

HOW DO FARMERS LEARN FROM EXTENSION SERVICES? EVIDENCE FROM MALAWI

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Though extension services have long since proved their value to agricultural production and farmer prosperity, their record in sub-Saharan Africa has been mixed. To study the impact of such programs on farmers' learning about agricultural technologies, we implemented a quasi-randomized controlled trial and collected detailed panel data among Malawian farmers. Based on those findings, we develop a two-stage learning framework, in which farmers formulate yield expectations before deciding on how much effort to invest in learning about these processes. Using data centered on farmer beliefs, knowledge, and constraints, we find evidence that beliefs about potential yields hinge on first-hand and local experience, and that these beliefs significantly impact learning efforts. Consistent with this, we find that farmers who participated in season-long, farmer-led demonstration plot cultivation plan to adopt more components of new multi-component technology, compared to farmers who were invited to attend only field-day events.

Key words: Agricultural extension, Learning, sub-Saharan Africa.

JEL codes: O13, O33, Q12, Q16, Q18.

Introduction

Agricultural extension can play a crucial role in overcoming farmer information constraints and encouraging the adoption of improved agricultural technologies, thereby increasing yields and incomes (Birkhaeuser, Evenson, and Feder 1991, Picclotto and Anderson 1997, Feder, Willet, and Zijp 1999, Anderson

and Feder 2007, Davis 2008, Birner et al. 2009, Waddington and White 2014). Supporting and enhancing cost-effective agricultural extension systems is especially important in developing countries. In Malawi, where this study is situated, agriculture employs nearly 70% of the population (2013 World Development Indicators). As information is commonly non-rival and non-excludable, primary responsibility for developing and disseminating agricultural education programs falls to governments.¹ Where responsibility resides with government extension services, effectiveness can vary. Birkhaeuser, Evenson, and Feder (1991) reports rates of return ranging from negative to over 100% (see also IEG 2011, Anderson and Feder 2007, and Ragasa and Mazunda (2018) provide an overview of evaluations set in Malawi).

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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 Denise Horner, Chris Barrett, Brad Barham, Ephraim Chirwa, Cheryl Palm, Wezi Mhango, Matt Embrey, J. V. Meenakshi, Giordano Paloni, Michael Lipton, and seminar participants at the AAEA meetings 2017, NEUDC 2017, 3IE-Delhi, 3IE-London, AGRA-Nairobi, the University of Gottingen and Virginia Tech for excellent comments and suggestions. We acknowledge financial support from the International Initiative for Impact Evaluation under TW4. Nourani acknowledges support from the National Science Foundation Graduate Research Fellowship under Grant No. DGE-1144153. Correspondence to be sent to: a.maertens@sussex.ac.uk

¹Krishnan and Patnam (2014) 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 assumed this role.

The effectiveness of agricultural extension depends on the model of extension employed. Extension can include systems of training and visits, demonstration plots, farmer field days and field schools (Anderson, Feder, and Ganguly 2006). These models not only range widely in terms of time and expense to both farmers and implementing agencies, but also have different implications for farmer learning and might result in different adoption patterns.

Demonstration plots, for instance, are designated plots where farmers experiment with a new technology under the supervision of an extension agent. They are commonly sited in the same village where participant farmers live, that is, where soil and climatic conditions are familiar and similar to most participants' conditions. Field days, in contrast, often take place further from farmers' communities, where local conditions might be quite different (and perhaps unknown). As returns to agricultural technologies are heterogeneous and depend on these conditions (Dufflo, Kremer, and Robinson 2008; Marenya and Barrett 2009; Suri 2011), farmers are more likely to learn something useful about the profitability of a new technology from local demonstration plots.²

In addition to learning about profits, farmers learn about enhancements to the production process including the optimal use of inputs. In Conley and Udry (2010), Ghanaian farmers concentrate on one dimension of a technology: the optimal amount of fertilizer on pineapple, a new crop in the region. Often though technologies involve adjusting among, and hence learning about, multiple production dimensions (see Beaman et al. 2013; Bulte et al. 2014; Emerick et al. 2016; Mponela et al. 2016; Nourani 2019).

In this study, we focus on integrated soil fertility management practices (henceforward ISFM), a group of techniques designed to increase the fertility of soils. ISFM includes application of mineral fertilizers, incorporation of organic matter, adoption of agroforestry, crop rotation and intercropping with legumes, and use of conservation agriculture practices. Learning about these numerous dimensions can be demanding and farmers make choices about what to pay attention (Schilbach, Schofield, and

Mullainathan 2016; Lichand and Mani 2020).³ Hence, extension service models, which include learning-by-doing and repetition, such as demonstration plots might be more effective (on the value of repetition in learning, see Brown, Roediger, and McDaniel 2014, Kim, Ritter, and Koubek 2013).

If learning about the production process comes at a significant cognitive cost, farmers might engage in what has been termed "rational inattention" (see Ghosh 2016 for a theoretical approach on rational inattention; and Gabaix 2017 for an overview). This might imply a two-stage learning process, as in Nourani (2019). Moreover, farmers using attention strategically may focus on dimensions of the technology where the perceived benefits might be most likely to exceed the perceived costs. For instance, credit-constrained farmers might focus on the more labor-intensive dimensions of a new production process.

In this paper we study the effects of farmer field days and farmer demonstration plots on farmer learning and adoption, and we present a model of farmer learning based on the insights from the evaluation. We exploit rich data on soil conditions, demonstration plot performance, and agronomic outcomes to understand how farmers direct their attention under time constraints and how spatial variability in growing conditions impacts farmer learning and adoption. To be clear at the outset, this paper is not a horserace between extension models. Instead, we are interested in contrasting field days and demonstration plots to gain broader and more generalizable insights into farmer learning.

The literature on the effects of extension struggles with two primary empirical challenges. First, farmers who seek out and receive extension services might be more skilled and motivated than farmers who do not seek such services.⁵ Moreover, areas that attract extension services are also often areas with better agronomic potential. Because such factors are often unobserved by researchers, they can cause omitted variable bias, threatening the causal interpretation of estimated parameters. A second challenge is that although an

²This is, assuming that farmers learn locally, i.e., contingent upon soil, climate, etc.; only a yield-draw from a plot that shares these conditions is likely to impact their own thinking and operations (on the implications of heterogeneity for social learning, see Munshi 2004, Tjernström 2015 and Crane-Droesch 2018; on Bayesian learning, see Lybbert et al. 2007).

³See Kahneman (1973, 2003), Gabaix et al. (2006), Fehr and Rangel (2011), Harstad and Selten (2013), and Rabin (2013) for an introduction to bounded rationality models.

⁴Hanna, Mullainathan, and Schwartzstein (2014) show that seaweed farmers in Indonesia only learn to be attentive to pod size—an important input dimension—after being presented with simple information pointing out that it is critical.

⁵Owens, Hoddinott, and Kinsey (2003) document the extent of such a bias in Zimbabwe.

extension program may be successful in terms of knowledge diffusion, adoption among farmers may be influenced by other factors (market failures, logistical challenges, etc.); and learning may not always translate into adoption. As standard household surveys often do not detail the learning process, studies have often faced challenges discerning whether such failures reside in the education process itself or in other circumstances down the line.

We designed our study to meet these challenges. We worked in partnership with the Clinton Development Initiative (henceforward CDI) in Malawi. CDI has set up a program of farmer-led demonstration plots and field days aiming to disseminate information about ISFM—with a focus on maize and soybean cropping systems. This process eliminates biases originating from between-village unobserved variation when establishing the effects of access to field days. Using detailed village-level data, we note that the villages in which CDI placed demonstration plots (which, unlike the field days, were not randomized) were comparable to the villages that merely received access to the field days. This observation allows us to use a regression approach when establishing the impacts of demonstration plots. We complement this quasi-randomized design with a household panel survey and focus group interviews documenting the adoption of ISFM technologies, as well as farmer knowledge of ISFM technology processes and yield expectations.

We find that farmers who participate in demonstration plots plan to adopt on average, about 14% more of the recommended ISFM technologies one year after the program's start, compared to similar farmers in control villages. Farmers who are invited to participate in a field day, on the other hand, do not plan to adopt more of the ISFM technologies relative to similar farmers in the control villages. We note that farmers who participate in demonstration plots know more about soybean production processes, compared to similar farmers in control villages.

Building on these results, and focus group interviews, we develop a learning model that captures the motivation and constraints to learn about ISFM technologies. Although both demonstration plot participants and field-day participants are learning, the model considers learning to be a choice, a choice that is constrained by factors such as credit, time, and cognitive resources. The learning model proceeds in two steps: farmers first assess potential profitability, before investing in

learning, subject to constraints. We apply the insights of the model to the data.

First, we find that, as predicted, the farmers' yield expectations in demonstration plot villages correlate with the observed yields of soybean and maize demonstration plots, and more strongly so if the farmers' soil is more similar to that of the demonstration plot.

Second, we predict that the amount of cognitive effort farmers commit to learning a new production process responds to these yield expectations. Accordingly, we note a positive correlation between demonstration plot yields and the farmers' understanding of ISFM production practices (this result holds using a reduced form approach using rainfall instruments).

Finally, we theorize that the learning process depends on farmer wealth and cognitive costs; as farmers who are constrained focus learning on the technologies they can realistically adopt. Accordingly, we find that demonstration plot participants' knowledge of ISFM practices for capital-intensive technologies, such as inputs for soybean cultivation, correlate positively with farmer wealth, conditional on high observed demonstration plot yields. For farmers who were invited to participate in field days, we note a similar correlation between being credit constrained and learning about soybean cultivation (it is notable that we find no such result for maize, for which recommended technologies are more labor rather than credit intensive).

Our theoretical and empirical results give a new meaning to the "rational but poor" farmers thesis originally proposed by Schultz (1964) and, subsequently tested by others, including Hopper (1965). Indeed, although farmers in our study might seem irrational at first, in that they show evidence of inattention to technologies that might be beneficial, their learning process appears more rational when one considers constraints imposed by heterogeneity. In effect, farmers in our study appear to decide actively how much effort to put into a given learning challenge and to focus on specific aspects which they find important. These aspects are determined by individual expectations and constraints, including market constraints.

CDI's ISFM Extension Program

Soil fertility is low and declining in sub-Saharan Africa (Sanchez 2002; Tully et al. 2015; Njoloma et al. 2016). ISFM

includes a range of agricultural technologies that improve the health of the soil, that is, its ability to store and gradually release nutrients and water. As such, ISFM both directly and indirectly improves yields through increasing effectiveness of other inputs. The benefits of ISFM in terms of increasing average yields and reducing yield variance can be substantial (Kerr et al. 2007; Duflo, Kremer, and Robinson 2008; Sauer and Tchale 2009; Fairhurst 2012; Bezu et al. 2014; Franke, Van Den Brand, and Giller, 2014; Manda et al. 2016; Droppelmann, Snapp, and Waddington 2017), albeit heterogenous, and conditional on farmer wealth and assets (Place et al. 2003, Vanlauwe, and Giller 2006, Marenya and Barrett 2007 and Mugwe et al. 2009).

However, the adoption of ISFM technologies in sub-Saharan Africa remains low (Wossen, Berger, and Di Falco 2015; Nkonya et al. 2016; Nkonya et al. 2017). Sheahan and Barrett (2017), using the World Bank's LSMS surveys for six countries in sub-Saharan Africa, note that although the uptake of inorganic fertilizers and agrochemicals is not uniformly low (and, in fact, is high in Malawi), there is low correlation between the use of commonly paired inputs (fertilizer and hybrid seed; or organic and inorganic fertilizer) at the household and, more importantly, plot level.⁶

CDI aims to increase the adoption of ISFM technologies among smallholder farmers in Malawi, through both extension and improved market access. In this study, we focus on CDI's extension activities: farmer-led demonstration plots and farmer field days. The annual implementation calendar for these activities follows Malawi's agricultural cycle. In central Malawi, where our study is set, the rainy season starts in November/December and ends in April/May.

In November, CDI sets up demonstration plots in central village locations, close to a road, and, according to their own account, on good quality plots. The exact location of the demonstration plot is selected through discussion with the local government extension agent and local farmers. Once the location is determined, a CDI extension agent sets up the plot together with a local farmers' club of

ten to twenty members. The CDI extension agent continues to guide the farmer's club throughout the season using telephone calls and in-person visits. The club is in charge of the day-to-day management and the implementation of the various plot activities, including planting, weeding, and fertilizing. All club members are expected to take part in these various activities as a team. These activities can be time consuming.⁷ At harvest, the members share the proceeds from the demonstration plot.

In March, CDI selects the best performing demonstration plots on which to hold farmer field days. Farmers in nearby locations are invited to attend these one-day events, with CDI providing transportation to and from the field-day location and a mid-day snack. Field days are held at the end of the growing season, and farmers observe the mature crop on the fields. Throughout the day, the CDI agent and local club explain and show the various ISFM techniques to the visiting farmers. CDI typically holds one field day per EPA (extension planning areas, a subdistrict administrative unit) and invites up to 1,000 farmers.

In the remainder of this paper, we distinguish between two types of treatments—a demonstration plot treatment and a field-day treatment. The first type of treatment refers to the active participation and working on a demonstration plot throughout the season. The second type of treatment refers to attending a one-day, field-day event.

In 2014–15, the growing season under consideration for this study, CDI focused on soybean, maize, groundnut, and common bean. We focus on soybean and maize demonstration plots, CDI's primary focus. Almost all farming households in Malawi cultivate maize: In 2016–17, 76% of fields were under maize cultivation (IHS 2017). Soybean cultivation has been increasing in central Malawi and is now an important cash crop. In our survey, 40% of households cultivated soybean in the 2013–14 season.

Demonstration plots feature both control and best practice agronomy (BPA) subplots. On best-practice subplots all locally recommended ISFM technologies are applied, including the use of a high-yielding hybrid variety, optimal plant spacing and seeding

⁶Using the same data, we note the prevalence of ISFM practices in Malawi: intercropping (53% of fields), application of mineral fertilizers (55% of fields), organic fertilizers (19% of fields), and herbicides/pesticides (2% of fields)—data from the 2016–17 round.

⁷In our study area planting takes, on average, three hours. Each follow-up activity takes, on average, twenty minutes per activity, with a total of 25–35 such activities over the season.

practices (soy seed treated with inoculants), mineral fertilizer, herbicides, pesticides, fungicide, and the use of organic fertilizer, such as crop residues, animal manure, compost, and fertilizer trees. Online Appendix A provides more detail on the demonstration plot design and layout.

Sample, Randomization, and Data Collected

In 2014, CDI was planning an expansion of their program into two districts in central Malawi: Dowa and Kasungu. Dowa is a densely populated district with lower than national poverty rate and an average climate. Kasungu has a lower population density, a large hinterland and higher than average poverty rate.⁸

Together with CDI, we selected two EPAs: 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.⁹ 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 study sample for this paper however is limited to 100 villages.¹⁰ In the remainder of this section, we will note the relevant numbers in both the project sample (250 villages) and the study sample (100 villages). Table 1 presents an overview of the study sample, treatment, and participation status: we have fifty-six treatment villages and forty-six control villages. We provide evidence of the success of the randomization in Appendix Table 1.

The villages in the treatment group were invited to form farmer clubs and to participate in CDI's program. Farmers formed clubs in

91 out of 125 treatment villages (in our study sample, this is 48 out of 56). Villages who formed clubs tended to be further away from markets and have a history of community action.

Seventeen of the ninety-one villages (and of the forty-eight villages in the study sample as well) received farmer-led demonstration plots during the 2014–15 growing season. These seventeen villages were selected by CDI in December 2014. By CDI's own account, these were villages with some familiarity with agricultural extension services, located in an accessible location and where people were in "unity." Recognizing the small sample, appendix table 2 compares the demonstration plot villages with the other treatment villages in the study sample and reports few significant observable differences between these two sets. All but five villages received a soybean/maize demonstration plot; the remaining five received either a groundnut/maize plot or a common bean/maize plot. The CDI agent set up the demonstration plot in all cases, with all CDI club members of the relevant village assisting him/her. An analysis of the field observation data reveals high participation levels.¹¹

In March 2015, CDI invited all farmer clubs in the ninety-one villages to a farmer field day (in the study sample, this is forty-eight villages, including the demonstration plot villages). 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 that 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. As table 1 notes, thirty-two villages out of forty-eight villages attended the field day. Not all farmers from these club participate in the field day. The buses had limited seating capacity, and farmer clubs were encouraged to select between one and three members to attend. On average, 2.13 club

⁸This area is a popular among NGOs and other organizations. However, their activities were evenly distributed between the treatment and control locations, and to our knowledge, none of these organizations focused on soy production.

⁹As CDI works through farmer clubs and the functioning of these clubs requires a minimum village size, we excluded the villages with less than fifty households.

¹⁰These 100 villages were selected as follows: First, we selected 90 villages randomly from the 250 project villages, stratified by EPA and treatment status. These ninety villages included seven villages with demonstration plots. Then, we included an additional ten villages that had been selected as demonstration plot villages by CDI (as to include all seventeen villages which were selected as a demonstration plot locations).

¹¹All club members participated in the planting activities. On average, 77% of all club members participated in post-planting activities, and, on average, 86% of club members participated in the harvesting activities. The self-reported data collected among farmers at endline is in line with these statistics: 80% of club members noted to participate in "all" or "almost all" activities on the demonstration plots, and only two individuals noted not to have participated in the activities.

Table 1. Sample, Treatment and Participation*Note: Number of villages; number of farmers in those villages in brackets*

	Treatment assignment	Villages with clubs	Villages with demonstration plots	Villages who attended field days
Treatment villages	56 (560)	48 (480)	17 (170)	32 (320)
Control villages	44 (440)	0 (0)	0 (0)	9 (90)
Total	100	48	17	41

Note: This table presents an overview of the number of villages and farmers within each treatment group as pertaining to the analysis sample of this paper. The information presented uses our administrative records on demonstration plot locations and self-reported club membership and field-day participation data collected at endline.

members attended in our sample of five club members.¹²

Data Collected

We collected data at baseline, before the treatment villages participated in the program activities (in fall 2014), and one year later (in fall 2015).¹³ The baseline was conducted in all 250 villages in the sample, whereas the data collection the following year included 100 villages.

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 ten households for each village: in the control villages and the treatment villages without a club, we randomly selected ten households from the village census. In the treatment villages with CDI clubs, we stratified the sample and sampled five households not participating in a CDI club and five participant households.¹⁴ One of the five households sampled was the household of the lead farmer of the club, who 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 the CDI club. Club members are wealthier, more educated, and better connected than non-club members.

¹²This self-reported data might be subject to measurement error. There are many field days in the area, and some respondents might have mixed up field days.

¹³Data of the project are available via FIGSHARE via: https://figshare.com/authors/ISFM_Malawi/6943355

¹⁴In case of multiple CDI clubs in a village, we selected the club to be included in the study randomly. In terms of the treatment, all CDI clubs are invited in their respective village-level assigned treatment.

At baseline, we conducted a village survey¹⁵, a household survey and analyzed soil samples from farmers' plots and demonstration plots. One year later, we followed up with household surveys, creating a household panel dataset.¹⁶ Between these two rounds of data collection, we collected field observation data at the demonstration plot sites on a weekly basis. We also conducted a series of focus group interviews and interviewed extension agents (see online Appendix B).

Household Survey

We conducted a household survey among 2,500 households in 250 villages at baseline and among the subset of 1,000 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.

At baseline, we collected data on household composition, groups, networks and information sources, landholding, marketing,

¹⁵Covered information on distance to paved roads, national highways, markets, and other services. We also collected demographic information 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.

¹⁶The attrition rate is 5%—specifically, there were fifty-one 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 (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 fifty-one households were replaced in the follow up survey using the random sampling methods outlined in the main text.

Table 2. Descriptive Statistics of Households at Baseline in 2014

Variable description	N	Mean	St. dev.
<i>Panel A: Socio-economic characteristics</i>			
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
Agriculture main activity of household head (1 = yes; 0 = no)	1,000	0.79	0.41
Land (in acres, owned) ¹	944	3.47	2.55
Are government extension agents one of three main sources of information (no = 0; yes = 1) ²	1,000	0.30	0.46
Are other farmers one of three main sources of information (no = 0; yes = 1) ²	1,000	0.75	0.42
Took credit in 2013–14 season (no = 0; yes = 1) ³	1,000	0.17	0.37
<i>Panel B - Perceived soil quality⁴</i>			
Perceived stagnant or declining soil fertility (no = 0; yes = 1)	960	0.82	0.34
Experienced soil erosion (no = 0; yes = 1)	960	0.47	0.44
Experienced nutrient depletion (no = 0; yes = 1)	960	0.57	0.45
Experienced water logging (no = 0; yes = 1)	960	0.23	0.37
Experienced acidity or salinity (no = 0; yes = 1)	960	0.05	0.20
<i>Panel C - Results of soil sample analysis⁵</i>			
pH (recall 7 is neutral, smaller is acid, larger is alkalic)	252	6.12	0.52
Active carbon (in mg/kg)	250	423	150
Limited N (no = 0; yes = 1)	252	1.00	0.00
Limited S (no = 0; yes = 1)	252	0.77	0.43
Limited K (no = 0; yes = 1)	252	0.33	0.47
Limited P (no = 0; yes = 1)	252	0.52	0.55
<i>Panel D - Crop and technology choices</i>			
<i>Crop and seed choices</i>			
Cultivated maize in 2013–14 (no = 0; yes = 1)	1,000	0.96	0.19
Cultivate hybrid maize in 2013–14 (no = 0; yes = 1)	961	0.62	0.49
Cultivated groundnut in 2013–14 (no = 0; yes = 1)	1,000	0.55	0.50
Cultivated common bean in 2013–14 (no = 0; yes = 1)	1,000	0.44	0.50
Cultivated soybean in 2013–14 (no = 0; yes = 1)	1,000	0.46	0.50
Inoculated soybean in 2013–14 (no = 0; yes = 1) ⁵	463	0.00	0.65
<i>Land preparation</i>			
Used intercropping in 2013–14 (no = 0; yes = 1)	1,000	0.49	0.50
Used crop rotation in the last 5 years (no = 0; yes = 1)	1,000	0.82	0.38
<i>Fertilizer</i>			
Use animal manure in 2013–14 (no = 0; yes = 1)	1,000	0.29	0.45
Incorporated crop residue in 2013–14 (no = 0; yes = 1)	1,000	0.14	0.35
Used inorganic fertilizer in 2013–14 (no = 0; yes = 1)	1,000	0.88	0.31
Planted fertilizer trees in 2013–14 (no = 0; yes = 1)	1,000	0.09	0.28
Used compost in 2013–14 (no = 0; yes = 1)	1,000	0.019	0.13
<i>Other inputs</i>			
Used pesticides in 2013–14 (no = 0; yes = 1)	1,000	0.00	0.00
Used herbicide in 2013–14 (no = 0; yes = 1)	1,000	0.05	0.21
Used fungicide in 2013–14 (no = 0; yes = 1)	1,000	0.00	0.00
<i>Panel E - Yield expectations</i>			
Harvest of maize expected (in kg/ha)	1,000	3,599	2,288
Harvest of soy expected (in kg/ha)	993	1,608	1,336

Note: 1: We dropped farmers with more than 13 acre (95% percentile) for these statistics. 2: We asked the respondent about the three main sources of information about agriculture, if the government extension agent was mentioned, we coded the first answer = yes (no otherwise); and if another farmer in the village was mentioned, we coded the second answer = yes (no otherwise). 3: We asked the respondent whether he/she took any loans in 2013–14. Note 4: We elicited characteristics of each field and averaged the responses across fields for each farmer (Note that the sample only includes respondents who own at least one field). 5: Panel C only includes the households who had a soil sample analysis done, 252 farmers. Definition of nutrient deficiencies: N: less than 42 mg NO₃⁻/kg soil; S: less than 10 mg/kg soil, P: less than 0.3 mg/kg soil; K: less than 20 mg/kg soil.

Note: Two inoculation statistics are conditional cultivating soybean; hybrid maize use is conditional on cultivating maize. Yield expectations were elicited in 50 kg bags per acre, or 50 kg bags per plot, and refer to the shelled product. Due to issues with farmers' estimation of acreage, we used the former here, which we converted to kg/ha, excluding outliers above the 95 percentile.

subsidies, credit,¹⁷ and assets. At both baseline and one year later, we collected information on the adoption of ISFM technologies and yield expectations. One year after baseline, we also collected data on participation in the program and knowledge of ISFM technologies. We inquired about the knowledge of CDI's programs, participation and experiences in CDI's field days, participation and experiences in CDI club activities, and demonstration plot activities.

Adoption of ISFM Technologies. At baseline, we collected information on current use of ISFM technologies. To obtain a longer term picture, we also collected information on ISFM technologies used in the past five years, asking the farmer whether in the last five years, they had (ever) used a particular technology.

One year later, we repeated the input-output questionnaire (this time focusing on the 2014–15 season) and added a new module on adoption plans. We asked whether or not the respondent planned to adopt a particular technology (in the 2015–16 season) and, if so, followed up with details and, if not, asked for reasons for non-adoption. Our choice to use adoption plans (and not actual adoption) was data driven. As our goal was to document the learning process, we returned to the villages after the growing season was finished but before the next growing season had started. This ensures quality data on knowledge and beliefs but limits the adoption analysis to adoption plans.¹⁸

Knowledge about ISFM Technologies. We build on Kondylis, Mueller, and Zhu (2015) and incorporated twenty questions designed to assess knowledge about the ISFM techniques introduced by CDI and field this module in the follow-up survey.¹⁹ The questions

¹⁷We asked the household head to list all lines of credits taken up in 2013–14, the terms of the credit, and where he/she would go if he would like to obtain credit for the next (2014–15) season (and how likely he/she believes credit can be obtained from this source).

¹⁸Using recall data collected five years after the baseline survey, mapped up adoption plans into recalled adoption. The accuracy ranges from 50% to 95%, with the error in the direction of under-reporting adoption (compared to the recall), except for with fertilizer tree and groundnut where the direction of the error is the opposite. The fact that the direction of the bias is opposite what one would expect (one would expect plans to “exceed” actions) is concerning. In addition, attrition and recall bias might play a role. Hence, we only report results regarding adoption plans in this paper.

¹⁹See Pan et al. (2018) for another example, we mapped up adoption plans with recalled adoption. See also Laajaj and Macours (forthcoming) for a critical discussion of various measures of ability, skill, and knowledge.

covered ISFM practices for soybean, groundnut, and maize. Responses were true/false, multiple choice, or 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).

Yield Expectations. We build on Delavande, Giné, and McKenzie (2011a); Delavande, Giné, and McKenzie (2011b); Dillon (2016); and Maertens (2017) to elicit yield expectations at both baseline and endline. We focus on soybean, groundnut and maize. At baseline, we asked the respondent: “Imagine that you would cultivate maize this coming year (and that maize is the only crop on the field, i.e., no intercropping), how much maize do you think you would harvest on one acre of land” We recorded the answer in 50 kg bags of shelled or unshelled maize. We then repeated these questions for soybean (in 50 kg bags of shelled soybean) and groundnut (in 50 kg bags of unshelled, dried groundnut).²⁰

Field Observations on Demonstration Plots

We visited the demonstration plots two weeks after planting to record germination and record activities and inputs used up to that date. Data on agronomic practices 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,

²⁰In our baseline data, 75% of the plots were monocropped, but intercropping was common. Due to the complexity in generating per-acre beliefs on intercropped fields, we asked the respondent to imagine a monocropped field. The unit was determined in qualitative interviews preceding the data collection as most common unit people think about for the crop. In addition, we recognize 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 measurement error due to the lack of ability to imagine exactly the size of one acre and also asked the respondent for the expected yields on a particular field, instead of a per-acre basis (see also Bevis and Barrett 2020).

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.

At harvest, we visited the demonstration plots and collected crop yield data. We recorded the stand count at harvest, the total biomass, grain yield, and stover or leafy biomass. Grain moisture content was determined using a Mini GAC plus moisture meter. It is important to note that the club members were present during these on-field activities and, hence, are expected to have good idea of the planting and harvesting counts.

Soil Sampling and Analysis. The key indicators of land fertility in the study area are soil pH and organic matter content (see Snapp 1998). We collected soil samples from a total of 252 farmers' fields in addition to the nineteen demonstration plots during November–December 2014 and 2015.²¹ It is important to note that the results of these soil analyses were not shared with the farmers until after the study was completed.

For each field, we recorded the cropping history, the GPS coordinates at the center of the field, and the field acreage by walking around the field. We then collected two soil samples at 0–20 cm soil depth. These samples were then mixed to make a composite sample. After collection, the soil samples are put in soil sampling bags and taken to the Bunda College Soil and Plant Analysis Laboratory for analysis. If the soils were wet upon arrival at the laboratory, the samples were first air dried. When dry, we sieved them through a 2 mm sieve and recorded the soil texture using the hand feel method.

We use the SoilDoc program to analyze the sample pH, nitrate nitrogen (NO_3^-), inorganic phosphorus (P), sulfur (S), exchangeable potassium (K) and electrical conductivity (EC), and active carbon (C). See Gatere (2013) and Weil and Gatere (2015)

for an introduction to SoilDoc. Note that we did not measure the total organic carbon matter, a measure of carbon contained within the soil organic matter, and generally accepted to be a good summary measure of overall soil fertility. Instead, we measured active carbon, which compared to total organic carbon, is more sensitive to management effects and more closely related to soil productivity and biologically mediated soil properties, such as respiration, microbial biomass and aggregation (Weil et al. 2003).

Descriptive Statistics

The households in our study area are land-poor and dependent on rainfed agriculture. Table 2, panel A, introduces the households. We present baseline statistics of the households in the 100 villages who were revisited one year after baseline. The average household head is 42 years and has 4.5 years of education. About 18% of household heads are female, and the average household has 5.22 household members. Only 17% of respondents stated that they had taken out credit the previous season. Respondents report receiving information from both government extension agents and fellow farmers. About 40% of respondents report having interacted with government extension agents, and another 20% report to interact often to very often. For 30% of respondents, extension agents are one of the main sources of information.

On average, households own 3.5 acres of land. Although this figure excludes outliers above the 95 percentile, it might still appear high. It is important to note however that the median field size is small, 1.5 acres, and likely to be an overestimate (these are self-reported acreages, which are often overestimated in the case of smaller plots; see Bevis and Barrett 2020 for a discussion).

Plots of land are small and population density is high in the area, according to the respondents' own account often the result of generations of plots being subdivided for inheritance. A lack of land can further reduce land quality, as leaving fields fallow or using crop rotation might no longer be options for many households. Soil fertility in the study area is low and declining. Soils are classified as Ferralsols, Lixisols, and Plinthosols (FAO Harmonized World Soil Database). A common feature of these soil types is that they

²¹First, we selected all ten sample farmers who live in villages where a CDI demonstration plot was set up. Second, we randomly selected twenty treatment villages and nine control villages, and approached all ten farmers in each village for soil sampling. Third, we selected ten villages purposefully, for their relatively higher share of female-headed households and collected a soil sample from all ten sample households in these villages. This results in a total of 560 farmers, of which 225 live in villages that were covered by our follow up survey.

depend on the addition of organic and inorganic matter to improve soil structure and overall fertility. Our respondents report soil fertility problems (see table 2, Panel B): 80% of farmers perceive the average soil fertility to be stagnant or declining. Common reported problems are soil erosion, water logging, and nutrient depletion.

The soil sample analysis results, summarized in table 2, panel C, confirm these reports. Soils are slightly acidic and with low to very low active carbon in 30% of soils tested and at a medium level in another 40%. Results indicate that organic carbon is mostly sufficient to maintain soil structure but still low. We document widespread nutrient deficiencies. All soils tested are nitrogen (N) deficient, 77% are sulfur (S) deficient, 52% are phosphorus (P) deficient and 33% are potassium (K) deficient. Over 50% of soils tested were deficient in three or more nutrients. The intraclass correlation between observations of the same village is below 0.5 for measures of nitrogen and potassium, indicating significant within-village variation in these measures.

Table 2, panel D, reports farmer cultivation practices in 2013–14. Almost all respondents cultivated maize (of which 62% opted for a hybrid variety) and less than half cultivated soybean, common bean, and groundnut. Over 80% had used crop rotation (in the last five years), whereas about half reported using intercropping in 2014–15. Nearly 88% had used mineral fertilizer (Malawi has a large-scale mineral fertilizer subsidy program targeting small-holder farmers). Animal manure had been used by 30% (but compost was not common), 14% had incorporated crop residue in the soil, and 9% had planted fertilizer trees. The use of other inputs is not very common. Less than 5% had used pesticides, herbicide or fungicide; and only two soy growing farmers had inoculated the seed.

Table 2 panel E reports on the farmers' baseline yield expectations for maize and soybean. Farmers expect to harvest, on average, 3,480 kg/ha (or 29 kg bags per acre) of maize. This is significantly larger than the average yield on the farmers' plots in 2013–14, which was 1,750 kg/ha for mono-cropped plots. However, it is important to keep in mind that: (a) the yield expectation distribution is not normal, with a long left tail—in effect the median of the distribution is 3,088 kg/ha; and (b) the beliefs are reflect also perceived acreage, which, in our data, are overestimated for

smaller plots and underestimated for larger plots (we know this, as for a subset of the plots, we also have the GPS measured acreage). Farmers expect to harvest, on average, 1,608 kg/ha or (13 kg bags per acre) of shelled soybean. This is larger than the average actual yield in 2013–14 (312.5 kg/ha, on mono-cropped plots). Again, the same disclaimers apply, and it should be noted that the median yield expectation is 1,235 kg/ha.

As a comparison, appendix table 3 presents the yields obtained on the demonstration plots in 2014–15. We focus on maize and soybean subplots. Maize grain yield was variable and ranged from 452 kg/ha under control treatment to 8,990 kg/ha under best practice agronomy. The latter is within the range of potential yields for maize, ranging from 6,000 to 14,000 kg/ha (depending on the variety, see MAIFS 2012). Overall, the use of best agronomy practices increased maize yield by 62% and 25% over the control and farmer practice treatments respectively. Differences in grain yield of soybean between the treatments and sites are also significant. Yields range from 0 (crop failure) to 2,218 kg/ha. The use of best agronomy practices increased the yield of soybean by 50.4% over the control. Overall, the yields of soybean are somewhat lower than the potential yield of 2,000–4,000 kg/ha but in the range of the attainable yields on small-holder farms (1,500–2,500 kg/ha) with good agronomic practices (MAIFS 2012).²²

Insights from Focus Group Interviews

We interviewed farmers who participated in demonstration plots, and farmers who participated in field days. The latter reported being impressed by the crops they saw during the field day but were unable to estimate the improvement in yields. They noted being convinced that pesticides and, more generally, “modern inputs” are important. However, when we inquired about specifics related to pesticide use, for instance, few of the field-day participants knew brand names, where to purchase these inputs, or how to prepare and apply the products. We hypothesize that by virtue of being matched to a plot that is further afield, they learned little about the profitability of ISFM technologies; and being less

²²The lower than attainable yield performance on some of the demonstration plots could also be attributed to the poor rainfall distribution in the 2014–15 cropping season.

Table 3. The Impact of the CDI Program on (Planned) Adoption and Knowledge of ISFM Technologies

Linear model with dependent variables:

	Adoption (1)	Knowledge (2)
Demonstration plot	0.535** (0.246)	0.29 (0.279)
Field day	0.063 (0.213)	-0.228 (0.254)
Constant	5.531*** (0.147)	7.952*** (0.161)
Observations	414	414
R-squared	0.012	0.007

Note: This table present the results of linear regressions with dependent variables: planned adoption (score out of 13) and knowledge (score out of 20). The independent variables are whether or not the individual is in a club which managed a demonstration plot and whether or not the individual is in a club that was invited to a farmer field day. The sample includes all but forty-two club-members and a comparable sample of farmers from the control villages identified through 1-to-1 matching without replacement following the psmatch2 Stata command developed by Leuven and Sianesi (2003). The control variables used in this first matching step include all village level characteristics included in appendix table 1, all household level characteristics included in appendix table 4 (and the square terms of the non-binary variables) and baseline adoption indicators.

***p < 0.01.

**p < 0.05.

*p < 0.1.

convinced about the benefits of the technology, as well as facing a strict time constraints, they focus on components of the technology they can realistically adopt. Consistent with this, these farmers reported to focus on labor-intensive technologies for maize, such as mulching and optimal planting practices.

Farmers who participated in a demonstration plot, on the other hand, were able to estimate yield improvements and recalled details about the inputs and production practices. For instance, these farmers were able to recount the inoculation process for soybean seeds, from preparing the inoculant to covering the seeds and planting them on ridges. We hypothesize that these farmers, having observed the yield improvements on a local plot, learned more about the profitability the technologies. In addition, they reported to face fewer time constraints and hence came away with stronger comprehension of ISFM technologies.

Online Appendix B provides more details.

A Model of Learning

We build on Foster and Rosenzweig (1995); Hanna, Mullainathan, and Schwartzstein (2014);

and Nourani (2019) to model the farmer's learning and adoption decision as an optimal portfolio choice with multiple objects of learning under a range of initial endowments.

Yields

We introduce three production technologies: a capital-intensive technology indexed K , a labor-intensive technology indexed L and a traditional, risk-free technology. Each risky technology K and L has average per-acre pay-offs (yields) of μ_j ($j \in \{K, L\}$) — yields associated with the risk-free technology are normalized to one. Furthermore, we assume that the yields from the capital-intensive technology are higher than the labor-intensive technology: $\mu_K > \mu_L > 1$.

Prices

We assume that the farmer does not need to learn about prices. The output price is normalized at 1. The input prices are denoted p_j .²³

Two-stage approach

The farmer first establishes a belief of the yield and then invests resources to generate knowledge, that is, learn about the production process, and makes decisions as to which technologies to adopt.

Learning about yields

We assume that the true value of μ_j is unknown to the farmer. Let the prior belief about μ_j , $\hat{\mu}_j$, be normally distributed, centered around the true value, with variance σ_μ^2 . So each farmer's prior belief represents a draw of the distribution:

$$(1) \quad \hat{\mu}_j \sim N(\mu_j, \sigma_\mu^2).$$

When observing yields on the demonstration plot, either in the village, or at a field

²³Farmers indicated that they base their output price beliefs on the previous year's prices, which were well known. Input prices could be obtained from local agro-dealers and might not be known. However, as the CDI program did not explicitly provide information on input prices nor did we collect details on learning about input prices, we abstain from modeling this component of the learning process. See also Michler et al. (2019) for a discussion.

day, the farmer receives an unbiased information signal v_j . This signal is the sum of the true yield μ_j plus a noise term, η_j , normally distributed around zero with variance σ_η^2 :

$$(2) \quad v_j = \mu_j + \eta_j \text{ with } \eta_j \sim N(0, \sigma_\eta^2).$$

Values of σ_η^2 can depend on a farmer's beliefs about the degree of similarity between conditions surrounding his own plot and those of the demonstration or field-day plot. However, to maintain simplicity, we will abstract from this farmer dependency in our notation. Assuming the farmer uses Bayesian updating, then noisier signals are down weighted in posterior beliefs. Posterior beliefs, μ_j^p , are characterized by:

$$(3) \quad \mu_j^p = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\mu^2} \hat{\mu}_j + \frac{\sigma_\mu^2}{\sigma_\eta^2 + \sigma_\mu^2} v_j$$

Thus, the posterior beliefs will decrease (relative to the prior) if the signal received is less than the prior and increase otherwise. The degree of change in posterior beliefs depends on the signal v_j and the farmer's perception of the relative noisiness of the signal.

Equation (3) implies that the posterior belief represents the weighted average between the prior belief and the signal received. In regression terms, this implies:

$$(4) \quad \mu_{ij}^p = \alpha + \beta_1 \hat{\mu}_{ij} + \beta_2 v_{ij} + \varepsilon_{ij}$$

Production process

If production inputs (e.g., fertilizer, herbicide, labor) are inaccurately applied farmers incur a *knowledge penalty* (Foster and Rosenzweig 1995). Specifically, let θ_j^* indicate the optimal amount of input required for technology j . If the farmer applies input θ_j instead of θ_j^* , he incurs a (per-unit) loss equal to $(\theta_j - \theta_j^*)^2 > 0$ for all $\theta_j \neq \theta_j^*$.

Learning about the production process

The optimal input use, θ_j^* , of technology j is also unknown. Let the prior belief, $\hat{\theta}_j$, be normally distributed and centered at θ_j^* :

$$(5) \quad \hat{\theta}_j \sim N(\theta_j^*, \sigma_{\theta_j}^2(e_j)) \mid e_j \in \{0, 1\},$$

Note the dependency of the belief on learning effort, denoted e_j . The beliefs are more precise if the farmer applies a discrete learning effort, $e_j = 1$, compared to no learning effort, $e_j = 0$. The knowledge penalty, $\mathbb{E} \left[(\theta_j - \theta_j^*)^2 \right] = \sigma_{\theta_j}^2(e_j)$, is therefore larger without learning effort.

$$(6) \quad \sigma_{\theta_j}^2(e_j = 1) < \sigma_{\theta_j}^2(e_j = 0)$$

Payoffs

The farmer holds initial wealth w_0 and is tasked with choosing the optimal amount of wealth to invest in each production technology, x_j , each unit of which costs p_j to purchase. At harvest, the farmer receives the following payoff:²⁴:

$$(7) \quad P = w_0 + x_1(1 - p_1) + \sum_{j \in \{K, L\}} [x_j(\mu_j^p - p_j) - [x_j(\theta_j - \theta_j^*)]^2] - \bar{e}_j 1(e_j = 1)$$

where \bar{e}_j represents the cognitive cost associated with gaining knowledge of production technique j and only contributes to payoffs when learning effort is applied (1 is the indicator function). The input amount for the risk-free technology is denoted x_1 and its cost p_1 .

Expected Payoff Maximization. Given the presence of credit market imperfections, the farmer's problem will be one of maximization of expected payoffs given a budget constraint. The farmer chooses values of x_j , θ_j , and e_j given values of μ_j^p and p_j for both $j \in \{K, L\}$. The choice of θ_j is straightforward if the farmer selects a positive value for x_j : he selects $\theta_j = \hat{\theta}_j$ to minimize expected square loss. We focus on whether the farmer applies effort toward learning to produce j (e_j) and the amount of x_j . Let P represent expected payoffs. The farmer's problem is now:

²⁴We abuse notation slightly here. This expression should use the realized yield and not the (posterior) belief, μ_j^p . This is rectified in the next expression, which refers to the expectation instead.

$$\begin{aligned} \max P = & \max_{(x_j, e_j)_{j \in \{K, L\}}} w_0 + x_1(1 - p_1) \\ & + \sum_{j \in \{K, L\}} [x_j(\mu_j^p - p_j) - x_j^2 \sigma_{\theta_j}^2(e_j) \\ & - \bar{e}_j 1(e_j = 1)] \end{aligned}$$

such that

$$(8) \quad (\lambda) : w_0 - \sum_{j \in \{K, L\}} p_j x_j \geq 0$$

Solution

Given the discrete nature of learning effort in our setup, we can find the solution to problem (8) by backward induction. We first determine the optimal value of x_j given each choice of e_j ; and then plug this value back into the objective function of problem (8) to determine which levels of effort result in the highest expected payoff.

First order conditions on x_j yield the following demand function:

$$(9) \quad x_j^* = \left(\frac{\mu_j^p - p_j(1 + \lambda)}{2\sigma_j^2(e_j)} \right)$$

Expression (9) intuitively shows that demand for production technology x_j is increasing in the net (perceived) returns of the production method and knowledge of the production process. Demand is decreasing with the penalty associated with violating the budget constraint, λ . The presence of borrowing constraints will result in corner solutions (of x_j), including non-adoption. Depending on the exact nature of the constraint, and the farmer’s belief regarding the expected profitability of technology j , the farmer may decide to limit his attention to only learning about one or the other technology. Specifically, the farmer chooses to allocate learning effort on a combination of technologies, resulting in four possible combinations in our setting: $\mathbf{e} = [\{0, 0\}, \{1, 0\}, \{0, 1\}, \{1, 1\}]$ where the first argument refers to technology K and the second argument refers to technology L . Notice that $P(x_K^*(e_K), x_L^*(e_L), e_K, e_L)$ can be calculated for each of the four discrete choices a farmer can make. Thus, the farmers optimal learning effort vector, \mathbf{e}^* , can be characterized by:

$$(10) \quad \mathbf{e}^* \text{ such that } \mathbf{e}' \in \{\{0, 0\}, \{1, 0\}, \{0, 1\}, \{1, 1\}\}$$

$$P(x_K^*(e_K^*), x_L^*(e_L^*), e_K^*, e_L^*) \geq P(x_K^*(e'_K), x_L^*(e'_L), e'_K, e'_L).$$

From (8) it is clear that the farmer will not exert effort in learning a new technology if its yields (net of costs) are smaller than 1—the yield of the risk-free technology. The choice of effort, in all other circumstances will depend on the decreased uncertainty arising from learning about technology j relative to alternative technologies as described in equation (10) and accounting for the cost of learning.

Holding the price of inputs and cost of learning effort fixed, this would imply a positive relationship between posterior yield beliefs and knowledge for any given technology. In regression terms, we test the hypothesis that $\beta_1 > 0$ in:

$$(11) \quad \textit{knowledge}_{ij} = \alpha + \beta_1 \mu_{ij}^p + \varepsilon_{ij}$$

Similarly, we expect to find a positive relationship between the posterior beliefs and the adoption of any given technology. In regression terms, this implies:

$$(12) \quad x_{ij} = \alpha + \beta_2 \mu_{ij}^p + \varepsilon_{ij}$$

Where we test the hypothesis $\beta_2 > 0$.

Choosing what to learn

Recall that we assumed that the capital-intensive technology generate higher average returns, that is, $\mu_K > \mu_L$. We now, in addition, assume that they are also more expensive to purchase, or: $p_K > p_L$. Furthermore, we denote π_j , the average profit gain from an added unit of technology j , (i.e., $\pi_j = \mu_j - p_j$), and we assume that $\pi_K > \pi_L$.

When the budget constraint binds, then $\lambda > 0$, and (8) can be solved by entering optimal values of x_j^* into the budget constraint and equating the left- and right-hand sides. In other words, we obtain a solution for λ when $w_0 - \sum_{j \in \{K, L\}} p_j x_j^* = 0$ by replacing expressions of x_j^* with the expression in equation (9).

$$(13) \quad \lambda = \begin{cases} \frac{p_L \pi_L \sigma^2(e_L) + p_K \pi_K \sigma^2(e_K) - 2w_0 \sigma^2(e_L) \sigma^2(e_K)}{p_L^2 \sigma^2(e_K) + p_K^2 \sigma^2(e_L)} & \text{if } w_0 = \mathbf{px}, \\ 0 & \text{otherwise.} \end{cases}$$

As can be seen, the Lagrangian multiplier, or borrowing-constraint penalty, λ , is decreasing

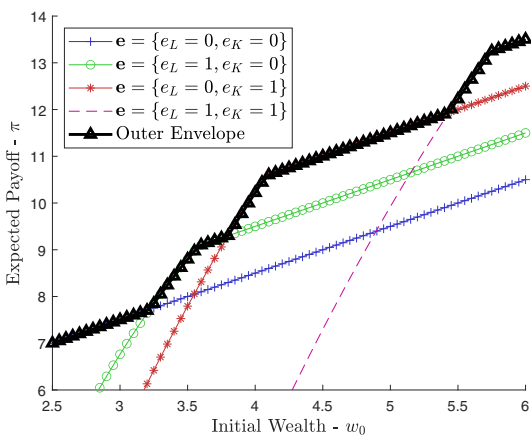


Figure 1. Predicted relationship between expected payoff and wealth (through applying various levels of effort).

Note: Parameters for the model are the following. $\pi_L = 5$; $\pi_K = 5.8$; $\sigma(0) = 3$; $\sigma(1) = 1$; $e = 3$.

in wealth and exhibits a complex relationship between input price and knowledge. Specifically, there is a cross-technology, knowledge-uncertainty trade off that manifests itself in the multiplication of the knowledge penalty of one technology with the price of the second technology. Depending on the underlying parameter space, this trade off will lead to selective learning about one technology over the other if the budget constraint binds.

We can now compute the expected payoffs for the optimal solution using equation (8). In particular, when borrowing constraints do not bind, then $\lambda = 0$ and x_j can be computed for all combinations of learning effort using equation (9). Plugging this information back into (8) will, by comparing across the four alternatives, yield the optimal combination of effort and technology uptake, and resulting expected payoff.

When borrowing constraints do bind, then λ is given by the top equation in (13), and we can similarly compute expected payoff for all combinations of learning effort. Again, we compare expected payoffs across the four alternatives (as per (10)) and identify P^* as the maximum value across the four alternatives.

Figure 1 shows the relationship between the expected payoff and the farmer’s initial wealth w_0 for each of the four possible learning combinations.²⁵ We graph each learning

²⁵This figure assumes that the cost of learning about technology L is the same as that of learning about

combination separately. The largest expected payoff is determined by the particular value of initial wealth each farmer holds. Notice that expected payoffs are monotonically increasing in wealth but that there are thresholds at which farmers may choose to learn about neither technology K or L (lowest wealth category), either one of K or L (mid-tier wealth), or both K and L (unconstrained by wealth). Thus, we should only expect wealthy farmers to learn about the most capital-intensive components of new technologies. However, this is strongly contingent on the assumption that $\pi_k \gg \pi_L$. If beliefs about π_k are not sufficiently high, then even a wealthy farmer will choose not to learn about technology K because it is preferable to specialize in the labor-intensive mode of production.²⁶ The regression implications of figure 1 is:

$$knowledge_{e_{iK}} = \alpha_K + \beta_{1K}\pi_{iK} + \beta_{2K}w_i + \beta_{3K}w_i\pi_{iK} + \varepsilon_{iK}, \tag{14}$$

where π_{iK} captures the profit gain observed by farmer i of technology K and w_i captures farmer i ’s wealth. We hypothesize that β_{3K} is positive.

Impact on Knowledge and Adoption Plans

To estimate the impact of the CDI program, one would ideally run a regression such as specification (15) linking outcomes Y_{ij} of farmer i from village j , on whether or not the farmer is a member of a club which is invited to participate in demonstration plots T_1 or only field days T_2 ²⁷:

$$Y_{ij} = \alpha_0 + \alpha_1 T_{1ij} + \alpha_2 T_{2ij} + \epsilon_{ij} \tag{15}$$

technology K and the knowledge benefit is similarly equivalent: $\{e_K, \sigma_K^2(0), \sigma_K^2(1)\} = \{e_L, \sigma_L^2(0), \sigma_L^2(1)\} = \{e, \sigma^2(0), \sigma^2(1)\}$.

²⁶This is demonstrated in Appendix Figure 2, which relaxes this assumption and varies the difference between π_K and π_L while holding w_0 fixed at a sufficiently high level (allowing adoption of the capital-intensive technology). Notice that the farmer will never choose to learn about K when $\pi_K - \pi_L$ is sufficiently small— and certainly will never learn about K when $\pi_k < \pi_L$.

²⁷Note that the demonstration plot villages were also invited to field days, implying that the demonstration plot effect should be seen as the demonstration plot plus field-day effect. In practice only about half of the demonstration plot participants attended a field day.

However, although being invited to a farmer field day is randomized at the village level, a critical aspect of participation is a choice: farmers have to sign up for CDI clubs in order to become eligible for the CDI activities. As one is unlikely to be able to control for all relevant confounding factors—many are unobservable to the researcher such as climatic factors and personal attributes—we might expect a correlation between ϵ_{ij} and T_{ij} and T_{ij} , resulting in omitted variable bias.

Appendix tables 2 and 4 shed light on this participation decision. Recall that forty-eight out of fifty-six treatment villages formed clubs. Appendix table 2 presents, in columns (8) through (14), the descriptive statistics of villages that formed CDI clubs and villages that did not form CDI clubs, along with the results of the t-test. Although the sample sizes are small, the CDI villages appear to be different from the eight villages that did not form clubs: the latter are better connected, a smaller acreage under soy, and have fewer existing organizations and groups. In appendix table 4, column (14), we show the result of t-tests testing the baseline differences between club and non-club members in the villages that formed clubs. Club members are different from non-club members in many dimensions, and this difference is both statistically and economically significant. Compared to non-club members, club members are better educated, have larger families and more land, and are also more likely to take agricultural credit.²⁸

Our estimation strategy tries to take this self-selection into account by constructing two comparable samples: the sample of households that received the CDI program and a comparable sample of households, in the control villages, that do not received the program. Using this approach, we assume that the treatment villages are comparable to the control villages; and we can use the latter to construct a similar sample (we presented evidence of the similarity between treatment and control villages in Appendix Table 1). In the first step we follow Hörner et al. (2019) and use propensity score matching to select a set of farmers from the control group comparable to the club farmers in the treatment group (see Rosenbaum and Rubin (1983, 1985) and Stuart and Rubin (2008) for an introduction). The

propensity, or probability, to join a club is a function of baseline characteristics as in:

$$(16) \quad P(\text{club}_{ij}) = \beta_0 + \beta_1 \mathbf{X}_{ij} + \beta_2 \mathbf{X}_j + \mu_{ij}$$

The control variables used in this first step include all village level characteristics included in Appendix Table 1 (\mathbf{X}_j), all household level characteristics included in appendix table 4 (and the square terms of the non-binary variables) and baseline adoption indicators (\mathbf{X}_{ij}). Appendix Figure 3 shows the result of this exercise: although we are able to identify a match for most treatment farmers, there are forty-two treatment farmers without a match, that is, which are off support, and the mean bias in the matched sample is 6%.²⁹

In the second step, we regress a series of outcome variables following regression equation (15) on the matched sample. The dependent variables y_{ij} include the planned adoption (2015–16 season) of soybean, inoculation of soybean, groundnut, hybrid maize, herbicide, pesticide, fungicide, inorganic fertilizer, fertilizer tree, intercropping, animal manure, crop residue, and compost, and whether or not each one of the questions in the knowledge test was answered correctly. We also compute an adoption score (out of 13) and knowledge score (out of 20).

Selection into T_{1ij} (as opposed to T_{2ij}) might still be a concern. However, as noted earlier, the demonstration plot villages are comparable to the other treatment villages (see appendix table 2). Appendix table 5 shows that this lack of selection might not hold at the individual level—as demonstration plot farmers appear somewhat wealthier and less credit-constrained than the CDI club members who did not manage demonstration plots. As a robustness check, we present the results of two alternative estimation strategies in online Appendix C, including a household fixed effect estimation, and an alternative matching technique that does not drop any observations in the treatment group.

Note that the study design and implementation have implications for the interpretation of results. The sampling frame (stratified along club-member status) and partial compliance among the clubs assigned to the field-day

²⁸This is consistent with Laajaj and Macours (2017) who find that when the village is asked to select farmers to run demonstration plots, that these are wealthier, higher educated, and with larger families.

²⁹We use 1-to-1 matching without replacement following the `psmatch2` Stata command developed by Leuven and Sianesi (2003). See also appendix table 10 for the result of a t-test comparing the treatment and control group of the matched sample.

Table 4. Correlates of Yield Expectations for Demonstration Plot Farmers at Endline, in 2015OLS Regression of Yield Expectations at Endline (in kg/ha)

	Soybean		Hybrid maize		Local maize	
	Similar (1)	Different (2)	Similar (3)	Different (4)	Similar (5)	Different (6)
Below/above median absolute difference between soil qualities						
Yield expectations at baseline [in kg/ha]	0.015 (0.096)	0.256 (0.240)	0.431* (0.201)	0.254 (0.151)	0.089 (0.132)	0.096 (0.132)
Difference between BPA/control subplots on local demonstration plot [in kg/ha]	0.777** (0.292)	0.121 (0.404)	1.003*** (0.155)	0.292 (0.454)	0.093 (0.204)	0.218 (0.378)
Observations	24	26	40	41	40	41
R-squared	0.459	0.496	0.414	0.299	0.186	0.169

Note: This table presents the results of a linear regression with dependent variable: Yield expectation at endline. Columns (1) and (2) refer to soybean, columns (3) and (4) to hybrid maize, and columns (5) and (6) to local maize. We split the sample according to absolute difference in soil quality between the local demonstration plot and the farmer's plot (measured by active carbon in mg/kg): columns (1), (3) and (5) include the observations below the median of this distribution ("similar"), whereas columns (2), (4) and (6) include the observations above the median of this distribution ("different") (the median absolute difference is 125 mg/kg for the soy demo sites, and 146 mg/kg for the maize demo sites). The yield expectations at baseline refer to the baseline expectations of soy in the case of columns (1) and (2) and maize in the case of the other columns. Similarly, the differences between BPA and control subplots refer to the mean differences between these two treatments on the local demonstration plot (adjusted for moisture content). 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), and whether the household cultivated hybrid maize in 2013–14 (for columns (3) through (6) only). Sample includes the club farmers in the demonstration plot villages (See Appendix Table 4). Whether or not farmer is in a club is determined by the self-reported club status at endline. Note that the sample size is lower than expected: 81 for the maize regressions and 50 for the soybean regressions. This is due to missing data on soil characteristics at the individual's level, and one case of missing demonstration plot yield data as farmers had harvested prior to the arrival of the research team. Village-clustered errors in parentheses.

***p < 0.01.

**p < 0.05.

*p < 0.1.

treatment, implies that we conducted an intent-to-treat (ITT) analysis on the sample of club members. This is thus neither the effect on those who attend the field day nor the average effect at the village level. Rather, it is the average effect of being invited to field days on those who are its primary targets. This estimate is of interest to both policymakers and practitioners. CDI formed the clubs with the purpose of information sharing and explicitly requested the club members who attended the field day to share the information with the other members, and, in a way, this is a measure of the success of this process.³⁰

Table 3, column (1), shows that demonstration plot participation increases planned adoption of ISFM practices by 0.54 points, which is 14%, whereas being invited to a field day does not produce such (statistically significant)

result. In appendix table 6, we present the results of a series of linear probability models. We note that being a member of a demonstration plot club increases the chances of planning to inoculate soybean (at the 1% level), using hybrid maize (at the 1% level) and planting fertilizer trees (at the 10% level), and being member of a club that was invited to a field day increases the chances of cultivating soybean. As a comparison point, the point estimates of the alternative matching strategy and farmer-fixed effects are, respectively, 0.79 points and 0.34 points (although only the former is statistically significant at the 5% level).

Table 3 column (2) presents the impacts on the knowledge score (out of 20).³¹ We do not

³⁰In appendix table 5 we present the p-values of a t-test, comparing farmers who attended field days, which those CDI club members who did not attend field days (column (7)). We note considerable differences: farmers who attend field days are higher educated, own more land and are overall wealthier and better connected, and are more likely to use credit. This is consistent with the observation that in most clubs, it is the lead farmer who attended the field days.

³¹In appendix table 7, we present the summary statistics. The overall knowledge score is 7.87 (with a standard deviation of 2.30). We note that although 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%—when we ask the respondent to tell us about the details of soybean input preparation and application. 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 fertilizer trees, but have limited knowledge of the details of the production process as well.

Table 5. Correlates of Knowledge for Demonstration Plot Farmers at Endline, in 2015OLS Regression of Knowledge Score at Endline

	Soybean		Hybrid maize	
	(1)	(2)	(3)	(4)
Yield on BPA subplot on local demonstration plot [in 50 kg bags/acre]	0.042		0.018**	
	(0.028)		(0.007)	
Start of the rain (days)		-0.018		-0.005
		(0.012)		(0.009)
Total amount of rain (mm)		0.001		0.001
		(0.001)		(0.001)
Number of times flood (flood = more than 50 mm/1 day)		-0.221*		-0.152
		(0.127)		(0.279)
Observations	61	68	101	101
R-squared	0.115	0.213	0.213	0.183

Note: This table presents the results of a linear regression with dependent variable: Knowledge score at endline. Columns (1) and (2) refer to soybean and columns (3) and (4) to hybrid maize. The knowledge score for soybean is a number out of 6, whereas the knowledge score for hybrid maize is a number out of 8. Columns (1) and (3) consider use yield on the BPA subplot as the main independent variable of interest, which refers to the maximum yield on the BPA subplots on the local demonstration plot. Columns (2) and (4) consider various rainfall aggregates as the main independent 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), relevant yield expectations at baseline, and whether the household cultivated hybrid maize in 2013–14 (for columns (3) and (4) only). Sample includes the club farmers in the demonstration plot villages. Whether or not farmer is in a club is determined by the self-reported club status at endline. Note that the sample size is lower than for the soybean regressions. This is due to missing data on demonstration plot yield data as farmers had harvested prior to the arrival of the research team. Village-clustered errors in parentheses.

***p < 0.01.

**p < 0.05.

*p < 0.1.

note a significant increase in overall knowledge score among either set of farmers. In appendix table 6, we present the result of the individual linear probability models, taking as a dependent variable whether or not the farmer answered each of the knowledge questions correctly. We note an increase in the knowledge of inoculation and possibly pesticides (and a negative effect on question (14)—but the negative, tricky formulation of that question cautions against over-interpretation). As a comparison point, the point estimates of the alternative matching strategy is 0.63 points for demonstration plot participants, which is about 8% (p-value of 0.11).

Analysis of the Learning Process

Correlates of Yield Expectations

In table 4 we estimate regression specification (4) for the demonstration plot farmers. We regress endline yield expectations for soybean, hybrid maize, and local maize (in kg/ha) on yield expectations at baseline (in kg/ha) and the performance of the local demonstration plots (in particular, the mean differences

between BPA and control subplots; also in kg/ha, and a series of control variables). In the seventeen demonstration plot villages, there were seventeen villages in which the demonstration plot included maize and twelve villages in which the demonstration plot included soybean. The total number of CDI club members in these seventeen villages is 101, and the total number of club members in the subset of twelve villages is 69.

We split the sample according to absolute difference in soil quality between the local demonstration plot and the farmer's plot (measured by active carbon in mg/kg): columns (1), (3) and (5) include the observations below the median of this distribution ("similar"), while columns (2), (4) and (6) include the observations above the median of this distribution ("different"). As farmers were not informed about the results of the soil tests until the end of the study, splitting the sample in this manner assumes that farmers are aware of the differences in soil quality (and that this awareness is captured by the active carbon measure) and test the hypothesis that heterogeneity in soil quality impedes learning. Berazneva et al. (2018) and Tittonell et al. (2005) provide evidence that this underlying assumption is not unreasonable in this context.

The results indicate that an increase of 1 kg/ha in the gap between the BPA and control soybean subplots is associated with an increase in the endline beliefs of 0.77 units (out of a possible score of 20) for farmers who have soils similar the demonstration plot soil and is not associated with an increase (or decrease) for farmers whose soils are more dissimilar. The results for hybrid maize are qualitatively similar. An increase of the BPA performance on the local demonstration plot (compared to the control plots) by 1 kg/ha is associated with an increase in endline beliefs of 1.00. There is no statistically significant effects for farmers whose soil is dissimilar, nor is there any effect on the yield expectations of local maize. The latter can be interpreted as a placebo test: the CDI demonstrations did not include local maize, and hence nothing could have been learned about this crop.³²

Correlates of Knowledge

In table 5 we estimate the relationship between beliefs and learning, as measured through the crop-specific knowledge score for the demonstration plot participants, per regression specification (11; again, including a series of control variables). We use demonstration plot yields to capture the farmer's beliefs about profitability early in the growing season. We find a statistically significant, and positive, relationship between the yields measured and learning of the demonstration plot participants (soybean is almost statistically significant at the 10% level)—in columns (1) and (3) for both soybean and hybrid maize. The point estimate suggests an increase in 50 kg/ha increases knowledge by 5%.

To interrogate the causal interpretation of the results, columns (2) and (4) present the results using attributes of the demonstration plot rainfall rather than plot yields. Indeed reverse causality could explain the results presented in columns (1) and (3): farmers with better knowledge have better results. Rainfall, on the other hand, does

not suffer this critique and is correlated with crop development (Bradford 1990; Çakir 2004; Lobell et al. 2011).³³ We present rainfall analysis in columns (2) and (4). We note the hypothesized correlation between rainfall patterns and knowledge of soybean (but no such correlation for hybrid maize, which suggests that either rainfall and germination rates were not as closely related, or farmers' learning was more uniform across the various plots, perhaps because maize is a historically important crop).^{34,35}

Role of Credit Constraints

In appendix table 13, we present the relationship between learning, measured using the knowledge score, and yield expectations for farmers who were invited to participate in field days. Columns (1) and (3) present the linear approximation of regression specification (14), whereas columns (2) and (4) include the interaction terms. Note that, due to data limitations, we approximate profit gain by yield expectations. As in previous analyses, we split the knowledge score into knowledge related to soybean and knowledge related to maize. But this time, based on figure 1, we include only the credit-intensive technologies in the soybean score and the labor-intensive technologies in the maize score. We focus on one control variable: farmer wealth. We use "having obtained input credit in the previous season" as a proxy for the relevant wealth variable. If the farmer answers no to this question, the farmer is likely more credit constrained.

We note a weak positive correlation between the credit access and the knowledge score for soybean (p-value 0.11) in column

³³We define three statistics of the distribution: start of the rainy season, the total amount of rainfall, and the number of flood days (defined as >50 mm/day). The latter, in particular at the start of the season, can be quite damaging for germination (Wenkert, Fausey, and Watters 1981; Martin, Cerwick, and Reding 1991; Githiri et al. 2006).

³⁴We also used rainfall as an instrument for observed demonstration plot yields but noted a weak instrument problem. Although using the reduced form estimation does not resolve this matter, it allows one to gain insight into the relationship between the instrument and the outcome variable (Murray 2006).

³⁵Appendix table 8 presents the results of the regression specification (12), correlating the (planned) adoption score with demonstration plot performance and rainfall indicators. Although we see little correlation between demonstration plot yields and overall adoption scores, we note that this is not unexpected because adoption interacts with budget constraints in a complicated manner in the absence of credit markets. In appendix table 9, we present the analysis for field-day farmers and find no statistically significant correlations. Measurement error in beliefs and omitted variable bias might play a significant role, and we refrain from overinterpretation.

³²Note that we did not estimate regression (4) for the field-day farmers. The goal of regression (4) is to investigate step 1 of the learning model, that is, the Bayesian updating process of yields. Although ideally one would like to compare these processes for the two sets of farmers, we have no variation in the demonstration plot performance observed by the field-day participants as they attended only one of two field-day sites (and we collected data only at one site within our study area). In addition, we did not collect soil data among all farmers in the field-day villages and noted that the quality of the yield expectation data was poorer in the non-demonstration plot villages, possibly as they had no experience measuring plots in the same way as demonstration plot participants had done as part of the research project.

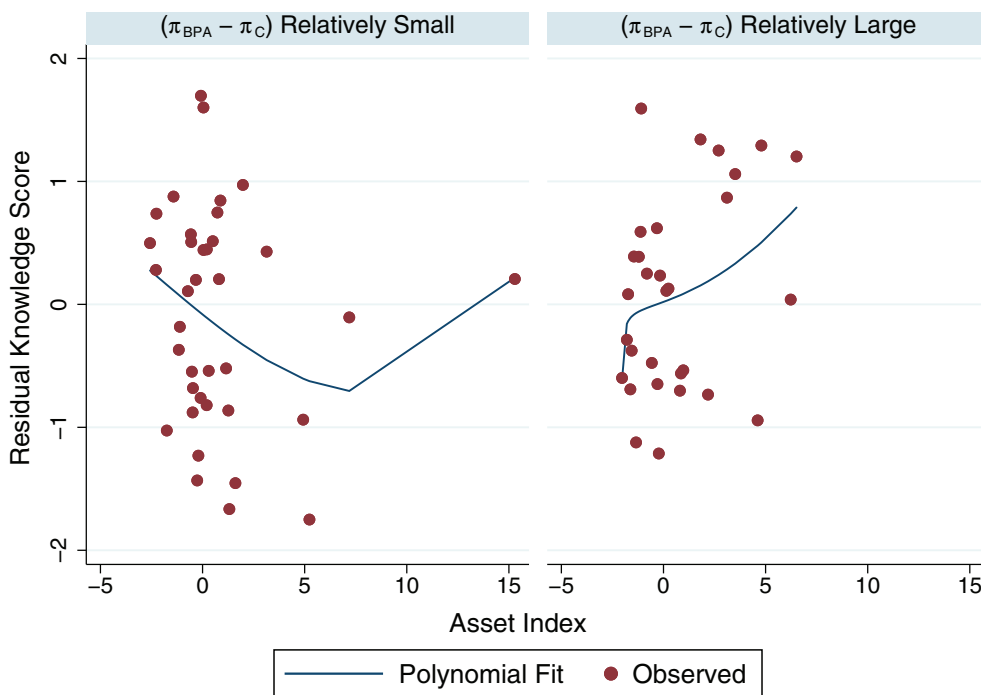


Figure 2. Relationship between knowledge of soy, demonstration plot realizations and wealth.

Note: This figure presents the non-parametric relationship between knowledge of soy and wealth. We apply a control-function approach to variable construction by using the predicted error term on the vertical axis after regressing farmer knowledge against 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, and acreage of land owned. The knowledge score for soybean is a number out of 5. The differences between BPA and control subplots by which the panels are split up refer to the mean differences between these two treatments on the local demonstration plot. Sample includes the club farmers in the demonstration plot villages. Whether or not farmer is in a club is determined by the self-reported club status at endline. Village-clustered errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

(1), but a nonsignificant interaction effect in column (2). The coefficient on our credit measure in column (1) suggests that farmers who are not credit constrained might be more likely to learn something about the (credit-intensive) soybean technologies. The (hybrid) maize results act as a placebo test. The knowledge maize questions included here focused on labor-intensive technologies; and we find no difference in learning between credit constrained and non-credit constrained farmers.

In figure 2, we consider a non-parametric version of equation (14) for demonstration plot farmers. In this case, we have a better measure for the profit gains, as we observed the demonstration plot performance. On the left-hand side of the panel in figure 2 are farmers who observed a small difference in yields between the soybean BPA and control plots (smaller than the median), whereas the right-hand side are farmers who observed relatively large differences (greater than the median). The horizontal axis represents farmer wealth levels using a principal-

component based asset index (Michelson, Muñiz, and DeRosa 2013) and the vertical axis represents farmers’ knowledge of soybean conditional on a set of individual characteristics. According to our hypothesis, only wealthy farmers on the right-hand side panel should exhibit higher levels of learning, which we are able to confirm. Note that figure 2 considers soybean only. This relies on the assumption that soybean production is more capital intensive and, therefore, more expensive. We do not expect knowledge scores for hybrid maize to change with wealth because its production does not require as costly of inputs as soybean production under CDI’s demonstrated best practices and in effect find no such relationship in the data (Appendix Figure 6).

Discussion

We studied farmers’ learning about agricultural technologies based on differential

exposure to commonly used extension methods that range in their intensity of interaction. The results suggest the presence of a two-stage learning process, in which learning is a choice, constrained by factors such as time, credit, and cognitive resources.^{36,37}

We find that farmers who participate in farmer-led demonstration plots form beliefs about the usefulness of the technologies, with beliefs conditional on both the agronomic performance of the demonstration plot and how similar their own soil conditions are to the demonstration plot soil conditions. These beliefs correlate with the formation of knowledge about the production processes. As a whole, these farmers learn about the production processes of ISFM technologies critical for actual adoption and are more likely to plan to adopt hybrid maize, inoculate soybeans, and plant fertilizer trees. Other researchers have found positive effects of demonstration plots on adoption including Duflo, Kremer, and Robinson (2008), Kondylis, Mueller, and Zhu (2017) and Lunduka, Snapp, and Jayne (2018). Note however that while demonstration plot are a common feature of agricultural extension and technology adoption projects in the region, details including who manages the plot (an individual farmer, agro-dealer, extension agent, or farmer group) and to what degree the plot includes experimental comparison with control and standard practice treatment can vary considerably. Hence, any comparisons between studies need to proceed carefully (Davis 2008; Kiptot and Franzel 2015).

Farmers attending field days in a different agro-climatic zones might not result in widespread adoption of a new technology, especially if farmers need to be convinced that the technology will increase yields *prior* to investing in learning. 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 stage of learning, even if

convinced about the technology's yield-increasing attributes. We find that farmers invited to attend field days learn considerably less about the production processes than those involved in managing demonstration plots. However, what they do learn is conditional on the degree to which they are credit constrained, and most field-day participants focus their attention on learning labor-intensive technologies, such as plant spacing and mulching. As a result, overall, farmers invited to participate in field days do not plan to adopt more ISFM technologies. Fabregas et al. (2017) find a similar low impact of farmer field days in Kenya.

Our results have implications for Malawi and other sub-Saharan African countries working to reform extension systems (Evenson 1997; Anderson, Feder, and Ganguly 2006; Davis 2008). The Malawian government's extension system is under significant strain. Under-resourced extension workers, generally equipped with a bicycle only, are expected to cover long distances and to conduct a range of government and non-government activities with minimal support (see Knorr, Gerster-Betaya and Hoffman 2007). In our study area, each government extension agent is in charge of 2,000 to 3,000 farming households. Many institutions for training agricultural extension agents have closed, and extension workers receive a relatively small fixed monthly salary. This situation has led to pervasive problems with moral hazard and adverse selection (MEAS 2012; CISA-NET 2013; MAIWD 2016).^{38,39}

Despite these challenges, government extension workers remain a main source of information for farmers. Ragasa and Niu (2017) note that almost 70% of Malawian households who received advice from external sources received it from government extension agents. In our study area, 60% of farmers report interacting with their government extension agent in the last year.

Our results have implications for such an extension system. Although farmers learn more from demonstration plots compared to farmer field-days, field days are often a less

³⁶Van Campenhout (forthcoming) provides a direct test of this model using a randomized controlled trial. The program randomizes the provision of knowledge about technologies and information about potential yields. He does not find an (average) effect on adoption of either program component among Ugandan farmers.

³⁷This distinction between knowing about the existence of the technology and learning its attributes has also been documented by others. Kabunga, Dubois, and Qaim (2012) noted that although many farmers in Kenya have heard about tissue culture in bananas, few know the details required to implement the technology. Lambrecht et al. (2014) find that although awareness about fertilizers has spread widely among farmers in Congo, direct contact with extension agents is what contributes to adoption.

³⁸BenYishay and Mobarak (2019) show that incentivizing extension agents by paying them for farmer knowledge improvements improves farmers' uptake of these technologies in Malawi. Dal Bó et al. (2018) show promising results from tracking extension workers via GPS in Paraguay.

³⁹Niu and Ragasa (2017) assess information efficiency along the knowledge transmission chain from researchers to extension agents, lead farmers, and other farmers, and note that information loss mostly happens at the extension agent to lead farmer link.

expensive option. In our study, hosting one farmer field day for around 200 farmers costs about 650 USD total, or about 3.25 USD per farmer, whereas organizing one demonstration plot for about 20 farmers costs 281 USD, about 14 USD per farmer.

We re-iterate that this study is not an evaluation of the relative effectiveness of field days versus demonstration plots, and we do not suggest that field days should be discarded as a strategy. Building on what we have learned, we suggest the following improvements in field days.

First, field days may provide too much information in too short a time period, giving farmers insufficient chance to absorb the details. This implies that, at field days, farmers should be given tools that will allow them to learn the information presented more effectively. Examples might include pamphlets with pictures of the inputs used and measuring spoons to measure the correct amounts of inputs (see Duflo et al. 2013).

Second, the fact that farmers' learning appears to be constrained by markets suggests that agricultural extension might need a recoupling with market activities and, in particular, credit interventions in order to be effective. In Malawi, extension agents used to perform an additional role as regional credit officers. Although 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.⁴⁰

Third, heterogenous growing conditions may play a role in influencing 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 low yield could 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.

Finally, it may be that field days could be used in sequence with demonstration plots or other more intensive methods of teaching

farmers. The field days could serve to introduce a new technology and to focus on its broad features, demands, and processes and this initial introduction could be followed by methods employing more detailed exposure, perhaps based on farmer demand.

In terms of further research, although the limited time frame of this study does permit a detailed study of learning spillovers (and, relatedly, strategic learning interactions), we recognize 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 lead farmers who 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, the identities of the first adopters, and whether and how lead farmers are encouraged (Griliches 1957; Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010; Chuang and Schechter 2015; Maertens 2017; Michelson 2017). Beaman et al. (2018) use a network-theory approach to better identify these lead farmers in order to maximize learning and adoption in their communities. Shikuku et al. (2019) and BenYishay and Mobarak (2019) both use a randomized control trial to vary incentives for, respectively, lead farmers and extension agents and find that both respond to incentives. We see this type of research, which combines network theory with realistic models of learning and behavior with heterogenous agents (in terms of cognitive ability as in Barham et al. 2018, more general, skills as in Laajaj and Macours Forthcoming, or "locus of control," as in Malacarna 2018) as a fruitful way forward in extension research.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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⁴⁰Ambler, de Brauw, and Godlonton (2017), using a randomized control trial set in Malawi, also note complementarities between cash transfers and a more intensive extension system. However, Ragasa and Mazunda (2018) find no effect of the interaction effect of access to Malawi's input subsidy program and having received advice from extension agents (but attribute some of the lack of effects to heterogeneities within the extension program).

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