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Seeing is believing? Evidence from an extension network experiment☆

Florence Kondylis[a,*], Valerie Mueller[b], Jessica Zhu[c]

[a] Development Research Group, The World Bank, United States
[b] Development Strategy and Governance Division, International Food Policy Research Institute, United States
[c] Agricultural and Applied Economics, University of Wisconsin, Madison, United States

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ABSTRACT

Extension is designed to enable lab-to-farm technology diffusion. Decentralized models assume that information flows from researchers to extension workers, and from extension agents to contact farmers (CFs). CFs should then train other farmers in their communities. Such a modality may fail to address informational inefficiencies and accountability issues. We run a field experiment to measure the impact of augmenting the CF model with a direct CF training on the diffusion of a new technology. All villages have CFs and access the same extension network. In treatment villages, CFs additionally receive a three-day, central training on the new technology. We track information transmission through two nodes of the extension network: from extension agents to CFs, and from CFs to other farmers. Directly training CFs leads to a large, statistically significant increase in adoption among CFs. However, higher levels of CF adoption have limited impact on the behavior of other farmers.

1. Introduction

Agricultural innovation is necessary to accelerate growth and achieve food security in Africa (Hazell, 2013). Despite availability of yield-enhancing technologies, adoption rates in Sub-Saharan agriculture remain low (Gollin et al., 2005). A growing literature identifies information failures as an impediment to the technological diffusion process in agriculture (Bandiera and Rasul, 2006; Conley and Udry, 2010; Munshi, 2004). Less documented are the modalities through which information can best diffuse and boost adoption of productive farming practices.

Agricultural extension services are designed to facilitate the diffusion of innovations from lab to farm. In developing countries, they account for large shares of government expenditures on agriculture (Akroyd and Smith, 2007). These substantive investments are seldom supported by causal evidence regarding their effectiveness as a whole, or of a particular modality (Anderson and Feder, 2004). Contact farmers (CFs), who serve as points of contact between extension agents (EAs) and other farmers, are ubiquitously used as messengers of information in developing countries. Efficacy of the CF modality rests on two key assumptions. First, EAs will effectively train CFs to adopt and demonstrate new technologies to peers. Frequent EA visits are supposed to elicit a process of experiential learning among CFs. Second, other farmers' exposure to CFs will encourage wider adoption in the community, through a peer learning process. Despite some evidence of implementation and accountability constraints, and perhaps for lack of a viable policy alternative, the CF model persists across Africa (Gautam, 2000). Formally documenting returns to additional low-cost, scalable interventions to help leverage these large investments in agricultural extension services could significantly affect the path of technology diffusion.

We exploit a large-scale, government-run randomized controlled trial (RCT) to measure the impact of augmenting the CF model with a direct training on the diffusion of a new technology in central Mozambique. Our treatment consists of adding a direct CF training to an existing CF model, holding everything else constant. In practice,

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* Corresponding author.
E-mail addresses: fkondylis@worldbank.org (F. Kondylis), v.mueller@cgiar.org (V. Mueller).

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CFs in treatment villages receive two three-day training (one in 2010, one in 2012) on a yield-enhancing technology at district headquarters, by the same experts and using the same curriculum as provided to EAs. All EAs were trained on sustainable land management (SLM) and were expected to train their local CFs to demonstrate the technology to other farmers in 200 villages. All CFs were provided demonstration kits to encourage adoption and diffusion of information to other farmers. We augmented the CF model by centrally training CFs on SLM in 150 randomly selected (treatment) communities. The training format was part lectures, part hands-on, with similar content and breadth as the EA training. The central training is the only difference between treatment and control, and all 200 villages adhere to the *status quo* CF model. We use two rounds of follow-up survey data on 200 CFs and a random sample of over 5000 other farmers to examine the impact of adding a central training on knowledge and adoption of the technology, as well as agricultural production.

The CF model enables a process of experiential learning among CFs through the use of demonstration activities and regular on-site feedback from EAs. This practice is similar to on-the-job, learning-by-doing processes in other labor markets. Neoclassical growth theories suggest learning-by-doing may be of equal importance to formal training in explaining human capital formation as a production input (Lucas, 1988). While learning-by-doing theories are supported in the context of firm or plant-level studies (Levitt et al., 2012; Thompson, 2010), empirical evidence of the significance of learning through extension programs on agricultural growth is mixed (Bindlish and Evenson, 1997; Purcell and Anderson, 1997; Gautam, 2000; Anderson and Feder, 2007; Benin et al., 2007; Davis et al., 2012; Waddington et al., 2014). We contribute to this research agenda by formally documenting the impact of augmenting an existing, decentralized extension model with a relatively low-cost centralized training modality.

Adding a direct training may affect technology adoption among CFs through three broad categories of mechanisms: increased quantity of information, enhanced learning experience, and channels other than knowledge. First, the curriculum in a direct training may increase the quantity of information transferred (e.g., number of techniques taught). Central trainings are offered in an enclosed setting under the supervision of project staff, and extension agents present the material from the course manual. This plausibly increases the chance that the intended curriculum is covered.

Second, the centralized format of the training may enhance the learning experience. For instance, the formal setting may add credibility to the information. While the use of course materials hardly affects learning indicators in other settings (Tan et al., 1999; Glewwe et al., 2004, 2009), use of computing technology as a complementary input to a standard curriculum has been shown to have a positive effect on learning (Banerjee et al., 2007; Linden, 2008). For these reasons, the information set shared during a training held at district headquarters may be (perceived to be) of higher quality than what is given during field visits from the EAs. Peer learning will also likely be more pronounced during a centralized training, as CFs with similar characteristics get to share information and jointly interact with the material.

Third, a direct training could increase CFs' adoption through other channels than knowledge. For instance, the training may improve EA-to-CF accountability. Directly trained CFs may demand more information from EAs (Björkman and Svensson, 2009; Banerjee et al., 2010). Being formally trained could also build empowerment, reinforcing the identity of the CF as community messenger and their propensity to lead village-level demonstration activities. Similarly, attending a training in the district town for a few days may make CFs feel “special” relative to control CFs. Alternatively, a centralized training could create a momentum among peers to adopt the new practices, akin to herd behavior (Banerjee, 1992; Karlan et al., 2014).

We find a statistically significant increase in CF adoption of SLM when CFs have access to a direct training in addition to the *status quo* extension modality. Private returns in the form of labor savings and yield benefits in dry years accompany increases in adoption. However, CFs' knowledge scores on the SLM curriculum are unaffected by the direct training.

Increasing demonstration of SLM practices could reinforce the perceived benefits of SLM among peers by increasing knowledge and reducing the uncertainty of SLM benefits (Foster and Rosenzweig, 1995). Yet, boosting CF demonstration and adoption through a direct training does not affect other farmers' practices within the community in our context. Patterns of CF-farmer interactions suggest that the direct training did not additionally stimulate CFs to fulfill their role as village messengers. Interestingly, variations in treatment effects by CF characteristics and similarity in cropping patterns indicate that relevance of expected cost–benefit margins affect the diffusion process. For example, pit planting adoption rates increase when a CF's crop portfolio matches the farmers'. Hence, our results corroborate the idea that the “proximity” of the source of information may be the primary constraint on changes in farmer behavior (Munshi, 2004; Feder and Savastano, 2006; Bandiera and Rasul, 2006; Conley and Udry, 2010) and, therefore, that the process of CF selection may affect the pace of diffusion (Beaman et al., 2014; BenYishay and Mobarak, 2014).

Overall, our findings suggest augmenting decentralized extension programs with a direct training modality can improve their effectiveness in getting CFs to demonstrate new technologies. Our cost–benefit analysis shows net private returns of up to USD 76 per CF. Yet, a direct CF training leads to modest diffusion to others in the community. Taken together, these results imply that adding a direct training modality on its own may not be enough to reform the speed of technology diffusion. Further study is needed to build up the evidence base, using larger samples, improved measurement techniques, and testing complementary policy actions to make extension services work for farmers.

In what follows, we detail the Mozambique extension policy and network at baseline (Section 2). We then describe the evaluation design and empirical strategies used to identify the impact of adding a direct CF training on technology diffusion (Section 3). Section 4 presents estimates of impact on CF knowledge, adoption, and productivity, other farmers' adoption and knowledge, as well as measures of cost-effectiveness. Section 5 discusses implications of this study for policy and future research.

2. Agricultural extension constraints in Mozambique

2.1. National extension coverage

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) has promoted and expanded extension networks (Eicher, 2002; Gemo et al., 2005). EAs are employed by the District Services for Economic Activities (Serviços Distritais de Actividades Económicas) and operate at the subdistrict level to disseminate information and new techniques. The system assumes that information flows linearly: agricultural innovations are created by researchers, then distributed by extension workers, and finally adopted by producers (Pamuk et al., 2014). Countrywide, 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 set of villages every year based on their achievements and potentials (Coughlin, 2006). Only 15 percent of farmers report receiving extension services (Cunguara and Moder, 2011).

At the time our study was designed, the present National Plan for Agricultural Extension and Extension Master Plan aimed to develop the decentralization of services at the district level; increase participation of targeted groups (women and marginal farmers); and enhance partnerships with other actors, such as the private sector and nongovernmental organizations (Gallina and Chidiamassamba, 2010). Given the importance the government places on decentralized extension services and the lack of rigorous evidence to date, formally documenting the impact of this policy action seems warranted (Gautam, 2000).[1] In what follows, we describe the details of the *status quo* extension model operating at baseline in our study area.

2.2. Study area

We worked in five districts of central Mozambique: Mutarara (Tete Province), Maríngue and Chemba (Sofala Province), and Mopeia and Morrumbala (Zambézia Province; Fig. 1). This area receives financing from a large World Bank–Government of Mozambique investment to support the development of the extension network (*Smallholder project*). The project provides three levels of agricultural technical assistance: each district has a facilitator, an environmental specialist, and eight EAs. A district is subdivided into four administrative posts (*posto administrativo*) that include about 8–10 communities (*aldeia*). EAs periodically receive training from the district specialists.[2] Each community has a designated contact farmer (CF) who receives direct assistance from the two EAs placed in his administrative post.[3,4] CFs receive visits from EAs monthly. They were instated to respond to other farmers' demands for technical assistance and provide advice through demonstration activities.

A CF model of extension may not foster learning and adoption among CFs. EAs are typically challenged to reach the communities they serve. Designating CFs may therefore not adequately address the supply-side constraints of extension services. Another concern is that information may get “diluted” from the central level to CFs. For instance, EAs may not cover all techniques, sufficiently train the CFs, nor adhere to the expected format. Since CFs do not know what curriculum their EA should follow, accountability may be low. Finally, periodic visits from the EA may not be sufficient in getting CFs motivated to demonstrate to others in their community.

The underlying assumption of the CF model is that, through peer learning, a change in CF demonstration effort should affect the process of diffusion to other farmers in the community. By exogenously affecting CFs' adoption of a new technology, our experiment directly tests whether the CF model is suited to promoting technology adoption on a large scale. Allowing the ITT estimates to vary by CF characteristics provides qualitative evidence of existing barriers to knowledge transfer.

3. Experiment and data

We run a large field experiment to test for effective knowledge diffusion under the CF model of extension, and isolate the additional impact of directly training CFs. A new technology, SLM, was disseminated through the extension network for the first time in 2010. Our study started in October 2010 and ended after the main 2013 cropping season, thus spanning three main agricultural seasons (Fig. 2). We collected three rounds of data: a rapid CF baseline and two CF and household-level follow-ups, respectively, 15 and 27 months after the first SLM demonstration season. By baseline, we refer to September 2010 and earlier. The initial demonstration season in our study was 2011. Our surveys captured the 2012 and 2013 adoption seasons. This section details the experiment and data sources.

3.1. Sustainable land management

Sustainable land management (SLM, or conservation farming) is a yield-enhancing farming technology that consists of a bundle of techniques adapted to local crops and agro-ecological conditions (Haggblade and Tembo, 2003; Thierfelder et al., 2015).[5] In the Zambezi valley, the recommended SLM technology package encompasses seven SLM techniques: Mulching, Crop Rotation, Strip Tillage, Pit Planting, Contour Farming, Row Planting, and Improved Fallowing.[6] Mulching covers the soil with organic residues to maintain soil humidity, suppress weeds, reduce erosion, and enrich 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. Pit planting consists of constructing permanent holes 15 cm deep 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 improves productivity by improving access to sunlight and facilitating weeding and other cultivation practices (for instance, mulching and intercropping) by providing space between rows. Improved fallowing reduces temporary productivity losses from fallowing through targeted planting of species that recharge the soil in a shorter time frame.

There are important complementarities across these techniques, which are expected to generate savings in labor time during the main season. For instance, combining strip-tillage with pit planting will ensure that pits do not need to be excavated every year. This should save labor at the seeding stage over the traditional methods of tillage and planting in ridges. Similarly, strip-tillage and contour farming combined will save time, since the terraces will not have to be prepared every year for seeding. Combining mulching and pit planting can also help maximize the nutrient retention of the soil around the maize crop and minimize the need for weeding.

We asked CFs to recall their familiarity with these techniques at baseline (Table A1). SLM exposure varied widely across techniques and farmer types. Twenty-one percent of CFs had heard of improved fallowing relative to 10 percent of other farmers. In contrast, 76 percent of CFs knew of mulching, compared to 34 percent of other farmers. This suggests that some, if not all, SLM technologies taught in the CF training and disseminated by EAs pose as reasonable instruments to track knowledge diffusion in the Zambezi valley.[7]

3.2. Training

We now describe the trainings delivered to EAs and CFs in the context of our study. First, all EAs serving administrative posts within our study area received two three-day training courses on SLM

[1] Recent work has employed a quasi-experimental design to evaluate the impact of extension and found a positive impact of extension on farm income in Mozambique (Cunguara and Moder, 2011)

[2] In October 2010 and November 2012, these trainings were dedicated to SLM.

[3] The ratio of EAs per administrative post in our study area is on par with the 2013 national average of 1.89 (Gemo and Chilonda, 2013). This ratio is calculated using the 2010 figures from the Direçåo Nacional de Extenså Agraria (DNEA), available at the following URL: http://www.worldwide-extension.org/africa/mozambique/s-mozambique.

[4] 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. CFs are typically chosen by the community. In 2010, CFs had been in their position for three years on average, with a standard deviation of 3. This indicates the majority of CFs were already commissioned by the project prior to our intervention.

[5] A direct implication is that, while positive yield effects of SLM are relatively well documented for Southern Africa (Haggblade and Tembo, 2003; Thierfelder et al., 2015), there is little evidence on the returns of individual SLM techniques.

[6] Intercropping was included in the curriculum, but is excluded 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 (not reported).

[7] 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.

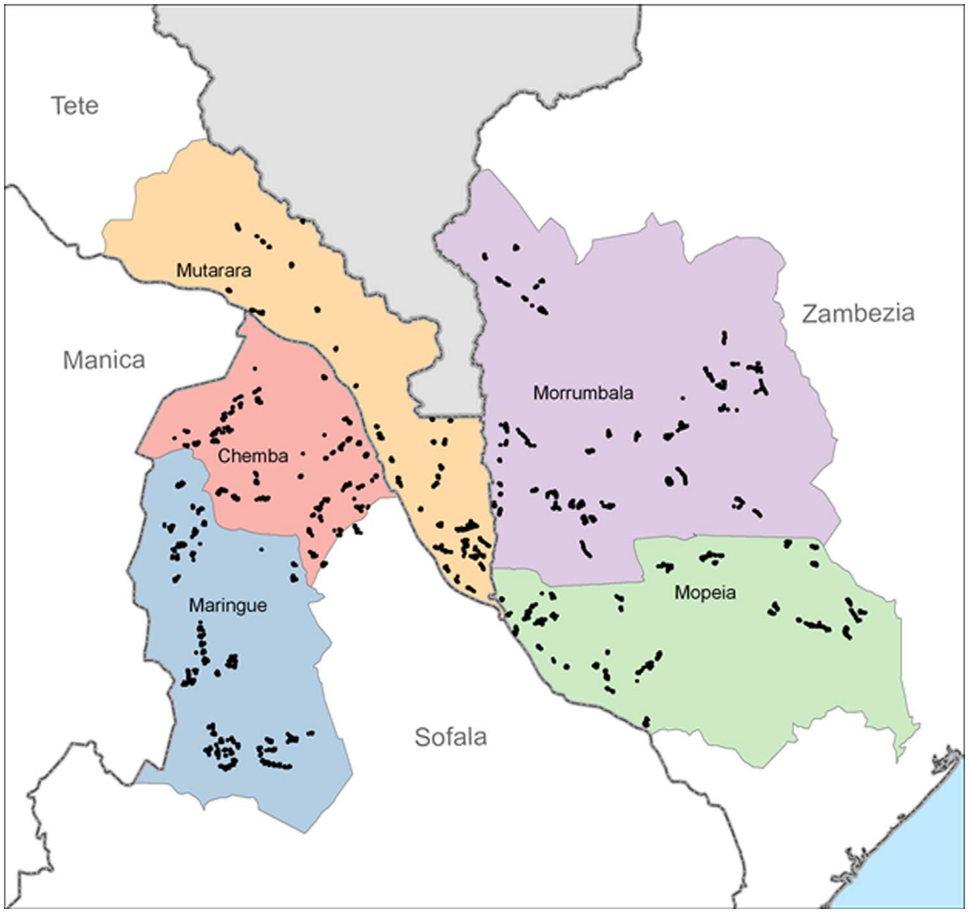
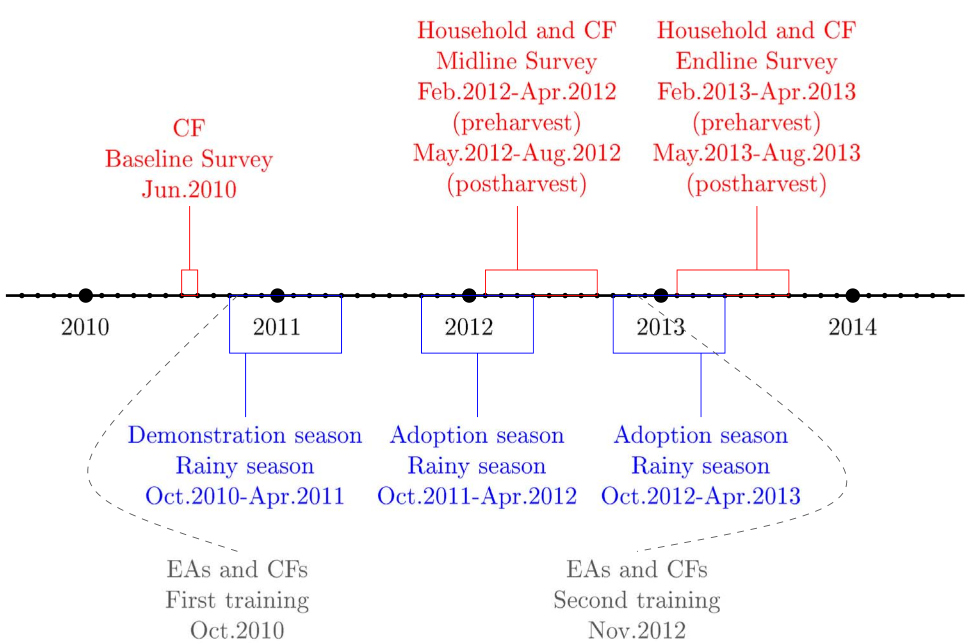


Fig. 1. Study area and spatial distribution of sampled households.



Notes: EA = extension agent. CF = contact farmer.

Fig. 2. Timeline of training and survey.

techniques in October 2010 and November 2012 (prior to the main planting season). Technical staff from the Ministry of Agriculture (MINAG) developed the educational agenda on SLM practices, and the training was delivered by MINAG's district technical staff with support from one staff from the central project team. Half of the training sessions were devoted to in-class lectures, and the other half consisted of hands-on demonstrations. The syllabus included a thorough review of the advantages of each SLM technique over less-environmentally desirable ones.[8] The EA training also highlighted good practices in fostering interactions between EAs and CFs.

The centralized CF trainings were held a few weeks after those of the EAs. The content of the CF training was similar to that received by EAs, and was delivered by the same district-level and central MINAG staff.[9,10] The cost of a direct training per CF per year was 74 USD. Over three agricultural seasons, this represents a modest 12.8 percent increase in the total salary and training cost of the extension network.[11]

After these trainings were completed, all EAs worked with their CFs to disseminate the SLM techniques most pertinent to their local area on their (own or communal) demonstration plots, regardless of their CFs' treatment status. All CFs received a new toolkit (a bicycle, tools to plow the land, and smaller articles).[12] A second toolkit with similar items (including a bicycle) was provided to all CFs again in July 2012. The only difference between treatment and control CFs is that treated CFs received an additional direct training on SLM.

3.3. Experimental design

At baseline, CFs and EAs in our five study districts operated under the CF model of extension in all communities. From these districts, we randomly selected 200 communities (with 200 CFs) in 16 administrative posts, to which 30 EAs were assigned. All EAs received SLM training. We randomly assigned CFs in 150 treatment communities to the augmented version of the CF model (treatment), stratifying the assignment at the district level. Control (50) and treatment (150) CFs received SLM training during visits from their EAs—the *status quo* CF extension modality. Treatment CFs additionally received the direct CF training described above.[13]

This design allows us to isolate the additional effect of a direct training, implicitly testing for effective knowledge diffusion under the CF model. For this purpose, we held constant all other extension interventions across treatment and control communities. Specifically, in line with the *status quo* modality, all CFs in the study area receive assistance from their EAs and a tool kit to set up and maintain a demonstration plot within the community. These demonstration plots are used by (1) EAs to teach and assist CFs in implementing at least one of the agricultural practices of the CF's choice, and (2) CFs to demonstrate the new techniques to other farmers in their community.

In practice, the CF-level random assignment was implemented as follows. Each EA team at the administrative post level was in charge of inviting treatment CFs to the central SLM trainings. During the EA trainings on SLM, district staff explained the physical impossibility of training all CFs at once and that a lottery had been used to select the participating CFs. EAs were then given the list of randomly chosen treatment CFs. An attendance sheet was taken at CF training by the district staff. In October 2010, only four treatment CFs did not attend the training (all in the Mopeia district), and there was no contamination to control CFs.[14] Since district staff 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 and verified attendance verbally. 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 results from these audits indicate that attendance was genuine.

Similar checks were performed on the 2012 training. While the attendance list was equally validated, participation was not universal and contamination was quite substantial. Of the treated communities, 63 percent had at least one CF attend the training, and 16 percent of control communities had a CF attend.[15] These figures signal statistically significant exposure of control CFs to the treatment in 2012. While this may hamper our ability to statistically differentiate the two training models on CF behavior in the 2013 (second follow-up) survey round, our results on other farmers at endline are arguably robust to this contamination. Increased demonstration by control CFs in the 2013 growing season is unlikely to have affected farmers' adoption in that same season.

There are two important limitations to our identification strategy: one concerns the intensive margin of EA support to treatment CFs relative to control CFs, while the other relates to the extensive margin of EA attention. First, direct training and EA support are likely complementary inputs. Therefore our estimates capture the overall effect of augmenting the CF model with a direct training. We cannot disentangle the impact of learning during the central training from that of improved learning during regular EA-to-CF tutorials as a result of the direct training.

Second, our design implies that each EA will work with both treatment and control CFs in his administrative post.[16] A threat to

[8] The main charts from the class can be found here: intrerrefhttp://siteresources.-worldbank.org/INTDEVIMPEVAINI/Resources/Flipchart_deAC_anonymized.pdfhttp://siteresources.worldbank.org/INTDEVIMPEVAINI/Resources/Flipchart_deAC_anonymized.pdf. The general curriculum used by the MINAGRI staff is provided on this site: http://siteresources.worldbank.org/INTDEVIMPEVAINI/Resources/Manual_AC_FINAL.pdf. The hands-on component of the training was not recorded but followed closely the techniques discussed in class.

[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. This may lead us to underestimate information flow in the central training arm, and overestimate it in pure CF model. Reassuringly, as mentioned above, we do not find that EAs devoted more time to visiting CFs in treatment communities, relative to control.

[10] Given the low literacy of farmers, a film covering all techniques substituted the initial lecture format in the second training of the CFs in 2012.

[11] The monthly EA salary costs were at USD 210 per EA from data provided by the DNPDR and the Smallholders project team, and EA training costs ran at USD 370 per training. Each EA supervised on average 5 treated CFs over the course of 36 months. There are obviously other, non-wage costs to running an extension network. To the extent that we do not account for these additional costs, we overestimate the relative cost of adding a direct CF training.

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

[13] The full design consists of multiple treatment arms. A second treatment arm was overlaid on 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 one CF in the community trained on SLM on farmers' outcomes. A third randomized treatment arm was overlaid on the first two that attempted to provide different performance-based incentives for the CFs to reach farmers in both villages that were assigned to the direct training and control communities. These incentives were never announced to the CFs, and we show that they did not have any statistically significant effect on our outcomes of interest (not reported). Nonetheless, we control for this third treatment arm in the regression analysis.

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

[15] The contamination likely was caused by a combination of self-selection and EA oversight. CFs in the control group could have easily learned about the trainings from peers in other communities. Since EAs and district staff were involved in organizing the training, it is easy to see how a well-connected CF might have been invited in.

[16] 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 A2).

our identification stems from the fact that CFs may request different levels of attention from their EAs across treatment assignments, displacing EA time away from the other treatment status—the extensive margin of EA attention across treatments. For instance, treatment CFs may request more follow-up visits from their EAs, cutting into the time EAs devote to control CFs. Reassuringly, we find that control and treatment CFs received equal amounts and types of attention from their EAs in the year after the training (Table A3).

3.4. Data

We conducted two follow-up surveys after the first training and demonstration season (October 2010 to April 2011). A 2012 (midline) round and a 2013 (endline) round form a panel of households and CFs in the study area.[17] We randomly sampled 18 non-CF households in each community from a full listing performed by our enumerators ahead of the survey. At both midline and endline, households were visited twice: pre- and postharvest. This allows us to observe SLM practices when they are most visible, just after planting (preharvest, from February to April), and to record production data after harvest (from mid-May on). Hence, our fieldwork ran from February to April and May to August in 2012 and 2013.

Midline and endline surveys gathered longitudinal CF and household information on the two main agricultural seasons that followed the first demonstration season. Our fieldwork included five survey instruments: a household questionnaire, a household agricultural production questionnaire, a CF questionnaire, an EA questionnaire, and a community questionnaire. The household survey was also administered to all 200 CF households, in addition to the specific CF survey. These surveys provide household demographics, SLM knowledge for the two main agricultural producers in the household, individual and plot-level SLM adoption, and production information for approximately 3600 non-CF households in 200 communities. Since the plot roster identifies the adult in charge of making agricultural decisions for each cultivated plot, we obtain individual measures of knowledge and adoption for a sample of 5884 and 5071 individuals at midline and endline, respectively.

A rapid baseline survey was administered to all CFs in August 2010, before the district-level randomization. This provided data to perform balance tests on the success of the randomization, using the pre-intervention characteristics of CFs by treatment status. Fig. 2 illustrates the timing of the surveys and CF trainings over the course of the four-year study.

3.5. Descriptive statistics

We briefly describe the average characteristics of farming individuals in our sample (Table A4). More than half of the individuals are women, and the prevalence of female headship is consistently high (approximately 30 percent) for the region (TIA, 2008). The average farmer is 38 years old with two years of schooling. Most plot owners are married with three children, and live in a single-room house made of mud and sticks with a palm or bamboo roof (not reported). Farmers possess 2.2 hectares of land on average, with a standard deviation of 2.1.

CFs are more knowledgeable (Tables 1 and 2), more educated, and wealthier (Table 3) than other farmers. While CFs are positively selected in attributes, they are also well known in their communities: 84 percent of farmers in the control group declared knowing them personally. However, only 72 percent of the same group of farmers reported knowing that these individuals assumed a role as CF in their community.

[17] Operational constraints precluded us from conducting a household survey at baseline.

Table 1
Contact farmers' characteristics by treatment status.

Variable	Treated			Control			Difference
	Mean	SD	*N*	Mean	SD	*N*	in mean
Baseline survey							
Age	38.858	9.348	148	40.160	10.559	50	−1.302
Formally trained	0.350	0.479	140	0.447	0.503	47	−0.097
Years since formal training	2.157	2.239	51	3.409	3.202	22	−1.252*
Years of experience as CF	2.243	2.401	144	2.653	2.570	49	−0.410
Number of farmers assisted in last 7 days	18.034	16.095	147	19.100	14.333	50	−1.066
Number of male farmers assisted in last 7 days	10.871	9.659	147	10.860	9.064	50	0.011
Number of farmers assisted in last 30 days	37.060	28.320	133	38.370	26.441	46	−1.309
Number 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 worked as CF per week	16.322	12.498	143	12.960	12.034	50	3.362
Total hectares of cultivated land	1.289	0.655	144	1.242	0.624	50	0.047
Number of households in the community	284.421	267.037	126	244.548	265.410	42	39.873
Number of plots in the community	459.269	430.130	108	436.063	426.578	32	23.206
Midline survey: Recalled							
Number of SLM techniques learned before 2010	2.839	2.362	137	3.286	2.255	42	−0.446
Number of SLM techniques adopted before 2010	1.409	1.210	137	1.167	0.935	42	0.242

Sources: Contact farmer baseline survey, 2010; Household survey, 2012.
Notes: ***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF, contact farmer.

We also note that usage of demonstration plots was quite high and not statistically different across treatment and control communities (Table A3). Of the CFs in treatment and control communities, 85 percent maintained a demonstration plot.[18] Thus, changes in patterns

[18] There was no instruction, however, as to what type of plot should be used for demonstration activities. CFs could choose to use their own, private plot or communal land. Hence, we present the demonstration results for any plot (own or not).

Table 2
Other farmers' characteristics by treatment status.

Variable	Treated		Control		Difference
	Mean	SD	Mean	SD	in mean
Midline survey: 2012					
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
Total hectares of owned land	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
Midline survey: Recalled					
Number of SLM techniques learned before 2010	1.236	4.514	1.303	4.563	−0.066
Number of SLM 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.*
Notes: *t*-test inferences are based on standard errors clustered at the community level.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
SLM, sustainable land management.

of CF-to-other-farmers information diffusion across the two modalities can be interpreted as resulting from variations at the intensive margin of CFs' activities (e.g., number of techniques demonstrated, quality of the demonstration).

3.6. Balance

We use data from the baseline CF survey as well as time-invariant and retrospective information collected in the 2012 household survey to check for balance across treatments. Table 1 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) and had 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 were similar, as were other farmers' (recalled) baseline SLM learning and adoption rates (Table 2).[20]

3.7. Measuring information diffusion and behavioral change

Central to identifying variations in information diffusion is measuring changes in learning and agricultural practices. Our study rests on the reliability of our markers of individual SLM knowledge and adoption. We focus on three outcomes: a knowledge score, the number of techniques the respondent identified by name, and the number of techniques the respondent reported having adopted on any plot.[21] The knowledge score is a continuous measure based on the number of correct responses provided in the 23-question exam, covering all SLM techniques. For CFs, the majority of the analysis rests on their self-reported adoption of techniques on any plot (demonstration or not).[22]

Since the CFs were encouraged to choose the techniques most relevant to their local conditions, our main results focus on unweighted aggregate measures of knowledge and adoption. However, we create a second set of weighted knowledge and adoption outcomes as a

Table 3
Socioeconomic and farming characteristics of contact farmers and other farmers.

	Means		Difference in mean
	CFs	Other farmers	
Household Characteristics: In the current year			
Is the head of household	0.994	0.590	0.405***
Age	42.364	38.243	4.121***
Years of schooling completed	5.481	2.054	3.427***
Single	0.011	0.056	−0.044*
Married	0.974	0.849	0.126***
Divorced, separated, or widowed	0.057	0.095	−0.038
Number of children (ages < 15 years)	3.744	2.830	0.913***
Total hectares of owned land	3.439	2.171	1.269***
Number of rooms in the house	1.763	1.423	0.340**
Housing walls made of brick[i]	0.168	0.099	0.068
Housing roof made of tinplate[i]	0.207	0.079	0.128**
Production: In the current rainy season			
Grew maize	0.725	0.637	0.088
Grew sorghum	0.139	0.255	−0.116
Grew cotton	0.133	0.076	0.058
Grew sesame	0.270	0.156	0.113*
Grew cassava	0.058	0.157	−0.099
Grew cow pea	0.278	0.347	−0.069
Grew pigeon pea	0.191	0.200	−0.009
Farm characteristics: In the current rainy season			
Plot size (hectares)	1.215	1.047	0.167
Plot was flat	0.727	0.616	0.111*
Plot was burnt	0.060	0.244	−0.184***
Used herbicides/pesticides/ fungicides	0.133	0.042	0.091***
Used natural fertilizer	0.484	0.351	0.133
Used chemical fertilizer	0.099	0.006	0.092***
Number of observations	351	10,960	11,311

Sources: *Household survey, 2012, 2013.*
Notes: *t*-test inferences are based on standard errors clustered at the community level.
CF, contact farmer.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
[i] This variable is only available in Midline.

[19] Given that 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.

[20] Balance tests for the CFs' and other farmers' knowledge and adoption of individual SLM techniques at baseline are reported in Tables A1 and A5. Because these values are based on recalled data, the tests should be interpreted with caution. 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.

[21] Our decision to focus on the knowledge score and self-reported adoption outcomes is motivated by the conclusions in Kondylis et al. (2015). Using the midline survey data, they find learning outcomes based on knowledge exams provide more precision than know-by-name questions, inasmuch 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. Objective adoption measures were also collected for two plots per household and largely corroborate the self-reported outcomes. In our triangulation of the self-reported versus observed adoption, we find that false reporting is negligible. Since objective measures of adoption are collected for only a subset of plots (one per respondent) at midline and a subset of the sample at endline, we instead focus on a more inclusive measure of adoption provided by self-reports of interviewed men and women.

[22] There are slight differences between adoption measures which include and exclude the demonstration plot. This is due to the fact that some CFs demonstrate on communal land (29%). We verify the results are not driven by communal propriety of the demonstration plot (not reported). Since 71% of demonstration activities are carried out on CFs' own plots, we choose to use pooled adoption on and off demonstration plots as our main marker of adoption. This improves our precision but does not affect our conclusions.

robustness check. Prior to aggregation, we multiply the technique by a weight based on its relative importance to maize revenue. This is done as follows. First, we compute a vector of weights, based on a regression of maize revenue on adoption of the seven individual practices. Second, we compute adoption and knowledge indices of practices weighted by these correlations between adoption and maize production.

We additionally explore patterns of knowledge and adoption specific to individual techniques. We use responses from the same knowledge exam to quantify farmer knowledge of individual SLM techniques, categorizing questions by technique. The knowledge of a specific technique is a [0,1] continuous variable that depicts the share of questions pertaining to the practice that the respondent has answered accurately. The adoption of a technique is captured by a binary variable that indicates whether the farmer adopted the technique on at least one of his plots.

Knowledge, adoption, and perception of the SLM techniques were collected at the individual level from the household questionnaire. Two respondents were interviewed: typically, the household head and the head's partner or spouse.[23] 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. Our final regressions samples consist of 347 CF-year observations and 10,955 person-year observations.[24] Selective sample attrition is of concern, and we address it in the next section.

3.8. Empirical strategy

We causally estimate the intent-to-treat (ITT) effects of a community being assigned to a direct CF training (relative to a *status quo* CF modality) on the SLM knowledge and adoption of CFs[25] and other farmers in the community, Y, using a simple reduced-form specification:

$$Y_{ihjt} = \beta_0 + \beta_1 T_j + \beta_2 \mathbf{X}_{i,h,j} + \nu_t + \epsilon_{i,h,j}. \tag{1}$$

T takes the value 1 for each community j with a trained CF. Individual i, household h, and community characteristics are included in the vector X to improve the precision of the estimated coefficients. An indicator for the second follow-up survey, ν_t, is also included to capture the effect of time-specific events on behavior.[26] We estimate all main regression models on the pooled sample, controlling for survey-year fixed effects. 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.[27,28]

4. Results

4.1. CF learning and adoption

We first examine the ITT estimates of a direct training on unweighted aggregate measures of CFs' knowledge and adoption (Panel A, Table 4). While control CFs adopted on average 3.74 techniques, we detect that CFs adopt on average a 0.73 additional technique in response to the training (statistically significant at the 5 percent level). The associated effect size is large at 0.39 standard deviations in the control group, or a 19.6% increase relative to the mean in the control. Next, we run similar specifications with the weighted versions of the outcome.[29] Control CFs adopt on average 60.1% of the practices, and directly trained CFs increased adoption by about 10.6 percentage points (statistically significant at the 5% level; Panel B, Table 4). This effect is similar in magnitude to that obtained on our unweighted index, with a similar effect size of 0.40 standard deviation in the control group, or a 17.6% increase relative to the mean in the control. Weighting our knowledge index confirms that directly training CFs did not affect their knowledge scores. Overall, unweighted and weighted results suggest that a direct training was effective in raising CFs' adoption of SLM practices, with little effect on knowledge scores.

To shed light on changes in the technique mix, we disaggregate the ITT estimates of adoption by technique (Table 5). Despite positive point estimates for all practices, statistical significance is achieved for only strip-tillage, pit planting and contour farming (statistically significant at the 10%, 1%, and 10% levels, respectively).[30] The magnitude of these effects is substantial, ranging from 28.3% to 65% increases relative to the control mean. To account for multiple hypothesis testing, we adjust our inferences for familywise error rates (Šidák, p-value=0.015; Bonferroni, p-value=0.014), following Abdi (2007). The effect on pit planting adoption is robust to multiple hypotheses testing (Fig. 4), with a 28 percent increase in adoption

[23] In the case of polygamous households, the main spouse was interviewed. Only 2.7 percent of our sampled households are polygamous.

[24] The number of villages that were administered the CF survey were 179 and 172 in 2012 and 2013, respectively. The number of farmers interviewed in 2012 were 6252, and 5290 in 2013. Sample sizes vary in descriptive statistic tables and some regression tables, due to the addition of variables excluded from the main analysis.

[25] CF-level regressions control for community-level CF outcomes and characteristics. In those communities where we (randomly) assigned an additional woman farmer to be trained, we measure increased village-level exposure by regressing the maximum value of CF outcomes within the village on the maximum (mean) value of binary (continuous) covariates. Switching to mean of outcomes, and controlling for mean and max of all covariates does not affect our conclusions.

[26] We include variables that reflect CF (or other farmer) demographic characteristics: age, primary school completion, whether the individual is single (and a separate widow dummy for the other farmer sample), number of children, total landholdings, the number of rooms in the house, the number of hours worked by the CF at baseline, an indicator for a missing response for the baseline CF variable, district indicators, and indicators for treatment arms not analyzed in the present study. Our results are robust to specifications that omit the demographic characteristics (Tables A6 and A7) or replace district with administrative post fixed effects (Tables A8 and A9).

[27] Attrition rates at the household and CF level are not statistically different (Table A10) nor correlated across treatment groups (Table A11). Household attrition rates

(*footnote continued*)
appear consistent with those of other studies in the same region (De Brauw, 2014). A probit regression reveals that the greater the percentage of household members away in 2012 and the incidence of being single produces a greater probability of the household moving out of the sample (Table A11). Age, the number of children of the household head, and exposure to a precipitation shock reduce the probability of moving out of the sample.

[28] We perform two additional robustness checks to examine the sensitivity of our results to attrition (not reported). The first diagnostic estimates (1) using the balanced panel. We show that the inclusion of individuals present in both rounds 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). This check confirms that selective attrition is unlikely to affect our conclusions.

[29] The linear model of maize revenue controls for adoption of each SLM technique, as well as household demographics, as in Table 4, and production inputs. The regression estimates are presented in Table A12. The vector of weights consists of the estimated regression parameter for each technique divided by the sum of the parameters over all seven techniques. Since some regression coefficients are negative, we use improved fallowing as the reference weight. Thus, mulching takes value 0.227, strip tillage, 0.177, pit planting, 0.157, contour farming, 0.201, crop rotation, 0.193, and row planting, 0.045.

[30] We note that adoption trended downward in both treatment and control villages (not reported). However, these changes are fully attributable to a fall in demonstration of SLM from midline to endline, while adoption on non-demonstration plots actually increases from midline to endline (not reported). We additionally use rainfall data to provide partial evidence that this trend cannot be explained by climatic conditions (NASA 1/2x 1/21981/2013 precipitation data available at http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/hirestimeser.cgi?email=daily@larc.nasa.gov). Indeed, a dry shock during the rainy season prior to our midline survey (2011) and endline (2012) surveys could affect adoption. Fig. 3 displays yearly standardized cumulative rainfall in the rainy season over the 1981/2012 period, and their 95% confidence intervals. We observe that rainfall in the study years (2010/2012) are within normal range. Nonetheless, we test whether adoption decisions vary by exposure to a dry spell over the rainy season (where *dry* is defined as whether the cumulative rainfall during the growing season was below the 31-year 25th percentile). We find that rainfall anomalies do not explain variations in adoption (Table A13).

Table 4
Effect of a direct SLM training on contact farmers' adoption and knowledge.

	Ctrl. Mean [SD]	ITT	*N*	R^2
Panel A: CFs' Knowledge and Adoption, unweighted				
Knowledge score	0.633 [0.173]	0.052 [0.055]	347	0.102
Number of techniques known by name	4.131 [1.626]	0.706 [0.546]	347	0.098
Number of techniques adopted on own plot	1.786 [1.309]	0.673** [0.225]	347	0.224
Number of techniques adopted on any plot	3.738 [1.889]	0.733** [0.250]	347	0.241
Panel B: CFs' Knowledge and Adoption, weighted				
Knowledge score	0.646 [0.189]	0.059 [0.056]	347	0.138
Number of techniques known by name	0.687 [0.236]	0.079 [0.076]	347	0.071
Number of techniques adopted on own plot	0.314 [0.220]	0.113** [0.031]	347	0.248
Number of techniques adopted on any plot	0.601 [0.265]	0.106** [0.034]	347	0.226

Table 5
Effect of a direct SLM training on contact farmers' adoption of individual SLM techniques.

Adoption on any plot	Ctrl. Mean	ITT	N	R^2
Mulching	0.929	0.026 [0.046]	347	0.040
Strip-tillage	0.548	0.159* [0.072]	347	0.125
Pit planting	0.560	0.159*** [0.023]	347	0.093
Contour farming	0.226	0.147* [0.067]	347	0.241
Crop rotation	0.726	0.066 [0.051]	347	0.166
Row planting	0.440	0.096 [0.058]	347	0.081
Improved fallowing	0.310	0.080 [0.070]	347	0.169

Sources: *Contact farmer survey*, *2010*, *2012*, *2013*; *Household survey 2012*,*2013*.
Notes: Regressions include the same explanatory variables as models in Table 4.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat; SLM=sustainable land management.

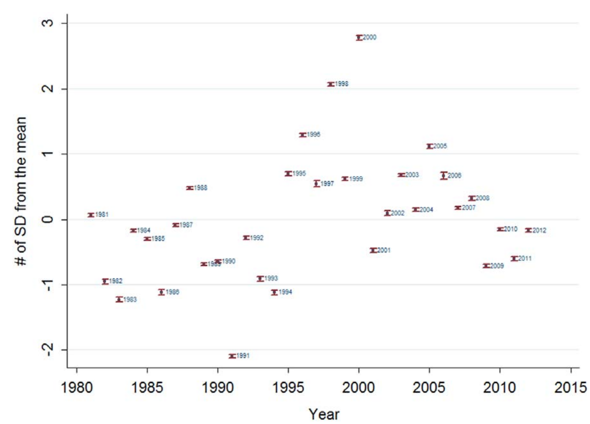


Fig. 3. Precipitation anomalies over time, *Notes*: Standardized cumulative rainfall in the 200 study communities over the rainy season period (October–February). The rainy season starting in October 2012 is labeled as 2012. Standardized values are computed as a ratio of the distance between cumulative rainfall and average historical cumulative rainfall to the historical standard deviation across all 200 communities. 95% confidence intervals are presented around each yearly value. Our study period includes 2010 (demonstration season), and 2011 and 2012 (adoption seasons). Midline and endline surveys correspond to 2011 and 2012, respectively.

relative to the control mean.[31]

Finally, we examine changes in technique-specific knowledge as a result of the direct training. In line with our aggregate measures of knowledge, Table 6 indicates that adding a direct training to the CF model did little to increase CFs' knowledge scores.

4.2. Private returns on SLM

Farmers will adopt a technique only if it demonstrates (public or private) positive returns. Recent observational and experimental evidence documents positive maize yield effects of SLM techniques in southern Africa, as well as substantial labor savings (Beaman et al., 2014; BenYishay and Mobarak, 2014; Haggblade and Tembo, 2003; Thierfelder et al., 2015). We examine private returns to SLM to explain the observed increase in adoption among CFs, beyond their willingness to comply with the training. In practice, we modify (1) to estimate the ITT effects on maize yields and revenue, input use, and on-farm labor allocation.

Table 7 (Panel A) presents maize yields (revenue per hectare) and total revenue accrued from a direct SLM training. Given our low level of statistical power, we present results on the full sample and winsorizing yields at 1% to account for outliers.[32] Results show positive though imprecise point estimates, indicating effect sizes on the order of 0.13–0.24 standard deviations.

Since most SLM practices disseminated have water-conserving properties (Liniger et al., 2011), we further account for the possibility that rainfall patterns in the main growing season may mediate the impacts of the intervention. In practice, we add a control variable to distinguish effects by whether the community experienced a dry spell

[31] We also follow Anderson (2008) and address multiple inference in two additional ways (not reported): (1) using a free step-down resampling method to our *p*-values for familywise error rate, and (2) employing the false discovery rate control methodology proposed by Benjamini and Hochberg (1995). All yield the same results.

[32] Winsorizing yields at 1% does not affect the control group mean as the entire top 1% of the distribution is in the treatment group.

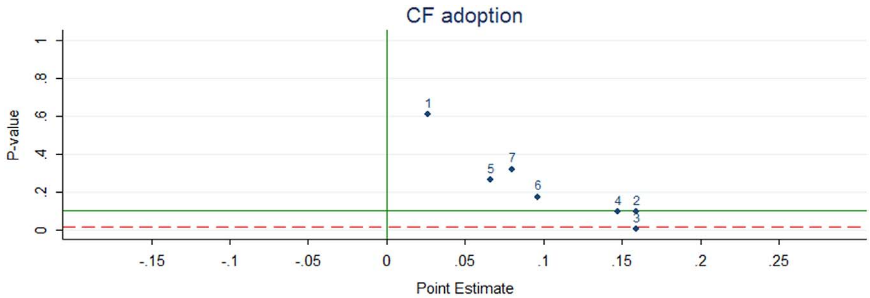


Fig. 4. Effect of SLM training intervention on contact farmers, controlling for familywise error rate.

Table 6
Effect of a direct SLM training on contact farmers' knowledge of individual SLM techniques.

Knowledge score	Ctrl. Mean	ITT	*N*	R^2
Mulching	0.893	0.043* [0.017]	347	0.135
Strip-tillage	0.512	0.089 [0.057]	347	0.095
Pit planting	0.798	0.050 [0.088]	347	0.075
Contour farming	0.520	0.127 [0.116]	347	0.098
Crop rotation	0.567	0.008 [0.046]	347	0.072
Row planting	0.310	−0.026 [0.113]	347	0.149
Improved fallowing	0.690	0.007 [0.040]	347	0.046

Sources: *Contact farmer survey*, *2010*, *2012*, *2013*; *Household survey 2012*, *2013*.
Notes: Regressions include the same explanatory variables as models in Table 4.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat; SLM=sustainable land management.

during the survey round: Dry Year, which takes value one if the cumulative precipitation in a given location fell below the 30-year first quartile, zero otherwise.[33] In line with recent experimental evidence on pit planting (Beaman et al., 2014), we find that training CFs on SLM has positive and large, if noisy, effects on maize yields and revenues during drier spells (Table 7, Panel B). The magnitude of the effects, on the order of 0.35 standard deviations, or 37% increase in both yield and total revenue, are in line with findings from the literature that claim increases of 50 to 100% (Haggblade and Tembo, 2003). The measured yield effects from receiving a SLM training corroborate the notion that farmer adoption of SLM technologies is motivated by short-term yield advantages. In the absence of any statistically significant differences in input use as a result of the direct training (Table 8), these yield effects in dry conditions are credibly attributable to SLM adoption.

An additional economic benefit of applying SLM is in the form of large labor savings that follow from refining tillage operations and herbicide applications (Mazvimavi et al., 2011). These gains are expected to materialize from the second adoption season onward, since the first year requires at least equal amount of land preparation as traditional practices (Haggblade and Tembo, 2003). Building on this literature and recent large-scale experimental evidence (BenYishay and Mobarak, 2014), our findings support a delayed contribution of SLM to labor savings. We witness a substantial reduction in the number of hours spent seeding over the week preceding the interview and the total weeks spent farming at endline (Table 9). In particular, CFs spent 6.6 fewer hours seeding in the last week (a relative effect size of 0.63 standard deviations) and 7.1 fewer weeks farming over the last year (a relative effect size of 0.37 standard deviations).[34] While large, these point estimates are in line with the magnitude of effects mentioned in the literature (30 days per year reported in Haggblade and Tembo, 2003). Since use of herbicides remained constant across treatment arms (Table 8), labor savings at endline are plausibly attributable to increased SLM adoption and complementary usage of the tools provided in the kit to minimize tillage operations.

4.3. Others farmers' knowledge and adoption

We now turn to CFs' ability to spread knowledge and adoption among other farmers in the community. We exploit the exogenous, positive shock in CFs' demonstration of SLM induced by the direct training to measure the extent of CF-to-others knowledge transmission. Since we cannot exclude the possibility that our treatment affected other farmers' adoption of SLM through channels other than demonstration, we adapt (1) and estimate the ITT of directly training CFs on adoption and knowledge on a random sample of other farmers in the community.

Table 10 reports the ITT estimates of directly training CFs on CF–farmer interactions and other farmers' aggregate knowledge and adoption of SLM. First, we note that the direct training did not increase farmers' access to CFs. Second, other farmers' SLM knowledge and adoption are unaffected by their exposure to a directly trained CF, despite the margin of gains in SLM awareness being larger than for CFs. These zero effects are robust to balancing the panel at midline, accounting for selective attrition at endline (not reported), and cannot be explained by anomalous precipitations over the study period (Fig. 3; (FEWS, 2012, 2013)). Looking at ITT effects by technique confirms this general pattern (Table A14) .

Recall the direct training led to a 15.9 percentage point increase in CF adoption of pit planting. Other farmers in treated communities were more likely to adopt pit planting by 2.8 percentage points (albeit a non-significant effect). Placing a 95% confidence interval around this point estimate allows us to rule out adoption rates higher than $(0.028 + 1.96 \times 0.018 =)6.3\%$ for pit planting among other farmers. A back-of-the-napkin calculation on this (weak) pit planting result rules out a propagation rate higher than $(6.3/15.9 =)39.6\%$. Adoption of pit planting by a CF would, at best, inspire less than half of a farmer in the community to adopt pit planting. This implies low and slow CF-to-other-farmers technology diffusion in the augmented CF model: increasing demonstration of SLM has little effect on other farmers' behavior.

Learning about other farmers' perceptions of labor savings asso-

[33] For these computations, we use NASA 1/2x 1/21981/2013 Precipitation data available at http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/hirestimeser.cgi?email=daily@larc.nasa.gov. This measure of weather event is used by others in the literature, see for instance Jayachandran (2006).

[34] These effects are robust to 1% top and bottom winsorizing.

Table 7
Effect of a direct SLM training on contact farmers' maize production.

		(1) Control mean [SD]	(2) *T*	(3) Dry year	(4) *T*× Dry year	(5) *N*	(6) R^2	(7) *T*+*T*× Dry year
Panel A: Without controlling for precipitation								
Revenue per Ha [MZN/Ha]	Original data	1441.540 [1417.638]	326.399 [319.157]			347	0.089	
	Winsorize at 1%	1441.540 [1417.638]	182.322 [121.077]			347	0.147	
Total revenue [MZN]	Original data	4408.667 [4687.363]	1137.593 [721.392]			347	0.121	
	Winsorize at 1%	4408.667 [4687.363]	722.089 [438.057]			347	0.152	
Panel B: Controlling for precipitation								
Revenue per Ha [MZN/Ha]	Original data	1441.540 [1417.638]	41.837 [399.865]	178.182 [451.867]	866.412* [354.536]	347	0.097	908.249 [431.334]
	Winsorize at 1%	1441.540 [1417.638]	9.163 [152.561]	133.582 [440.298]	528.280 [257.942]	347	0.157	537.443* [237.038]
Total revenue [MZN]	Original data	4408.667 [4687.363]	744.990 [632.045]	19.641 [1014.573]	1185.839** [359.641]	347	0.124	1930.829 [977.493]
	Winsorize at 1%	4408.667 [4687.363]	264.976 [310.816]	−213.874 [996.793]	1370.718** [453.943]	347	0.156	1635.694* [664.713]

Sources: *Contact farmer survey, 2010*; *Household survey 2012, 2013*; *NASA 1/2x 1/21981/2013 Precipitation data.*
Notes: Dry year is a dummy indicating cumulative precipitation in the rainy season is in the first quartile of the 1981–2013 historical average. All models include the same explanatory variables as models in Table 4.
T+*T*×dry year (col 7) presents the total effect of the treatment *T* and its interaction with dry year on maize yield and revenue. The associated standard errors are in brackets. Significance on the additive effect is determined by a Wald test.
×=multiplied by; SLM=sustainable land management; MZN=Mozambican Metacais; Ha=hectare.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.

Table 8
Effect of direct SLM training intervention on contact farmers' input use.

	Ctrl.Mean [SD]	ITT	*N*[a]	R^2
Burnt farm plot	0.167	−0.015 [0.060]	347	0.037
Used natural fertilizer	0.524	0.129 [0.067]	343	0.166
Used chemical fertilizer	0.071	0.065 [0.042]	343	0.037
Amount of chemical fertilizer used (kg)	2.681 [21.992]	35.227 [19.514]	341	0.027
Amount of chemical fertilizer used (l)	3.855 [27.973]	1.282 [5.836]	341	0.033
Use herbicides/pesticides/fungicides	0.250	0.022 [0.032]	343	0.082
Amount of herbicides/pesticides/fungicides used (kg)	0.060 [0.361]	0.374 [0.223]	341	0.014
Amount of herbicides/pesticides/fungicides used (l)	4.367 [11.714]	−0.928 [1.582]	341	0.048

Sources: Contact farmer survey, 2010; Household survey, 2012, 2013.
Notes: All models include the same explanatory variables as models in Table 4.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat; SLM=sustainable land management.
[a] The main sample has 347 observations. Sample size varies across models due to missing values in the dependent variables.

ciated with each SLM practice may shed light on the mechanisms underlying adoption—or, in our context, a lack thereof. We asked farmers whether they perceived each technique to require more labor effort, equivalent labor effort, or less labor effort than traditional cultivation practices. Farmers in the control group perceived all techniques to be labor intensive, with a range of less than 1 percent to 16 percent of farmers declaring the techniques to decrease the amount of labor required (not reported). Exposure to a trained CF does not favorably affect farmers' perceptions of adoption costs (not reported). These measures of communication and perceptions indicate that a direct training did not contribute to increasing CF-other farmers interactions, and that CFs' increased demonstration and use of SLM had little impact on other farmers' perceptions of these techniques.

Lastly, we explore whether CFs' characteristics provoke heterogeneous responses among farmers. We focus on four CF indicators: above median educational attainment, above median age, above median landholdings, and production of the same two crops as the farmer.[35] Each regression separately adds an interaction of the treatment variable with one of the four indicators and the interacted indicator on its own. Working with an existing network of CFs, we could not exogenously vary their education, age, wealth, or cropping patterns. Thus, the results that follow cannot be interpreted causally, but as descriptive evidence. In addition, CFs are, on average, of higher status than other farmers, which reduce the number of variations we have access to in establishing a counterfactual. Finally, to yield interpretable results, we need this exercise to focus on a single technique rather than on an aggregate measure of adoption. We focus on the adoption of pit planting among other farmers as the outcome, since it is the only single practice which was statistically significantly adopted by CFs, when adjusting our inference for multiple hypothesis testing.

Table 11 displays the results from interacted regression models accounting for farmer heterogeneity in the treatment effects, with the additive effect of the treatment and its interaction with the CF characteristic reported in the last row. Overall, we find CFs with above median total landholdings were 4.4 percentage points more likely to convince other farmers to adopt pit planting, a 64.7% increase relative to the control (significant at the 10% level). Credibility in the source of information appears to influence all farmers, CFs with larger farms perhaps commanding more trust and respect within the community.

[35] Our specification implies that having similar primary crops as the CF is an exogenous decision. Specifically, we assume cropping decisions are made before adoption decisions, and cropping decisions are independent of the treatment. While we cannot verify the order of the respective planting decisions, we find that other farmers' propensity to grow the same primary two crops as the CF is not affected by the treatment (not reported).

Table 9
Effect of a direct SLM training intervention on contact farmers' labor allocation.

	Pooled Sample				Endline			
	Control mean [SD]	ITT	N	R^2	Control mean [SD]	ITT	N	R^2
Hours spent on preparation of land	6.095	−2.822	346	0.032	6.429	−1.272	168	0.073
	[14.550]	[3.356]			[15.353]	[2.998]		
Hours spent on seeding	8.214	−3.558**	346	0.021	10.357	−6.567*	168	0.065
	[15.996]	[1.069]			[17.862]	[2.943]		
Hours spent on transplantation	2.607	−1.408	346	0.062	1.738	−0.917	168	0.087
	[7.973]	[0.957]			[6.666]	[0.736]		
Hours spent on irrigation	0.000	−0.038	346	0.028				
	[0.000]	[0.044]						
Hours spent on sacha	10.583	0.454	346	0.198	5.833	−0.690	168	0.072
	[15.576]	[1.098]			[14.252]	[1.514]		
Hours spent on protection	0.000	0.969	346	0.042	0.000	0.513	168	0.122
	[0.000]	[0.922]			[0.000]	[0.499]		
Hours spent on harvesting	11.012	−2.288	346	0.122	15.810	−2.234	168	0.114
	[18.260]	[1.417]			[19.573]	[1.164]		
Total weeks spent on farming in last year	28.262	−2.986	346	0.029	30.381	−7.084**	168	0.069
	[18.386]	[2.210]			[19.196]	[2.508]		

Sources: *Contact farmer survey*, *2010*; *Household survey*, *2012*, *2013*.
Notes: All models include the same explanatory variables as models in Table 4.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat effect; SLM=sustainable land management.

Table 10
Effect of a direct SLM training intervention on other farmers' access to contact farmers, adoption, and knowledge.

	Ctrl. Mean [SD]	ITT	N	R^2
Access to CF				
Has access to any contact farmer in the last half year	0.170	0.032	10,955	0.046
		[0.027]		
Other Farmer Knowledge and Adoption, unweighted				
Knowledge score	0.341	−0.004	10,955	0.055
	[0.200]	[0.012]		
Number of techniques known by name	1.654	0.000	10,955	0.022
	[1.538]	[0.120]		
Number of techniques adopted	0.845	−0.034	10,955	0.060
	[0.891]	[0.071]		

Sources: *Contact farmer survey*, *2010*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the following variables: a constant, age, a completed primary school dummy, a dummy for male, a single dummy, a widow dummy, number of children, total landholdings, the number of rooms in the dwelling, baseline CF's number of years since formal training, a dummy for missing the baseline CF variable, district indicators, an incentive treatment dummy, and an endline dummy.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF=contact farmer; ITT=intent-to-treat effect; SLM=sustainable land management.

More interestingly, similarities in crop portfolios between CFs and other farmers appear to influence adoption rates. Other farmers' adoption grew an additional 5.2 percentage points when they had access to a directly trained CF who grew similar crops to theirs. This is consistent with the idea that homogeneous farming conditions are conducive to social learning (Munshi, 2004). Delays in adoption may stem from differences in production technologies and an inability to extrapolate demonstrated activities to their own plot.

4.4. Cost–benefit analysis

To provide perspective on the cost-effectiveness of the program, we compare the average annual costs of directly training each CF to the average annual benefits realized by the CF. We consider three scenarios where the private returns to a direct CF training are in the form of maize revenue, labor earnings, and both.[36] To compute the value of labor savings, we multiply the estimate of the intervention's impact on farm labor savings by the shadow value of labor.[37] Benefits to other farmers are excluded from all three scenarios given the non-significant (negative) ITT point estimates on adoption.

Calculations for the three scenarios are presented in Table 12. Positive net benefits over one adoption season exist when we account for the labor benefits only, and when we account for both labor and yield benefits. The costs of training represent 12.8 percent of the total annual costs of running the extension system,[38] with benefits ranging from USD -55 to USD 76 per CF per season.

Although we fail to measure diffusion to other farmers in our context, the predicted returns from CF's labor savings justify scaling a program of this nature. This motivates further research in extension modalities to improve the delivery of information to other farmers to augment the pool of program beneficiaries. For instance, providing performance-based incentives to CFs and tempering the selection of CFs does appear to achieve greater rates of technological adoption within communities (Beaman et al., 2014; BenYishay and Mobarak, 2014; BenYishay et al., 2015).

5. Discussion

Decentralized extension modalities continue to garner support in Africa despite criticism, often anecdotal, of their inefficacy in reaching most farmers and providing relevant information. We designed an experiment in Mozambique to examine whether adding an in-depth centralized training on a new technology improves the knowledge and adoption of innovative

[36] This approach ignores the social benefits produced by the technologies which cannot be quantified over a short-term horizon, such as soil and water quality.

[37] We price the shadow value of labor at the minimum agricultural wage offered in Mozambique. Minimum wage rates are provided by the U.S. State Department: http://www.state.gov/e/eb/rls/othr/ics/2013/204700.htm. Agriculture is the lowest wage rate at 74 USD per month.

[38] We focus on the costs specific to the SLM intervention, which include the annual per community cost of an extension agent and per community cost of the SLM training.

Table 11
Effect of a direct SLM training intervention on other farmers' adoption of pit planting, by CFs' characteristics.

CF characteristics	Educ > Median	Age ≥ Median	Land ≥ Median	Same crop
T	0.029	0.035*	0.018	0.025
	[0.021]	[0.020]	[0.019]	[0.019]
CF characteristics	0.011	−0.010	−0.014	0.003
	[0.020]	[0.016]	[0.016]	[0.023]
T×CF characteristics	0.000	−0.011	0.025	0.026
	[0.025]	[0.023]	[0.022]	[0.027]
N	9,836	9,836	9,836	9,968
R^2	0.010	0.011	0.010	0.010
Control mean	0.068	0.068	0.068	0.069
T+*T*×CF characteristics	0.029	0.023	0.044*	0.052*
	[0.025]	[0.023]	[0.024]	[0.030]

Sources: *Contact farmer survey, 2010*; *Household Survey, 2012, 2013*.
Notes: Regressions include the same explanatory variables as models in Table 10.
The cutoff values for CF characteristics correspond to the median values of education (7 years), age (41 years at ML, 43 years at EL), and landholdings (2.75 ha at ML, 3.5 at EL) in the sample of CFs.
T+T×CF characteristics (bottom row) presents the total effect of the treatment T and its interaction with the CF characteristic. The associated standard errors are in brackets. Significance on the additive effect is determined by a Wald test.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
×=multiplied by; CF=contact farmer; SLM=sustainable land management. ML=midline; EL=endline.

Table 12
Cost−benefit analysis of a direct SLM training intervention.

	Yield benefits	Labor benefits	Yield and labor benefits
Number of Beneficiaries per community			
CFs	1	1	1
Average Costs per Beneficiary			
Total cost of trainings	22,262	22,262	22,262
Annual cost of training	11,131	11,131	11,131
Annual training cost per farmer	74	74	74
Annual cost of extension agent per farmer	505	505	505
Average Benefits per Beneficiary			
Annual maize revenue	19	0	19
Weekly agricultural wage rate	19	19	19
Number of weeks in labor savings	0	7	7
Annual labor earnings	0	131	131
Net Average Benefits per Beneficiary			
Total net benefits per CF	−55	57	76

Notes: CF=Contact farmer. Figures presented in terms of 2012 USD, assuming exchange rate of 38 Metacais per 1 USD.
Annual cost per extension agent is based on the monthly salary of the extension agent (211 USD) and assumes one extension agent services five communities.
Annual benefits in maize revenue obtained from estimates of the ITT in the winsorized specification in Table 7.
Annual benefits in endline labor savings taken from estimates of the ITT on the number of weeks worked in Table 9.

agricultural practices. We show that adding a direct training to an existing CF model increases adoption of SLM among CFs. Net private returns come mostly in the form of labor savings associated with the new practices.

Despite these gains in adoption, adding a direct training to the CF modality had little impact on CF knowledge scores. This could of course be the result of poor quality testing and measurement error (Laajaj and Macours, 2015). Alternatively, relative to the *status quo* extension modality, the direct training may not have changed adoption by increasing CFs' knowledge. Knowledge is not a necessary condition for adoption of a new technology, as manifestations of herd behavior indicate (Banerjee, 1992; Karlan et al., 2014). Instead, the direct training intervention may have gotten more CFs to adopt SLM by strengthening their sense of identity as communicators in their community. The absence of differences in the use of a demonstration plot, interactions with other farmers, and subjective happiness (not reported) across treatment arms however suggests CFs' dedication and esteem were unaffected. Another possibility is that adding a centralized CF training may have heightened the quality and credibility of the information, beyond the scope of our knowledge test. The participatory nature of the training may have helped CFs convert the information into productive behavior, and fostered higher peer learning.

Although adding a direct CF training successfully encouraged adoption of a new technology at the village level relative to the *status quo* model of extension, it failed to encourage higher diffusion to other farmers in the community. There are a number of reasons why this may be the case. First, increased demonstration may not effectively address other barriers to adoption. Having access to a demonstration plot may need to be complemented by other learning inputs, such as CF time or other farmers' time. Adding a direct CF training does not address the fact that CFs' opportunity costs of time may limit interactions with peers. For instance, adding a performance-based incentive payment for contact farmers is shown to positively affect their impact in Malawi (BenYishay and Mobarak, 2014). Similarly, increasing demonstration of a yield-enhancing practice may not address other demand-side inefficiencies, such as the tendency to delay adoption until profitable (Foster and Rosenzweig, 1995), heterogeneity in farming conditions (Conley and Udry, 2010; Munshi, 2004), and social distance between messengers and peers (Feder and Savastano, 2006; Beaman et al., 2014; BenYishay and Mobarak, 2014).

An alternative explanation is that farmers may learn more from their own experience than from their peers (Foster and Rosenzweig, 1995; Bryan et al., 2014; Dupas, 2014). Failing to notice a gap between knowledge and actual practice, and not the information set itself, may also pose a key barrier to learning. Hanna et al. (2014) find that seaweed farmers in Indonesia acted on the information received only when it included descriptions of the relationship between yield and pod size from their own plot. If the main constraint to adoption of a profitable practice such as SLM is not a lack of exposure or knowledge, but a failure to notice its benefits, then augmenting the CF model will have little effect on the pace of diffusion within the community.

While we cannot reject that adding a direct training to a decentralized extension model is a cost effective intervention, more work is needed to understand the potential of community-level demonstration activities on technology diffusion. The profile of the "seed adopters" influences whether farmers act on the information they receive. When focusing on farmers with similar cropping patterns as their CF, we observe modest (yet statistically significant) technology diffusion. Complementary interventions, such as assigning different types of seed adopters (Beaman et al., 2014; BenYishay and Mobarak, 2014; BenYishay et al., 2015) or encouraging experiential learning in the community (Jones et al., 2015), may increase the pace of technology diffusion in the context of decentralized extension services.

Appendix A. Additional Tables

See Tables A1-A14.

Table A1
Pre-intervention See Tables A1 to A14. SLM training across treatment status (recalled).

Variables	Treated mean	Control mean	Difference in mean
Contact Farmers: before 2010			
Learned mulching	0.620	0.762	−0.141*
Learned strip-tillage	0.321	0.429	−0.107
Learned pit planting	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[a] : before 2010			
Learned mulching	0.306	0.337	−0.031
Learned strip-tillage	0.182	0.227	−0.045
Learned pit planting	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

Source: *Household survey, 2012.*
Notes:
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
SLM=sustainable land management.
[a] *t*-test inferences are based on standard errors clustered at the community level.
[*] Significance at the 10 percent critical level for *t*-statistics.

Table A2
Extension agents' characteristics by treatment status.

Variables	Treated		Control		Difference
	Mean	SD	Mean	SD	in 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 worked as EA	6.388	5.919	5.355	4.329	1.033
Number of years worked in agricultural section, before became an EA	4.451	2.893	4.412	2.994	0.038
Number of training received over the past 5 years	9.624	5.265	9.645	5.563	−0.021
Received training from the Ministry of Agriculture	0.344	0.477	0.289	0.460	0.055
Received training from Smallholders' project	0.752	0.434	0.816	0.393	−0.064
Number of weeks in training during the last 12 months	1.244	0.601	1.276	0.601	−0.032
One of the main topics covered in the trainings was conservation agriculture	0.944	0.231	0.974	0.162	−0.030
Number of villages	125		38		163

Table A3
Effect of a direct SLM training intervention on contact farmers' use of demonstration plots and access to extension agents.

	Ctrl. Mean	ITT	N	R^2
Used demonstration plot during the last year	0.845	−0.034	347	0.043
		[0.066]		
EA visited CF at least once/month	0.512	0.001	347	0.033
		[0.073]		
EA visited CF at least once/half year	0.631	0.055	347	0.047

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Table A3 *(continued)*

	Ctrl. Mean	ITT	N	R^2
		[0.123]		
EA visited CF at least once/year	0.667	0.143	347	0.048
		[0.123]		

Sources: *Contact farmer survey, 2010, 2012, 2013*; *Household survey, 2012, 2013.*
Notes: Regressions include the following variables: a constant, age, a completed primary school dummy, a single dummy, number of children, total landholdings, the number of rooms in the dwelling, baseline CF's number of years since formal training, a dummy for missing the baseline CF variable, district indicators, an incentive treatment dummy, and an endline dummy.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF=contact farmer; EA=extension agent; ITT=intent-to-treat effect.

Table A4
Other farmers' characteristics.

Variables	Mean	SD
Is the head of household	0.590	0.492
Age	38.243	14.430
Years of schooling completed	2.054	2.798
Single	0.056	0.229
Married	0.849	0.359
Divorced, separated, or widowed	0.095	0.293
Number of children [ages < 15 years]	2.830	2.041
Total hectares of owned land	2.171	2.064
Number of rooms in the house	1.423	0.724
Number of observations	10,960	

Sources: *Household survey, 2012, 2013.*

Table A5
Pre-intervention SLM adoption by treatment status (recalled).

Variables	Treated mean	Control mean	Difference in mean
Contact farmers: before 2010			
Adopted mulching	0.489	0.405	0.084
Adopted strip-tillage	0.248	0.214	0.034
Adopted pit planting	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: before 2010[a]			
Adopted mulching	0.181	0.203	−0.022
Adopted strip-tillage	0.087	0.118	−0.031
Adopted pit planting	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

Source: *Household survey, 2012.*
Notes:
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
SLM=sustainable land management.
[a] *t*-test inferences are based on standard errors clustered at the community level.

Table A6
Effect of a direct SLM training intervention on contact farmers' knowledge and adoption, basic specification.

	Ctrl. Mean [SD]	ITT	N	R^2
CFs' Knowledge and Adoption, unweighted				
Knowledge score	0.633	0.046	347	0.019
	[0.173]	[0.049]		
Number of techniques known by name	4.131	0.646	347	0.018
	[1.626]	[0.571]		
Number of techniques adopted on own plot	1.786	0.594*	347	0.023
	[1.309]	[0.232]		
Number of techniques adopted on any plot	3.738	0.752**	347	0.020
	[1.889]	[0.244]		

Sources: *Contact farmer survey*, *2010*, *2012*, *2013*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the following variables: a constant, treatment variables, an endline dummy, and district indicators.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF=contact farmer; ITT=intent-to-treat effect; SLM=sustainable land management.

Table A7
Effect of a direct SLM training intervention on other farmers' knowledge and adoption, basic specification.

	Ctrl.Mean [SD]	ITT	N	R^2
Other Farmers' Knowledge and Adoption, unweighted				
Knowledge score	0.341	−0.003	10,955	0.049
	[0.200]	[0.012]		
Number of techniques known by name	1.654	0.013	10,955	0.012
	[1.538]	[0.119]		
Number of techniques adopted	0.845	−0.020	10,955	0.049
	[0.891]	[0.071]		

Sources: *Contact farmer survey*, *2010*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the following variables: a constant, treatment variables, a male dummy, an endline dummy, and district indicators.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat effect; SLM=sustainable land management.

Table A8
Effect of a direct SLM training intervention on contact farmers' adoption and knowledge, includes administrative post fixed effects.

	Ctrl. mean [SD]	ITT	N	R^2
CFs' Knowledge and Adoption, unweighted				
Knowledge score	0.633	0.046	347	0.103
	[0.173]	[0.036]		
Number of techniques known by name	4.131	0.859**	347	0.105
	[1.626]	[0.367]		
Number of techniques adopted on own plot	1.786	0.726***	347	0.256
	[1.309]	[0.216]		
Number of techniques adopted on any plot	3.738	0.658**	347	0.244
	[1.889]	[0.258]		

Sources: *Contact farmer survey*, *2010*, *2012*, *2013*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the same explanatory variables as models in Table 4, except replacing district indicators with administrative post indicators.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF=contact farmer; ITT=intent-to-treat; SLM=sustainable land management.

Table A9
Effect of a direct SLM training intervention on other farmers' access to contact farmers, adoption, and knowledge, includes administrative post fixed effects.

	Ctrl. Mean [SD]	ITT	N	R^2
Other Farmers' Knowledge and Adoption, unweighted				
Knowledge score	0.341	−0.007	10,955	0.057
	[0.200]	[0.012]		
Number of techniques known by name	1.654	−0.001	10,955	0.020
	[1.538]	[0.116]		
Number of techniques adopted	0.845	0.003	10,955	0.053
	[0.891]	[0.066]		

Sources: *Contact farmer survey*, *2010*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the same explanatory variables as models in Table 10, except replacing district indicators with administrative post indicators.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
CF=contact farmer; ITT=intent-to-treat; SLM=sustainable land management.

Table A10
Attrition of contact farmers and other farmers.

Variables	Treated		Control		Difference
	Mean	SD	Mean	SD	in mean
CFs attrited from Midline	0.109	0.313	0.048	0.216	0.062
Number of Observations	137		42		179
Household attrited from Midline[a]	0.090	0.372	0.087	0.374	0.003
Number of Observations	2750		935		3685

Sources: *Household survey*, *2012*, *2013*; *Contact farmer survey*, *2012*, *2013*.
Notes: CF=contact farmer.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
[a] *t*-test inferences are based on standard errors clustered at the community level.

Table A11
Determinants of attrition (contact farmers and other farmers).

	CFs		Other farming HH
Treatment 1	0.053	Treatment 1	0.014
	[0.066]		[0.013]
Treatment 3	0.002	Treatment 3	−0.013
	[0.055]		[0.012]
Age	−0.006**	Age	−0.001**
	[0.003]		[0.000]
Completed at least	0.056	HH head completed at	−0.004
primary school	[0.060]	least primary school	[0.012]
Single	−0.091	HH head Single	0.023
	[0.190]		[0.020]
		HH head divorced,	0.045***
		widow, or separated	[0.017]
Total number	−0.011	Total number	−0.007**
of children	[0.013]	of children	[0.003]
Total landholding	0.005	Total landholding	−0.005
[hectares]	[0.011]	[hectares]	[0.003]
Total number of rooms	−0.037	Total number of rooms	−0.003
	[0.032]		[0.008]
Number of years	−0.034*	Number of years	0.004
since formal training	[0.020]	since formal training	[0.003]
Missing above	−0.145*	Missing above	0.001
variable	[0.076]	variable	[0.015]
Household head	−0.035	Household head	−0.002
was female	[0.088]	was female	[0.013]
% of household	−0.436	% of household	0.171***
members was away	[0.350]	members was away	[0.065]
HH has non-own	0.023	HH has non-own	−0.013
farming work	[0.078]	farming work	[0.012]
HH has outside	−0.015	HH has outside	0.003

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Table A11 *(continued)*

	CFs		Other farming HH
employment	[0.073]	employment	[0.017]
2012 precipitation	−0.001	2012 precipitation	−0.001*
shock	[0.002]	shock	[0.000]
Constant	0.352	Constant	0.043
	[0.308]		[0.058]
N	178	*N*	3662
R^2	0.099	R^2	0.014

Sources: *Contact farmer survey, 2010, 2012, 2013*; *Household survey, 2012, 2013.*
Notes: Regressions include district fixed effect. CF=contact farmer; HH=household. Household attrition measured by whether a household surveyed in 2012 could not be interviewed in 2013. The CF attrition outcome reflects whether the village had at least one CF interviewed in 2012 but not in 2013.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.

Table A12
Effects of contact farmers' adoption of SLM practices on maize revenue.

	Total Maize Revenue
Adopted mulching on own plot	1458.547
	[1032.677]
Adopted strip tillage on own plot	723.044
	[572.914]
Adopted pit planting on own plot	436.835
	[1502.123]
Adopted contour farming on own plot	1078.387
	[3145.182]
Adopted crop rotation on own plot	957.972
	[960.541]
Adopted row planting on own plot	−1206.388
	[1472.065]
Adopted improved fallowing on own plot	−1871.335
	[968.155]
N	342
R^2	0.187

Sources: *Contact farmer survey, 2010, 2012, 2013*; *Household survey, 2012, 2013.*
Notes: Regressions include the same explanatory variables as models in Table 4.
Additional controls include dummies for usage of all inputs displayed in Table 8, as well as labor allocated to maize production as displayed in Table 9.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.

Table A13
Effect of a direct SLM training intervention on contact farmers' adoption of individual SLM techniques, controlling for lagged rainfall.

Adoption any plot	(1) Control Mean	(2) T	(3) Dry Year	(4) T× Dry Year	(5) N	(6) R^2	(7) T+T× Dry Year
Mulching	0.929	0.045	0.034	−0.058	347	0.042	−0.013
		[0.059]	[0.077]	[0.060]			[0.035]
Strip-tillage	0.548	0.174	0.101	−0.050	347	0.127	0.124
		[0.099]	[0.129]	[0.119]			[0.072]
Pit planting	0.560	0.161***	0.125	−0.017	347	0.097	0.144**
		[0.026]	[0.104]	[0.059]			[0.046]
Contour farming	0.226	0.146	0.052	−0.002	347	0.242	0.145**
		[0.097]	[0.086]	[0.099]			[0.043]
Crop rotation	0.726	0.059	−0.054	0.025	347	0.166	0.084
		[0.047]	[0.164]	[0.098]			[0.100]
Row planting	0.440	0.040	0.198	0.137	347	0.117	0.178**
		[0.089]	[0.111]	[0.132]			[0.050]

(continued on next page)

Table A13 *(continued)*

Adoption	(1)	(2)	(3)	(4)	(5)	(6)	(7)
any plot	Control	T	Dry Year	T×	N	R^2	T+T×
Improved fallowing	0.310	0.101	0.166***	−0.074	347	0.175	0.027
		[0.065]	[0.035]	[0.038]			[0.078]

Sources: *Contact farmer survey*, *2010*, *2012*, *2013*; *Household survey*, *2012*, *2013*.
Notes: Dry year indicates that the precipitation amount falls in the first quartile of the historical distribution of cumulative rainfall during the rainy season (1981-2013).
Regression model includes the same controls as in Table 4.
T+T×Dry Year (col 7) presents the total effect of the treatment T and its interaction with Dry Year on adoption. The associated standard errors are in brackets.
Significance on the additive effect is determined by a Wald test.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.

Table A14
Effect of a direct SLM training intervention on other farmers' SLM adoption.

Adoption	Ctrl. Mean	ITT	N	R^2
Mulching	0.336	−0.022	10,955	0.056
		[0.033]		
Strip-tillage	0.181	−0.035	10,955	0.031
		[0.028]		
Pit planting	0.071	0.028	10,955	0.016
		[0.018]		
Contour farming	0.005	−0.003	10,955	0.006
		[0.003]		
Crop rotation	0.153	0.017	10,955	0.005
		[0.018]		
Row planting	0.079	−0.012	10,955	0.018
		[0.015]		
Improved fallowing	0.020	−0.007	10,955	0.003
		[0.006]		

Sources: *Contact farmer survey*, *2010*; *Household survey*, *2012*, *2013*.
Notes: Regressions include the same explanatory variables as models in Table 10.
***, **, and * significance at the 1, 5, and 10 percent levels, respectively.
ITT=intent-to-treat; SLM=sustainable land management.

References

Abdi, H., 2007. The bonferonni and šidák corrections for multiple comparisons. Encycloped. Meas. Stat. 3, 103–107.
Akroyd, S., Smith, L., 2007. Review of public spending to agriculture. A Joint Study by the Department for International Development and the World Bank, 5.
Anderson, J.R., Feder, G., 2004. Agricultural extension: Good intentions and hard realities. World Bank Res. Obs. 19 (1), pp. 41–60.
Anderson, J.R., Feder, G., 2007. Agricultural extension. Handbook of Agricultural Economics, vol. 3, pp. 2343–2378.
Anderson, M., 2008. Multiple inference and gender differences in the effects of early intervention: a reevaluation of the abecedarian, perry preschool, and early training projects. J. Am. Stat. Assoc. 103 (484), 1481–1495.
Bandiera, O., Rasul, I., 2006. Social networks and technology adoption in northern Mozambique*. Econ. J. 116 (514), 869–902.
Banerjee, A., 1992. A simple model of herd behavior. Q. J. Econ. 107, 797–817.
Banerjee, A., Cole, S., Duflo, E., Linden, L., 2007. Remedying education: evidence from two randomized experiments in india. Q. J. Econ. 122 (3), 1235–1264.
Banerjee, A.V., Banerji, R., Duflo, E., Glennerster, R., Khemani, S., 2010. Pitfalls of participatory programs: Evidence from a randomized evaluation in education in India. Am. Econ. J. Econ. Policy, 1–30.
Beaman, L., BenYishay, A., Magruder, J., Mobarak, A. M., 2014. Can network theory based targeting increase technology adoption.
Benin, S., Nkonya, E., Okecho, G., Pender, J., Nahdy, S., Mugarura, S., Kayobyo, G., 2007. Assessing the impact of the national agricultural advisory services (naads) in the uganda rural livelihoods. IFPRI Discussion Paper.
BenYishay, A., Jones, M., Kondylis, F., Mobarak, A.M., 2015. Are gender differences in performance innate or socially mediated?
BenYishay, A., Mobarak, A., 2014. Social learning and communication. NBER Working Paper 20139.
Bindlish, V., Evenson, R.E., 1997. The impact of t & v extension in africa: The experience of Kenya and Burkina Faso. The World Bank Research Observer, pp. 183–201.
Björkman, M., Svensson, J., 2009. Power to the people: evidence from a randomized field experiment of a community-based monitoring project in Uganda. Q. J. Econ. 124 (2), 735–769.
Bryan, G., Chowdhury, S., Mobarak, A., 2014. Under-inversment in a profitable technology: the case of seasonal migration in Bangladesh. Econometrica 82 (5), 1671–1748.
Conley, T.G., Udry, C.R., 2010. Learning about a new technology: pineapple in Ghana. Am. Econ. Rev., 35–69.
Coughlin, P.E., 2006. Agricultural intensification in Mozambique infrastructure, policy and institutional framework-when do problems signal opportunities. Maputo, EconPolicy Research Group, sponsored by Sida.
Cunguara, B., Moder, K., 2011. Is agricultural extension helping the poor? Evidence from rural Mozambique. J. Afr. Econ., (ejr015).
Davis, K., Nkonya, E., Kato, E., Mekonnen, D.A., Odendo, M., Miiro, R., Nkuba, J., 2012. Impact of farmer field schools on agricultural productivity and poverty in East Africa. World Dev. 40 (2), 402–413.
De Brauw, A., 2014. Gender, control, and crop choice in northern Mozambique. Technical Report, International Food Policy Research Institute (IFPRI).
Dupas, P., 2014. Short-run subsidies and long-run adoption of new health products: evidence from a field experiment. Econometrica 82 (1), 197–228.
Eicher, C.K., 2002. Building african models of agricultural extension: A case study of Mozambique. In: Workshop Extension and Rural Development: A Convergence of Views on International Approaches, pp. 12–15.
Feder, G., Savastano, S., 2006. The role of opinion leaders in the diffusion of new knowledge: the case of integrated pest management. World Dev. 34 (7), 1287–1300.
FEWS, January 2012. Agromet update: 2011/2012 agricultural season.
FEWS, March 2013. Agromet update 2012/2013 agricultural season.
Foster, A., Rosenzweig, M., 1995. Learning by doing and learning from others: human capital and technical change in agriculture. J. Polit. Econ., 1176–1209.
Gallina, A., Chidiamassamba, C., 2010. Gender aware approaches in agricultural programmes—Mozambique country report: A special study of the national agricultural development programme (proagri ii). Technical Report, Swedish International Development Cooperation Agency.
Gautam, M., 2000. Agricultural extension: The Kenya experience: An impact evaluation. World Bank Publications.
Gemo, H.R., Chilonda, Pius, 2013. Why did Mozambique's public extension halt the implementation of the National Agrarian Extension Program (PRONEA)?. International Food Policy Research Institute (IFPRI), Washington, DC, USA.
Gemo, H., Eicher, C.K., Teclemariam, S., 2005. Mozambique's Experience in Building a National Extension System. Michigan State University Press.
Glewwe, P., Kremer, M., Moulin, S., 2009. Many children left behind? Textbooks and test scores in Kenya. Am. Econ. J. Appl. Econ. 1 (1), 112–135.
Glewwe, P., Kremer, M., Moulin, S., Zitzewitz, E., 2004. Retrospective vs. prospective

analyses of school inputs: the case of flip charts in Kenya. J. Dev. Econ. 74 (1), 251–268.
Gollin, D., Morris, M., Byerlee, D., 2005. Technology adoption in intensive post-green revolution systems. Am. J. Agric. Economics 87 (5), 1310–1316.
Haggblade, S., Tembo, G., 2003. Conservation farming in Zambia. International Food Policy Research Institute EPTD Discussion Paper #108.
Hanna, R., Mullainathan, S., Schwartzstein, J., 2014. Learning through noticing: theory and evidence from a field experiment. Q. J. Econ. 129 (3), 1311–1353.
Hazell, P., 2013. What makes african agriculture grow?. 2012 global food policy report. Washington, DC: International Food Policy Research Institute (IFPRI).
Jayachandran, S., 2006. Selling labor low: wage rresponse to productivity shocks in developing countries. J. Polit. Econ. 114 (3), 538–575.
Jones, M., Kondylis, F., Mobarak, A.M., Stein, D., 2015. Evaluating the integrated agriculture productivity project in Bangladesh.
Karlan, D., Ratan, A.L., Zinman, J., 2014. Savings by and for the poor: a research review and agenda. Rev. Income Wealth 60 (1), 36–78.
Kondylis, F., Mueller, V., Zhu, S.J., 2015. Measuring agricultural knowledge and adoption. Agric. Econ. 46 (3).
Laajaj, R., Macours, K., January 2015. The reliability and validity of skills measurement in rural household surveys.
Lee, D.S., 2009. Training, wages, and sample selection: estimating sharp bounds on treatment effects. Rev. Econ. Stud. 76 (3), 1071–1102.
Levitt, S., List, J., Syverson, C., 2012. Toward an understanding of learning by doing: evidence from an automobile assembly plant. J. Polit. Econ. 121 (4), 643–681.
Linden, L.L., 2008. Complement Or Substitute?: The Effect of Technology on Student Achievement in India. InfoDev.
Liniger, H., Studer, R.M., Hauert, C., Gurtner, M., 2011. Sustainable land management in practice-guidelines and best practices for sub-saharan africa. TerrAfrica, World Overview of Conservation Approaches and Technologies ((WOCAT)) and Food and Agriculture Organization of the United Nations ((FAO)).
Lucas, R., 1988. On the mechanics of economic development. J. Monet. Econ. 22 (1), 3–42.
Mazvimavi, K., Myathi, P., Murendo, C., 2011. Conservation agriculture practices and challenges in zimbabwe. In: Proceedings of the 5th World Congress of Conservation Agriculture Incorporating 3rd Farming Systems Design Conference, September 2011 Brisbane, Australia.
Munshi, K., 2004. Social learning in a heterogeneous population: technology diffusion in the indian green revolution. J. Dev. Econ. 73 (1), 185–213.
Pamuk, H., Bulte, E., Adekunle, A.A., 2014. Do decentralized innovation systems promote agricultural technology adoption? Experimental evidence from africa. Food Policy 44, 227–236.
Purcell, D., Anderson, J.R., 1997. Agricultural extension and research: Achievements and problems in national systems. World Bank Publications.
Tan, J.-P., Lane, J., Lassibille, G., 1999. Student outcomes in Philippine elementary schools: An evaluation of four experiments. World Bank Econ. Rev. 13 (3), pp. 493–508.
Thierfelder, C., Matemba-Mutasa, R., Rusinamhodzi, L., 2015. Yield response of maize (*zea mays* l.) to conservation agriculture cropping system in southern africa. Soil Tillage Res. 146, 230–242.
Thompson, P., 2010. Learning by doing. Handbook of the Economics of Innovation 1, pp. 429–476.
TIA, 2008. National agricultural household survey. Michigan State University and The Ministry of Agriculture of Mozambique (MINAG). URL ⟨http://fsg.afre.msu.edu/Mozambique/survey/index.htm⟩.
Waddington, H., White, H., Anderson, J., 2014. Farmer field schools: from agricultural extension to adult education. Syst. Rev.Summary 1.