How do Farmers Learn from Extension Services? Evidence from Malawi

Annemie Maertens, Hope Michelson and Vesall Nourani*

26 July 2017 - DRAFT

Abstract

Resource-constrained agricultural extension systems in developing countries tend to rely on two primary models for disseminating information about new technologies: farmer field-days and farmer-led demonstration plots. A randomized control is used to study the effects of these two primary models on farmer learning about and adoption of components of integrated soil fertility management (ISFM), a basket of technologies designed to improve soil health and improve crop yields. We find that farmers who participate in demonstration plots adopt more of the components of ISFM; we find no effects on production of farmers who participate in a field-day. Further analysis and focus group interviews suggest that these differential effects relate to how and what farmers learn from the models, in particular with respect to details of promoted technologies and beliefs about yield effects on their own land.

JEL CODES: O13; O33; Q18

Keywords: Agricultural Extension, Learning, Sub-Saharan Africa

*Annemie Maertens (a.maertens@sussex.ac.uk) at Sussex University; Hope Michelson (hopecm@illinois.edu) at the University of Illinois at Urbana-Champaign and Vesall Nourani (vn75@cornell.edu) at Cornell University. We thank the field team of Wadondo Consulting for collecting data and Eric Kaima and Ephraim Chirwa for supervising the data collection. We acknowledge excellent research support from Tsegay Teklelassie and Kwabena Krah. We are grateful to Chris Barrett, Ephraim Chirwa, Cheryl Palm, Wezi Mhango, Matt Embrey and participants at the AAEA meetings in Boston 2016 for feedback. We acknowledge financial support from the International Initiative for Impact Evaluation under TW4.

Introduction

Agricultural extension can play a crucial role in relieving farmer information constraints, encouraging the adoption of improved agricultural technologies, and thereby increasing yields and incomes (for an overview see, among others, Birkhauser et al. 1991, Picciotto and Anderson 1997, Anderson and Feder 2007, Davis 2008). Supporting and enhancing cost-effective agricultural extension systems is especially important in developing countries where the economy centers around agriculture. In Malawi, where this study is situated, agriculture represents 30% of the GDP and employs nearly 70% of the population (2013 World Development Indicators). As information is - to varying degrees - non-rival and non-excludable, the government takes primary responsibility for developing and disseminating agricultural education programs, especially at the start of a diffusion process where private sector operations are unable or unwilling to take this responsibility. Krishnan and Patnam (2012), for instance, note that in Ethiopia, in 1999, government extension agents served as farmers' primary source of information about hybrid seeds, but that ten years later private-sector seed companies had almost entirely assumed this role. Where responsibility resides with government extension services, their effectiveness varies widely. Birkhauser et al. (1991) reports rates of returns ranging from negative to over 100% (see also IEG 2011).

Much of this variability in extension effectiveness may be attributable to the range of extension models employed, from conventional plans in which extension agents visit and train lead farmers (see Anderson et al. 2006), to farmer-led demonstration plots (plots located within the village where a group of farmers experiment with a a new technology, often guided by an extension agent), and farmer field-days on demonstration plot sites to which extension agents invite farmers for the day and explain technologies on-site.

Even when introducing the same technology, these models have different implications for farmers' learning and hence might result in different adoption patterns. The farmer-led demonstration plot model, for instance, is often sited in a village where soil and climatic conditions are likely to be familiar to most participants. Farmer field-days, in contrast, often take place further afield, where local conditions might be quite different from what visiting farmers face at home. As returns to agricultural technologies are heterogeneous and depend on soil and climatic conditions (Marenya and Barrett 2009, Dulfo et al. 2008, Suri 2011), farmers are more likely to learn something "useful" about the profitability of a new technology when the demonstrations are situated nearby: Assume the main goal of the farmer is to learn the moments of a profit function. While farmers might approach this task in a more-or-less Bayesian manner (Lybbert et al. 2007), they will learn locally, i.e., contingent upon soil, climate, etc.; only a yield-draw from a plot which shares these conditions is likely to impact their own thinking and operations (on the implications of heterogeneity for social learning, see, among others, Munshi 2004 and Tjernstrom 2016).

In addition to learning about expected profits, farmers learn about the production process, i.e., the optimal use of inputs (Nourani 2016 studies the implications of these two steps in terms of social learning). In Conley and Udry (2010), Ghanian farmers learn about the optimal amount of fertilizers for producing pineapple, a new crop in the region. In our context, farmers learn about the amount of inputs to apply but also application timing and techniques. Learning here has numerous dimensions which can be cognitively demanding; we argue that it is plausible that the repetition embedded in managing a farmer-led demonstration plot facilitates learning relative to farmer field-days (on the value of repetition in learning, see Brown et al. 2014).

In this study, we aim to establish the causal impact of farmer-led demonstration plots and farmer field-days on farmer learning about Integrated Soil Fertility Management technologies (henceforward ISFM) and adoption of ISFM.

ISFM is a basket of technologies designed to increase the fertility of soils (and hence both short-term and long-term yields). These technologies include, among others, optimal planting practices, leguminous intercropping, organic and inorganic fertilizers, mulching, and the use of hybrid seeds. In Sub-Saharan Africa, a continent where soil fertility is low and declining (see, among others, Tully et al. 2015 and Njoloma et al. 2016), the yield benefits of ISFM can be substantial (for evidence in Sub-Saharan Africa, see, among others, Kerr et al. 2007, Duflo et al. 2008, Sauer and Tchale 2009, Fairhurst 2012, Bezu et al. 2014, Franke et al. 2014 and Manda et al. 2015). While studies have found that farmers recognize the value of increased soil fertility (Lambrechts et al. 2015), this understanding does not necessarily imply that farmers also value ISFM technologies. For instance, Ortega at al. (2016) find that farmers significantly discount legume yields in favor of maize yields despite the additional soil fertility benefits provided by legumes. Overall adoption of ISFM technologies in Sub-Saharan Africa remains low: (see, for instance, Wossen et al. 2015). In Malawi, 17% of farming households use inorganic fertilizers, 77% organic fertilizers, 5% cultivates soybeans and 26% groundnut (data from IHS 2010-11; see also Chinangwa 2006, Munthali 2007, Mhango et al. 2013 and Mponela et al. 2016 for studies on ISFM adoption in Malawi).[1]

Assessing accurately the effects of agricultural extension in these regions is a complex challenge. Farmers who seek out and receive extension services might be more skilled and motivated than farmers who do not seek such services (see, for instance, Owens et al. 2003 who document the extend of such a bias in Zimbabwe); moreover, areas that attract extension services are often areas with better agronomic potential. Because such factors can be difficult to discern, they can cause omitted variable bias, threatening the causal interpretation of the estimator. A second challenge is that although an extension program may be successful in terms of knowledge diffusion, adoption among farmers may be influenced by other factors (market failures, logistical challenges, etc); technology learning may not always translate into adoption. As standard household surveys often do not detail the learning process, most studies cannot discern whether such failures reside in the education process itself, or in other circumstances down the line.

Our study was set up to meet these challenges. We work in partnership with an NGO, the Clinton Development Initiative (henceforward CDI), which has established a program of farmer-led demonstration plots and farmer field-days in Malawi. This program focusses on ISFM technologies for maize, soy, and groundnut. We selected 250 villages and randomized access to CDI's farmer field-days. This process eliminates biases originating from between-village unobserved variation when establishing the effects of access to farmer field-days. To confirm the effects of the farmer-led demonstration plots (which, unlike the field-days, were not randomized), we collected detailed village-level geographical data (including location

[1] Of course groundnut and other grain legumes can be cultivated by farmers without being a part of a broader ISFM strategy.

data using GPS). These data allow us to build a propensity score of whether or not a village was selected as a demonstration plot location; and to identify the effect of demonstration plots by comparing villages with/without access to demonstration plots with the same propensity score.

To establish a clear and robust narrative of the learning process, we conducted focus group surveys and interviewed (government and CDI's) extension agents. We complement this qualitative data with a quantitative panel household survey, documenting not only adoption of ISFM technologies but also knowledge of ISFM technologies and yield expectations. In addition, we collected detailed input-output data at every demonstration plot site.

We find that farmers who participate in demonstration plots adopt more of the recommended ISFM technologies (compared to the farmers who do not participate in any CDI activities) and that farmers who participate in a field-day do not adopt more of the ISFM technologies (again, compared to the farmers who do not participate in any CDI activities).

Focus group interviews suggests that this apparent lack of success of field-days can be partially attributed to a lack of learning. For instance, farmers who attended field-days reported: (1) that they were impressed by the possible soy yields and (2) that they were convinced that pesticides are important for soy cultivation. However, when we inquired about the specifics of pesticide use, few of our respondents knew brand names, or where to buy what they needed, or how to prepare and apply the product. In other words, though farmers did acquire some knowledge about improving the yields, they retained very little information with regard to production logistics and possible outcomes on their own land. Farmers who participate in a farmer-led demonstration plot, on the other hand, reported to have learned-by-doing on a local plot; and to have gained useful information to apply to their own operations.

Quantitative results confirm these findings. First: Compared to farmers who participate in farmer-led demonstration plots, farmers who attend a field-day learn, on average, less about the production process. The aspects of the production process they do learn suggest the existence of a costly, but rational, learning process in which cognitive constraints are binding (see Ghosh 2016 for a theoretical approach on rational inattention, and Kahneman 1973, Gabaix et al. 2006, Fehr and Rangel 2011 for an introduction to cognitive constraints more general). The poor in particular might have limited "cognitive bandwidth", see Schilback et al. (2016) and Lichand and Mani (2017). We find that farmers at field-days who are credit-constrained are less likely (compared to non-credit constrained farmers) to learn about credit-intensive technologies, and more likely to learn about some more labor-intensive technologies. In the focus group interviews, farmers who had attended field-days noted that have learned (and adopted) the project recommended one seed per planting station planting method for maize, a labor-intensive technology. Farmers who attended demonstration plots learn, on average, substantially more about the recommended ISFM technologies (though, they too are less likely to learn about credit-intensive technologies when they are credit-constrained). Second: Famers who participate in demonstration plots show decreased variance in yield beliefs for soy, while farmers who participate in a field-day do not display such an decrease.

The structure of the rest of this paper is as follows. In the next section, we introduce CDI's program. In the second section we explain the study design and data collected. We present descriptive statistics in section three. In the fourth section, we provide a descriptive account of the learning process. In section five we present the empirical specification and the results. Section six concludes.

CDI's Anchor Farm Program

CDI established its Anchor Farm Program in Malawi in 2008. The program aims to increase agricultural production, incomes and food security of smallholder farmers in central Malawi through the adoption of ISFM. To reach this goal, CDI disseminates information about ISFM and improves farmer market access. In this study, we focus on CDI's two primary extension activities: farmer-led demonstration plots and farmer field-days.[2] The annual implementation calendar for these activities follows Malawi's agricultural cycle. In central Malawi, the rainy season starts in November/December and ends in April/May. Hence, CDI works with farmer groups to initiate demonstration plots in November/December and holds farmer field-days in March/April.

The CDI model is similar to many government and NGO extension activities. CDI sets up demonstration plots in central village locations, close to a primary road, and, according to their own account, on good quality plots. The exact location of the demonstration plot is usually selected through discussion with the local government extension agent and local farmers. Once the location is determined, a CDI extension agents sets up the plot together with a local farmers' club of typically 10 to 20 members. The CDI extension agent continues to guide the local farmer's club throughout the season through calls and in-person visits, but it is the club who is in charge of the day-to-day management and the implementation of the various activities, such as planting, weeding, fertilising, and applying pesticides.

In March/April, CDI selects some of the best performing farmer-led demonstration plots to hold farmer field-days. Farmers in nearby locations are invited to attend this one-day event, CDI provides transportation to and from the field-day location and a mid-day snack. During the field-day, the CDI extension agent together with the demonstration plot's farmers' club, explained the visitors how they went about applying the new technologies. These field-days can be attended by up to 1000 farmers.

In 2014-15, the (growing) season under consideration for this study, CDI focussed on the following crops: soybean, maize, groundnut and common bean. Almost all farming households in Malawi cultivate maize, which is the main staple. As mentioned earlier, 26% of farming households in Malawi cultivate groundnut and 6% soybean (data from IHS 2010-11). In Kasungu, one of the districts which we study, soy has begun to take over tobacco as a cash crop, in 2010-11, 26% of farming households cultivated soy; today the share is likely higher.

To showcase ISFM practices and technologies applied to these four crops, CDI sets up three types of demonstration plots: (1) Soybean/Maize; (2) Groundnut/Maize and (3) Common Bean/Maize. Each demonstration plot features 8 to 10 10-by-10 meter subplots. A subset of these are classified as farmer's practice, understood as "the local method to cultivate a crop". Another subset is classified as "Best Practice Agronomy". These were defined

[2] Initially, this program centered around the activities of a large commercial farm, which CDI titled an Anchor Farm, Later on however, most activities were no longer linked up to the Anchor Farm. In this study, we focus on CDI's extension activities - away from the Anchor Farm activities.

as follows:

- Maize: Use of a high-yielding variety, SC719, optimal plant spacing and seeding practices, regular herbicide (harness and roundup) and fertiliser application (23:21:0+4S and urea), the use of fertiliser trees and rotation with soybean.

- Soybean: Treat the seed of a high-yielding variety, Squire, with innoculants, optimal plant spacing and seeding practices, regular pesticide (cypermethrin), herbicide (harness and roundup) and fungicide (folicur) applications.

- Groundnut: Use of a high-yielding variety, CG7, optimal plant spacing and seeding practices, regular fertiliser (D-compound, single superphosphate and gypsum), pesticide (dimethoate and dithane) and herbicide (harness and roundup) applications.

- Common bean: Use of a high-yielding variety, Khlopete, optimal plant spacing and seeding practices, regular fertiliser (D-compound), pesticide (cypermethrine) and herbicide (harness and roundup) applications.

All best practice subplots feature ridges and are covered by crop residuals between planting and harvest. Mulching of crop residues and other biomass is encouraged as well. Each demonstration plot also included control subplots. These aimed to provide a benchmark for the best practice subplots, and used the same cultivar and planting techniques, but did not include any external inputs, such as innoculants, fertiliser, pesticides and herbices.

Sample, Randomization and Data Collected

In 2014, CDI was planning an expansion of their program into two districts in central Malawi: Dowa district, north of Lilongwe, the country's capital, in the central region of Malawi and Kasungu district, North-West of Lilongwe, bordering Zambia. Together with CDI, we selected two EPAs (Extension Planning Areas, a sub-district administrative unit): Chibvala in Dowa district and Mtumthama in Kasungu district. The 2014 village census listing of the District Agricultural Offices included 360 villages in these two EPAs. We randomly selected 250 from the 303 villages which counted at least 50 households, stratified by EPA. [3] Half of these villages, again randomly selected and stratified by EPA, were assigned to the treatment group and the other half to the control group. The villages in the treatment group were invited to form farmer clubs and to participate in CDI's program. Farmers formed clubs in 87 out of 125 treatment villages.

Seventeen of these 87 villages received farmer-led demonstration plots during the 2014-15 growing season. These 17 villages were selected strategically by CDI, as to maximize expected program impact. According to CDI's own account, these were villages with some familiarity with agricultural extension services, located in an accesible location and where people were in 'unity'. All but two villages received only one type of demonstration plot, i.e., either Soybean/Maize, Groundnut/Maize, or Common Bean/Maize. Specifically, there

[3] As CDI works through farmer clubs and the functioning of these clubs requires a minimum village size, we excluded the villages with less than 50 households.

were three Groundnut/Maize plots, four Common Bean/Maize plots and the remainder were Soybean/Maize plots.

In March 2015, CDI invited all farmer clubs in the 87 villages to a farmer field-day. Two field-days were held in the study area. Farmers in Mtumthama EPA were invited to a local farmer field-day at the best performing CDI farmer-led demonstration plots in the EPA. Farmers in Chibvala EPA were invited to join a farmer field-day in a neighboring EPA (Lisasadzi EPA), due to, according to CDI's account, the lack of exemplary demonstration plots in Chibvala EPA itself. Both field-days took place at a Soybean/Maize demonstration plot.

Data Collected

We collected data at baseline, before the treatment villages participated in the program activities, and one year later. The baseline was conducted in all 250 villages in the sample, while the data collection the following year included 100 villages.[4] Before collecting baseline data, we generated a census of all households in the 250 villages as well as a census of all CDI club members in the treatment villages. We used these two census lists to draw a sample of 10 households for each village: In the control villages and the treatment villages without a club, we randomly selected 10 households from the village census. In the treatment villages with CDI clubs, we stratified the sample and sampled five household who do not belong to a CDI club and 5 households who belong to a CDI club.[5] One of the five households sampled was the household of the lead farmer of the club, whom serves as the point of contact between CDI and the club. The other four CDI households were randomly selected from the list of households who belong to a CDI club.

At baseline, we conducted a village survey and a household survey. One year later, we followed up with household surveys; creating a panel dataset.[6] Between these two rounds of data collection, we collected agronomic data at the demonstration plot sites on a weekly basis. We also conducted a series of focus group interviews and interviewed extension agents. We discuss these data sources below.

[4]These 100 villages were selected as follows: First, we selected selected 90 villages randomly from the 250 sample villages, stratified by EPA and treatment status. These 90 villages included 7 villages with demonstration plots. Then, we included an additional 10 villages which had been selected as demonstration plot villages by CDI (as to include all 17 villages which were selected as a demonstration plot locations).

[5]In case of multiple CDI clubs, we selected the club to be included in the study randomly. In terms of the treatment, all CDI clubs are invited to the farmer field day while only one club was engaged per demonstration plot (this would be the same club which we interviewed).

[6]The attrition rate is 5% - specifically, there were 51 households who were present at the baseline who were not present in the follow up survey. The households who left the sample are uniformly distributed geographically and in terms of treatment status. The households who left the sample have household heads who are slightly younger and (0.01 years – significant at the 5% level) and slightly more educated (0.05 years – significant at the 10% level) but do not differ in terms of household composition and asset wealth. To keep the sample size intact, these 51 households were replaced in the follow up survey using the random sampling methods outlined above.

Village survey

We administered a village questionnaire at baseline in each of the 250 villages with a knowledgeable individual, often the village head or the secretary to the village head. This village questionnaire covered information on the village's distance to paved roads, national highways, (seasonal) markets and other services (such as banks). In addition, we collected demographic information (number of residents, ethnic distribution), and information on access to government and NGO extension, civic organizations and the price of casual agricultural labor in different seasons. We noted the location of the village center using GPS.

Household survey

We conducted a household survey among 2500 households in 250 villages at baseline, and among a subset of 1000 households in 100 villages one year later. The survey was collected in the months of October and November, about five months after harvest and right before planting for the next season. We interviewed the head of the household each time, and covered topics including household activities, assets (including land), adoption of ISFM technologies, knowledge of ISFM technologies and yield expectations. We detail the latter three modules below.

Adoption of ISFM technologies At baseline, we collected information on current use of ISFM technologies using input-output plot-level questionnaires. We focus on the technologies introduced by CDI and include seed treatment, seed selection, plot lay-out (intercropping, rotation, fallow, etc.), fertilizers (inorganic, organic and fertilizer trees), and other inputs: pesticide, herbicide, fungicide. To obtain a longer term picture, we also collected information on ISFM technologies used in the past five years, again, with a focus on CDI technologies, asking the farmer whether in the last five years, they had (ever) used a particular technology. One year later, we added a module on adoption plans. In the latter, again, we focussed on CDI technologies and asked whether or not the respondent plans to adopt a particular technology (in the 2015-16 season). Recall that the household survey was conducted in the month preceding planting. Hence, most respondents were comfortable with these forward looking questions and had no difficulty in responding.

Knowledge about ISFM technologies In the follow up survey, one year after the baseline, we build on Kondylis et al. (2015) and incorporated twenty questions which aimed at testing knowledge about the ISFM techniques introduced by CDI. The questions covered ISFM practices for soybean, groundnut and maize. All questions had a known (by us, and by CDI) correct response. Responses were true/false, multiple choice or a numerical. Questions ranged from listing the general benefits of certain ISFM practices, such as the benefits of growing soy bean in crop rotation, and covering the soil with crop residues, as well as knowledge about how-to-apply ISFM practices including: how many weeks after planting should you apply urea fertilizer on maize; what chemical is best for controlling soy rust; where on the field should one plant fertilizer trees; and when mixing inoculant, how many table spoons of sugar should one add to the inoculant bag. We code the answers as correct/incorrect and compute a total knowledge score (out of 20).[7]

Yield expectations We build on Delavande et al. (2010 and 2011), Dillon (2014) and Maertens (2017) to elicit yield expectations. We focus on soybean, groundnut and maize. At baseline, we asked the respondent: "Imagine that you would cultivate maize this coming year and imagine that maize would be the only crop on the field, so no other crops are present, how much maize do you think you would harvest on one acre of land? (in 50 kg bags of shelled or unshelled maize?"[8] We then repeated these questions for soybean (in 50 kg bags of shelled soybean) and groundnut (in 50 kg bags of unshelled, dried groundnut). One year later, we expanded this module. To obtain a probability distribution, we first asked the respondent to describe the best growing conditions, average conditions and worst conditions he/she could imagine for maize.[9] Respondents, in response, often noted variance in weather, pest pressure etc. Then, we asked him/her to state how much maize he/she would harvest under the best condition, the average condition and the worst condition, respectively. Finally, we asked the respondent to distribute ten equal size stones (each representing a 10% probability) in three equal-sized circles drawn on the ground, the first circle representing the best condition, the second the average conditions and the third the worst conditions. We repeated these questions for soybean and groundnut.

Qualitative data

We conducted focus group discussions in ten villages before the CDI program, and one and two years after the program. We interviewed CDI clubs whom had been invited to a field-day and clubs who managed demonstration plots. We followed best practices (see Morgan 1996 and Krueger and Casey 2008) and focussed on learning about agricultural technologies, the club's activities and challenges faced, and relationships with extension agents.

We conducted semi-structured interviews with two government extension agents and two CDI extension agents in our study area, before the program and one and two years after the program. We focussed on the constraints and opportunities facing extension agents, and their relationship with the farmers.

Field observations on demonstration plots

We visited the demonstration plots two weeks after planting to record germination, and activities and inputs used to that date. Data on agronomic practices and crop performance were recorded via a phone call with the lead farmer on a weekly basis between planting and harvesting. During this weekly phone call we recorded any activity that had taken place,

[7] Respondents could also opt for a "don't know" response, which we coded as incorrect.

[8] The question was formulated as such to avoid complications associated in measuring yield on intercropped fields. In our baseline data, mono-cropping was the norm, with 75% of the plots mono-cropped. The unit was determined in qualitative interviews preceding the data collection as most common unit people think about for the crop. In addition, we recognise the difficulty in imagining the exact size of one acre of land, and in the formulation of this question we often referred to a 70 by 70 feet area or provided a comparison field in the village. However, we do expect a certain degree of remaining measurement error in this variable (see also Bevis and Barrett 2016 on the possible direction of this bias).

[9] In this round, we distinguished between hybrid maize and local maize.

such as applying fertilizer or other inputs, and the number of club members and other visitors present for the activity (including whether the CDI extension agent was present). Rainfall gauges were mounted on each demonstration plot and the lead farmer was trained to record rainfall on a daily basis. We used an established protocol by Columbia University to record grain yield, grain moisture content as well as residue production at harvest time.

Descriptive Statistics

Table 1 introduces the villages, focusing on the 100 villages for which we have panel data. The average distance to a tarmac road is 0.2 km and the distance to a market where agricultural inputs can be purchased with the season is about 5.4 km. Villages exhibit considerable variation in distance to services, with some villages situated almost as far as 40 km from local markets. Villages are relatively small, just 61 households on average. The villages are visited by government extension agents, on average, seven times per year, and by other extension agents, on average, 15 times per year. The variation in the number of yearly visits is substantial, with some villages benefiting from weekly visits, while others reporting no visits.

Table 2 - Panel A - introduces the households. The average household head is 42 years and has 4.5 years of education. About 18 percent of household heads are female. The average household has 5.22 household members and 4.6 acres of land.

Panel B reports soil-related descriptive statistics. Soils in the area are classified as Ferralsols, Lixisols and Plinthosols (FAO Harmonised World Soil Database).[10] A common feature of these soil types is that they depend on the addition of organic and inorganic matter to improve soil structure and overall fertility.

Accordingly, the households in our sample report soil fertility problems. Even though the fields are rated to be, on average, 'average quality' to 'good quality', 80 percent of farmers perceive the average soil fertility to be 'stagnant' or 'declining'. Common problems reported are: soil erosion (by 47 percent of households), water logging (by 23 percent of households) and nutrient depletion (by 57 percent of households). Acidity is not a main concern. The soil samples, confirm this perception of the farmers: soils have an average Ph of 6.7 (with 70 percent of soils tested within the optimal range) but nutrient deficiencies are considerable: All soils tested are Nitrogen (N) deficient, and almost 60 percent of soils were deficient in three or more nutrients. The total organic carbon matter, a measure of carbon contained within the soil organic matter, and a good summary measure of overall soil fertility, is considered 'low' to 'very low' in 30 percent of soils tested and at a 'medium' level in another 40 percent.

Panel C reports farmer cultivation practices. All farmers had cultivated maize and most cultivated soybean and groundnut. Over 80 percent of farmers had used intercropping and crop rotation. Over 90 percent had used mineral fertilizer (Malawi has a large-scale mineral fertilizer subsidy program targeting small farmers). Animal manure had been used by 63

[10] The former are old, weathered soils, sandy-loam free-draining with resulted low nutrient content and possibly acid Ph. Lixisols are more sandy-textured version of Ferralsols and hence more subject to erosion. Plinthosols typically have a hardened layer of iron and/or alumninum deposits impeding water flow and root development.

percent of farmers, 37 percent had used compost and 24 percent had used fertilizer trees. The use of other inputs is not very common. Only 22 percent had used pesticides and herbicides, and merely two percent (of farmers who cultivated soy) treated the seeds with innoculant. It should be noted that the statistics in Panel C refer to adoption in the five years preceding the baseline data collection. As there is considerable amount of experimentation and disadoption among the farmers in the sample, these numbers can be considerably lower for any given year.

In summary, farmers are aware of the low soil fertility in the region, and note significant nutrient depletion in their own soils. Despite this awareness, adoption of ISFM technologies has been relatively low, especially of certain credit and-information intensive technologies such as the use of pesticides, herbicides, fungicides, fertilizer trees, compost, and innoculation.

Descriptive Account of the Learning Process

In this section, we present a descriptive account of the learning process based on the qualitative interviews and descriptive statistics. Farmers, by their own account, learn about new agricultural technologies through own experimentation, from others and from extension agents. A demonstration plot combines these sources of learning, and farmers in CDI clubs, by their own account, are keen on establishing a demonstration plot in their village to learn about production processes. Demonstration plots have been central to much of Malawi's extension history (see Knorr et al. 2007), and farmers, prior to the program, stressed in focus group discussions that the best way to learn is to work on a demonstration plot together.

When we spoke with the farmers one year, and even two years after they had begun working on a demonstration plot together, many were able to recall the exact names of the ISFM inputs used, report the amounts used and explain how the inputs should be applied. They stated feeling "comfortable" with the techniques. Farmers who had only attended the field-days stated that they were impressed by the productivity of the crops presented at the field-day, and reported that they learned about the importance of herbicide and pesticide (and in some cases innoculants) for soy, as well as plant spacing and the importance of using crop residuals for mulching and plant spacing. However, few field-day participants were able to recall the details: which input was used; the amounts required; and the method of application. This is consistent with what farmers told us before the CDI program started in the region: while learning from extensions services at field-days and the radio is common, they also noted that they rarely immediately adopted the new technologies after visiting a field-day or hearing something on the radio, as through these channels they are less aware of the intricacies of how the technologies work and less certain as to how they can be applied on their fields.

To further illustrate the differences between what farmers learn from demonstration plots and what farmers learn from field-days, refer to Figure 2, which plots the answers to the question - "Which chemical is best for controlling soya rust"? Soya rust is caused by fungi, and one of the most common soy diseases; an affected field can lose up to 80% of its yield and hence CDI recommends the use of preventative fungicide. Figure 2 shows that 14 percent of control farmers correctly answered this question, versus 15 percent of farmers who attended the field-days and 23 percent of farmers who attended the demonstration plots (the difference between the control farmers and the farmers who participated in demonstration plots is statisticaly significant at the 5% level).

It is not correct to assume that farmers at field-days are not learning anything. Results of focus group discussions indicate that field-day farmers learn about the production processes of some of the more labor-intensive ISFM technologies, such as mulching and optimal plant spacing. This suggests that farmers, who are likely constrained as to what they can focus on during one field-day, zoom in on these technologies that they are most likely to successfully implement. Many of the recommended inputs – pesticides, herbicides and innoculants – are not available in local markets. As few households own cars or motorbikes and public transport is limited, distance could represent an additional barrier to participation in input markets. Many farmers also noted that, even if such inputs were readily available, they would not have the funds available to purchase these inputs.

Farmers noted that the technologies that requiring minimal funds to implement, such as optimal plant spacing and mulching, were of particular use. Farmers reported that mulching, for instance, was a labor-intensive but useful technology to combat striga (a common weed in maize fields which can cause heavy crop losses), and also the very common drought spells.

In Figure 3, we return to the question - "Which chemical is best for controlling soya rust?" This time, however, we distinguish between farmers with a lower than median asset holding (in the left panel) and a higher than median asset holding (in the right panel). We only include farmers who attended field-days, demonstration plots, or both. Of the farmers with an asset holding above the median, 28 percent answered this question correctly, versus 16 percent for farmers who have an asset holding below the median. This difference is statistically significant at the 5 percent level, suggesting that higher-wealth farmers are more likely to learn about this credit-intensive production technology.

In the next section, we study this learning process more formally and estimate the effects of the CDI program on knowledge formation.

Analysis and Results

Effects on knowledge

Table 5 presents summary statistics for the knowledge test administered to farmers about ISFM technologies, organised by topic. The first set of questions relates to soy production, the next set groundnut, and the last two sections maize and nitrogen fixing shrubs and trees ("fertilizer trees"). Note that while most respondents are aware of the general benefits of soy, fewer know the details of the production process in terms of which pesticides and fungicides one should apply following best practices. The share of correct answers drops even further - to under 10 percent - when we ask the respondent to tell us about the details of soy input preparation and application. Groundnut presents a similar case: farmers are again, generally aware of the benefits, but understand less about the specifics of the recommended production processes. For maize, a crop with which farmers have extensive experience, farmers seem to be aware of certain ISFM technologies, such as the use of crop residues and fertiliser trees with limited more knowledge of other aspects of the production process.

To now estimate the impact of the CDI program, one would ideally run a regression such as specification (1) linking outcome, for instance, knowledge score Y_{ij} of farmer i from village j, on the two treatments: T_{1ij} (field-days) and T_{2ij}(demonstration plots):

$$Y_{ij} = \alpha_0 + \alpha_1 T_{1ij} + \alpha_1 T_{2ij} + \beta X_{ij} + \epsilon_{ij} \tag{1}$$

To control for possibly confounding factors, the regression could includes X_{ij} - farmer's characteristics such as education, gender, age and village's attributes such as ethnic composition and geography. However, one is unlikely to be able to control for all relevant confounding factors - many are likely to be unobservable us, the researchers, such as, climatic factors and personal attributes. This can create a correlation between ϵ_{ij} and T_{ij} resulting in omitted variable bias.

We use two complementary approaches to deal with this. In the first approach, we exploit the fact that access to the farmer field-days was randomized across villages, effectively eliminates biases originating from between-village unobserved variation when establishing the effects of access to farmer field-days. However, the demonstration plot locations were selected purposefully. To further establish the effects of the demonstration plots, we use detailed village-level geographical data and build a propensity score of whether or not a village was selected as a demonstration plot location.

In Appendix Figure 1, we present the results of a regression predicting whether or not a treatment village received a demonstration plot as a function of village characteristics (ethnic composition, contacts with extension agents, existing community groups, distance to various facilities and distance to the district capital). We classify 91% of the villages correctly. We control for this predicted probability (or propensity as in Rosenbaum and Robin 1983) in the regression analysis as follows:

$$y_{ij} = \alpha_0 + \alpha_1 T_{1ij} + \alpha_2 T_{2,ij} + \alpha_3 T_{2ij} * P(demo)_j + \alpha_4 P(demo)_j + \lambda X_{ij} + \varepsilon_{ij} \tag{2}$$

Where y_{ij} is a knowledge outcome of farmer i from village j and P(demo) is the probability that village j is selected as a demonstration plot location.

To test whether being a member of a club which was invited to a field-day has an effect on learning, we test:

$$H_0 : \alpha_1 = 0 \tag{3}$$

To obtain the effect of being member of a demonstration plot club, we test the following hypothesis (for villages with a zero probability to be selected as a demonstration plot location):

$$H_0 : \alpha_1 + \alpha_2 = 0 \tag{4}$$

(Recall that all demonstration plots were also invited to attend the field-days). And for villages which have a predicted probability of being selected as a demonstration plot location of 1, this would be:

$$H_0 : \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 0 \tag{5}$$

As club participation is a choice, we recognise that individual-level confounding factors could still be a problem, for instance, one might expect more motivated or resourced individuals to join the club. We attempt to minimize this bias using a range of individual level controls. The set of control variables X_{ij} in specification (2) includes: gender, age and education of the farmer, household size, number of adult household members, maximum education level in the household, acreage of land owned and total asset value of the non-land assets, and whether or not a household is credit-constrained.[11] To account for the predicted nature of P(demo), we bootstrap the standard errors ε_{ij}.

In Table 4, we present the results of the effect of the CDI program on farmer knowledge using specification (2). In Column (1), we present the effect on an aggregate knowledge score, which is a score that can range between zero and 20 - with one point for every question the farmer answered correctly. We note that being a member of a demonstration plot club (in the case P(demo)=0) increases the knowledge score by 2.3 points, about 30 percent. In contrast, being invited to a farmer field-day does not (statistically significantly) alter one's knowledge score.

In Columns (2) through (21) we present the result of 20 linear probability models, taking as a dependent variable whether or not the farmer asked each of the 20 questions correctly. We include an interaction effect to test for a differential effect on credit-constrained farmers. Regarding the effect of farmer field-days and comparing farmers who were credit-constrained with those who were not: credit-constrained farmers are less likely to learn about credit-intensive technologies such as fertiliser trees (question 17) or urea (question 15) but they are more likely to learn about labor-intensive technologies, such as plant spacing (question 8) and health and safety guidelines (question 20). In the case of demonstration plot participation, the interpretation of the coefficients is a little more complex, as one needs to take into account the P(demo) effect. Focusing on villages with P(demo)=0, we find that credit-constrained farmers are also less likely to learn about fertiliser trees (even though we have a positive coefficient on question 19), urea, and pesticides. In addition, they are less likely to know the general attributes of soybean and groundnut.)

Effects on adoption

Having established the effects of the extension components on farmer knowledge, we now analyze the impact of the CDI program on farmer adoption of ISFM technologies. We use a similar specification as in (2):

$$y_{ij} = \alpha_0 + \alpha_1 T_{1ij} + \alpha_2 T_{2,ij} + \alpha_3 T_{2ij} * P(demo)_j + \alpha_4 P(demo)_j + \lambda X_{ij} + \varepsilon_{ij} \tag{6}$$

The dependent variables y_{ijt} now include: the adoption of soybean, hybrid maize and groundnut and the adoption of the following technologies: Innoculation of soy, Herbicide, Pesticide, Fungicide, Inorganic Fertilizer, Intercropping, Crop residue, Animal Manure and Compost. We also compute an aggregate adoption score (out of 13).

Table 5 presents the results of specification (6). Demonstration plot participation increases the overall adoption score by 1.17 points, which is about 32 percent (in the case of

[11] A household is considered credit constrained if the farmer did not take input credit in the 2013-14 season (credit-constrained =1 if the farmer did not take any credit that year and 0 otherwise).

P(demo)=0), while being invited to a farmer field-day does not produce such (statistically significant) result.

Specifically, being a member of a demonstration plot club increases the chances of planting soy (at the 10% level for Pdemo=0), innoculating soy (at the 5% level for Pdemo=1), using fungicide (at the 5% level for Pdemo=0), using inorganic fertiliser (at the 1% level for Pdemo=1), planting fertiliser trees (at the 5% level for Pdemo=0), and applying crop residues (at the 5% level for Pdemo=0). Being in a club which was invited for a farmer field-day, on the other hand, appears to decrease the chances of planting groundnut and using pesticides (even though we find a positive and significant effect on planting soybean).

As a robustness check, we now presents the results of an alternative identification strategy. We take advantage of the panel data structure of a sub-set of the dataset and regress adoption on treatment status in the presence of household fixed effects. These estimations obviate challenges related to time-invariant household-level unobservables. We use the household survey data collected at baseline, in 2014, on technologies adopted in 2013-14 and one year later, in 2015, on planned adoption for 2015-16, to create a panel dataset.

Denote by i = farmer i, j = village j and t year t. Using a linear (or linear probability for the binary dependent variables) regression model, we regress:

$$y_{ijt} = \alpha_0 + \alpha_1 T_{1ijt} + \alpha_2 T_{2ijt} + \gamma Y_t + \mu_{ij} + \varepsilon_{ijt} \tag{7}$$

The dependent variables y_{ijt} (again) include: the adoption of soybean, hybrid maize and groundnut and the adoption of the following technologies: Innoculation of soy, Herbicide, Pesticide, Fungicide, Inorganic Fertilizer, Intercropping, Crop residue, Animal Manure and Compost and the aggregate adoption score (out of 13). T_1 is a dummy variable which equals 1 if the farmer belongs to a CDI club invited to attend a farmer field-day (but does not run a demonstration plot), and 0 otherwise; and T_2 is a dummy variable which equals 1 if the farmer belongs to a CDI club which runs a demonstration plot. Y equals 1 if the year is 2015 and 0 if the year is 2014. Note the inclusion of μ_{ij}, a farmer-level fixed effect; which absorbs any observable and unobservable time-invariant factors at the household level.

Table 6 presents the results. The results are broadly consistent with the estimates presented in Table 5. Farmers who are members of a demonstration plot club have a significantly higher adoption score, 0.43 points, an 10 percent effect size. Being a member of a club invited to attend a field-day does not result in an equivalent increase in adoption score. In fact, in this case, attending a field-day seems to result in a decrease of the likelihood that one plants soybean. Being in a demonstration plot club, on the other hand, increases the chances of planting hybrid maize, innoculating soy and planting fertiliser trees. The coefficient on the 2015 year dummy variable is positive and statistically significant for most outcome variables, indicating an increased adoption over time regardless of treatment status.

Effects on yield expectations

What effect do the extension efforts have on what farmers expect about yield possibilities for their own fields? Again, we use both panel and cross-sectional analyses to examine the question. We begin by regressing yield expectations on treatment status in the presence of household fixed effects, using a similar panel data approach as in (7). The panel of expectations uses data from the household survey data collected at baseline, in 2014, and one year later, in 2015.

Denote by i = farmer i, j = village j and t year t. Using a linear regression model, we regress:

$$y_{ijt} = \alpha_0 + \alpha_1 T_{1ijt} + \alpha_2 T_{2ijt} + \gamma Y_t + \mu_{ij} + \varepsilon_{ijt} \tag{8}$$

Where T_1 is a dummy variable which equals 1 if the farmer belongs to CDI club which was invited to attend a farmer field-day (but does not run a demonstration plot), and 0 otherwise; and T_2 is a dummy variable which equals 1 if the farmer belongs to a CDI club which runs a demonstration plot. Y equals 1 if the year is 2015 and 0 if the year is 2014. The dependent variable y_{ijt} refers to the response to the question: "How much maize/soy/groundnut do you think you would harvest on one acre of land?"

Table 7 presents the results. We find members of a demonstration plot club decrease their soy yield and groundnut expectations. These effects are substantial in magnitude: a 2.4 points or 18 percent reduction in the expected soy yield and a 5.4 points or 27 percent reduction in expected groundnut yield. We see a very different effect for members of clubs invited to attend field-days; these farmers increase their yield expectations of hybrid maize by 5.6 points or 29 percent.

At first sight, these results might appear to contradict the adoption results presented previously. Surely (planned) adoption of yield-increasing ISFM technologies should increase the yield expectations of the relevant crops in the case of demonstration plots? However, keep in mind that, first, the question asked did not explicitly refer to median, average, or another moment - and hence the interpretation was up to the respondent. It is, for instance, possible that the farmer's entire belief distribution changed. In effect, Bayesian learning would predict a decrease in perceived variance of this distribution, and a movement towards the real mean for the farmer (which might be below his/her prior expectations). Second - the baseline data collection did not distinguish between hybrid maize and non-hybrid maize; we allocated the respondent's belief to one category or the other depending on their choice of maize that year.

Hence, we present the results of an alternative specification in Table 8. This time, we explicitly distinguish between the effects on the average and the standard deviation of the beliefs distribution, and use specification (6) using the 2015 data only. In this specification, being a member of a club invited to attend a farmer field-day does not alter one's beliefs. However, being a member of a demonstration plot club does, lowering the standard deviation of one's belief's distribution for soy (these results are true for P(demo)=0 and P(demo)=1).

Before we conclude this section, two points of discussion. First, on complementarities between technologies. Complementarities between certain technologies are well known. The farmers in our survey seem to be aware of some of these complementarities. For instance, looking at the farmers adoption plans for 2015, we note that generally it is the farmers who plan to adopt soy who also plan to adopt pesticides and herbicides. Similarly, generally farmers planning to adopt hybrid maize are those who plan to adopt mineral fertilisers.

Second, on the distinction between being invited to participate and actual participation. In the case of demonstration plots, this distinction does not exist: all CDI club farmers who were invited participate in demonstration plot activities actually did. In the case of farmer field-days, the estimated effect should be interpreted as the intent-to-treat effect, as not all clubs invited to the farmer field-days participated.In addition, within a club which attended a CDI field-day, we do not distinguish between the club members who attended the field-days and the club members who did not. CDI requested the club members who attended the field-day to share the information with the other members; as such, while this learning of the others has a 'social component' an explicit social learning model is not quite appropriate. In effect, one could think of all club members being connected in a star-shaped network to the leader, and receiving, first hand, in a group setting the information.

Conclusion

We establish the causal impact of farmer-led demonstration plots and farmer field-days on Malawian farmers' learning of ISFM technologies. We find that farmers who participated in a farmer-led demonstration plot learn more about the production processes of ISFM technologies, such as, the type and amount of pesticide to be used on soy, compared to farmers who attended farmer field-days. While the latter might now know of the existence of ISFM technologies, they learn less about the production processes and and in their learning seem to focus more on labor-intensive ISFM technologies, such as plant spacing and mulching, especially if they are credit-constrained.

This distinction between knowing about the existence of the technology and learning its attributes has also been documented by others. Kabunga et al. (2012) noted that while many farmers in Kenya have heard about tissue culture in bananas, few know the details required to implement the technology. Lambrechts et al. (2014) find that while awareness about fertilisers has spread widely among farmers in Congo, direct contact with extension agents is what contributes to adoption. Hanna and Mullainathan (2014) show that seaweed farmers in Indonesia do not usually pay attention to pod size, an important input dimension, and that farmers only learn once presented with simple information about the optimal pod size.

Differences in the substance of what farmers learn are reflected in farmer adoption plans. Farmers participating in demonstration plots are more likely to adopt hybrid maize, innoculate soy and plant fertiliser trees. Field-day participants do not on average, adopt more ISFM technologies than control farmers. Other researchers have also reported positive effects of demonstration plots on adoption, especially among the farmers who were directly involved, such as Duflo et al. (2006) in Kenya. Extension models also variably impact farmers' yield expectations. Famers who participate in farmer-led demonstration plots demonstrate more precise yield beliefs, while farmers who participate in a field-day, on average, do not display such an change.

Our results suggest that farmer field-days in different agro-climatic zones might not result in widespread adoption of a new technology, especially if, as in Nourani (2017) farmers need to be convinced that the technology will increase average yields *prior* to experimentation. If, in addition, a field-day is too short to learn all of the production processes, farmers might not be able to easily progress to this second experimental stage of learning, even if convinced about the technology's yield-increasing attributes. In our study, farmers indeed stated that they were propelled to experiment if they believed the new technology might increase crop yield, but were discouraged if they were not sure about how to apply the new technology, had relatively little land and low access to complementary inputs.

Our results have implications for Malawi and other Sub-Saharan African countries. Many of these countries are working to reform farmer extension, moving from traditional training and visit systems to systems designed to be more demand-driven, participatory/needs-based, accountable and cost-effective. This change is the result of a combination of declining budgets for extension, partially due to a donor retreat from extension, and the perceived lack in effectiveness of traditional extension systems (see, for instance, Davis 2008, Evenson 1997, Anderson et al. 2006). The Malawian government extension system is under significant strain, under-resourced and under-incentivised. In our study area, each extension agents are in charge of 2,000 to 3,000 farming households. Equipped with a bicycle only and on a fixed monthly salary, agents often restrict themselves to visiting the villages relatively near to their own homesteads.[12] The heterogenous coverage of the extension services is consistent with the household's perspective. About 40 percent of the farmers report having "sometimes" interacted with government extension agents, while another 40 percent reports "never" interacting with government extension agents, and another 20 percent report interacting "often" to "very" often' (in the past one year). Only 30 percent of households consider the government extension agent among their primary sources of information about agriculture (out of three, elicited through an open question). Some of the farmer clubs stated that they were never visited by government extension agents, while other stated that the agents visited several times every month.

Our results have implications for such under-resourced extension systems.

First, farmer field-days may provide too much information in too short a time period, giving farmers small chance to absorb the details. This is especially expected to be the case for the type of technologies that are now typically introduced, technologies that involve implementation of multiple techniques or technologies, such as, ISFM. To realise the optimal yield associated with ISFM, for instance, farmers need to alter practices and input use among many dimensions (see Beaman et al. 2013, Emerick et al. 2016 and Bulte et al. 2014 and Mponela et al. 2016). This implies that, at field-days, farmers should be given tools which will allow them to learn the information presented better. Examples might include pamphlets

[12] Knorr et al. (2007) report that, in Malawi, ratios of current extension staff per farmer are now between 1/1500 and 1/3900 down from their 1970s-1980s highs of 1/750 to 1/850. Extension workers are reported overburdened and under-resourced - expected to cover long distances on bicycles and to cover a range of government and non-government activities with little knowledge of new agricultural technologies and management practices. While the government is not the only actor providing extension services in Malawi - extension services are provided by NGOs and private companies, in particular cotton and tobacco trading companies, in practice, these services are inter-linked. For instance, in our study area, NGOs relied on government extension agents to reach and engage farmers. Many institutions for agricultural extension training have closed and the ones remaining now require that students themselves pay their fees for a MS degree in extension. In turn, extension workers receive a comparatively small, monthly fixed salary. This situation has led to reportedly pervasive problems with moral hazard and adverse selection. Some have suggested that the type of student that can afford the requisite training is not generally interested in returning to work in rural areas and are often employed by NGOs or other private institutions after graduation - draining the government extension system. Others have suggested that the fixed salary reduces the (uncontractable) effort of extension officers. BenYishay and Mobarak (2013) using an RCT in Malawi show that incentivising extension agents by paying them for knowledge improvements of the farmers significantly improves farmer uptake of these technologies.

with pictures of the inputs used and measuring spoons to measure the correct amounts of inputs.[13]

Second, the fact that farmers' learning appears to be constrained by markets suggests that agricultural extension might need a re-coupling with market, and in particular, credit interventions in order to be effective. In Malawi, extension agents used to perform an additional role as regional credit officers. While conflict of interest should be avoided, providing farmers access to credit while introducing a new intervention, is likely to affect uptake and learning given evidence that credit access itself influences how open the farmer is to receiving information on capital-intensive technologies.

Third, heterogenous growing conditions might also have played a role in terms of what farmers take away from field-days. In this regard, an in-village demonstration plot might be a better choice, with the caveat that a bad yield can result in a "non-adoption" trap. Demonstration plots in various conditions are to be recommended; with participants being matched to attend field-days at demonstration plots that match their own growing conditions.

Fourth, while cell phone penetration is not as high in Malawi as it is ino ther Sub-Saharan African countries, using cell phone as a medium might provide an appealing alternative (for an overview on ICT-based extension systems, see Aker 2011 and Davis 2008). But even in this case, SMS messages would need to use simple language, be growing-condition specific and might need to be accompanied by market information.

We conclude with a note on further research. While we have not explicitly discussed spillovers in this study, we recognise their importance and appeal to extension models: In the training and visit extension model, for example, extension agents are updated with the latest technologies and generally visit selected lead farmers who on their turn are expected to teach farmers in their community. The extent to which adoption spreads through the communities through social learning is expected to depend on the degree of heterogeneity between farmers, as well as the structure of the social network, and who the first adopters are (Griliches 1957, Foster and Rosenzweig 1995, Munshi 2004, Bandiera and Rasul 2006, Conley and Udry 2010, Chuang and Schechter 2015, Kondylis et al. 2017, Maertens 2017). Beaman et al. (2013) use a network-theory approach to better identify these lead farmers in order to maximize learning and adoption in their communities. We see this type of research, which combines network theory with limited rationality models of learning in across heterogenous environments and with heterogenous agents in terms of cognitive ability (as in Barham et al. 2017) and skills (as in Laajaj and Macours 2017) a fruitful way forward in extension research.

[13] Duflo et al. (2013) find a large demand for fertilizer measuring spoons in Kenya.

References

[1] Aker, J.C., 2011. "Dial “A” for agriculture: A Review of Information and Communication Technologies for Agricultural Extension in Developing Countries." *Agricultural Economics*, 42(6), pp.631-647.

[2] Anderson, J.R. and Feder, G., 2007. "Agricultural Extension." in: *Handbook of Agricultural Economics*, 3, pp.2343-2378.

[3] Anderson, J.R.,Feder, G. and Ganguly, S. 2006. "The rise and fall of Training and Visit extension: An Asia mini-drama with an African Epilogue," in A.W. Van den Ban and R.K Samantha (eds.) Changing Role of Agricultural Extension in Asian nations. new Delhi: B.R Publishing Corporation, pp. 149-74.

[4] Bandiera, O. and Rasul, I., 2006. "Social Networks and Technology Adoption in Northern Mozambique." *The Economic Journal*, 116(514), pp.869-902.

[5] Barham,B.L., Chavas,J.P., Fitz, D. and L. Schechter. 2017. "Receptiveness to Advice, Cognitive Ability, and Technology Adoption: An Economic Experiment with Farmers." Working Paper.

[6] Beaman, L., Karlan, D., Thuysbaert, B. and Udry, C., 2013. "Profitability of Fertilizer: Experimental Evidence from Female Rice Farmers in Mali." *The American Economic Review*, 103(3), pp.381-386.

[7] Beaman, L., BenYishay, A., Magruder, J., and A.M. Mobarak. 2013. "Can Network Theory-based Targeting Increase Technology Adoption?" Working Paper.

[8] BenYishay, A. and Mobarak, A.M., 2013. "Communicating with Farmers through Social Networks." Working Paper.

[9] Bevis, L.E., Barrett, C.B. and Welcome, C.V., 2016. "Close to the Edge: Do Behavioral Explanations Account for the Inverse Productivity Relationship? Working Paper.

[10] Bezu, S., Kassie, G.T., Shiferaw, B. and Ricker-Gilbert, J., 2014. "Impact of Improved Maize Adoption on Welfare of Farm Households in Malawi: A Panel Data Analysis." *World Development*, 59, pp.120-131.

[11] Birkhaeuser, D., Evenson, R.E. and Feder, G., 1991. "The Economic Impact of Agricultural Extension: A Review." *Economic Development and Cultural Change*, 39(3), pp.607-650.

[12] Brown, P.C., Roediger, H.L. and McDaniel, M.A., 2014. *Make it Stick*. Harvard University Press.

[13] Bulte, E., Beekman, G., Di Falco, S., Hella, J. and Lei, P., 2014. "Behavioral Responses and the Impact of new Agricultural Technologies: Evidence from a Double-blind Field Experiment in Tanzania." *American Journal of Agricultural Economics*, 96(3), pp.813-830.

[14] Chinangwa, L.L.R., 2006. Adoption of Soil Fertility Improvement Technologies among Smallholder Farmers in Southern Malawi. Master's Thesis, Department of International Environment and Development Studies, Norwegian University of Life Sciences.

[15] Chuang, Y. and Schechter, L., 2015. "Social Networks in Developing Countries." *Annual Review of Resource Economics*, 7(1), pp.451-472.

[16] Conley, T.G. and Udry, C.R., 2010. "Learning about a New Technology: Pineapple in Ghana." *The American Economic Review*, 100(1), pp.35-69.

[17] Davis, K., 2008. "Extension in sub-Saharan Africa: Overview and Assessment of Past and Current Models and Future Prospects." *Journal of International Agricultural and Extension Education*, 15(3), pp.15-28.

[18] Delavande, A., Giné, X. and McKenzie, D., 2011A. "Eliciting Probabilistic Expectations with Visual Aids in Developing Countries: How Sensitive are Answers to Variations in Elicitation Design?" *Journal of Applied Econometrics*, 26(3), pp.479-497.

[19] Delavande, A., Giné, X., and D. McKenzie. 2011B. "Measuring Subjective Expectations in Developing Countries: A Critical Review and New Evidence." *Journal of Development Economics*, 94 (2): 151-163.

[20] Dillon, B., 2015. "Measuring Subjective Probability Distributions." Working Paper.

[21] Duflo, E., Kremer, M. and Robinson, J., 2008. "How High are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya." *The American Economic Review*, 98(2), pp.482-488.

[22] Duflo, E., Kremer, M., Robinson, J. and F. Schilbach, 2013. "Technology Diffusion and Appropriate Use: Evidence from Western Kenya." Working Paper.

[23] Emerick, K., de Janvry, A., Sadoulet, E. and Dar, M.H., 2016. "Technological Innovations, Downside Risk, and the Modernization of Agriculture." *The American Economic Review*, 106(6), pp.1537-1561.

[24] Evenson, R., 1997. "The Economic Contributions of Agricultural Extension to Agricultural and Rural Development." In: *Improving agricultural extension. A Reference Manual.* Swanson, B.E. (ed.) Bentz, R.P. (ed.) Sofranko, A.J. (ed.) / FAO, Rome (Italy). Research, Extension and Training Div. , p. 27-36.

[25] Fairhurst, T., 2012. *Handbook for Integrated Soil Fertility Management.* Africa Soil Health Consortium. Nairobi.

[26] Fehr, E. and Rangel, A., 2011. "Neuroeconomic Foundations of Economic Choice—Recent Advances." *The Journal of Economic Perspectives*, 25(4), pp.3-30.

[27] Foster, A.D. and Rosenzweig, M.R., 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of political Economy*, 103(6), pp.1176-1209.

[28] Franke, A.C., Van Den Brand, G.J. and Giller, K.E., 2014. "Which Farmers Benefit Most from Sustainable Intensification? An ex-ante Impact Assessment of Expanding Grain Legume Production in Malawi." *European Journal of Agronomy*, 58, pp.28-38.

[29] Gabaix, X., Laibson, D., Moloche, G. and Weinberg, S., 2006. "Costly Information Acquisition: Experimental Analysis of a Boundedly Rational Model." *The American Economic Review*, 96(4), pp.1043-1068.

[30] Ghosh, S. 2016. "Costly Social Learning and Rational Inattention." Working Paper.

[31] Griliches, Z., 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4), pp.501-522.

[32] Hanna, R., Mullainathan, S. and Schwartzstein, J., 2012. "Learning Through Noticing: Theory and Experimental Evidence in Farming." National Bureau of Economic Research Working Paper Number 18401.

[33] Independent Evaluation Group (IEG). 2011. *Impact Evaluations in Agriculture: An Assessment of the Evidence*. Washington, DC: World Bank.

[34] Kabunga, N.S., Dubois, T. and Qaim, M., 2012. "Heterogeneous Information Exposure and Technology Adoption: The Case of Tissue Culture Bananas in Kenya." *Agricultural Economics*, 43(5), pp.473-486.

[35] Kahneman, D., 1973. *Attention and Effort*. Prentice-Hall Series in Experimental Psychology. Englewood Cliffs, NJ: Prentice-Hall.

[36] Kerr, R.B., Snapp, S., Chirwa, M., Shumba, L. and Msachi, R., 2007. "Participatory Research on Legume Diversification with Malawian Smallholder Farmers for Improved Human Nutrition and Soil Fertility." Experimental Agriculture, 43(04), pp.437-453.

[37] Knorr, J., Gerster-Betaya, M. and V. Hoffman. 2007. *The History of Agricultural Extension in Malawi.* Margraf Publishers GMbH, Scientific books.

[38] Kondylis, F., Mueller, V. and J. Zhu, 2017 "Seeing is believing? Evidence from an extension network experiment," *Journal of Development Economics,* 125, pp. 1–20.

[39] Kondylis, F., Mueller, V. and J. Zhu. 2015. "Measuring Agricultural Knowledge and Adoption." *Agricultural Economics*, 46:449-462.

[40] Krishnan, P. and Patnam, M., 2012. Neighbours and Extension Agents in Ethiopia: Who Matters more for Technology Diffusion? Working Paper

[41] Krueger, R.A. and Casey, M.A. 2010. "Focus Group Interviews." in: Handbook of Practical Program Evaluation. Evaluation, 3rd Edition, (eds.) Joseph S. Wholey, Harry P. Hatry, Kathryn E. Newcomer. San Fransisco, Josset-Bass, a Wiley Imprint.

[42] Laajaj, R. and Macours, K. 2017. "Measuring Skills in Developing Countries." Working Paper.

[43] Lichand, G. and A. Mani, 2017. "Cognitive Droughts." Working Paper.

[44] Lipton, M and R Longhurst, 1989. *New Seeds and Poor People*. Routledge Library Editions: Development.

[45] Lybbert, T.J., Barrett, C.B., McPeak, J. G., and Winnie K. Luseno. 2007. "Bayesian Herders: Updating of Rainfall Beliefs In Response to External Forecasts," *World Development* 35, pp. 480-497.

[46] Maertens, A., 2017. "Who Cares what Others Think (or do)? Social Learning and Social Pressures in Cotton Farming in India." *American Journal of Agricultural Economics.*

[47] Manda, J., Alene, A.D., Gardebroek, C., Kassie, M. and Tembo, G., 2016. "Adoption and Impacts of Sustainable Agricultural Practices on Maize Yields and Incomes: Evidence from Rural Zambia." J*ournal of Agricultural Economics*, 67(1), pp.130-153.

[48] Marenya, P.P. and Barrett, C.B., 2009. "State-Conditional Fertilizer Yield Response on Western Kenyan Farms." *American Journal of Agricultural Economics*, 91(4), pp.991-1006.

[49] Mhango, W.G., Snapp, S.S. and Phiri, G.Y., 2013." Opportunities and Constraints to Legume Diversification for Sustainable Maize Production on Smallholder Farms in Malawi." *Renewable Agriculture and Food Systems*, 28(03), pp.234-244.

[50] Morgan, D.L., 1996. *Focus Groups as Qualitative Research*. Series on Qualitative Research Methods (Vol. 16). Sage Publications.

[51] Mponela, P., Tamene, L., Ndengu, G., Magreta, R., Kihara, J. and Mango, N., 2016. "Determinants of Integrated Soil Fertility Management Technologies Adoption by Smallholder Farmers in the Chinyanja Triangle of Southern Africa." *Land Use Policy*, 59, pp.38-48.

[52] Munthali, M.W., 2007. "Integrated Soil Fertility Management Technologies: A Counteract to Existing Milestone in Obtaining Achievable Economical Crop Yields in Cultivated Lands of Poor Smallholder Farmers in Malawi." in: Bationo A., Waswa B., Kihara J., Kimetu J. (eds.) *Advances in Integrated Soil Fertility Management in Sub-Saharan Africa: Challenges and Opportunities*, pp.531-536.

[53] Munshi, K., 2004. "Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution." *Journal of Development Economics*, 73(1), pp.185-213.

[54] Njoloma, J.P., Sileshi, W.G., Sosola, B.G., Nalivata, P.C. and Nyoka, B.I., 2016. "Soil Fertility Status Under Smallholder Farmers Fields in Malawi." *African Journal of Agricultural Research*, 11(19), pp.1679-1687.

[55] Nourani, V. 2016. "Social Network Effects of Technology Adoption: Investing with Family, Learning from Friends and Reacting to Acquaintances". Working paper.

[56] Ortega, D.L., Waldman, K.B., Richardson, R.B., Clay, D.C. and Snapp, S., 2016. "Sustainable Intensification and Farmer Preferences for Crop System Attributes: Evidence from Malawi's Central and Southern Regions." *World Development*, 87, pp.139-151.

[57] Owens, T., Hoddinott, J. and Kinsey, B., 2003. "The Impact of Agricultural Extension on Farm Production in Resettlement Areas of Zimbabwe." *Economic Development and Cultural Change,* 51(2), pp.337-357.

[58] Piciotti, R. and J.R. Anderson, 1997. "Reconsidering Agricultural Extension." *World Bank Research Observer*, 12(2), pp. 249-59.

[59] Rogers E. M., 1995. *Diffusion of innovations.* Free Press; New York.

[60] Rozenbaum, P.R., and P. Rubin, 1983. "The Central Role of the Propensity score in Observational Studies for Causal Effects." 70 (1), pp. 41-55.

[61] Sauer, J. and Tchale, H., 2009. "The Economics of Soil Fertility Management in Malawi." *Review of Agricultural Economics,* 31(3), pp.535-560.

[62] Schilbach, F., Schofield, H. and S.Mullainathan. 2016. "The Psychological Lives of the Poor." *American Economic Review*, 106(5): 435-40.

[63] Suri, T., 2011. "Selection and Comparative Advantage in Technology Adoption." *Econometrica*, 79(1), pp.159-209.

[64] Tjernström, E., 2015. "Signals, Similarity and Seeds: Social Learning in the Presence of Imperfect Information and Heterogeneity." Working Paper.

[65] Tully, K., Sullivan, C., Weil, R. and Sanchez, P., 2015. "The State of Soil Degradation in Sub-Saharan Africa: Baselines, Trajectories, and Solutions." *Sustainability*, 7(6), pp.6523-6552.

[66] Wossen, T., Berger, T. and Di Falco, S., 2015. "Social Capital, Risk Preference and Adoption of Improved Farm Land Management Practices in Ethiopia." *Agricultural Economics*, 46(1), pp.81-97.

Table 1: Descriptive statistics of villages at baseline in 2014

Variable description	Mean	Standard Deviation	min	max	N
Distance to all-paved/ all weather road (km)	2.22	4.4	0	28	100
Where is the closest place where you can find fertiliser, pesticides and seeds at any time of the year? (km)	13.3	10.7	0.1	47	100
Where is the closest place where you can find fertiliser, pesticides and seeds in season? (km)	5.4	5.4	0.1	38	100
Number of households	61	41	18	276	100
Number of visits by government extension agents in the past one year	7.7	17.7	0	100	100
Number of visits by other extension agents in the past one year	15.7	24.6	0	144	100

Table 2: Descriptive statistics of households at baseline in 2014

Variable description	N	Mean	St. Dev.
Panel A: Socio-economic characteristics			
Gender of household head (0=male; 1=female)	1,000	0.18	0.38
Age of household head (years)	1,000	42.45	15.01
Education of household head (years of education)	1,000	4.59	3.43
Number of household members	1,000	5.22	2.14
Land (in acres, owned)	1,000	4.62	6.75
Is main source of information a govt. extension agent (no=0; yes=1)[1]	1,000	0.30	0.46
Panel B - Soil quality			
Perceived soil quality (value from 1 to 5 with 1 being the worst)[2,3]	960	4.40	1.00
Experienced stagnating or declining soil fertility (no=0; yes=1)[2]	960	0.82	0.34
Experienced soil erosion (no=0; yes=1)[2]	960	0.47	0.44
Experienced nutrient depletion (no=0; yes=1)[2]	960	0.57	0.45
Experienced water logging (no=0; yes=1)[2]	960	0.23	0.37
Ph (recall 7 is neutral, smaller is acid, larger is alcalic)	245	6.12	0.52
Organic carbon (between 0 and 1)	243	0.30	0.46
Fields with nitrogen limiting only[4]	245	0.02	0.14
Fields with two elements limiting [4]	245	0.39	0.49
Field with three or more elements limiting[4]	245	0.59	0.49
Panel C - Crop and technology choices			
Cultivated soybean in the last 5 years (no=0; yes=1)	1,000	0.84	0.37
Cultivated groundnut in the last 5 years (no=0; yes=1)	1,000	0.92	0.28
Used intercropping in the last 5 years (no=0; yes=1)	1,000	0.84	0.36
Used crop rotation in the last 5 years (no=0; yes=1)	1,000	0.82	0.38
Use animal manure in the last 5 years (no=0; yes=1)	1,000	0.63	0.48
Incorporated crop residue in soil in the last 5 years (no=0; yes=1)	1,000	0.65	0.48
Used inorganic fertiliser in the last 5 years (no=0; yes=1)	1,000	0.93	0.25
Planted fertiliser trees in the last 5 years (no=0; yes=1)	1,000	0.24	0.43
Used compost in the last 5 years (no=0; yes=1)	1,000	0.37	0.48
Innoculated soybean in 2013-14 (no=0; yes=1)[5]	463	0.00	0.60
Used pesticides in the last 5 years (no=0; yes=1)	1,000	0.22	0.41
Used herbicide in the last 5 years (no=0; yes=1)	1,000	0.22	0.41
Used fungicide in the last 5 years (no=0; yes=1)	1,000	0.025	0.15

Notes: 1: We asked the respondent about the three main sources of information about agriculture, if the government extension agent was mentioned, we coded this answer = yes (no otherwise). 2: We elicited characteristics of each field and average the responses across fields for each farmer. 3: We elicited overall perceived soil quality as follows: "What is the soil fertility of this field?" Choices were: Very poor (1), Poor (2), Average (3), Good (4), Very Good (5). 4: These statistics originate from the soil samples conducted in the farmers' fields. We classified the soils as per element deficiency using the SoilDof program: including N deficient, NK deficient, NS deficient, NPK deficient, NPS deficient, NKS deficient and NPKS deficient. 5: This is

Table 3: Descriptive statistics of knowledge questions in 2015

	Question asked	Obs	Mean	Std. Dev.
1	From the following list, identify which is not a benefit of growing soybeans	1,000	0.60	0.49
2	True or False: The innoculation of soybean seed enhances nodule formation which in turn enhances plant growth	1,000	0.69	0.46
3	When mixing innoculant, how many table spoons of sugar should you add to the innoculant bag?	1,000	0.08	0.27
4	What chemical is best for controlling soyabean rust?	1,000	0.16	0.36
5	When controlling soybean rust, how many milliliter of Folicur should you add to a 15l/16l sprayer?	1,000	0.01	0.07
6	What chemical is best for controlling insect pests in soya?	1,000	0.36	0.48
7	From the following list, identify which is not a benefit of growing groundnut.	1,000	0.63	0.48
8	What is the recommended number of rows per ridges for groundnut?	1,000	0.26	0.44
9	From the following list, choose the fertiliser used at early flowering stage for groundnut.	1,000	0.10	0.30
10	From the following list, identify the pesticide which should be used to control for cutworms.	1,000	0.25	0.43
11	Which of the following options are a sign of groundnut maturity?	1,000	0.98	0.13
12	From the following options, identify the method which is not used for controlling witch weed	1,000	0.27	0.44
13	In cm, what is the recommended plant spacing for maize?	1,000	0.09	0.28
14	Which of the following is not a benefit from covering the field with crop residue, for maize?	1,000	0.54	0.50
15	How many weeks after planting should you apply urea fertilisers?	1,000	0.41	0.49
16	Which are not a benefit of soil fertility trees?	1,000	0.73	0.45
17	True or false: Leaves should be exposed to the sun after the tree has been cut out?	1,000	0.39	0.49
18	Where exactly on the field should fertiliser trees be planted?	1,000	0.70	0.46
19	How many weeks after planting the main crops should you plan fertiliser trees?	1,000	0.19	0.39
20	In which direction should you face when spraying chemicals?	1,000	0.46	0.50

Note: This table presents the descriptive statistics of the knowledge questions collected one year after the CDI program. The sample includes all 1000 households in 100 villages. All questions are binary yes (1) - no(0) questions.

Table 4: The impact of the CDI program on knowledge about ISFM technologies

Linear and Linear Probability Model with Dependent Variables:

		Whether or not a specific question is correct					
	Knowledge	Q1	Q2	Q3	Q4	Q5	Q6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
In a club which was invited	-0.167	0.064	0.103	-0.007	0.123	0.032	0.038
to a farmer field day	(0.285)	(0.095)	(0.122)	(0.058)	(0.082)	(0.037)	(0.088)
* credit-constrained		-0.016	-0.043	0.009	-0.091	-0.022	-0.035
		(0.090)	(0.137)	(0.060)	(0.091)	(0.030)	(0.100)
In a demonstration plot club	2.488***	0.223	-0.587***	0.107	-0.108	-0.036	0.552***
	(0.544)	(0.166)	(0.195)	(0.075)	(0.135)	(0.037)	(0.188)
* credit-constrained		-0.393**	-0.007	0.036	0.054	0.017	-0.025
		(0.165)	(0.146)	(0.081)	(0.195)	(0.030)	(0.152)
In a demonstration plot club * P(demo)	-3.429***	-0.183	0.989***	-0.329***	0.256	0.009	-0.969**
	(0.974)	(0.360)	(0.167)	(0.124)	(0.160)	(0.016)	(0.413)
P(demo)	0.684	0.080	0.075	0.074	0.027	0.003	0.132
	(0.493)	(0.071)	(0.079)	(0.051)	(0.058)	(0.010)	(0.133)
Credit-constrained		0.020	0.014	0.001	0.075***	0.003	0.123**
		(0.052)	(0.052)	(0.029)	(0.028)	(0.002)	(0.051)
Constant	8.095***	0.563***	0.820***	0.106*	0.009	0.019	0.287***
	(0.487)	(0.105)	(0.101)	(0.054)	(0.072)	(0.012)	(0.102)
Observations	814	814	814	814	814	814	814
Rsquared	0.026	0.019	0.030	0.020	0.016	0.022	0.04

Notes: This table present the results of a linear regression with dependent variables: Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Whether or not farmer is in a club is determined by the self-reported club status at baseline (in 2014). P(demo) refers to the predicted probability of a village receiving a demonstration plot. Boostrapped clustered errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 (continued): The impact of the CDI program on knowledge about ISFM technologies

Linear and Linear Probability Model with Dependent Variables:

	Whether or not a specific question is correct								
	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15
	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
In a club which was invited	0.043	-0.165**	-0.013	-0.023	-0.017	-0.024	-0.005	-0.018	0.136
to a farmer field day	(0.096)	(0.079)	(0.042)	(0.091)	(0.040)	(0.102)	(0.052)	(0.096)	(0.091)
* credit-constrained	-0.146	0.185**	0.005	0.023	0.036	0.054	0.022	-0.033	-0.159
	(0.115)	(0.092)	(0.052)	(0.105)	(0.040)	(0.099)	(0.056)	(0.116)	(0.100)
In a demonstration plot club	0.212	0.286	0.371**	0.703***	0.028	0.537**	-0.038	0.069	0.088
	(0.147)	(0.293)	(0.179)	(0.166)	(0.040)	(0.233)	(0.152)	(0.200)	(0.230)
* credit-constrained	-0.262*	-0.112	-0.141	-0.444**	-0.037	-0.093	-0.003	-0.148	-0.136
	(0.139)	(0.208)	(0.101)	(0.189)	(0.040)	(0.102)	(0.114)	(0.177)	(0.157)
In a demonstration plot club * P(demo)	0.311	-0.229	-0.546**	-0.477***	-0.030	-1.060***	0.179	0.065	-0.258
	(0.409)	(0.483)	(0.266)	(0.119)	(0.021)	(0.312)	(0.156)	(0.235)	(0.329)
P(demo)	0.016	-0.013	0.006	-0.105	0.025*	0.083	-0.004	0.264***	0.006
	(0.080)	(0.080)	(0.072)	(0.086)	(0.014)	(0.093)	(0.045)	(0.080)	(0.093)
Credit-constrained	0.003	-0.012	0.057**	0.038	-0.002	-0.014	0.003	-0.108**	-0.088
	(0.055)	(0.051)	(0.029)	(0.048)	(0.011)	(0.045)	(0.033)	(0.053)	(0.055)
Constant	0.672***	0.175*	-0.011	0.373***	0.953***	0.147*	0.073	0.607***	0.400***
	(0.096)	(0.090)	(0.067)	(0.094)	(0.026)	(0.074)	(0.052)	(0.093)	(0.110)
Observations	814	814	814	814	814	814	814	814	814
Rsquared	0.015	0.022	0.039	0.031	0.016	0.027	0.029	0.043	0.026

Notes: This table present the results of a linear regression with dependent variables: Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Whether or not farmer is in a club is determined by the self-reported club status at baseline (in 2014). P(demo) refers to the predicted probability of a village receiving a demonstration plot. Boostrapped clustered errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 (continued): The impact of the CDI program on knowledge about ISFM technologies

Linear and Linear Probability Model with Dependent Variables:

	Whether or not a specific question is correct				
	Q16	Q17	Q18	Q19	Q20
	(17)	(18)	(19)	(20)	(21)
In a club which was invited	-0.051	0.135	0.041	-0.086	-0.369***
to a farmer field day	(0.085)	(0.093)	(0.087)	(0.078)	(0.098)
* credit-constrained	-0.018	-0.205**	-0.007	0.000	0.320***
	(0.107)	(0.102)	(0.093)	(0.085)	(0.103)
In a demonstration plot club	0.097	-0.013	0.442**	0.609***	0.799***
	(0.202)	(0.295)	(0.196)	(0.184)	(0.157)
* credit-constrained	-0.127	-0.157	-0.271*	-0.201	-0.368
	(0.219)	(0.146)	(0.154)	(0.123)	(0.261)
In a demonstration plot club * P(demo)	0.137	0.093	-0.222	-0.768***	-0.254
	(0.225)	(0.393)	(0.398)	(0.266)	(0.206)
P(demo)	0.023	0.017	0.060	-0.136	0.064
	(0.087)	(0.108)	(0.070)	(0.083)	(0.068)
Credit-constrained	-0.076*	0.090	-0.018	0.003	-0.011
	(0.041)	(0.056)	(0.052)	(0.048)	(0.057)
Constant	0.807***	0.485***	0.742***	0.274***	0.436***
	(0.104)	(0.100)	(0.099)	(0.079)	(0.104)
Observations	814	814	814	814	814
Rsquared	0.025	0.033	0.044	0.028	0.044

Notes: This table present the results of a linear regression with dependent variables: Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Whether or not farmer is in a club is determined by the self-reported club status at baseline (in 2014). P(demo) refers to the predicted probability of a village receiving a demonstration plot.

Table 5: The impact of the CDI program on (planned) adoption of ISFM technologies

1.17

Linear and Linear Probability Model with Dependent Variables:

	Adoption (1)	Soybean (2)	Hybrid maize (3)	Groundnut (4)	Innoculation soy (5)	Herbicide (6)	Pesticide (7)	Fungicide (8)
In a club which was invited	-0.098	0.088***	0.043	-0.099**	0.005	-0.022	-0.077**	-0.031
to a farmer field day	(0.192)	(0.029)	(0.042)	(0.049)	(0.034)	(0.020)	(0.032)	(0.025)
In a demonstration plot club	1.268	-0.034	-0.135	-0.023	0.093	0.106	0.231	0.302**
	(0.936)	(0.040)	(0.152)	(0.288)	(0.206)	(0.119)	(0.181)	(0.131)
In a demonstration plot club * P(demo)	-0.801	-0.192***	0.179	0.467	0.411	-0.260	-0.218	-0.494
	(2.009)	(0.070)	(0.254)	(0.556)	(0.382)	(0.169)	(0.329)	(0.319)
P(demo)	0.786*	0.157***	-0.019	-0.121	0.071	0.181***	0.069	0.119
	(0.445)	(0.050)	(0.069)	(0.092)	(0.063)	(0.068)	(0.080)	(0.076)
Constant	4.937***	0.865***	0.845***	0.725***	0.066	-0.010	0.070	0.013
	(0.312)	(0.059)	(0.070)	(0.083)	(0.076)	(0.041)	(0.057)	(0.039)
Observations	814	814	814	814	718	814	814	814
Rsquared	0.079	0.060	0.085	0.021	0.068	0.045	0.027	0.034

Notes: This table present the results of a linear regression with dependent variables: Adoption (score out of 13), Soybean (binary variable), Hybrid Maize (binary variable), Groundnut (binary variable), Innoculation soy (binary variable, conditional on soy adoption), Herbicide (binary variable),Pesticide (binary variable), Fungicide (binary variable), Inorganic fertiliser (binary variable), fertiliser tree (binary variable), intercropping (binary variable), crop residue (binary variable), animal manure (binary variable) and compost (binary variable). These refer to planned adoption in the 2015-16 season. Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Whether or not farmer is in a club is determined by the self-reported club status at baseline (in 2014). P(demo) refers to the predicted probability of a village receiving a demonstration plot. Boostrapped clustered errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 (continue): The impact of the CDI program on (planned) adoption of ISFM technologies

Linear and Linear Probability Model with Dependent Variables:

	Inorganic fertiliser (9)	Fertiliser tree (10)	Inter-cropping (11)	Crop residue (12)	Animal manure (13)	Compost (14)
In a club which was invited	0.009	-0.005	0.010	-0.017	0.012	-0.015
to a farmer field day	(0.035)	(0.043)	(0.040)	(0.049)	(0.060)	(0.037)
In a demonstration plot club	0.040	0.308**	0.024	0.351**	0.008	-0.01
	(0.056)	(0.147)	(0.114)	(0.150)	(0.177)	-0.049
In a demonstration plot club * P(demo)	-0.062	-0.259	0.140	-0.353	-0.179	0.024
	(0.062)	(0.564)	(0.232)	(0.512)	(0.416)	(0.071)
P(demo)	0.118**	0.134*	-0.041	0.136	0.003	-0.025
	(0.046)	(0.072)	(0.084)	(0.106)	(0.135)	-0.062
Constant	0.896***	0.010	0.927***	0.150	0.271**	0.114**
	(0.062)	(0.064)	(0.065)	(0.095)	(0.104)	-0.057
Observations	814	814	814	814	814	814
Rsquared	0.056	0.05	0.04	0.037	0.03	0.023

Notes: This table present the results of a linear regression with dependent variables: Adoption (score out of 13), Soybean (binary variable), Hybrid Maize (binary variable), Groundnut (binary variable), Innoculation soy (binary variable, conditional on soy adoption), Herbicide (binary variable),Pesticide (binary variable), Fungicide (binary variable), Inorganic fertiliser (binary variable), fertiliser tree (binary variable), intercropping (binary variable), crop residue (binary variable), animal manure (binary variable) and compost (binary variable). These refer to planned adoption in the 2015-16 season. Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Whether or not farmer is in a club is determined by the self-reported club status at baseline (in 2014). P(demo) refers to the predicted probability of a village receiving a demonstration plot. Boostrapped clustered errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: The impact of the CDI program on (planned) adoption of ISFM technologies - Fixed Effects Approach

Linear and Linear Probability Regression Model with Dependent Variables:

	Adoption (1)	Soybean (2)	Hybrid maize (3)	Groundnut (4)	Innoculation soy (5)	Herbicide (6)	Pesticide (7)	Fungicide (8)
In a demonstration plot club	0.435**	-0.048	0.096*	-0.050	0.211***	-0.002	0.060	0.039
	(0.220)	(0.060)	(0.056)	(0.055)	(0.066)	(0.036)	(0.040)	(0.031)
In a club which was only invited	0.025	-0.090*	0.058	-0.056	0.049	-0.015	-0.017	-0.013
to a farmer field day	(0.183)	(0.048)	(0.051)	(0.049)	(0.041)	(0.027)	(0.028)	(0.020)
2015-16 year dummy	1.813***	0.434***	0.171***	0.239***	0.083***	0.021*	0.119***	0.060***
	(0.084)	(0.021)	(0.021)	(0.022)	(0.017)	(0.012)	(0.012)	(0.009)
Constant	3.599***	0.463***	0.617***	0.547***	0.002	0.050***	0.000	0.000
	(0.035)	(0.009)	(0.009)	(0.009)	(0.010)	(0.005)	(0.005)	(0.004)
Observations	1,898	1,898	1,898	1,898	1,272	1,898	1,898	1,898
R-squared	0.429	0.364	0.110	0.136	0.159	0.004	0.126	0.065
Number of qnum	949	949	949	949	862	949	949	949

Notes: This table present the results of a fixed-effects regression with dependent variables (xtreg, fe): Adoption (score out of 13), Soybean (binary variable), Hybrid Maize (binary variable), Groundnut (binary variable), Innoculation soy (binary variable, conditional on soy adoption), Herbicide (binary variable),Pesticide (binary variable), Fungicide (binary variable), Inorganic fertiliser (binary variable), fertiliser tree (binary variable), intercropping (binary variable), crop residue (binary variable), animal manure (binary variable) and compost (binary variable). The fieldday clubs include all the CDI clubs which were invited to the fielddays. We use adoption of 2013-14 as elicited at baseline (in 2014), and planned adoption elicited in 2005 referring to the 2015-16 season. Robust standard errors in parentheses. Whether or not farmer is in a club is determined by the self-reported club status in 2015. *** p<0.01, ** p<0.05, * p<0.1

Table 6 (continued): The impact of the CDI program on (planned) adoption of ISFM technologies - Fixed Effects Approach

Linear and Linear Probability Regression Model with Dependent Variables:

	Inorganic fertiliser (9)	Fertiliser tree (10)	Inter-cropping (11)	Crop residue (12)	Animal manure (13)	Compost (14)
In a demonstration plot club	0.017	0.154***	0.018	0.010	-0.044	0.015
	(0.040)	(0.053)	(0.063)	(0.059)	(0.066)	(0.035)
In a club which was only invited	0.047	0.020	-0.041	0.051	0.06	-0.037
to a farmer field day	(0.035)	(0.045)	(0.054)	(0.048)	-0.058	-0.024
2015-16 year dummy	-0.027	0.034**	0.359***	0.139***	0.123***	0.064***
	(0.017)	(0.017)	(0.022)	(0.021)	-0.023	(0.012)
Constant	0.890***	0.086***	0.495***	0.139***	0.291***	0.019***
	(0.007)	(0.007)	(0.010)	(0.009)	-0.01	-0.005
Observations	1,898	1,898	1,898	1,898	1,898	1,898
R-squared	0.003	0.024	0.265	0.070	0.044	0.04
Number of qnum	949	949	949	949	949	949

Notes: This table present the results of a fixed-effects regression with dependent variables (xtreg, fe): Adoption (score out of 13), Soybean (binary variable), Hybrid Maize (binary variable), Groundnut (binary variable), Innoculation soy (binary variable, conditional on soy adoption), Herbicide (binary variable),Pesticide (binary variable), Fungicide (binary variable), Inorganic fertiliser (binary variable), fertiliser tree (binary variable), intercropping (binary variable), crop residue (binary variable), animal manure (binary variable) and compost (binary variable). The fieldday clubs include all the CDI clubs which were invited to the fielddays. We use adoption of 2013-14 as elicited at baseline (in 2014), and planned adoption elicited in 2005 referring to the 2015-16 season. Robust standard errors in parentheses. Whether or not farmer is in a club is determined by the self-reported club status in 2015. *** p<0.01, ** p<0.05, * p<0.1

Table 7: The impact of the CDI program on (planned) adoption of yield expectations - Fixed Effects Approach

Regression with dependent variable yield expectation of:

	Hybrid Maize	Local Maize	Soybean	Groundnut
	(1)	(2)	(3)	(4)
In a demonstration plot club	-0.221	4.825	-2.404*	-5.413*
	(3.284)	(4.155)	(1.408)	(2.955)
In a club which was only invited	5.611*	1.324	0.494	2.941
to a farmer field day	(3.259)	(2.432)	(0.922)	(2.227)
2015-16 year dummy	-0.928	-11.625***	-0.528	0.188
	(1.052)	(1.035)	(0.520)	(0.970)
Constant	29.145***	27.543***	13.075***	20.484***
	(0.605)	(0.682)	(0.213)	(0.418)
Observations	1,521	1,300	1,890	1,896
R-squared	0.008	0.291	0.007	0.007
Number of qnum	948	946	949	949

Notes: This table present the results of a fixed-effects regression with dependent variables (xtreg, fe): Average yield expectation of hybrid maize (in 50 kg bags, shelled), local maize (in 50 kg bags, shelled), soy (in 50 kg bags, shelled) and groundnut (in 50 kg bags, unshelled and dried). The beliefs variables elicited at baseline, in 2014, did not distinguish between local maize and hybrid maize. We allocated the respondent's beliefs to the type of maize the respondent was cultivating in 2013-14 (very few respondents cultivate both types). The wording on the 2015 version is slightly different. Robust standard errors in parentheses. Whether or not farmer is in a club is determined by the self-reported club status in 2015. *** p<0.01, ** p<0.05, * p<0.1

Table 8: The impact of the CDI program on (planned) adoption of yield expectations

Linear Regression with dependent variable yield expectation and standard deviation

	Hybrid Maize		Local Maize	Soybean		Groundnut
	Expected	St. Dev.	Expected	Expected	St. Dev.	Expected
	(1)	(2)	(3)	(4)	(5)	(4)
In a club which was invited	2.885	0.671	1.451	0.210	1.188	3.173
to a farmer field day	(2.501)	(1.035)	(1.301)	(0.921)	(0.949)	(2.32)
In a demonstration plot club	-5.108	-3.639	1.342	3.037	-3.063*	3.83
	(7.623)	(3.456)	(2.982)	(3.927)	(1.673)	(5.158)
In a demonstration plot club * P(demo)	-8.791	-0.766	2.313	-9.874	0.584	2.986
	(12.899)	(4.224)	(11.988)	(7.717)	(3.039)	(4.643)
P(demo)	1.276	0.798	3.989**	0.594	-2.613**	-0.256
	(3.447)	(1.277)	(1.970)	(1.621)	(1.306)	(2.645)
Constant	21.324***	8.125***	12.651***	10.961***	8.811***	13.537**
	-3.32	-1.26	(2.303)	(1.761)	(1.969)	(5.709)
Observations	814.00	809.00	810	813	813	813
Rsquared	0.093	0.044	0.082	0.042	0.026	0.034

Notes: This table present the results of a linear regression with dependent variables: Expectation and standard deviation of yield beliefs assuming a step-wize probabilistic function. Crops included: hybrid maize (in 50 kg bags, shelled), local maize (in 50 kg bags, shelled), soy (in 50 kg bags, shelled) and groundnut (in 50 kg bags, unshelled and dried). Other control variables included but not reported: Gender household head, age household head, education household head (years), number of household members, number of adult household members, maximum education level in the household, acreage of land owned, value of all assets (excluding land), dummy variable as to whether the household is credit constrained, dummy variable as to whether the village has a demonstration plot and dummy variable as to whether the village belongs to the treatment group. Sample includes the random sample of 90 villages. Bootstrapped clustered errors in parentheses. Whether or not farmer is in a club is determined by the self-reported club status in 2015. *** p<0.01, ** p<0.05, * p<0.1

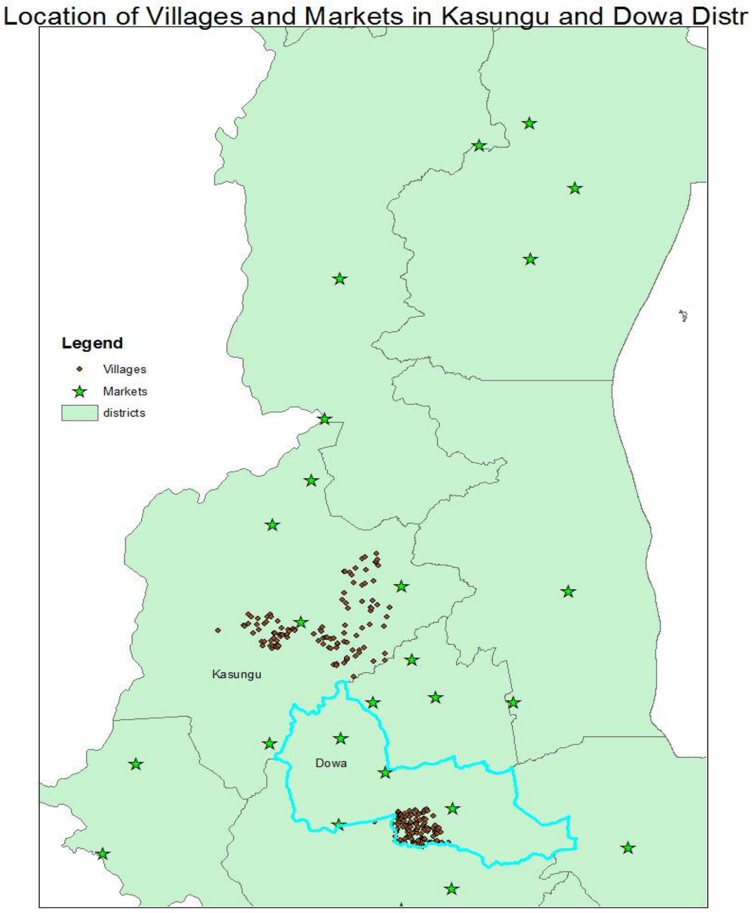


Figure 1: Location of 250 study villages (red dots) and local market towns (green stars)

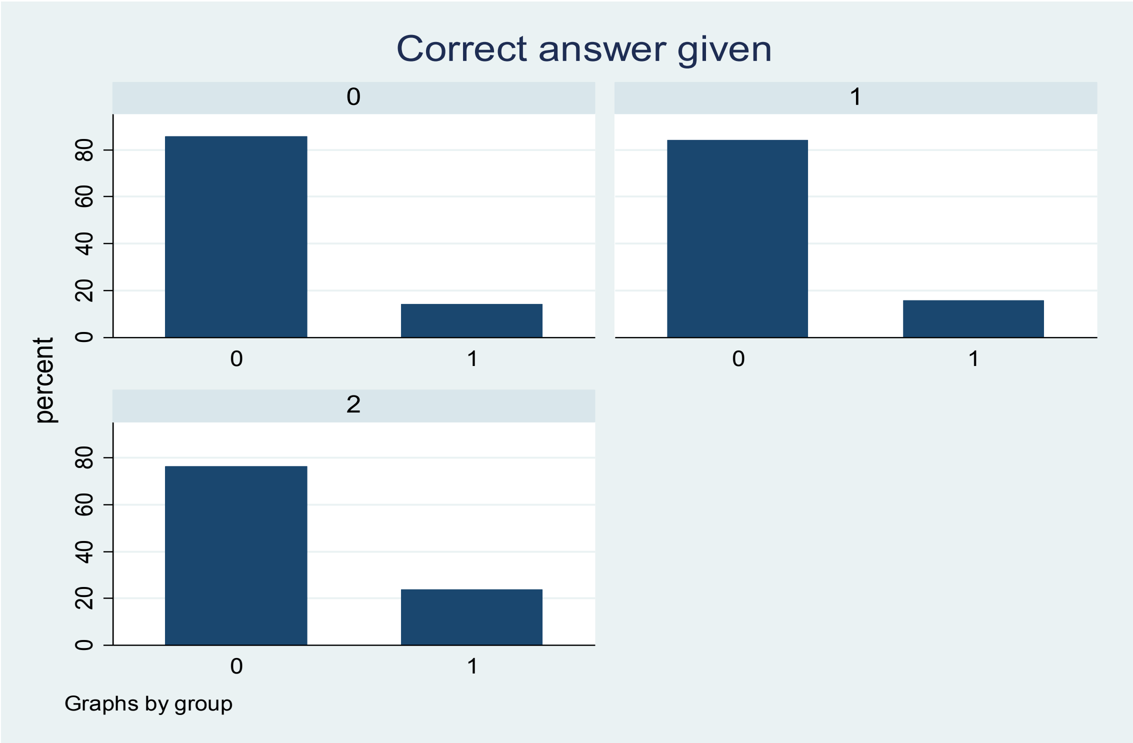


Figure 2: Histogram of the question: What chemical is best for controlling soyabean rust? (correct answer=1 ; incorrect answer==0)

Group=0 farmers who did not attend farmer field day or demonstration plots

Group=1 farmers who attended field days

Group=2 farmers who attended demonstration plots

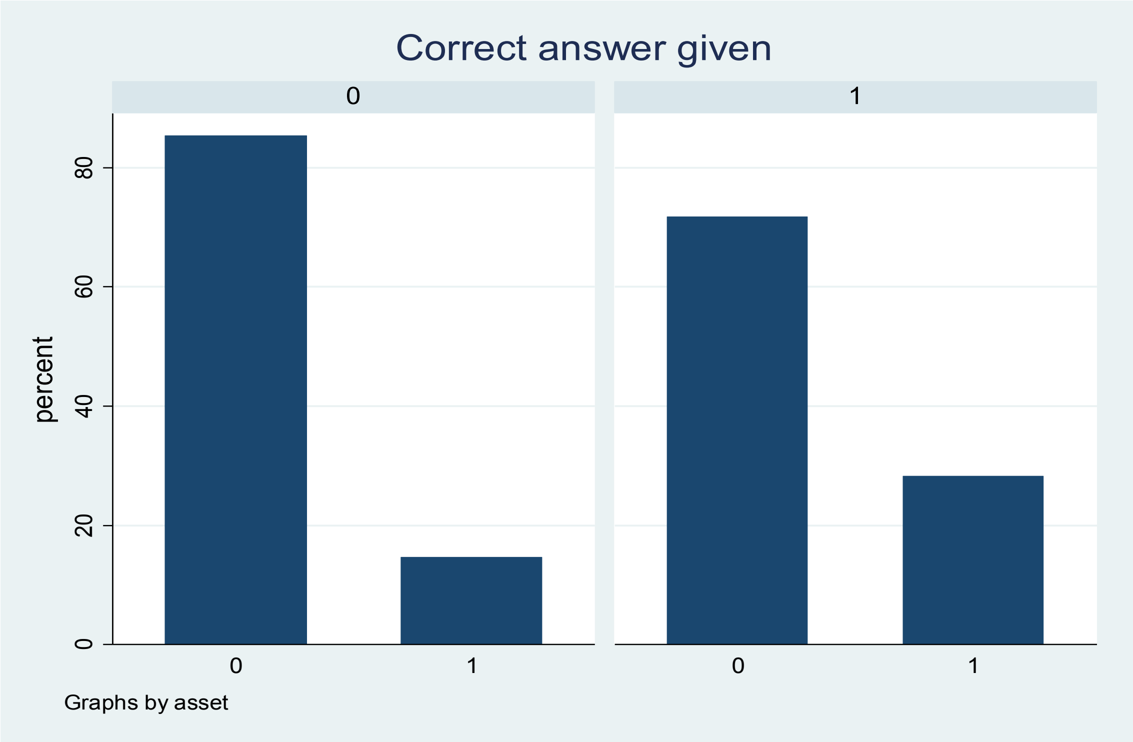
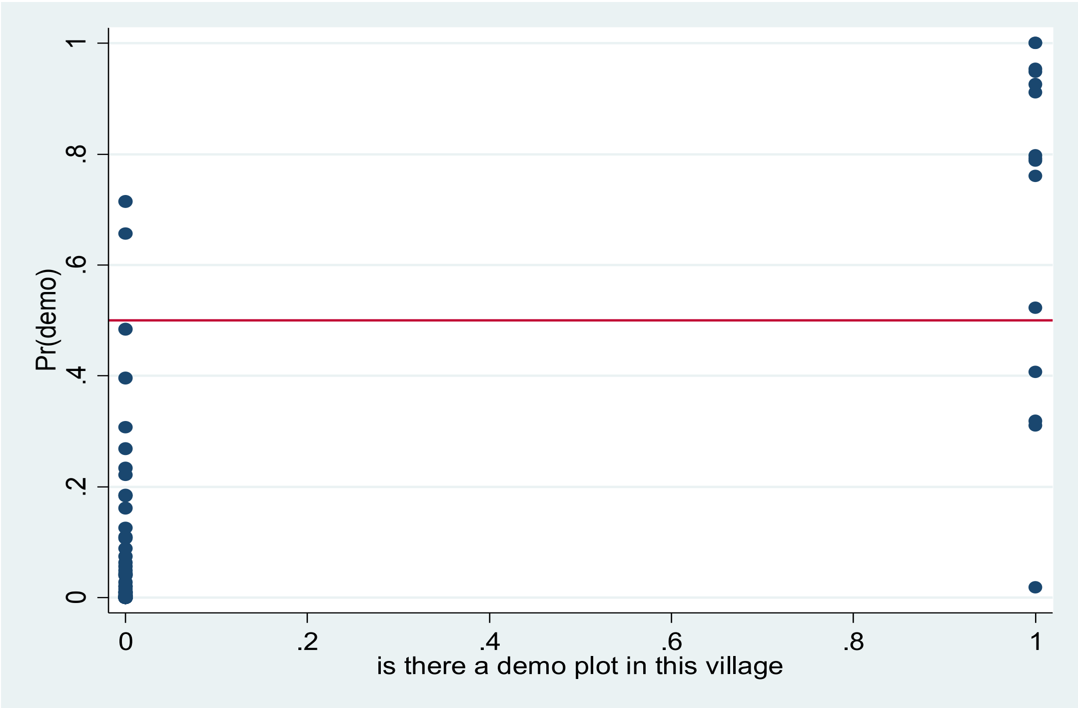


Figure 3: Histogram of the question: What chemical is best for controlling soyabean rust? (correct answer=1 ; incorrect answer==0)

First panel = households with lower than median asset holding

Second panel = households with higher than median assetholding



Appendix Figure 1: Predicting demonstration plot locations at baseline