134)			(1.468)	(0.194)		
	Male	1.709	0.068	2475	0.018	2.025	-0.193	2141	0.008
		(1.588)	(0.146)			(1.610)	(0.197)		
# of techniques adopted	Female	0.664	-0.045	3592	0.007	0.938	0.078	3098	0.005
		(0.777)	(0.075)			(0.944)	(0.110)		
	Male	0.749	-0.047	2475	0.012	1.175	-0.044	2141	0.000
		(0.820)	(0.083)			(1.002)	(0.128)		

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, district 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 Bound

		Midline (Balanced Sample)†				Endline (Lee's Bound)					
		Control Mean(SD)	ITT	N	Adjusted R2	Treatment Bound Lower	Treatment Bound Upper	Con. Interval Lower	Con. Interval Upper	# of Sel. Obs. # of Obs.	Trimming Proportion
Access to CFs											
Has access to any	Female	0.113	0.029	2838	0.013	0.020	0.036	-0.013	0.077	2838	0.015
contact farmer			(0.030)			(0.019)	(0.024)			3592	
in the last half year	Male	0.135	0.062	1889	0.019	-0.010	0.013	-0.063	0.058	1889	0.022
			(0.040)			(0.031)	(0.026)			2475	
Performance											
Knowledge score	Female	0.301	0.011	2838	0.008	-0.004	0.008	-0.024	0.031	2838	0.015
		(0.161)	(0.018)			(0.012)	(0.013)			3592	
	Male	0.314	0.020	1889	0.02	-0.019	-0.005	-0.045	0.02	1889	0.022
		(0.162)	(0.019)			(0.015)	(0.015)			2475	
# of techniques	Female	1.541	0.135	2838	0.027	-0.043	0.051	-0.165	0.232	2838	0.015
known by name		(1.510)	(0.143)			(0.072)	(0.107)			3592	
	Male	1.783	0.028	1889	0.024	-0.264**	-0.127	-0.464	0.041	1889	0.022
		(1.609)	(0.160)			(0.120)	(0.100)			2475	
# of techniques	Female	0.686	-0.033	2838	0.007	-0.026	0.026	-0.101	0.123	2838	0.015
adopted		(0.790)	(0.079)			(0.045)	(0.057)			3592	
	Male	0.785	-0.075	1889	0.021	-0.130**	-0.048	-0.254	0.055	1889	0.022
		(0.830)	(0.089)			(0.074)	(0.062)			2475	

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

Adoption of Micro-Basins	Ctrl. Mean	ITT	T+T* Ed>7years	T+T* Age≥41	T+T* Land≥2.75	T+T* Same Crop	N	Adj. R2
				Midline				
Female	0.039	0.021	0.033				3408	0.003
		(0.022)	(0.023)					
Male	0.039	0.047*	0.072††				2362	0.010
		(0.024)	(0.028)					
Female	0.039	0.016		0.029†			3408	0.005
		(0.029)		(0.017)				
Male	0.039	0.048**		0.065††			2362	0.010
		(0.024)		(0.025)				
Female	0.039	0.010			0.040†		3408	0.005
		(0.025)			(0.022)			
Male	0.039	0.051**			0.062††		2362	0.011
		(0.021)			(0.028)			
Female	0.039	0.023				0.056†	3404	0.003
		(0.019)				(0.027)		
Male	0.039	0.064***				0.024	2356	0.012
		(0.020)				(0.042)		
Adoption of				Endline				
Micro-Basins	Ctrl. Mean	ITT	T+T* Ed>7years	T+T* Age≥43	T+T* Land≥3.5	T+T* Same Crop	N	Adj. R2
Female	0.087	0.040	0.037				2603	0.003
		(0.029)	(0.038)					
Male	0.137	0.017	0.009				1791	0.001
		(0.039)	(0.055)					
Female	0.087	0.068**		0.016			2603	0.008
		(0.034)		(0.032)				
Male	0.137	0.034		-0.001			1791	0.003
		(0.046)		(0.043)				
Female	0.087	0.015			0.065†		2603	0.005
		(0.028)			(0.036)			
Male	0.137	-0.001			0.034		1791	0.005
		(0.039)			(0.048)			
Female	0.087	0.028				0.115††	2678	0.006
		(0.026)				(0.047)		
Male	0.137	0.008				0.010	1863	0.001
		(0.036)				(0.065)		

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

Figure A.1: Effect of SLM Training Intervention on Contact Farmers with Adjustment of Familywise Error Rate

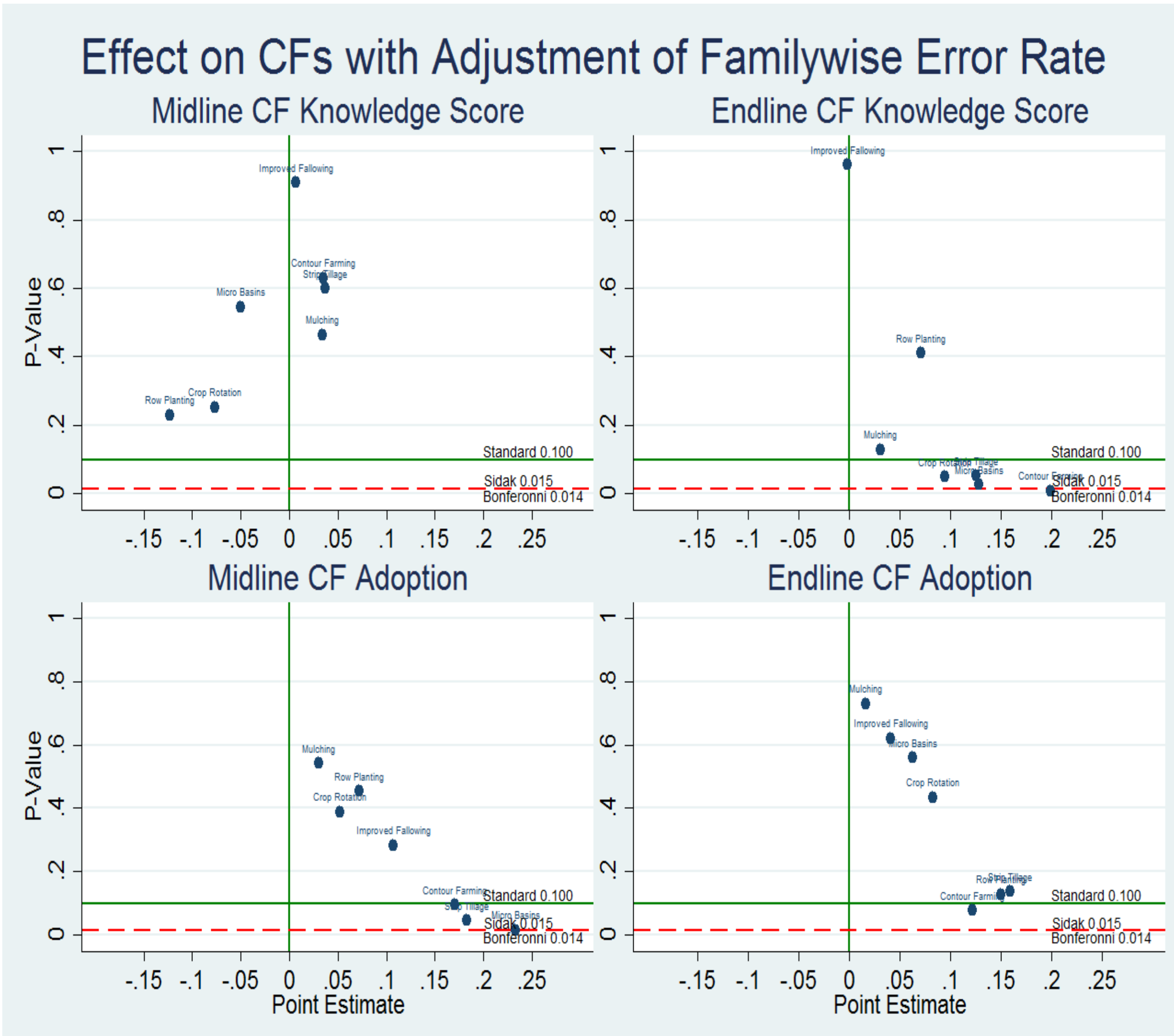

Table A.1: Extension Agents' Characteristics in Treated and Control Communities at Midline

Variables	Treated		Control		Difference
	Mean	SD	Mean	SD	of Mean
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
Number of years being EA	6.388	5.919	5.355	4.329	1.033
Number of years working in agriculture sector	4.451	2.893	4.412	2.994	0.038
Number of agricultural training received in past 5 years	9.624	5.265	9.645	5.563	-0.021
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.

Table A.2: Effect of SLM Training Intervention on Contact Farmers (Include Intercropping)

	Midline				Endline			
	Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Knowledge Score	0.642	-0.015	179	-0.043	0.661	0.073***	168	0.061
	(0.152)	(0.034)			(0.121)	(0.023)		
# of techniques known by name	5.214	0.283	179	-0.014	5.024	1.123***	168	0.098
	(1.601)	(0.361)			(1.689)	(0.365)		
# of techniques adopted on own plot	2.048	0.772***	179	0.089	3.310	0.504*	168	0.095
	(1.125)	(0.276)			(1.352)	(0.298)		
# of techniques adopted on any plot	5.429	0.856**	179	-0.005	4.000	0.617*	168	0.057
	(1.965)	(0.395)			(1.562)	(0.353)		

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.3: Effect of SLM Training Intervention on Other Farmers (Include Intercropping)

		Midline				Endline			
		Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Knowledge score	Female	0.343	0.012	3592	0.014	0.415	-0.010	3098	0.009
		(0.144)	(0.013)			(0.177)	(0.017)		
	Male	0.358	0.018	2475	0.025	0.449	-0.015	2141	0.013
		(0.148)	(0.015)			(0.162)	(0.016)		
# of techniques known by name	Female	2.401	0.120	3592	0.023	2.520	-0.033	3098	0.000
		(1.534)	(0.135)			(1.542)	(0.187)		
	Male	2.652	0.070	2475	0.018	2.941	-0.184	2141	0.008
		(1.622)	(0.143)			(1.666)	(0.193)		
# of techniques adopted	Female	1.419	-0.068	3592	0.006	1.785	0.055	3098	0.002
		(0.884)	(0.085)			(1.062)	(0.106)		
	Male	1.560	-0.076	2475	0.015	2.044	-0.044	2141	0.001
		(0.924)	(0.088)			(1.100)	(0.123)		

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.4: SLM Learning before 2010 in Treated and Control Communities (Recall)

Variables	Treated Mean	Control Mean	Difference of Mean
Contact Farmers			
Learned mulching	0.620	0.762	-0.141 *
Learned strip tillage	0.321	0.429	-0.107
Learned micro-basins	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
Other Farmers†			
Learned mulching	0.308	0.338	-0.030
Learned strip tillage	0.182	0.226	-0.044
Learned micro-basins	0.145	0.113	0.031
Learned contour farming	0.039	0.049	-0.010
Learned crop rotation	0.359	0.361	-0.003
Learned row planting	0.104	0.115	-0.010
Learned improved fallowing	0.099	0.102	-0.003
Number of observations	4,525	1,542	6,067

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.

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

Variables	Treated Mean	Control Mean	Difference of Mean
Contact Farmers			
Adopted mulching	0.489	0.405	0.084
Adopted strip tillage	0.248	0.214	0.034
Adopted micro-basins	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
Other Farmers†			
Adopted mulching	0.184	0.204	-0.020
Adopted strip tillage	0.091	0.121	-0.030
Adopted micro-basins	0.059	0.037	0.022
Adopted contour farming	0.002	0.000	0.002
Adopted crop rotation	0.122	0.134	-0.011
Adopted row planting	0.054	0.059	-0.005
Adopted improved fallowing	0.005	0.005	0.001
Number of observations	4,525	1,542	6,067

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.

Table A.6: 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
Production						
Grew maize	0.650	0.599	0.051	0.748	0.581	0.167 ***
Grew sorghum	0.122	0.308	-0.186 ***	0.177	0.354	-0.177 ***
Grew cotton	0.188	0.023	0.165 ***	0.087	0.007	0.080 ***
Grew sesame	0.248	0.095	0.153 ***	0.187	0.091	0.096 **
Grew cassava	0.198	0.153	0.046	0.168	0.120	0.048
Grew cowpea	0.265	0.379	-0.113	0.351	0.358	-0.007
Grew pigeon pea	0.204	0.165	0.038	0.212	0.184	0.028
Farm Characteristics						
Plot size (hectares)	1.015	0.833	0.182 ***	1.270	1.012	0.258 ***
Plot was flat	0.606	0.635	-0.029	0.559	0.548	0.011
Plot was burnt	0.243	0.259	-0.016	0.231	0.241	-0.010
Used herbicides/pesticides/fungicides	0.124	0.017	0.107 ***	0.046	0.001	0.044 ***
Used natural fertilizer	0.278	0.292	-0.014	0.501	0.422	0.079
Used chemical fertilizer	0.009	0.003	0.006	0.006	0.001	0.005
Number of observations	568	802	1370	481	690	1171

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.

Table A.7: 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	0.591	0.492	0.450	0.099 ***	0.141 ***	0.042
Age	38.215	35.826	36.435	2.389 ***	1.780 **	-0.609
Years of schooling completed	1.927	2.265	2.659	-0.338 **	-0.732 ***	-0.394 *
Single	0.058	0.069	0.112	-0.011	-0.054 **	-0.043 **
Married	0.847	0.865	0.799	-0.018	0.048 *	0.066 ***
Divorced, widow, or separated	0.094	0.058	0.089	0.036 ***	0.005	-0.031 **
Total number of children	2.809	2.818	2.784	-0.009	0.025	0.034
Total number of rooms	1.421	1.513	1.406	-0.093	0.015	0.107
Total landholdings	2.033	1.934	2.393	0.099	-0.360 **	-0.459 ***
Number of observations	4727	1340	527			

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.

Table A.8: Treatment Effect on CF Village & Household Attrition

	ITT	Constant	N	Adjusted R2
CF villages attrited from Midline†	0.060	0.335**	179	-0.001
	(0.063)	(0.151)		
Households attrited from Midline††	0.011	0.116***	3868	0.003
	(0.013)	(0.020)		

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

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

†† Regressions include the following variables: a constant, hh head age, hh head completed at least primary school dummy, hh head single dummy, hh head widow dummy, number of children, total landholdings, the number of rooms in the household, district indicators, and incentive treatment.

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

Table A.9: Descriptive Statistics of Other Farmers' Characteristics

Variables	Pooled		Men	Women	Difference
	Mean	SD	Mean	Mean	of Mean
Midline					
Is the head of household	0.569	0.495	0.940	0.313	0.627 ***
Age	37.687	14.399	40.312	35.879	4.433 ***
Years of schooling completed	2.002	2.812	3.362	1.064	2.298 ***
Single	0.061	0.239	0.074	0.052	0.021
Married	0.851	0.356	0.904	0.814	0.090 ***
Divorced, separated, or widowed	0.086	0.281	0.021	0.132	-0.111 ***
Number of children (ages $<$ 15 years)	2.811	2.027	2.925	2.732	0.193 **
Landholdings	2.011	1.805	2.118	1.937	0.181 *
Number of rooms in the house	1.441	0.737	1.493	1.406	0.087
Number of observations	6,067		2,475	3,592	
Endline					
Is the head of household	0.577	0.494	0.912	0.344	0.568 ***
Age	38.700	14.213	41.196	36.972	4.224 ***
Years of schooling completed	2.125	2.799	3.626	1.086	2.540 ***
Single	0.047	0.212	0.057	0.041	0.016 **
Married	0.855	0.352	0.915	0.813	0.103 ***
Divorced, separated, or widowed	0.097	0.297	0.028	0.146	-0.118 ***
Number of children (ages $<$ 15 years)	2.916	2.080	3.071	2.809	0.261 **
Landholdings	2.439	2.343	2.610	2.321	0.289 **
Number of rooms in the house	1.419	0.723	1.463	1.389	0.074
Number of observations	5,254		2,150	3,104	

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.

Table A.10: 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	0.034	179	-0.009	0.952	0.031	168	-0.035
	(0.258)	(0.047)			(0.139)	(0.021)		
Strip Tillage	0.460	0.037	179	-0.036	0.563	0.126*	168	0.003
	(0.345)	(0.071)			(0.270)	(0.065)		
Micro-Basins	0.798	-0.050	179	0.004	0.798	0.128**	168	-0.010
	(0.399)	(0.082)			(0.332)	(0.057)		
Contour Farming	0.524	0.035	179	-0.034	0.516	0.199***	168	0.045
	(0.369)	(0.073)			(0.405)	(0.074)		
Crop Rotation	0.540	-0.077	179	-0.035	0.595	0.095**	168	0.016
	(0.329)	(0.067)			(0.271)	(0.048)		
Row Planting	0.476	-0.123	179	0.020	0.143	0.071	168	-0.046
	(0.505)	(0.102)			(0.354)	(0.086)		
Improved Fallowing	0.738	0.007	179	-0.040	0.643	-0.002	168	-0.056
	(0.276)	(0.058)			(0.229)	(0.051)		

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.11: Other Farmers: Learning SLM Techniques from Whom?

		Midline				Endline			
		Ctrl. Mean	ITT	N	Adj. R2	Ctrl. Mean	ITT	N	Adj. R2
Any SLM technique	extension agent	0.056	0.009 (0.015)	6067	0.024	0.047	-0.012 (0.012)	5239	0.009
	contact farmer	0.130	0.040 (0.029)	6067	0.014	0.286	-0.004 (0.037)	5239	0.012
	other farmer	0.800	0.003 (0.031)	6067	0.003	0.792	-0.016 (0.030)	5239	0.006
Mulching	extension agent	0.043	-0.006 (0.011)	6067	0.019	0.037	-0.012 (0.010)	5239	0.010
	contact farmer	0.097	0.015 (0.023)	6067	0.011	0.232	-0.011 (0.035)	5239	0.011
	other farmer	0.296	-0.007 (0.044)	6067	0.021	0.311	-0.022 (0.037)	5239	0.002
Strip Tillage	extension agent	0.008	0.004 (0.005)	6067	0.005	0.005	0.002 (0.004)	5239	0.002
	contact farmer	0.028	0.007 (0.010)	6067	0.004	0.059	-0.013 (0.018)	5239	0.002
	other farmer	0.163	-0.022 (0.033)	6067	0.029	0.162	0.008 (0.036)	5239	0.003
Micro-Basins	extension agent	0.008	0.011** (0.006)	6067	0.011	0.006	0.000 (0.004)	5239	0.001
	contact farmer	0.042	0.029 (0.018)	6067	0.007	0.088	-0.008 (0.023)	5239	0.012
	other farmer	0.095	0.041* (0.022)	6067	0.004	0.083	0.023 (0.023)	5239	0.004
Contour Farming	extension agent	0.002	0.003 (0.002)	6067	0.006	0.004	-0.004* (0.002)	5239	0.002
	contact farmer	0.006	0.012** (0.005)	6067	0.003	0.016	0.002 (0.007)	5239	0.005
	other farmer	0.036	0.003 (0.012)	6067	0.011	0.013	-0.007 (0.006)	5239	0.002
Crop Rotation	extension agent	0.022	0.001 (0.009)	6067	0.010	0.012	-0.003 (0.005)	5239	0.005
	contact farmer	0.033	0.019* (0.012)	6067	0.009	0.117	-0.016 (0.029)	5239	0.011
	other farmer	0.303	0.002 (0.030)	6067	0.007	0.252	0.034 (0.032)	5239	0.001
Row Planting	extension agent	0.004	0.002 (0.003)	6067	0.001	0.005	-0.002 (0.003)	5239	0.000
	contact farmer	0.011	0.003 (0.004)	6067	0.000	0.030	0.000 (0.014)	5239	-0.001
	other farmer	0.098	0.012 (0.025)	6067	0.004	0.051	0.002 (0.018)	5239	0.001

Continued.

		Midline				Endline			
		Ctrl. Mean	ITT	N	Adj. R2	Ctrl. Mean	ITT	N	Adj. R2
Improved Fallowing	extension agent	0.007	0.001 (0.005)	6067	0.002	0.005	-0.004* (0.002)	5239	0.001
	contact farmer	0.010	0.002 (0.006)	6067	0.001	0.025	-0.004 (0.009)	5239	0.003
	other farmer	0.072	-0.012 (0.018)	6067	0.003	0.085	-0.010 (0.020)	5239	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.12: Other Farmers' Perceptions: Compared to the Traditional Method

Technique Saves Labor Time		Control Mean	Midline ITT	N	Adjusted R2
Mulching	Female	0.131	-0.032	3592	0.005
			(0.033)		
	Male	0.142	-0.026	2475	0.013
			(0.033)		
Strip Tillage	Female	0.157	-0.020	3592	0.009
			(0.038)		
	Male	0.177	-0.045	2475	0.006
			(0.042)		
Micro-Basins	Female	0.009	0.011**	3592	0.002
			(0.005)		
	Male	0.008	0.019**	2475	0.001
			(0.008)		
Contour Farming	Female	0.004	0.008	3592	0.003
			(0.005)		
	Male	0.008	-0.003	2475	0.002
			(0.005)		
Crop Rotation	Female	0.067	0.011	3592	0.002
			(0.018)		
	Male	0.090	0.015	2475	0.005
			(0.023)		
Row Planting	Female	0.041	0.006	3592	0.003
			(0.014)		
	Male	0.055	0.005	2475	0.007
			(0.019)		
Improved Fallowing	Female	0.033	-0.002	3588	0.006
			(0.014)		
	Male	0.043	-0.009	2475	0.005
			(0.016)		

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.13: Effect of SLM Training Intervention on Contact Farmers' Labor Time

	Midline				Endline			
	Control Mean(SD)	ITT	N	Adj. R2	Control Mean(SD)	ITT	N	Adj. R2
Hours spent on preparation of land	5.762	-4.027**	178	-0.005	6.429	-0.874	168	-0.021
	(13.879)	(1.880)			(15.353)	(2.717)		
Hours spent on seeding	6.071	-1.322	178	-0.013	10.357	-6.351**	168	-0.011
	(13.767)	(2.701)			(17.862)	(2.901)		
Hours spent on transplantation	3.476	-2.014	178	0.050	1.738	-0.749	168	-0.014
	(9.094)	(1.589)			(6.666)	(1.516)		
Hours spent on irrigation	0.000	-0.047	178	-0.044				
	(0.000)	(0.368)						
Hours spent on sacha	15.333	2.102	178	-0.014	5.833	-0.737	168	-0.006
	(15.550)	(3.289)			(14.252)	(2.390)		
Hours spent on protection	0.000	1.416*	178	-0.040	0.000	0.519	168	0.052
	(0.000)	(0.795)			(0.000)	(0.619)		
Hours spent on harvesting	6.214	-1.416	178	-0.060	15.810	-2.794	168	0.028
	(15.645)	(2.338)			(19.573)	(3.506)		

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.