DEPARTMENT OF ECONOMICS
YALE UNIVERSITY

P.O. Box 208268
New Haven, CT 06520-8268

http://www.econ.yale.edu/

Economic Growth Center Discussion Paper No. 1030

Economics Department Working Paper No. 121

Communicating with Farmers through Social Networks‡

Ariel BenYishay
University of New South Wales

A. Mushfiq Mobarak
Yale University

August 2013

Communicating with Farmers through Social Networks[ǂ]

Ariel BenYishay, University of New South Wales

A. Mushfiq Mobarak, Yale University

August 2013

Abstract

Low adoption of productive agricultural technologies is a puzzle. Agricultural extension services rely on external agents to communicate with farmers, although social networks are known to be the most credible source of information about new technologies. We conduct a large-scale field experiment on communication strategies in which extension workers are partnered with different members of social networks. We show that communicator actions and effort are susceptible to small performance incentives, and adoption rates vary by communicator type. Communicators who face conditions most comparable to target farmers are the most persuasive. Incorporating communication dynamics can enrich the literature on social learning.

Keywords: Social learning, Agriculture, Technology Adoption, Malawi

JEL Codes: O33, O13, Q16

[ǂ] Contact: BenYishay: a.benyishay@unsw.edu.au, or Mobarak: ahmed.mobarak@yale.edu. Maria Jones managed all aspects of fieldwork extremely well. Niall Kelleher, Sylvan Herskowitz, Cristina Valverde and the IPA-Malawi country office provided invaluable support for data collection. Andrew Carter, Tetyana Zelenska, Johann Burnett and Imogen Halstead provided excellent research assistance. The World Bank Gender and Agriculture Program, WB Development Impact Evaluation Initiative (DIME), the Millennium Challenge Corporation, Yale Center for Business and Environment, and the Macmillan Center at Yale University provided financial support. We thank Chris Udry, Florian Ederer, Jonathan Feinstein, Arthur Campbell, Ken Gillingham, Florence Kondylis, Arik Levinson, Mark Rosenzweig, and seminar participants at Yale University, Georgetown, Vassar College, the University of Sydney, Monash University, University of Queensland, the University of New South Wales, Stanford University SITE, and the 24th BREAD conference for comments. All errors are our own.

1. Introduction

Many agricultural technologies with demonstrated productivity gains, such as efficient and timely fertilizer application, investments in improved seed varieties, organic composting, and reduced tillage planting techniques, have not been widely adopted in developing countries, and in Sub-Saharan Africa in particular (Duflo, Kremer and Robinson 2011, Udry 2010). The 2008 World Development Report vividly documents the associated costs – agricultural yields and productivity have remained low and flat in sub-Saharan Africa over the last 40 years (World Bank 2008). Investing in new technologies is risky, and lack of reliable and persuasive sources of information about new technologies, their relevance to local agronomic conditions, and details on how to apply them, are potential deterrents to adoption.[1] Farmers care about the expected performance of the technology at their own plot of land, and the social proximity, relevance and credibility of the source of the information may therefore matter.

The economics and sociology literatures have long recognized the importance of social learning from peers in overcoming such "information failures" in both developed (Griliches 1957, Rogers 1962) and developing (Foster and Rosenzweig 1995, Bandiera and Rasul 2006, Conley and Udry 2010) countries. This literature has largely focused on documenting the *existence* of social learning using careful empirical strategies.[2] These models explore the conditions under which farmers choose to incorporate others' experiences, implicitly assuming that farmers costlessly observe the field trials of their neighbours without any friction in the flow of information, and then update their expectations about the technology's profitability.

In this paper, we propose that the transmission of information from one farmer to another is not necessarily automatic. Communicating with others and convincing them to adopt may require costly effort, while the benefits are external. To explore these communication

[1] Other deterrents examined by the literature recently include imperfections in credit markets (Croppenstedt, Demeke and Meschi 2003, Crepon et al 2011), insurance markets (Cole, Giné and Vickery 2012, Bryan, Chowdhury and Mobarak 2013, Karlan et al 2012), land rights (Goldstein and Udry 2008, Ali, Deininger, and Goldstein 2011), and output markets (Ashraf, Giné, and Karlan 2009). Jack (2013) offers a careful review of this literature.

[2] Distinguishing peer effects from incidental correlations in the behaviour of social contacts has been the perennial empirical challenge with which this literature has grappled (Manski 1993).

dynamics, we design a randomized controlled trial (RCT) in which we vary the dissemination strategy for two new agricultural technologies across 168 villages in Malawi. We assign, in turn, the role of main communicator about the new technology to (a) government-employed extension workers, or (b) 'lead farmers' who are educated and able to sustain experimentation costs, or (c) 'peer farmers' who are more representative of the general population and whose experiences may be more applicable to the average recipient farmer's own conditions. Random subsets of these communicators are offered performance-based incentives in the experimental design. In the process, we extend the literature on social learning in a policy-relevant direction: Is it possible to incorporate the power of social influence – a phenomenon well documented by social scientists - to enhance the dissemination of new technologies in developing countries?

We first document that providing incentives to communicators affects the flow of information in these villages. This by itself implies that the process of social learning is not automatic, and suggests a future research direction for the vast literatures on social learning: communication dynamics need to be explored, especially if we are interested in promoting new technologies. Existing models of social learning (Foster and Rosenzweig 1995, Bardhan and Udry 1999, Munshi 2004) ignore communication and assume automatic transmission of knowledge. We therefore present a framework with communication embedded in the standard target-input model to clarify the contribution of this RCT to that literature.

The experimental design and data allow us to delve deeper into the questions of which types of communicators are optimal to incentivize, whether their effort or their credibility are affected by incentives, and the types of target farmers that are persuaded to adopt by each communicator type. We find that without incentives, peer farmers (PFs) do not bother to learn about the technologies themselves or put any effort into disseminating (and therefore others in the village do not learn or adopt), but when a small performance-based incentive (a bag of seeds) is added, PFs represent the most effective strategy to convince other farmers to adopt new technologies. Peer farmers are thus more responsive to incentives than lead farmers, as predicted by the framework we present. The effectiveness of PFs could stem from their greater social proximity, credibility, or physical proximity, but our data indicate that "comparability" is what matters. Peer farmers whose farm sizes and input use are the most similar to those of the recipient farmers are the most persuasive. In other words, farmers appear to be most convinced by the advice of others who face agricultural conditions that are comparable to the conditions they face themselves.

This work is related to a growing literature that shows that social relationships are an important vector for the spread of information in a variety of contexts, including educational choices (Garlick 2012; Bobonis and Finan 2009; Carrell and Hoekstra 2010; de Giorgi et al 2010; Duflo, Dupas, and Kremer 2011), financial decisions (Burzstyn et al 2012; Duflo and Saez 2003; Beshears et al, 2011), job information (Beaman 2011; Magruder 2009), health inputs (Miguel and Kremer 2007, Godlonton and Thornton 2009, Oster and Thornton 2012; Miller and Mobarak 2012), energy choices (Alcott 2011) and doctors prescribing drugs (Coleman et al. 1957, Iyengar et al 2011). Recognizing the potential for peer-based promotion implied by these networks, other projects have also introduced 'ambassadors' and 'injection points' to promote new products, similar to the design of our program (e.g., Kremer et al 2011, Ashraf, Bandiera and Jack 2012, Banerjee et al. 2013). Our nuanced empirical findings on communication with and without incentives help explain why many of these studies document peer influence, while others—notably Duflo, Kremer and Robinson (2011)—find little evidence of social learning.

Our work also relates to the theoretical literature on incentives for communication of non-verifiable information (beginning with Crawford and Sobel 1982) and verifiable information requiring effort on the part of senders and receivers (Dewatripont and Tirole 2005). Our experiment varies types of senders who have different effort costs, and introduces incentives that change the sender's stake in the communication. There is a lengthy literature on the effects of performance-based incentives in the production of public goods, reviewed by Bowles and

Polania-Reyes (2012). The marketing literature also explores conditions under which incentives stimulate word-of-mouth referrals (Biyalogorsky, Gerstner Libai 2011; Kornish and Li 2010)

For policy, the results suggest that the power of social learning can be harnessed to cost-effectively improve public agricultural extension services. As many as 400,000 extension workers are currently employed in developing countries, and Anderson and Feder (2007) note that this "may well be the largest institutional development effort the world has ever known." The impact of these efforts has been disappointing in many respects: the use of modern varieties of seeds and other agricultural inputs have remained low and relatively stagnant in sub-Saharan Africa (Udry 2010). In Ethiopia, Krishnan and Patnam (2013) find weak effects of extension agents on improved seeds and fertilizer take-up, and stronger effects of social learning from neighbours. A recent synthetic review by Waddington et al (2011) finds that farmer field schools—a leading extension model— do not translate into productivity improvements.

The deficiencies in government extension programs can often be traced back to a lack of qualified personnel and insufficient resources, which suggests that leveraging social networks may be an effective way to address these failures. Approximately 50% of government extension positions remain unfilled in Malawi, and each extension worker in our sample is responsible for 2450 households on average. The shortage of staff means that much of the rural population has little or no contact with government extension workers. According to the 2006/2007 Malawi National Agricultural and Livestock Census, only 18% of farmers report participating in any type of extension activity. Thus, extending the reach of existing personnel in a cost-effective manner - by having them partner with nodes in social networks who may be able to communicate more frequently and more effectively with their own neighbours - may be a promising approach.

This paper is structured as follows: Section 2 describes the context and experimental design. Section 3 presents a social learning model with an endogenous communication component. The data are described in Section 4 and empirical results presented in sections 5, 6 and 7. Section 8 contains concluding remarks about policy implications.

2. Context and Experimental Design

Our experiment takes place in eight districts across Malawi. Approximately 80% of Malawi's population lives in rural areas, and agriculture accounts for 31% of Malawi's GDP (WDI 2011). Agricultural production and policy is dominated by maize.[3] More than 60% of the population's calorie consumption derives from maize, 97% of farmers grow maize, and over half of households grow no other crop (Lea and Hanmer 2009). The maize harvest is thus central to the welfare of the country's population, and has been subject to extensive policy attention.

The existing agricultural extension system in Malawi relies on government workers who both work with individual farmers and conduct village-wide field days. These Agricultural Extension Development Officers (AEDOs) are employed by the Ministry of Agriculture and Food Security (MoAFS). These workers are notionally responsible for one agricultural extension section each, typically covering 15-25 villages (although given the large number of vacancies, extension workers are often in fact responsible for multiple sections). Section coverage information provided by MoAFS in July of 2009 indicated that 56% of the AEDO positions in Malawi were unfilled.

Partly in response to this shortage, MoAFS had begun developing a "Lead Farmer" extension model, in which AEDOs would be encouraged to select and partner with one lead farmer in each village. The aim was to have these lead farmers reduce AEDO workload by training other farmers in some of the technologies and topics for which AEDOs would otherwise be responsible. We incorporate this lead farmer model in our experimental design.

No formal MoAFS guidance existed on the use of other types of partner farmers to extend an AEDO's reach (or reduce his workload). We introduce a new extension model: the AEDO collaborating with a group of five *peer farmers* in each village, who are selected via a village focus group and are intended to be representative of the average village member in their wealth level and geographically dispersed throughout the village.

[3] While there has been some recent diversification, the area under maize cultivation is still approximately equivalent to that of all other crops combined (Lea and Hanmer 2009).

2.1. Experimental Variation in Types of Communicators

We designed a multi-arm study involving two cross-cutting sets of treatments: (1) communicator type, and (2) incentives for dissemination. We randomized assignment into these treatments at the village level. Each village was randomly assigned to one type of communication strategy:

(a) AEDO only

(b) Lead Farmer (LF) - supported by AEDO

(c) Peer Farmers (PFs) - supported by AEDO

In all three arms, the extension worker responsible for each sampled village was invited to attend a 3-day training on a targeted technology relevant for their district (discussed below). In each of the two farmer-led treatments, the extension worker was then to train the designated LF or PFs on the specific technology, mobilize them to formulate workplans with the community, supervise the workplans, and distribute technical resource materials (leaflets, posters, and booklets). Appendix A1 provides some additional details.

The following guidance was given to AEDOs for the selection of partner LFs:

1. The AEDO convokes a meeting with local leaders and community members to identify a short list of potential lead farmers. The AEDO selects one of the farmers on the short list to be the lead farmer, in consultation with village leaders.
2. The AEDO announces his choice to the village, to be sure that the community will endorse the new lead farmer.

The following guidance was given to AEDOs for the selection of partner PFs:

1. The AEDO convokes and facilitates a meeting with village members to identify five farmers that represent different social groups in the village, and who are willing to try out the new technology. The meetings must be well attended (including by those who may work with the extension agent most often), and there should be representatives from all the different social groups in the village (males, females, elders, adolescents, people from different clubs or church groups, etc).

2. Participants at the meeting identify the different important social groups in the village, and each group nominates one representative. From the group of people nominated as potential peer farmers, meeting participants work together with the AEDO and village leaders to narrow the set down to five, while ensuring that the five represent different groups.
3. The farmers nominated by the community agree that they understand their role and responsibility as peer farmers, and they are presented to the village for endorsement.

Lead farmers and peer farmers were identified in *all* villages using the first step of the LF and PF selection processes described above. However, in only the villages randomly assigned to the LF (PF) treatment arm, was the selected LF (set of PFs) trained by the extension worker on the specific technology and given the responsibility to spread information about the technology and carry out the prescribed workplan. Therefore, our experimental design only varied the actual assignment of lead and peer farmers to specific tasks, holding the selection process constant in all villages. This strategy has the additional advantage of identifying "shadow" PFs and LFs in all villages – i.e. we know the (counterfactual) identities of individuals who *would have been* chosen as PFs or LFs in all villages, had the PF or LF treatment arm been assigned to this village. This creates an experimental comparison group for the *actual* PFs and LFs, and allows us to report pure experimental effects of the treatments on an intermediate step in the flow of information (from extension workers to partner communicators), and on the effort expended by these communicators.

2.2. Experimental Variation in Incentives for Communicators

In addition to the random variation in communicator type, we also introduced performance incentives for a random subset of communicators in a cross-cutting experiment. Half of all communicators in each of the three treatment types were provided incentives conditional on performance. Performance was defined on the basis of "output" – i.e. effects on *other*, recipient farmers in the village. The ministry expected most recipient farmers to hear about the new technologies by the end of the first year (or first agricultural season), and make actual adoption decisions only by the end of the second year. Therefore, in the first year of the program, each communicator in the incentive treatment was told he would receive an in-kind reward if the average *knowledge score* among sampled respondents in his targeted village rose by 20 percentage points. For the second year of the program, the threshold level was set as a 20 percentage point increase in *adoption rates* of the designated technology. We measured knowledge by giving randomly chosen farmers in each village exams that tested whether they had retained various details of the technologies. Appendix A2 details the exam questions and acceptable answers for each technology. We measured adoption by sending a skilled enumerator to directly observe practices on the farm at the right time during the agricultural season. The technologies we promote, described below, leave trails that are easily verifiable.

The training of AEDOs was conducted in August of 2009, using a three-day curriculum involving both in-class and direct observation of the technologies. In September of 2009, AEDOs who were assigned to work with LFs or PFs were to conduct the partner farmer trainings. Incentive-based performance awards were provided shortly after the survey and monitoring data (described below) became available. Figure 1 provides a calendar of intervention and data collection activities along with an agricultural calendar.

Figure 2 describes the six treatment arms, and sample sizes allocated to each treatment. We added a seventh group of 48 control villages, where we did not disseminate any information about the new technologies at all. The control group was randomly selected from the same sampling frame (i.e., the subset of villages which were staffed by an extension worker) in order to preserve comparability to the treatment villages. The extension workers continued to operate as they normally would in these pure control villages, but received no additional training on the two new technologies introduced by the project.

Appendix A3 presents tests of balance in key baseline characteristics across our treatment arms. To control for district-level variation, these tests include district fixed effects and cluster standard errors at the village level. In 3 out of 81 tests, we find differences that are significant at the 5% level, consistent with standard sampling differences.

2.3. Dimensions of Variation across Treatment Groups

Each of the treatment arms represents a "bundle" of characteristics. The identity of the communicator varies across PF and LF treatments, but so does the number of communicators (5 vs 1). The treatment effects we report will be the joint effect of communicator identity and number. We present a framework in section 3 that highlights "similarity" between communicators and target farmers as the key mechanism, and we interpret the experimental results in section 5 using that framework. In section 6, we study heterogeneity in the treatment effects to explore whether alternative mechanisms (such as variation in the number of communicators) could also explain the experimental findings.

Irrespective of the specific mechanisms at play, the treatment effects associated with each communication bundle represent valuable comparisons, because the three different communication strategies are budget neutral from the perspective of the Ministry of Agriculture. The LFs and PFs are not paid a salary, and the AEDO receives the same salary across all arms. For policy evaluation, this is a useful comparison on a level playing field. For the incentive treatments, each communicator type was to receive a specific award type (extension officers received bicycles, lead farmers received a large bag of fertilizer, and peer farmers each received a package of legume seeds), but the maximum total value of awards for each village was specified as 12,000 MWK (roughly US$80). In other words, we held the total size of the incentive roughly constant across treatment (communicator) types, even though the peer farmer treatment involved more partner farmers. The incentive experiment across communicator treatments was therefore also budget-neutral from the Ministry's perspective.

The key tradeoff underlying our experimental design is that while the LF and PF treatments engage additional agents (potentially) performing the task of dissemination, they also introduce additional layers in the communication process. AEDOs are simply asked to disseminate via these partner farmers in these treatments, while in the status-quo extension worker treatment, the AEDO may or may already employ some version of such communication strategies. The marginal costs induced by this project are the village meetings required to identify PFs and LF, and training the AEDO to disseminate via these partners.

The PF- versus LF-based communication also embodies an important trade-off: Individuals designated as lead farmers generally command higher social status and respect, while peer farmers may enjoy greater credibility because they are closer to other villagers in social, financial, or agricultural technology space. It is therefore not obvious ex-ante which of the three strategies would perform best.

2.4. Technologies Disseminated

The project promoted two technologies to improve maize yields: pit planting and "Chinese composting". Pit planting involves planting seeds in a shallow pit in the ground, in order to retain greater moisture for the plant in an arid environment, while minimizing soil disturbance. Appendix A2 describes the technique specifications as disseminated.

Ridging had been the conventional method of land preparation in Malawi, but it has been shown to deplete soil fertility and decrease agricultural productivity over time (Derpsch 2001, 2004). Studies of pit planting in southern Africa have found returns of 50-100 percent for maize production (Haggblade and Tembo 2003) within the first year of production. However, pit planting involves some additional costs. First, only a small portion of the surface is tilled with pit planting, and extensive hand weeding or herbicide application is therefore required. Second, digging pits is a labor-intensive task with potentially large up-front costs. However, land preparation becomes easier over time, since pits should be excavated in the same places each year, and estimates suggest that land preparation time falls by 50% within 5 years (Haggblade and Tembo 2003). We collect data to directly examine these costs and changes in input use.

Chinese composting is the other technology that this project promoted in a different set of districts.[4] Chinese composting is primarily a post-harvest activity. Once maize crops are harvested, crop residues can serve as useful composting material (described in further detail in Appendix A2). Sub-Saharan Africa has experienced large declines in soil mineral content over the past three decades: estimates suggest losses in excess of 22 kg of nitrogen (N), 2.5 kg of phosphorus (P) and 15 kg of potassium (K) per hectare of cultivated land annually due to soil mining (Sanchez 2002). In Malawi, over 30 kg per hectare of N are reported to be depleted annually (Stoorvogel, Smaling and Janssen 1993). Studies of compost application in Malawi indicate soil fertility improvements and substantial returns on maize plots (Mwato et al 1999, Nyirongo et al 1999, Nkhuzenje 2003).

Despite the large returns observed in other studies from these technologies, the baseline levels of awareness and adoption in our sample were quite limited. Pit planting is a relatively new technology in Malawi, and only 12% of respondents in our control villages had heard of the technology at baseline. Most of the farmers who had heard of pit planting were not actually familiar with the details of the technology, or how to implement it. Only 2% of the respondents in control villages knew the recommended dimensions of the pits (allowing for a margin of error of +/- 25%), and only 1% had ever used pit planting.

Moreover, lack of knowledge of pit planting was the most frequently cited reason for non-adoption. Eighty five percent of non-adopters cited information as the primary reason for not having used the technology. By comparison, the next most cited constraint—lack of time—was mentioned by only 5% of non-adopters.

Farmers were generally more familiar with composting than pit planting, since the general idea behind compost heaps has a much longer history: 54% of respondents had heard of

[4] The profitability of pit planting and Chinese composting vary substantially with agro-climactic factors: pit planting is appropriate in drier areas and composting in areas with greater water availability. Thus, the intervention we study saw each technology promoted in the four study districts in which it was most relevant. Pit planting was promoted in the arid districts of Balaka, Chikwawa, Neno, and Rumphi, while Chinese composting was promoted in Dedza, Mchinji, Mzimba, and Zomba. Any one village in our sample therefore received information on only one of the two technologies.

some type of composting at baseline. However, the specific type of composting promoted in this study (Chinese composting) was far less commonly known—only 7% of respondents in control villages had head of this composting technology. Again, knowledge of the recommended specifications for Chinese compost was low: Only 21% of respondents who had heard of this type of compost could list at least three recommended materials, and similarly low shares could recall other relevant details.

We observe baseline adoption of any type of compost as 19% in our baseline sample, although virtually none of this was adoption of Chinese composting. Adoption of Chinese composting was not statistically different from zero at baseline.

3. Framework Motivating the Experiments

In this section we provide a simple conceptual framework to clarify how the experiments contribute to and extend the existing literature on social learning. We embed a model of communication between "informed" farmers and others in an otherwise standard target input model used in several prominent papers in the development economics literature on learning and technology adoption, reviewed in Bardhan and Udry (1999). In this type of model, the basic form of the technology is known, but one random parameter (the 'target') remains unknown.[5] In our context, the closest interpretation of this parameter is the suitability of each technology for an individual farmer. Pit planting imposes labor and pesticide costs, composting imposes capital costs (and ox-cart has to be rented to transfer compost heaps), while benefits depend on the rainfall realized on each farm. Net benefits are therefore farmer specific, and unknown ex-ante.

We assume that there is a continuum of farmers normally distributed on a line, with mean zero and variance one. They can produce a good using either a "traditional" technology

[5] An input target is not the most natural way to model a technology like pit planting (where the decision is to either do it or not), but prominent papers in this literature (Foster and Rosenzweig 1995, Munshi 2004, Bandiera and Rasul 2005) use this framework to model analogous choices, like the decision to adopt and improved seed variety. We therefore stick with this framework because we would like to be clear about the key differences that emerge when we add communication dynamics to this 'standard' model, without conflating differences due to other modeling choices. This approach helps to clearly identify the contribution of this experiment to the literature. Furthermore, the key intuition on communication that we derive is not dependent on this modeling choice.

with known profit $\underline{q}$, or a "new" technology for which the optimal amount of input, k^*, is unknown. Namely, if farmer θ uses input k_θ with the new technology, his profit is $q_\theta = 1 - (k_\theta - k^*)^2$.[6]

There is a common prior belief regarding the optimal amount of input needed for the new technology, which is normally distributed with mean 0 and variance σ^2. We can think of $1/\sigma^2$, the precision with which farmers know this information, as his/her innate ability. Therefore, if the farmers use the technology, they have expected payoff $1-\sigma^2$. We assume that with no further information, the farmers would not use the new technology, that is, $\underline{q} > 1 - \sigma^2$.

The "communicator" or "sender" is an informed farmer located at *x*, and s/he knows k^*. It is costly for the communicator to transmit this information about the target input level. The communicator can choose to send a signal with precision $\rho \in [0, \infty)$, by bearing a cost $c(\rho)$ which is increasing in the precision or quality of the signal sent.

This is where our model differs from existing models in the social learning literature, and helps to delineate the specific contribution of this paper. In existing papers, all other farmers automatically observe (possibly with some error) any one farmer's input choice, and they therefore automatically benefit from others' experimentation. In contrast, the decision to communicate is endogenous in this model, and this motivates the study of communication and agricultural extension services.

We assume that if farmer *x* sends the signal, farmer θ receives a noisy message, and the noise is a function of the distance between *x* and θ:

$$s_{x\theta} = k^* + \frac{|x-\theta|}{\rho} \qquad (1)$$

Proximity between two farmers can be interpreted in different ways: the distance between their farms, their social status, or how well they know each other, etc. Given the way $|x - \theta|$ enters in the model, it is most sensible to interpret it as how relevant the communicator *x*'s signal is to θ's

[6] Following the literature, we are abstracting from the farmer's profit maximization problem and assuming a quadratic loss function increasing in deviations from the optimal level of the target input, k^*.

agricultural decision-making. In other words, it should signify proximity between x and θ in terms of similarity in agricultural practices, so that the signal from x is a more precise and meaningful indicator for θ's profits.

Farmer θ updates his beliefs about k^* after receiving the signal $s_{x\theta}$, and the posterior mean and variance are given by:

$$E[k^*|s_{x\theta},\ \rho] = \frac{\sigma^2\rho^2 s_{x\theta}}{\sigma^2\rho^2+(x-\theta)^2} \tag{2}$$

$$VAR[k^*|s_{x\theta},\rho] = \frac{1}{\frac{1}{\sigma^2}+\frac{\rho^2}{(x-\theta)^2}} \tag{3}$$

Note that the ex-post variance of k^* is increasing in σ^2 and in distance from communicator $(x-\theta)^2$, and decreasing in ρ^2. This leads to a proposition with clear implications for the experiment and the data:

Proposition 1. The farmer's expected payoff of using the new technology increases in his innate ability, proximity to the sender, and the precision of the signal received:

$$E[q_\theta|s_{x\theta}] = 1-\frac{1}{\frac{1}{\sigma^2}+\frac{\rho^2}{(x-\theta)^2}} \tag{4}$$

Proposition 1 implies that all farmers close enough to the sender will adopt the new technology, and that distance threshold for adoption is given by:

$$(x-\theta)^2 \leq \frac{\rho^2}{\frac{1}{1-\underline{q}}-\frac{1}{\sigma^2}} \tag{5}$$

Given the assumption $\underline{q} > 1-\sigma^2$, at least a few farmers will benefit from this signal for an arbitrary small but positive ρ.

3.1. Incentives for Communicators

We now consider how the interventions in the experiment would affect communicator and other (recipient) farmer behavior in this model, in order to generate empirical predictions for the randomized controlled trial. We introduce "target incentives" for the sender, where farmer x (the informed communicator) receives a payoff if a certain mass of farmers adopt the new technology. The incentives in our experiment were exactly of this form.

The incentive provides a reason for the sender to incur the cost of acquiring and transmitting information. Given our assumption of a normal distribution of farmers, only senders sufficiently close to the mean location would respond to the incentive of a given size, because equation (5) implies that senders in the most populated, dense part of the distribution will find it cheaper to convince a sufficient number of farmers to win the incentive:

Proposition 2. If the distribution of farmers is symmetric and single-peaked (such as the normal distribution), then there is a threshold x^* such that senders located at $x \in [-x^*, x^*]$ send a message with precision $\rho(x)$ in response to the incentive. x^* is increasing in the size of the incentive.

If the target for incentives becomes more demanding, it becomes more costly for the sender to fulfill the requirements. Fewer senders will then find it profitable to send the message. In summary, senders who are most "similar" to target farmers (i.e. in the dense part of the distribution of farmers) are most likely to react to the incentive.

As σ^2 gets smaller (maintaining $\underline{q} > 1 - \sigma^2$), more recipient farmers are pre-disposed towards the new technology. So, it requires less precision from the sender to convince the farmers to adopt the new technology. As a consequence, the threshold x^* increases with the recipient farmers' innate ability. We should observe communicators spending more effort on those who are already pre-disposed.

Given the target (threshold) structure of the incentive (rather than linear incentives that are increasing in the share of recipient farmers convinced to adopt), the precision of the signal sent by the communicator will vary inversely with the mass of communicators who are induced by the incentive to send a signal. For example, the precision sent is "U-shaped" symmetrically around 0, since senders in the most populated part of the distribution do not have to put in much effort to convince the target number of farmers (required to win the incentive payment) to adopt. When recipients' innate ability increases (lower σ^2), the signal precision decreases for every communicator who had been convinced by the incentive to acquire and transmit information.

3.2. Empirical Implications and Mapping to the Experiment and Data

We have collected data on a variety of activities and actions of both the communicators and the target farmers in our experiment, so that we have a mapping of all the key theoretical concepts to our data. In the model, communicators have to first decide whether to incur the cost of acquiring information and sending the signal. For the experiment, we collected data on each communicator's willingness to learn about the technology himself as the empirical counterpart for this concept. Identifying and collecting data on the actions of "shadow" communicators in non-treated villages – farmers who *would have been* assigned the roles of LF or PF, had that intervention been implemented in this village - was therefore critical for us to be able to report experimental results on the effects of the treatment on communicators' first-stage decisions to acquire and retain information. For this analysis, we compare the actions of the lead or peer farmers to these shadow communicators.

Second, the precision of the signal that the communicator chooses to transmit in the model is proxied in our experiment using measures of the effort that communicators expend to teach others about the new technology. We obtained reports from all sample farmers as to whether the communicator held any activities, such as demonstration days or group trainings. We also tracked how often the communicators interacted with individual recipient farmers – whether the PF or LF walked by their house more often, or had individual conversations.

Finally, the information recipient's decision to adopt is measured in the first year using farmers' knowledge gains and retention of the details of the information presented to them on how to apply the new agricultural technologies. In the second year of the experiment, we move beyond knowledge gains and focus more on actual adoption of the new technologies by the target farmers. This closely parallels the way in which our incentive payments in the experimental design were structured.

Given this mapping of theoretical concepts to the data, the model yields the following predictions for our empirical setting:

1. Incentives increase communicators' own willingness to learn about the technology (i.e. acquire and send the signal $s_{x\theta}$)
2. Communicators most "centrally located" (i.e. there are many others in the village similar to him or close to him in social or geographic space) are most likely to respond to incentives and learn about technology themselves. This follows directly from Proposition 2. Given our method for selecting partner (lead or peer) farmers, this implies that peer farmers, who are much closer to the majority of other farmers in the village in resource access, technology or relevance space, should respond most strongly to incentives.
3. The technology adoption rate by recipient farmers should also be most responsive to incentives in the peer farmer villages, since peer farmers were explicitly chosen to be, on average, closer to target farmers. This implication follows directly from Proposition 1.

It is important to note that there are mechanisms outside our model that may lead to a reversal in prediction 3. For example, receiving a payment may undermine the credibility of communicators. Their message about the positive attributes of the new technology may be less persuasive once recipient farmers realize that the communicator is being paid an incentive to deliver that message. We will collect data on recipient farmers' perceptions of the credibility and honesty of communicators to directly test this mechanism.

4. Data

We collected primary data using household surveys and direct observation of farm practices in a rolling sample of farming households. In September and October of 2009, we conducted a baseline survey interviewing the heads of 25 randomly selected households in each of the 168 sample villages, in addition to surveys of the actual and shadow LFs and PFs in these villages (a total sample of 5,208 respondents). We do not rely solely on respondent self-reports regarding technology adoption: we subsequently conducted on-farm monitoring of pit planting and composting practices in the 2009-2010 agricultural season, where enumerators trained in the maize farming process visited the farms of 1,400 households to directly observe land preparation and any evidence of composting.[7] At the conclusion of the 2009-2010 season, we conducted a second round of surveying which we called a midline. Both the primary decision-maker on agriculture and his or her spouse were interviewed (separately) during the midline survey.

During the on-farm-monitoring and the midline, we rotated the set of households within the village who were sampled, so that there is not a perfect overlap of households across survey rounds. Not surveying the same households across rounds is a costly strategy, but it lessens any biases from intensive monitoring, and also makes it more difficult for the communicators to target a minority of households in order to win the incentive payment. Furthermore, our sample of control villages included some villages that fall under the jurisdiction of the same AEDOs in charge of a few of the treatment villages, so that we can study whether there was any displacement of AEDO effort in favour of treatment villages (where they could win incentives), at the expense of control villages where they also should have been spending some time.

The following year, we conducted another round of on-farm monitoring of PP practices in 34 villages during the 2010-2011 season. At the end of that season, we conducted a second follow-up survey (called an endline) in July-October 2011, again interviewing the primary agricultural decision-maker and spouse in 25 households in the village, plus all the actual and shadow LF and PF households. The endline survey collected careful information on all agricultural outputs, revenues, inputs and costs with sufficient detail to be able to compute farming yields, input use and profits. The endline survey also included on-farm verification of reported compost heaps.

We study the effects of the treatments on (a) whether the communicators (the actual LFs and PFs) retain knowledge on the details of how to apply the technology, (b) whether the communicators expend effort and hold information sessions, have more conversations with other farmers, or spend more time with them, and (c) whether the "recipient" farmers who are surveyed or whose farms are monitored – who are the ultimate targets for our intervention –

[7] Budget constraints prevented us from conducting this monitoring on all sample farms.

learn about and/or adopt the new technologies that were disseminated. Adoption among the recipient is measured primarily using knowledge gains in the first year, and actual application of the technology on their plot in the second year. Knowledge is measured using a score capturing each respondent's accuracy in specifying the key features of the relevant technology promoted in her district. For pit planting, this score captures accuracy of the respondent's knowledge regarding the length, width, and depth of each pit (allowing for a $\pm 25\%$ error bound), the number of seeds to be planted in each pit, the quantity of manure to be applied in the pit, and the optimal use of maize stalks after harvest. For composting, this score captures the optimal materials, time to maturity, heap location, moistness level and application timing (see Appendix A2 for the specific questions). Many respondents reported never having heard of these technologies; and these respondents were therefore assigned a knowledge score of 0.

The primary measures of adoption for the second year are the use of pit planting on at least one household plot[8] or the existence of at least one compost heap prepared by the household. We directly observe the use of PP during on-farm monitoring, and the monitoring results are consistent with, and largely validate, the survey responses. Summary statistics on our sample are presented in Table 1.

5. Empirical Results

5.1 Communicator Characteristics

Both the experimental design and the empirical predictions from the theory cast PFs (rather than LFs) as more 'similar' to the target farmers. We therefore begin by assessing communicators characteristics at baseline. Table 2 compares lead and peer farmers to each other and to the rest of our sample (of non-communicator maize farmers who are the 'recipients' or targets of the messages). Lead farmers are indeed better educated and cultivate more land than both the general population and those chosen as peer farmers (differences in their housing quality and incomes are also substantial but not statistically significant). Generally, peer farmers fall between

[8] Malawian farmers typically prepare the land for an entire plot in using a uniform method (e.g. pit planting, ridging)

LFs and the general population in all of these dimensions, and they are slightly better off than the general population. The data therefore verifies a key aspect of our experimental design and theoretical setup: that PFs are more similar to the target farmers.

The PF-target farmer similarity can be an advantage to communication in multiple ways; it could lead to greater social proximity, greater physical proximity or greater comparability in other dimensions. To investigate, Table 3 examines how LFs and PFs are perceived by, and related to, other farmers at baseline. Social proximity does not appear to be the advantage that PFs possess: Using first-order links for analysis, it turns out that LFs are more central in social networks than the average peer farmer. Respondents are significantly more likely to be related to LFs and to talk more regularly with LFs than to PFs. The five peer farmers in a village will jointly have more links than the one lead farmer, but a one-to-one comparison suggests that LFs possess more links. Villagers also perceive LFs more favourably: they are more highly rated in terms of trustworthiness and farming skills.[9]

PFs do appear to have a distinct advantage in a different dimension: the average respondent considers them to be more comparable (to themselves) in terms of farm size and input use. At baseline, 42.7% of respondents consider the average PF in their village to have a farm size of equal or similar size to their own (compared to 33.9% for LFs), while 27.7% consider the average PF uses the same or fewer inputs on her farm (23.1% for LF). Thus, LFs do have somewhat greater social stature than do PFs, but—partly as a result—have agricultural experiences that are further from those of the mean respondent.

5.2 Incentives and communicator retention of knowledge

The theory predicts that performance incentives increase communicators' own willingness to acquire the information presented, and relay the signal ($s_{x\theta}$) to their neighbours. To examine this prediction empirically, we test all communicators during the first follow-up survey on how

[9] These perception questions were not asked at baseline, so we rely on comparisons in our control sample to estimate differences in these characteristics.

well they retained information on the technologies they were trained on. The dependent variable is a knowledge score based on communicators' performance in these tests (see Appendix A2).

We created these scores for both the actual communicators who were assigned the task of transmitting information (the peer farmers in the PF treatment village and the lead farmer in the LF treatment), as well as "shadow" peer farmers and shadow lead farmers who were chosen using the same process as the communicators, but not officially assigned any task. The shadow PFs and LF are the correct counterfactual comparison group. Appendix A4 verifies that the actual and shadow communicators are statistically similar in terms of their baseline demographic and economic characteristics.

We regress communicator knowledge scores on (actual versus shadow) communicator status using the following specification:

$$knowledge_{cvd} = \alpha + \beta_1 shadow\ LF_{cvd} + \beta_2 actual\ LF_{cvd} + \beta_3 actual\ PF_{cvd} + Z_{cvd}\,\Gamma + D_d + \epsilon_{cvd}$$

The subscripts denote communicator *c* residing in village *v* in district *d*, Z_{cvd} is a matrix of individual -level controls and D_d denote district fixed effects. In this specification, our reference group are shadow PFs. We run this regression separately for the two sub-samples of villages where incentives were or were not offered. In Table 4 we report results with and without individual controls and district fixed effects.

Those chosen as lead farmers (who are richer and more educated, as we have seen) generally perform better on the tests compared to those chosen as peer farmers. Without incentives, actual peer farmers (who are trained by the extension workers, and assigned the task of communicating) do not perform as well lead farmers without incentives, and their performance is more comparable to shadow lead farmers who are not directly trained by extension workers. It is even difficult to statistically distinguish their exam performance from that of shadow peer farmers. In summary, peer farmers do not appear to retain knowledge about new technologies when they are **not** provided incentives.

When incentives are introduced, we observe the strongest improvements in the knowledge scores for peer farmers. With incentives, peer farmers are just as knowledgeable about the technologies as the actual lead farmers with incentives. As Table 4 shows, incentives improve PFs' knowledge scores by about 19-20 percentage points, which represents a doubling of knowledge scores relative to shadow PFs. This incentive effect for peer farmers is both quantitatively and statistically significant (with a p-value of 0.0375, comparing columns 2 and 4). Incentives also increase lead farmer knowledge scores by about 7 percentage points, but this is not a statistically significant increase. In summary, incentives increase communicators' own willingness to learn about the technology (i.e. acquire and send a signal), especially for peer farmers. The overall increase and the larger increase for PFs (who are on average 'closer' to the target farmers), are both consistent with the theoretical model.

5.3 Incentives and communicator effort

Next, we test whether communicators undertake costly effort to adjust the precision of the signal sent (ρ) in response to the offer of incentives. Our dependent variable now indicates whether the assigned communicator in the village held at least one activity to train others (typically either a group training or a demonstration plot). This variable is drawn from the midline household survey and captures the share of households in the village who responded that the assigned communicator held such an activity. We use the following specification:

$$effort_{ivd} = \beta_1 AEDO_{ivd} + \beta_2 LF_{ivd} + \beta_3 PF_{ivd} + Z_{ivd}\Gamma + D_d + \epsilon_{ivd}$$

where O_{ivd} , LF_{ivd} , and PF_{ivd} now denote the communicator treatment assignment and *i* indexes the household respondents. We estimate this specification using OLS regressions with standard errors clustered by village, again both unconditionally and conditional on respondent household characteristics and district dummies. As the survey question references the assigned communicator, control villages (where no communicator was assigned) are omitted from this regression. The regression output in Table 5 omits the constant term, so that coefficients β_1, β_2, and β_3 can be interpreted as the mean effort levels for each communicator type. We report the results separately for villages without communicator incentives (columns 1 and 2), and those provided incentives (columns 3 and 4).

In the sample without incentives, AEDO and LF effort are statistically comparable. However, AEDOs are significantly more likely to hold activities than were PFs (between 10 and 12 pp more so, statistically significant with 90% confidence). In contrast, when incentives are provided (columns 3 and 4), PFs are the communicators most likely to hold activities. All types of communicators put substantially (and statistically significantly) more effort with incentives, but the effect is largest for peer farmers. PF effort levels more than double when incentives are added. In contrast, when incentives are provided (columns 3 and 4), PFs are the communicators most likely to hold activities. Both PFs and LFs put substantially (and statistically significantly) more effort with incentives, but the effect is largest for peer farmers, and is significantly larger than it is for other communicators.[10] PF effort levels more than double when incentives are added. 75% of all respondents attend a dissemination activity when PFs with incentives are the assigned extension partner. This effort is also significantly greater than that incurred by extension workers (p-value=0.108 in column 4) or lead farmers (p-value=0.084). The analyses in both sections 5.2 and 5.3 suggest that communicators who are most "centrally located" (i.e. there are many others in the village similar to him or close to him in social or geographic space) respond most strongly to incentives.

5.4 Technology adoption by recipient farmers

We now move beyond communicator actions, and study technology adoption by the 'target' (recipient) farmers as a function of the randomized treatments. We proxy take-up at the end of the first season with the knowledge scores described above – i.e. whether recipient farmers retained the details about how to apply the technologies in the field. With the second year of data we study actual adoption – by measuring technology use in the field. In Table 6, we show results from estimating the knowledge equation using midline data on the sample of

[10] Statistically significant at 95% (90%) when compared to the incentive effect for LFs (AEDOs). These confidence levels are based on regressions (omitted for brevity) using the full sample of all villages (including both villages with incentives and without), where incentive treatment is interacted with communicator type.

target/recipient (i.e. non-communicator) households, where the targets' knowledge retention (rather than the communicators') is now the dependent variable:

$$knowledge_{ivd} = \alpha + \beta_1 AEDO_{ivd} + \beta_2 LF_{ivd} + \beta_3 PF_{ivd} + Z_{ivd}\,\Gamma + D_d + \epsilon_{ivd}$$

In villages without incentives (columns 1 and 2) compared to pure control villages, recipient households exhibit knowledge scores that are 18-20 pp higher in AEDO villages, 7-9 pp higher in the LF villages, and 3 pp higher (but not statistically different from zero) in PF villages. When incentives are provided (columns 3 and 4), however, we find that knowledge scores are 6, 8, and 12 pp higher in AEDO, LF, and PF villages than in the controls, which are large relative to the mean score of 0.09 in the pure control villages.[11] There is no apparent incentive effect in LF villages, but knowledge scores in PF villages are significantly larger (p-value = 0.02) when the peer farmers are provided incentives. The extra effort expended by peer farmers in incentive villages (that we documented earlier) results in greater knowledge transmission, and this is all consistent with the theoretical framework. The lack of knowledge retention by recipient farmers in PF villages without incentives is not at all surprising, since we have already observed (in table 4) that the PF communicators themselves do not retain any of the information without incentives, and therefore really have nothing to pass on.

Next, we study actual adoption by the target farmers, or the use of the technologies in the field measured two years after the (randomized) communication treatments were introduced in these villages. Our dependent variables are now the use of pit planting on at least one household plot, or the production of at least one compost heap, pile, or pit by the household during the 2010/11 agricultural season. We use the following specification:

$$Prob(adopt_{ivd}) = \Phi(\alpha + \beta_1 AEDO_{ivd} + \beta_2 LF_{ivd} + \beta_3 PF_{ivd} + Z_{ivd}\,\Gamma + D_d)$$

where Φ is the cumulative normal distribution function. We estimate this specification using probit separately for the two different technologies (and separately for incentive and non-incentive villages), because adoption rates for the two technologies were very different at

[11] The larger effects in the AEDO villages without incentives are both surprising and statistically significant at the 1% level. However, this counter-intuitive effect does not generally persist when we examine adoption decisions after two years (which we will report next).

baseline. For pit planting villages, we report results for both self-reported adoption in the endline survey, and directly observed adoption for the subsample of 34 villages where on-farm monitoring was conducted, recognizing that the smaller sample size may weaken precision in the latter case. Direct observation monitoring was conducted for the full composting village sample.

Table 7 reports marginal effects from the Probit estimation. In villages without communicator incentives, self-reported adoption of pit planting is 2.2 pp higher in AEDO villages than in the controls, and very close to and statistically indistinguishable from zero in the LF and PF villages (column 1). When incentives are added, adoption is 5.5, 6.3, and 10.2 pp higher in AEDO, LF, and PF villages, respectively, than in the controls (column 2). These are large effects relative to mean adoption in pure control (0.01) or in AEDO villages (0.03). The incentive effect in PF villages (the move from 1.7 to 10.2 pp) is both statistically significant (p-value = 0.02) and dramatically larger than the effect of incentives among the other communicators.

In the directly observed (on-farm monitoring) subsample (columns 3 and 4), we see a similar pattern: usage of pit planting is highest in the incentivized PF treatment (13.6 pp), and this adoption rate is significantly greater than it is for other communicator types. The differential response to incentives also exists when we assess target farmers' plans for adoption in the following season (columns 5 and 6). 17.6% of target farmers in PF villages planned to adopt the following year.

Only 1% of farmers in control villages practice pit planting, and only 1% of target farmers in all treatment villages practiced pit planting at baseline. Adoption rates we observe under the PF-incentive based dissemination strategy (of 10.2%, 13.6% and 17.6% through self-reports, on-farm-monitoring, or future plans, respectively) all represent meaningful gains relative to baseline and relative to the pure control group.

Columns 7 and 8 of Table 7 report effects on composting adoption. Without incentives, adoption rates are no different than in pure control villages where Chinese composting was not introduced by us at all. When incentives are provided, we observe large gains in the adoption of composting across our communicator treatments. Adoption is 19.0, 14.4, and 26.1 pp higher in AEDO, LF and PF villages with incentives, respectively, than in our control villages.[13] The incentive effect in peer farmer villages (of 33.4 pp extra adoption among target farmers) is highly statistically significant (p-value <0.000). The PF-incentive effect is also significantly larger than the LF-incentive effect. These effects are also quite dramatic given baseline adoption levels of any type of compost of only 19%. Parallel to the communicator knowledge retention and communicator effort results, we see a differentially stronger response to incentives among peer farmers, i.e. communicators who are "most like" the target farmers. This is true for both types of technologies introduced to two different sets of districts.

5.5 What type of 'proximity' matters most?

To summarize, the set of empirical results conform to the basic intuition derived from our framework. Peer farmers, who are most 'similar' to the target farmers, respond most strongly to the incentive treatment, in terms of their own retention of knowledge and effort expended to communicate with and convince others. This in turn leads to greater technology adoption among target farmers who reside in villages randomly assigned to PF communication.

"Proximity" between PFs and recipient farmers rationalize these findings, but our model is silent about the specific dimension of proximity that matters. We model farmers as being distributed on a line, but do not specify the social or geographic definition of this line. Indeed, Tables 2 and 3 show that PFs are closer to target farmers (relative to LFs) in a *variety* of dimensions, including poverty, education, farm size.

In this sub-section, we empirically explore which of these dimensions help to explain the relative success and incentive-response of PFs. We do this in two ways. First, we run the

[13] It is reasonable to worry that the provision of incentives, if it became widely known, could undermine the credibility of our extension partners, as recipients became less likely to listen to the advice of communicators who are being paid to provide that advice. We ask all respondents to rate their assigned communicators' honesty, skill and agricultural knowledge in the midline survey. Using these data, Appendix A5 shows that incentives do not undermine communicators' credibility. Target farmers appreciate peer farmers' extra effort in incentive villages, and rate them as *more* knowledgeable and honest. Lead farmers, whose effort is not responsive to incentives, do not receive similar recognition, but are not penalized either.

technology adoption regression using the sample of incentive villages, and add interaction terms between the PF treatment and various household-PF characteristics (like similarity, geographic and social proximity, or social interactions measured at baseline). This allows us to explore the *types* of PFs (with incentives) that are most successful. Are PFs with wider social networks, or ones with more frequent social interactions, or the PFs most comparable to target households in terms of farm size and input use the most persuasive? These results are displayed in Table 8.

The specifications in Table 8 control for each interaction term individually, and the last column then jointly controls for all the different interaction terms representing each dimension of "proximity": family relationships, joint group memberships, and similarity in terms of income and education. Target farmers are generally a little poorer (e.g. cultivate less land, have access to less inputs, less income, less education) than peer farmers on average, so we use measures such as "PF has *smaller* farm"[14] to proxy for comparability. Whether we control for the interaction terms individually or jointly, the factor that emerges as quantitatively and statistically most significant is comparability in terms of land size. Peer farmers with incentives whose land size is most comparable to others in their village are significantly (36 percentage points) more likely to convince target farmers to adopt. Peer farmers with larger immediate or extended family networks are not differentially more successful, and surprisingly, those with more frequent social interactions at baseline (prior to the introduction of these interventions) actually perform worse. Peer farmers who share group membership with higher numbers of other respondents (e.g. the PF and the respondent belong to the same church group) perform better, but the statistical significance of this variable disappears when all the interactions are added jointly. In summary, agricultural comparability is the factor that appears most robust in explaining which peer farmers are most successful.

Second, we examine whether the incentive-response of the peer farmers varies across different types of target farmer households. We study the PF effect on technology adoption

[14] This can be interpreted as the share of households who had larger farm than each PF, averaged over all of the PFs in the village.

separately for incentive and non-incentive villages, and conduct a statistical test of differences in peer farmer performance across the two types of villages.[15] These results are shown in Table 9.

We report the mean marginal effect of each PF characteristic (e.g. comparable in terms of land size or agricultural inputs, or PFs who are family members) on the adoption decisions of target farmers in incentive and in non-incentive villages. The first column shows that in incentive villages, the share of target farmers who report that the group of PFs, on average, have less cultivable land than they do *increases* the target's adoption propensity by 24 percentage points. That effect in non-incentive villages is -14.3 pp. The difference between the incentive and non-incentive villages is statistically significant, implying that such types of PFs respond very strongly to the incentive. We find similar results when we consider relative input use in the second column (the share of targets who report that PFs use the same or fewer inputs than they do increases adoption by 25 percentage points in incentive villages, and -5 pp in non-incentive villages). These results, coupled with our model's prediction on the types of communicators expected to respond to incentives, imply that farm size and input use are the key farmer characteristics that matter for information dissemination. Communicators find it easier to convince farmers whose access to land and other agricultural inputs are closer to them.

We do not observe analogous differences across the mean educational attainment of PFs, or a measure of their poverty (columns 3 and 4), or any other measure of socio-economic characteristics such as other housing features and asset holdings (results omitted for brevity). Because the total value of the incentives was equal across communicator types, one might suspect that PFs respond more intensely to the incentives because they are generally poorer and thus the marginal utility of the payments is higher for them; it does not appear that such differences in marginal utility are driving our results. We do not see differential incentive effects for family members either, but common group membership does induce an incentive-response.

[15] We pool both technologies, and run a Probit regression in PF villages: $Prob(adopt_{ivd}) = \alpha + \beta_1 Incentives_{vd} + \beta_2 PF\ Characteristics_{vd} + \beta_3 Incentives_{vd} * PF\ Characteristics_{vd} + Z_{ivd}\,\Gamma + D_d + \epsilon_{ivd}$. $Incentives_{vd}$ is an indicator of incentive treatment in village *v* in district *d*, and $PF\ Characteristics_{vd}$ is a measure of the mean baseline characteristics, averaged across the five peer farmers in the village.

Finally, when we include the PF farm size, input use, education and housing characteristics simultaneously in a single regression, similar farm size is the characteristic that retains statistical and quantitative significance.

In summary, while our model does not provide specific guidance on the type of proximity that lead peer farmers to respond most strongly to our incentive treatment, the data (i.e. treatment heterogeneity analysis, where the PF treatment is interacted with baseline characteristics) suggest that comparability in terms of agricultural inputs (cultivable land and other inputs) is the dimension of proximity between peer and target farmers that matters most.

6. Alternative Mechanisms underlying the Peer Farmer Performance

Our experiment randomly varies both the communicator type and the incentive eligibility of these communicators. However, several other features of our design differ in the PF treatment arm, which could explain the differential response of PFs to the incentives. There are five communicators rather than one, and the incentives are joint, with each communicator receiving the incentive payment conditional on the joint performance of all PFs in the village. These differences suggest two alternative hypotheses for the differential effect of incentives on PF effort and adoption in PF villages: (1) the effects of the incentives could be non-linear, and (2) the jointness of the incentives could induce PFs to coordinate, collaborate, or otherwise influence one another to induce greater effort. These alternatives do not necessarily undermine what we learn from this experiment. As explained above, all treatments across communicator-type (AEDO, LF, PF) were budget neutral, both in the incentive and the non-incentive arm. If peer farmers out-perform other communication strategies on this level playing field due to other mechanisms, this result still contains valuable policy and economics lessons. Nevertheless, we return to our data to evaluate these alternative mechanisms.

Each incentivized PF was eligible to receive a reward equal to 1/5 of that received by each incentivized LF, and it is possible that aiming at 1/5 of the target for 1/5 of the reward was disproportionately attractive.[16] Recall that performance for purposes of our incentives was based on percentage gains in villages, not levels, and thus was independent of village size. We can thus compare the adoption treatment effects of LFs in relatively small villages to those of PFs in relatively large villages. In these settings, each LF must communicate with the same number of households as each PF, but would earn dramatically higher rewards for doing so. We show the results in columns 1-4 of Table 10. In columns 1 and 2, we show that the incentive treatment does not affect adoption in LF villages with fewer than 65 households (the median in our sample) or 50 households. In PF villages, however, we observe large differences in adoption due to incentives even in villages with greater than 65 households (column 3) and 100 households (column 4). Even in these subsamples, we continue to find that adoption in PF villages responds dramatically more to communicator incentives than does adoption in LF villages.

Finally, it is also possible that the joint-ness of the incentives for PFs could induce teamwork or other peer effects among these groups. We note that joint incentives do not always lead to more positive group outcomes, as such groups must solve free riding and other collective action problems. However, in cases where groups are composed of individuals who know each other well and who interact in other dimensions or settings, joint incentives could lead individuals to both coordinate and monitor one another. Such arguments would be akin to those for joint liability lending in microfinance. To test whether such joint-ness is driving the differential response of PFs, we compare the effects of incentives in villages where PFs were closely linked to one another at baseline with those in villages where PFs were not closely linked. To do so, we estimate the following specification:

$$Prob(adoption_{ivd}) = \alpha + \beta_1 Incentives_{vd} + \beta_2 PF\ Links_{vd} + \beta_3 Incentives_{vd} * PFLinks_{vd} + \epsilon_{ivd}$$

where $PF\ Links_{vd}$ is a series of measures of the average likelihood that each PF in a village is related to, in a group with, or talks daily with each other PF. These measures capture the share of strong bimodal relationships between PFs among all potential relationships. In columns 5-7

[16] Note that such an argument would run counter to the higher marginal utility typically associated with higher-powered incentives.

of Table 10, we present the mean marginal effects of the incentive treatment at both the 25th and 75th percentiles of the PF links measures. We find that the incentive effect is not statistically distinguishable across any of these measures. Even in villages where PF are not particularly well-connected at baseline, the presence of incentives dramatically improves outcomes. These results suggest that the joint-ness of incentives is not likely to be driving the differential response of PFs to these incentives.

Finally, it is also possible that some communicators compete with target farmers in the product market, and teaching others how to farm more maize might undermine the price that the communicator receives in the market for his maize. If lead or peer farmers sell maize to different extents, their differential financial incentives could explain the differential performance of the communication treatments. This turns out to be an unlikely explanation, because we see very little sale of maize among any of our sample farmers at baseline. Fewer than 20% of households sold any maize, and less than 10% of all maize harvested was sold. The share of harvests sold by lead or peer farmers are not statistically different from each other.

7. Effects of Technology Adoption on Yields and Input Use

We collect detailed data on yield, revenues, labor, materials and capital costs from all farmers to calculate the effects of the technologies on productivity and input use and costs. This exercise serves three important functions. First, our interventions induce farmers who are not technically trained to communicate technical information. To properly evaluate the success of this method, it is therefore important to verify that the way recipient farmers implement the new methods is technically correct, and generate gains in yield. Second, the two technologies we promote are relatively new, and their performance in the field with a large-scale trial is unknown. The technologies may impose additional input and labor costs, and those need to be accounted for to infer profitability. Third, measures of yield improvement are required to conduct a proper cost-benefit analysis of the communication strategies (that impose new incentives and monitoring costs for the Malawi Ministry of Agriculture) that we introduced.

The PF-incentive treatment led to a large increase in the adoption of both technologies, and we use the random variation induced by this treatment to report the average effects of each technology on maize yields, input use, and labor use recorded in the endline survey. In Appendix A6, we show these impacts on survey-based maize yields two seasons after the initial training. To account for outliers, we winsorize maize yields by district at the 95% level (i.e., assign the top 5% of values the 95th percentile value). We also include district fixed effects to account for district-specific shocks in yields. The intent-to-treat (ITT) effect of pit planting in column 1 shows that the incentive assignment raises yields by 298 kg/ha, or 18% of the baseline mean yield of 1678 kg/ha in this sample. In column 2, we further control for baseline yields and find that these incentive treatment impact is 179 kg/ha, or 10.7% of the mean baseline yield. Given differences in adoption of pit planting of 9.5% in response to PF incentives (see Table 7), we estimate a treatment effect on the treated (TOT) of 113%. This estimate is very large and indicates that pit planting dramatically improved yields in PF villages, and we cannot statistically distinguish it from the range of estimates cited in the prior literature (50-100% gains). Finally, in column 3, we estimate an instrumental variables regression using the incentive treatment as an instrument for each household's adoption decision. We find that adoption of pit planting raises yields by 5,020 kg/ha. This coefficient is not significantly different from zero, and we cannot distinguish it from our aforementioned TOT estimate.

Turning to composting, we find far weaker evidence of yield gains. In column 4 of Appendix A6, we find an ITT of 66 kg/ha due to PF incentives that is not statistically significant (7.4% increase in mean yields). Conditioning on baseline yields in column 5, we find even smaller effects. Finally, our IV regressions again indicate only very small effects from the production of compost in our sample.

Appendix A7 examines whether pit planting affected farmers' input use. Farmers are much more likely to use a tool for land preparation, herbicide to prevent weeds in the pits, and to intercrop their maize plots with beans and other crops (practices recommended by MoAFS in conjunction with pit planting). There are no significant effects on the use of manure, basal, or top dress fertilizer. The herbicide use can raise production costs.

In Appendix A8, we assess the impacts of pit planting on the total labor hours devoted to land preparation, planting, fertilizer application, weeding, and harvesting. Our surveys very carefully collect detailed data on labor hours, separately for paid and unpaid men, women, and children, across all plots in the household. Again, we assess the ITT and TOT effects of incentives in our PF villages, with district fixed effects included throughout. We find that pit planting leads to significant reductions in hours devoted to land preparation, with an ITT of -6.5 hours. Pit planting was believed to require greater land preparation effort, but it turns out, it is not as intensive as ridging, which is the traditional land preparation method. We also find small reductions in fertilizer application and in harvesting, and no impacts on planting or weeding hours due to incentives. In total, we find an ITT reduction of 14.4 hours across all labor categories in the prior season. This reduction lowered production costs.

We find no evidence of any differential impacts on input use in the composting districts. Of particular note, we find no differences in either basal or top dress fertiliser use across incentive treatments. We also do not find any evidence of labor hour impacts from composting.

Using these yield and cost measures, we develop a back-of-the-envelope cost effectiveness calculation of our PF-incentive treatment, by conservatively assuming that the full research and data collection costs we incurred is required to implement such a treatment. Programmatic costs for the training of AEDOs, baseline, midline, and endline rounds of knowledge and adoption monitoring data collection, two rounds of incentives, and paying local support staff cost us US$1,843 per village treated (or US$ 17.07 per household). Given our estimated adoption impacts of 10.2 pp for pit planting and 26.1 pp for composting, the program costs are US$167 per household adopting pit planting and US$65 per household adopting composting. Our estimated yield gains from pit planting adoption suggest that each treated household gained US$77 (this is the ITT estimate of 298kg of maize, priced at 2011 harvest-period maize prices and foreign exchange rates) in the first year alone. This yields a benefit/cost ratio of 4.5 : 1. Continued use of pit planting among adopting households—or even expansion to additional households in these villages—would raise this ratio considerably.

8. Conclusions

A primary contribution of this research to the vast social learning literatures in economics and sociology is to demonstrate that communication dynamics between agents are important determinants of information dissemination. Our models can be enriched by studying the incentives that govern whether (and how) people communicate about new technologies with their peers. Such an approach would also make the social learning and peer effects documented by economists in a variety of contexts more policy-relevant. As this experiment shows, agricultural extension services can be improved by incorporating social learning in communication strategies.

Leveraging the power of social interactions to improve development policy in this way is likely highly cost-effective, because network-based communication and other forms of peer effects are already present, and only need to be harvested. This idea has already been applied successfully in joint-liability micro-credit group lending schemes. Put simply, extension partners who are incentivized with a bag of seeds generate knowledge gains and adoption exceeding that generated by professional agricultural extension staff working alone. The cost of these incentives is certainly small relative to the cost of having an extension worker to regularly visit a village, especially in a context where extension positions in remote, rural areas remain unfilled.

Our results help reconcile divergent findings in the literature on the existence of social learning (e.g. Conley and Udry 2010 versus Duflo, Kremer and Robinson 2011). Moreover, we find that "early adopter" models favoured by many extension efforts may result in lower levels of social learning and adoption than would efforts that make use of incentivized peer farmers whose constraints and access to resources are more representative of other farmers in the village, making their advice more credible.

Using recent developments in social network theory to further refine the communication partner selection process would be a useful avenue for future research. For agricultural policy, developing low-cost methods to identify extension partners who would be most influential would provide policymakers with an improved tool to disseminate new technologies that can raise yields and reduce pressure on scarce land and other ecological resources.

References

Alcott, H. 2011. "Social Norms and Energy Conservation," *Journal of Public Economics* 95: 1082-1095

Ali, D., K. Deininger and M. Goldstein 2011. "Environmental and Gender Impacts of Land Tenure Regularization in Africa Pilot evidence from Rwanda." World Bank Policy Research Working Paper 5765.

Anderson, J, and G Feder (2007). "Agricultural Extension." In *Handbook of Agricultural Economics* 3, pp. 2343-2378.

Ashraf, N., X. Giné, and D. Karlan. (2009). "Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya." *American Journal of Agricultural Economics* 91(4): 973-990.

Banda, M. (2007). Agricultural History of Malawi.*in* J. Williams, editor., Lilongwe, Malawi, cited in Williams, Joseph. "Adoption of Conservation Agriculture in Malawi", Duke University .

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). The Diffusion of Microfinance. Science, 341(6144). doi: 10.1126/science.1236498

Bardhan, P. and C. Udry (1999). *Development Microeconomics*. Oxford University Press.

Beaman, L. (2012) "Social Networks and the Dynamics of Labor Market Outcomes: Evidence from Refugees Resettled in the U.S." *Review of Economic Studies*, 79(1), pp. 128-161.

Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian, and Katherine L. Milkman (2011). "The Effect of Providing Peer Information on Retirement Savings Decisions," NBER Working Paper 17345.

Biyalogorsky, E., Gerstner, E., & Libai, B. (2001). "Customer Referral Management: Optimal Reward Programs," *Marketing Science*, 20(1), 82-95. doi: 10.2307/193223

Bobonis, G. and F. Finan (2009). "Neighborhood Peer Effects in Secondary School Enrollment Decisions," *Review of Economics and Statistics* 91 (4): 695-716.

Bowles, Samuel, and Sandra Polania-Reyes. (2012). "Economic Incentives and Social Preferences: Substitutes or Complements?." *Journal of Economic Literature*, 50(2): 368-425.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2013). "Escaping Famine through Seasonal Migration," Working Paper, Yale University.

Carrell, Scott E. and Mark L. Hoekstra, (2010). "Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids," *American Economic Journal: Applied Economics*, 2 (1), pp. 211-228.

Cole, S., X. Giné, and J. Vickery (2013). "Barriers to household risk management: Evidence from India." *American Economic Journal: Applied Economics*, 5(1), 104–135.

Coleman, James, Katz, Elihu, & Menzel, Herbert. (1957). The Diffusion of an Innovation Among Physicians. Sociometry, 20(4), 253-270.

Conley, T. and C. Udry (2010). "Learning about a New Technology." *American Economic Review,* 100(1), pp 35-69.

Crawford, Vincent and Joel Sobel. 1982. "Strategic Information Transmission," *Econometrica*, 50 (6): 1431-1451.

Crepon, B., F. Devoto, E. Duflo and W. Pariente (2011). "Impact of microcredit in rural areas of Morocco: Evidence from a randomized evaluation." Working Paper.

Croppenstedt, A., M. Demeke and M. Meschi (2003). "Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia." *Review of Development Economics* 7: 58-70.

De Giorgi, G., M. Pellizzari and Silvia Redaelli (2010). Identification of Social Interactions through Partially Overlapping Peer Groups, *American Economic Journal: Applied Economics* 2 (2), April.

Derpsch, R. (2001). "Conservation tillage, no-tillage and related technologies." *Conservation Agriculture, A Worldwide Challenge* **1**:161-170.

--------------. (2004). "History of Crop Production, With & Without Tillage." *Leading Edge*. March: 150–154.

Dewatripont, Mathias and Jean Tirole. 2005. "Modes of Communication." *Journal of Political Economy*, 113(6): 1217-1238.

Duflo, E., P. Dupas, and M. Kremer, (2011). "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya," *American Economic Review*, 101 (5), pp. 1739-1774.

Duflo, E., M. Kremer, and J. Robinson (2011). "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya." *American Economic Review*, 101(6), pp. 2350-90.

Duflo, Esther and Emmanuel Saez, (2003). "The Role of Information and Social Interactions in Retirement Plans Decisions: Evidence from a Randomized Experiment," *Quarterly Journal of Economics*, 118 (3), pp. 815-842.

Foster, Andrew and Mark Rosenzweig (1995). "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture". *Journal of Political Economy* 103(6), pp. 1176-1209.

Garlick, Robert (2012). "Academic Peer Effects with Different Group Assignment Policies." U. of Michigan mimeo.

Godlonton, Susan and Rebecca Thornton (2012). "Peer Effects in Learning HIV Results," *Journal of Development Economics* 97(1): 118–129.

Goldstein, M. and C. Udry (2008). "The profits of power: Land rights and agricultural investment in Ghana." *Journal of Political Economy* 116(6): 981-1022.

Grilliches, Zvi (1957). "Hybrid Corn: An Exploration in the Economics of Technical Change." *Econometrica* 25(4), pp. 501-522.

Haggblade, S. and G. Tembo (2003). "Conservation Farming in Zambia." International Food Policy Research Institute EPTD Discussion Paper #108.

Iyengar, R., Van den Bulte, C., & Valente, T. W. (2011). Opinion leadership and social contagion in new product diffusion. *Marketing Science*, 30(2), 195-212.

Jack, B. Kelsey. 2013. "Constraints on the adoption of agricultural technologies in developing countries." Literature review, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley).

Karlan, D., R. Osei, I. Osei-Akoto and C. Udry (2012). "Agricultural decisions after relaxing credit and risk constraints." NBER Working Paper No. 18463.

Kornish, L. J., & Li, Q. (2010). Optimal referral bonuses with asymmetric information: Firm-offered and interpersonal incentives. *Marketing Science*, 29(1), 108-121.

Kremer, M. and E. Miguel (2007). "The Illusion of Sustainability." *Quarterly Journal of Economics* 112(3), pp. 1007-1065

Kremer, M., E. Miguel, S. Mullainathan, C. Null and A. Zwane (2011). "Social Engineering: Evidence from a Suite of Take-up Experiments in Kenya" Mimeo, UC Berkeley.

Krishnan, Pramila and Patnam, Manasa (2013). "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?" *American Journal of Agricultural Economics* 95(4).

Lea, N. and L. Hanmer (2009). "Constraints to Growth in Malawi". World Bank Policy Research Working Paper No. 5097.

Magruder, J. (2010) "Intergenerational Networks, Unemployment, and Inequality in South Africa." *American Economic Journal: Applied Economics*, 2(1), pp 62-85.

Manski, C. (1993). "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60(3), pp. 531-542.

Miller, Grant and A. M. Mobarak (2012). "Learning about New Technologies through Opinion Leaders and Social Networks: Experimental Evidence on Non-Traditional Stoves in Rural Bangladesh." Yale University mimeo.

Munshi, K. (2004). "Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution." *Journal of Development Economics*, 73(1), pp 185-215.

Mwato, I.L., Mkandawire, A.B.C. and Mughogho, S.K. (1999). "Combined Inputs of Crop Residues and Fertilizer for Smallholder Maize Production in Southern Malawi." *African Crop Science Journal* 7 (4): 365-373.

Nkhuzenje, H. (2003). "Contribution of promiscuous and specific soybean variety residues to soil fertility improvement and maize yield under smallholder farms in Zomba District, Southern Malawi." Thesis submitted in partial fulfilment of the requirements of Master of Science degree in agronomy (Soil science).

Nyirongo, J., S. Mughogho, and J. Kumwenda (1999). "Soil Fertility Studies with Compost and Igneous Phosphate Rock Amendments in Malawi." *African Crop Science Journal*, 7(4), pp. 415-422.

Oster, Emily and Rebecca Thornton (2012). "Determinants of Technology Adoption: Private Value and Peer Effects in Menstrual Cup Take-Up." *Journal of the European Economic Association* 10(6):1263-1293, December.

Sanchez, P.A. (2002). Soil fertility and hunger in Africa. *Science* 295: 2019-2020.

Stoorvogel, J.J., Smaling, E.M.A. and Janssen, B.H. (1993) "Calculating soil nutrient balances in Africa at different scales. I. Supranational scale." *Fertilizer Research* 35: 227-235.

Udry, Christopher (2010). "The Economics of Agriculture in Africa: Notes Toward a Research Program." *African Journal of Agricultural and Resource Economics* forthcoming.

Waddington, Hugh, Birte Snilstveit, Jorge Hombrados, Martina Vojtkova, and Howard White (2011). "The Impact of Farmer Field Schools: A Systematic Review." Mimeo, International Initiative for Impact Evaluation.

Figure 1: Intervention, Data Collection, and Agricultural Calendar

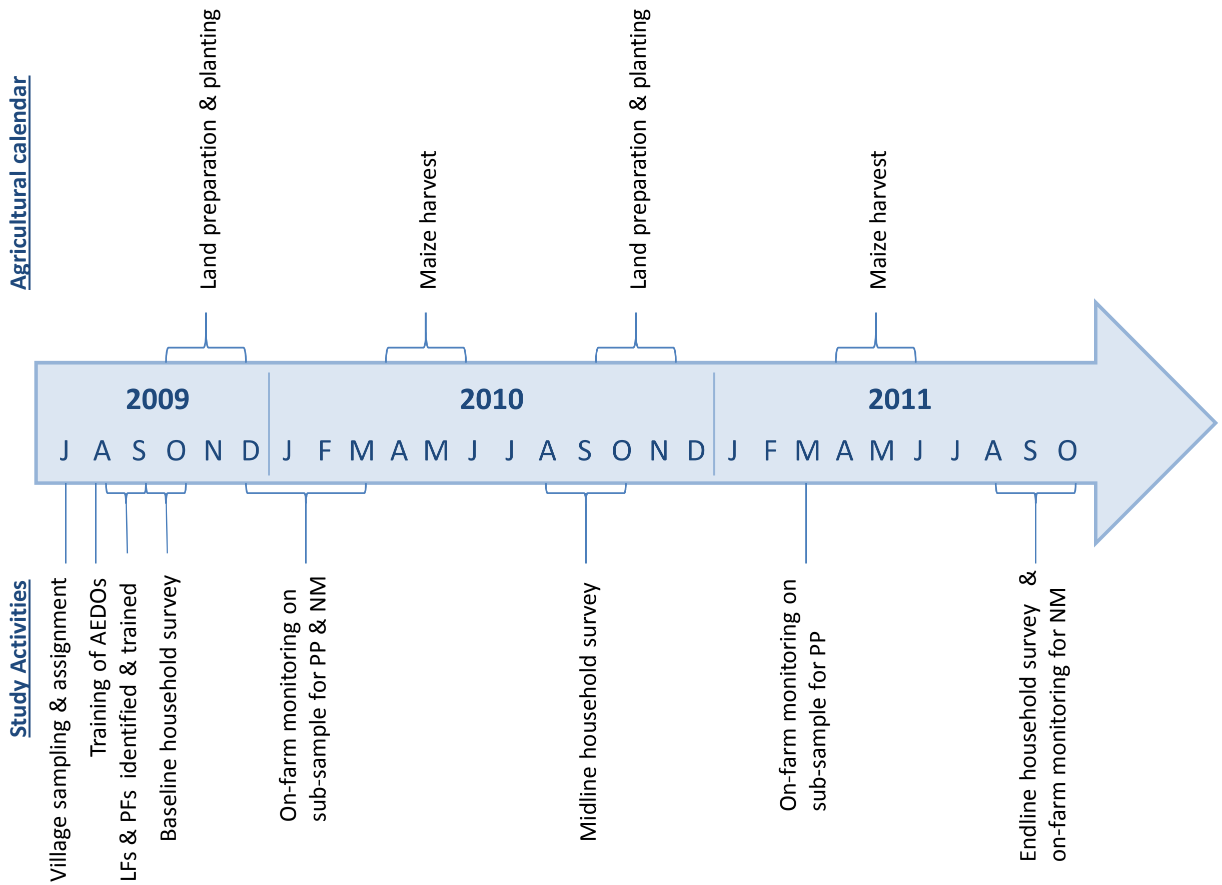

Figure 2: Treatment Arms

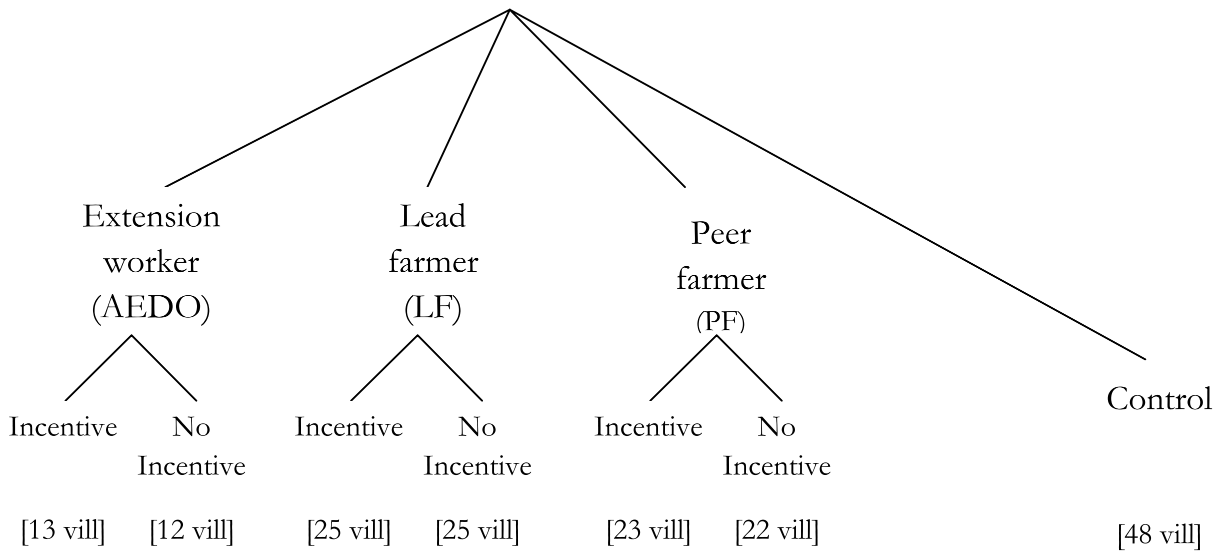

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max	N
Technology knowledge and use					
Knowledge score on targeted technology at midline	0.155	0.273	0	1	4286
Household used targeted technology at endline	0.147	0.354	0	1	4787
Only treatment villages					
Assigned communicator held at least one activity at midline	0.517	0.500	0	1	3177
Only pit planting districts					
Household used pit planting at endline	0.040	0.197	0	1	2604
Only composting districts					
Household produced compost at endline	0.295	0.456	0	1	2183
Household head characteristics					
Male	0.711	0.453	0	1	4250
Age	42.1	16.6	19	81	3850
Education level (1-8)	3.395	1.461	1	8	4237
Household wall material					
Mud and poles	0.065	0.247	0	1	4276
Unburned bricks	0.276	0.447	0	1	4276
Compacted earth	0.155	0.362	0	1	4276
Burned bricks	0.466	0.499	0	1	4276
Household roof material					
Grass	0.734	0.442	0	1	4276
Iron	0.233	0.423	0	1	4276
Primary water source in dry season					
River	0.111	0.314	0	1	4276
Unprotected well	0.066	0.249	0	1	4276
Protected well	0.143	0.350	0	1	4276
Communal tap	0.086	0.280	0	1	4276
Borehole	0.552	0.497	0	1	4276
Assets and income					
Number of animals owned by HH	1.394	1.137	0	7	4276
Number of assets owned by HH	4.791	2.239	0	17	4276
Own farm is primary source of income	0.807	0.394	0	1	4276
HH derives income from *ganyu* (paid labor on others' farms)	0.468	0.499	0	1	4276
HH derives income from business	0.431	0.495	0	1	4276
HH member has taken out a loan	0.059	0.236	0	1	4276

Table 2: Differences in demographics between communicators and the general population

Characteristic	Non-communicators	Peer Farmers	Lead farmers	p-value LF = PF
Household head is male	0.711	0.760	0.928	0.000
	(0.0129)	(0.0253)	(0.0235)	
Household head age	42.10	43.03	40.93	0.364
	(0.411)	(0.947)	(1.991)	
Household head's highest level of education completed (levels: 1-8)	3.395	3.811	4.322	0.007
	(0.0700)	(0.121)	(0.239)	
House walls are made of burnt bricks	0.466	0.539	0.634	0.140
	(0.0263)	(0.0402)	(0.0721)	
House roof is made of grass	0.734	0.654	0.560	0.264
	(0.0209)	(0.0658)	(0.0400)	
Number of animals owned by the household	1.394	1.676	1.778	0.545
	(0.0579)	(0.0901)	(0.190)	
Number of assets owned by household	4.791	5.482	5.752	0.524
	(0.103)	(0.184)	(0.422)	
Own farm is household's primary income source	0.807	0.831	0.902	0.312
	(0.0140)	(0.0387)	(0.0522)	
Total household cultivated land 2008/09 (hectares)	0.987	1.065	1.336	0.024
	(0.0233)	(0.0456)	(0.123)	

Standard errors clustered by village in parenthesis

Table 3: Differences in social links, perceptions & comparability between communicators

Communicator	LF	PF (mean)	LF - PF
Related to respondent	0.515	0.475	0.040***
	(0.0237)	(0.0219)	(0.00822)
Immediate family of respondent	0.218	0.113	0.105***
	(0.0146)	(0.00938)	(0.0121)
Talk daily with respondent	0.175	0.150	0.025***
	(0.0156)	(0.0136)	(0.00614)
Group together with respondent	0.142	0.136	0.006
	(0.0112)	(0.0107)	(0.00572)
Communicator uses same or fewer inputs than respondent	0.231	0.277	-0.045***
	(0.0161)	(0.0136)	(0.0100)
Communicator's farm is same or smaller than respondent	0.339	0.427	-0.087***
	(0.0198)	(0.0144)	(0.0141)
Trustworthiness rating [1-4]ł	3.58	3.45	0.134***
	(0.464)	(0.457)	(0.0587)
Farming skill rating [1-4]ł	2.88	2.71	0.175***
	(0.0798)	(0.0662)	(0.0600)

*** p<0.01, ** p<0.05, * p<0.1. ł denotes variables only available at midline, thus sample is limited to control villages. Based on individual-level data, clustered at the village level.

Table 4: Acquiring and Sending Any Signal

	Dependent variable: Knowledge scores in household survey			
	Unincentivized communicators		Incentivized communicators	
	(1)	(2)	(3)	(4)
Shadow LF	0.0731***	0.0865***	0.0729***	0.0552
	(0.0414)	(0.0394)	(0.0357)	(0.0380)
Actual LF assigned to Communication	0.153***	0.154***	0.223***	0.221***
	(0.0685)	(0.0584)	(0.0561)	(0.0654)
Actual PF assigned to communication	0.0517	0.0669***	0.201***	0.185***
	(0.0450)	(0.0377)	(0.0486)	(0.0474)
PP District	0.319***	0.337***	0.361***	0.160
	(0.0397)	(0.101)	(0.0341)	(0.113)
District FE	N	Y	N	Y
Additional baseline controls	N	Y	N	Y
Observations	571	534	562	515
R-squared	0.236	0.371	0.349	0.392
p-values for				
Actual LF = Actual PF	0.213	0.196	0.757	0.649
Actual LF = Shadow LF	0.336	0.332	0.0288	0.0343
Mean of Dep. Var. for Shadow PFs	0.219	0.209	0.200	0.191

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by village in parentheses. Excluded group is shadow PF. Additional baseline controls in columns 2 and 4 include household head gender, education and age, household wall and roof construction materials and primary source of water in dry and wet seasons, staple food consumed by household, number of animals and assets owned by household, primary sources of farming income (own farm, others' farm, own business), and whether anyone in the household had taken a loan in the preceding 12 months. Dependent variable includes zero scores for respondents who answered that they were not aware of the technology.

P-value for incentive = non-incentive	
Actual LF	0.451
Actual PF	0.0375

Table 5: Communicator Effort

	Dependent variable: Designated communicator held at least one activity			
	Unincentivized communicators		Incentivized communicators	
	(1)	(2)	(3)	(4)
AEDO treatment	0.450***	0.499***	0.642***	0.602***
	(0.0489)	(0.111)	(0.0603)	(0.126)
LF treatment	0.360***	0.476***	0.632***	0.594***
	(0.0704)	(0.122)	(0.0572)	(0.113)
PF treatment	0.350***	0.386***	0.747***	0.704***
	(0.0621)	(0.102)	(0.0689)	(0.135)
Pit Planting Dummy	Y	Y	Y	Y
District FE	N	Y	N	Y
Additional baseline controls	N	Y	N	Y
Observations	1,590	1,338	1,587	1,385
R-squared	0.441	0.511	0.615	0.655
p-values for				
AEDO = LF	0.174	0.715	0.892	0.894
AEDO = PF	0.099	0.052	0.166	0.108
LF = PF	0.895	0.135	0.112	0.084

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by village in parentheses. Sample excludes control villages. Additional baseline controls in columns 2 and 4 include household head gender, education and age, household wall and roof construction materials and primary source of water in dry and wet seasons, staple food consumed by household, number of animals and assets owned by household, primary sources of farming income (own farm, others' farm, own business), and whether anyone in the household had taken a loan in the preceding 12 months.

P-value for incentive = non-incentive	Unconditional	Conditional
AEDO	0.208	0.024
LF	0.055	0.102
PF	0.001	0.000

Table 6: Knowledge after one season among recipient farmers

	Dependent variable: Knowledge scores in household survey			
	Unincentivized communicators		Incentivized communicators	
AEDO treatment	0.195***	0.183***	0.0595***	0.0605***
	(0.0574)	(0.0477)	(0.0264)	(0.0248)
LF treatment	0.0850***	0.0685***	0.0757***	0.0780***
	(0.0315)	(0.0263)	(0.0256)	(0.0263)
PF treatment	0.0273	0.0302	0.127***	0.121***
	(0.0269)	(0.0238)	(0.0358)	(0.0337)
PP District	0.190***	0.293***	0.220***	0.229***
	(0.0254)	(0.0363)	(0.0213)	(0.0345)
District FE	N	Y	N	Y
Additional baseline controls	N	Y	N	Y
Observations	2,699	2,323	2,696	2,370
R-squared	0.191	0.269	0.222	0.258
p-values for				
AEDO = LF	0.073	0.026	0.557	0.550
AEDO = PF	0.007	0.006	0.069	0.084
LF = PF	0.092	0.172	0.163	0.217
Mean of Dep. Var. for Control Villages	0.092	0.092	0.092	0.092
Mean of Dep. Var. for AEDO Villages	0.287	0.298	0.134	0.138

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by village in parentheses. Excluded group is control villages. Additional baseline controls in columns 2 and 4 include household head gender, education and age, household wall and roof construction materials and primary source of water in dry and wet seasons, staple food consumed by household, number of animals and assets owned by household, primary sources of farming income (own farm, others' farm, own business), and whether anyone in the household had taken a loan in the preceding 12 months. Dependent variable includes zero scores for respondents who answered that they were not aware of the technology.

P-value for incentive = non-incentive	Unconditional	Conditional
AEDO	0.064	0.026
LF	0.914	0.725
PF	0.025	0.023

Table 7: Adoption after two seasons

Technology	Pit Planting						Composting	
Dependent variable	Used on at least one household plot in 2010/11		Directly observed usage on at least one plot in 2010/11		Plan to use next year		Household produced at least compost heap	
Communicator incentives	Non-incentive	Incentive	Non-incentive	Incentive	Non-incentive	Incentive	Non-incentive	Incentive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AEDO treatment	0.022***	0.055***	0.089***	-0.022	0.084***	0.036	-0.035	0.190***
	(0.010)	(0.019)	(0.014)	(0.053)	(0.036)	(0.032)	(0.073)	(0.099)
LF treatment	0.002	0.063***	0.0340	0.062***	0.021	0.115***	-0.049	0.144***
	(0.010)	(0.026)	(0.024)	(0.035)	(0.038)	(0.048)	(0.060)	(0.065)
PF treatment	0.017	0.102***	0.082	0.136***	0.082***	0.176***	-0.073	0.261***
	(0.013)	(0.019)	(0.073)	(0.037)	(0.040)	(0.041)	(0.057)	(0.061)
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,716	1,569	261	469	1,716	1,666	1,373	1,209
p-values for								
AEDO = LF p-value	0.067	0.722	0.006	0.229	0.095	0.071	0.871	0.622
AEDO = PF p-value	0.725	0.009	0.926	0.016	0.975	0.000	0.653	0.478
LF = PF p-value	0.246	0.045	0.498	0.088	0.143	0.179	0.667	0.076
Mean of Dep. Var. for Control Villages	0.009	0.010	0.009	0.010	0.087	0.087	0.246	0.246
Mean of Dep. Var. for AEDO Villages	0.052	0.033	0.0769	0.000	0.213	0.123	0.173	0.444

*** p<0.01, ** p<0.05, * p<0.1. Estimates in columns (3) and (4) are OLS coefficients; all other columns report average marginal effects from probit regression. Standard errors clustered by village in parentheses. Excluded group is control villages.

P-value for incentive = non-incentive	(1)–(2)	(3)–(4)	(5)–(6)	(7)–(8)
AEDO	0.805	0.738	0.052	0.061
LF	0.024	0.329	0.080	0.051
PF	0.024	0.289	0.059	0.000

Table 8: Social proximity

Dependent variable: Household adopted target technology in 2010/11 season VARIABLES	PF has smaller farm than respondent (1)	PF uses same or fewer inputs than respondent (2)	PF educational attainment (3)	PF house has grass roof (4)	PF in immediate family (5)	PF in extended family (6)	PF in group with respondent (7)	Respondent talks daily with PF (8)	Full set of interaction terms (9)
AEDO treatment	0.0858	0.0744	0.0891	0.0747	0.0851	0.0889***	0.0856	0.0886***	0.0833
	(0.0557)	(0.0542)	(0.0563)	(0.0570)	(0.0520)	(0.0523)	(0.0585)	(0.0530)	(0.0545)
LF treatment	0.0520***	0.0515***	0.0609***	0.0676***	0.0452	0.0529***	0.0486	0.0649***	0.0914***
	(0.0293)	(0.0303)	(0.0320)	(0.0338)	(0.0304)	(0.0297)	(0.0293)	(0.0326)	(0.0381)
PF treatment	0.0378	0.0586	0.334***	0.196***	0.167***	0.182***	0.0798***	0.186***	0.195
	(0.0765)	(0.0680)	(0.0937)	(0.0641)	(0.0375)	(0.0501)	(0.0399)	(0.0387)	(0.145)
PF treatment X mean(PF has smaller farm than respondent)	0.321***								0.363***
	(0.191)								(0.200)
PF treatment X mean(PF uses fewer inputs than respondent)		0.212							
		(0.208)							
PF treatment X mean(PF education)			-0.0494***						-0.0448
			(0.0270)						(0.0272)
PF treatment X mean(PF grass roof)				-0.0620					-0.0509
				(0.0937)					(0.0726)
PF treatment X mean(PF in respondent's immediate family)					-0.103				
					(0.343)				
PF treatment X mean(PF in respondent's extended family)						-0.0727			0.0778
						(0.128)			(0.162)
PF treatment X mean(PF in group with respondent)							0.416***		0.230
							(0.223)		(0.209)
PF treatment X mean(PF talks daily with respondent)								-0.190***	-0.289***
								(0.109)	(0.154)
Constant	0.254***	0.246***	0.241***	0.258***	0.262***	0.280***	0.276***	0.259***	0.201***
	(0.0952)	(0.0900)	(0.109)	(0.0979)	(0.0896)	(0.0918)	(0.0846)	(0.0898)	(0.118)
Observations	2,309	2,309	2,267	2,267	2,309	2,309	2,309	2,309	2,267
R-squared	0.225	0.225	0.228	0.225	0.220	0.220	0.225	0.225	0.243

Standard errors in parentheses. *** $p<0.1$, ** $p<0.05$, * $p<0.01$. Sample includes all non-communicator households in villages where incentives are provided. Standard errors clustered by village in parentheses. All regressions control for district FE and the same set of control variables as in prior tables. Each regression also controls for the main effect (of "smaller farm", "same or fewer inputs", "education",...etc), but only the interaction terms with the PF treatment are shown for brevity.

Table 9: Social proximity

	Dependent variable: Household adopted target technology in 2010/11 season							
	Agricultural comparability		Poverty		Social Links:			
Baseline village mean of:	PF has smaller farm than respondent	PF uses same or fewer inputs than respondent	PF educational attainment	PF house has grass roof	PF in immediate family	PF in extended family	PF in group with respondent	Respondent talks daily with PF
	Conditional	Conditional	Conditional	Conditional	Conditional	Conditional	Conditional	Conditional
Average marginal effect of characteristic for:								
Non-incentive villages	-0.143	-0.0504	0.001	0.005	0.430***	0.170	-0.00245	0.0853
	(0.186)	(0.134)	(0.015)	(0.079)	(0.258)	(0.107)	(0.127)	(0.107)
Incentive villages	0.240***	0.253***	-0.015	-0.008	0.410	0.0402	0.317***	0.134
	(0.0955)	(0.139)	(0.015)	(0.070)	(0.385)	(0.125)	(0.113)	(0.102)
p-value for incentive village X characteristic	*0.088*	*0.137*	*0.467*	*0.893*	*0.965*	*0.413*	*0.101*	*0.759*
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Household baseline controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,063	1,063	1,063	1,063	1,063	1,063	1,063	1,063

*** p<0.01, ** p<0.05, * p<0.1. Estimates shown are average marginal effects from probit regression. Sample includes all non-communicator households in PF villages. Standard errors clustered by village in parentheses. Pit planting village dummy included in all specifications. Conditional specifications also include household head gender, education and age, household wall and roof construction materials and primary source of water in dry and wet seasons, staple food consumed by household, number of animals and assets owned by household, primary sources of farming income (own farm, others' farm, own business), and whether anyone in the household had taken a loan in the preceding 12 months.

When included jointly...	*p-value*
PF has smaller farm than respondent	0.088
PF uses same or fewer inputs than respondent	0.137
PF educational attainment	0.467
PF house has grass roof	0.893

Table 10: Testing Alternative Hypotheses

	Dependent variable: Household adopted target technology in 2010/11 season						
Alternative hypothesis:	Non-linearity of incentives				Jointness of incentives		
	LF villages with <=65 hh	LF vill. with <= 50 hh	PF vill. with > 65 hhs	PF vill. with > 100 hs	PFs related to one another	PFs in group with one another	PFs talk daily with one another
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average marginal effect of							
Incentive village	0.0719	0.00274	0.249***	0.279***			
	(0.0632)	(0.0458)	(0.0430)	(0.0523)			
Incentive village @ 25th percentile of PF links					0.248***	0.188***	0.201***
					(0.0402)	(0.0463)	(0.0496)
Incentive village @ 75th percentile of PF links					0.187***	0.246***	0.232***
					(0.0652)	(0.0369)	(0.0534)
p-value for incentive @ 25th pct = incentive @ 75th pct					*0.311*	*0.171*	*0.632*
Mean of Dep Var in LF Non-incentive Villages	0.137	0.111					
Mean of Dep Var in PF Non-incentive Villages			0.106	0.0828	0.104	0.104	0.104
Observations	766	550	512	332	1,415	1,415	1,415

*** p<0.01, ** p<0.05, * p<0.1. Estimates shown are average marginal effects from probit regression. Pit planting village dummy included in all specifications. Sample includes all non-communicator households. Standard errors clustered by village in parentheses.

Appendix A1: Training Protocol

In August 2009, the Ministry of Agriculture and Food Security (MoAFS) conducted trainings for all the Agricultural Extension Development Officers (AEDOs) and Agricultural Extension Development Coordinators (AEDCs; supervisors of AEDOs) covering the 120 treatment sections. The Department of Agricultural Extension Services (DAES) coordinated the trainings, which were jointly facilitated with the Departments of Agricultural Research Services (DARS) and Land Resources Conservation (DLRC). Four training sessions were conducted nationally, at the MoAFS Residential Training Centers in Lunzu, Thyolo and Mzimba. Staff in areas targeted for the conservation farming intervention were training separately from those in areas targeted for the nutrient management intervention. AEDOs and AEDCs were trained only in the technology relevant to their work area. Trainings lasted for three days, and covered the following:

- Day 1
  - Overview of the research study, focusing on motivation and research questions
  - Review of the concept of lead farmer. DAES had promoted working with lead farmers since 2006, so some (but not all) of the AEDOs were familiar with the role of a lead farmer and how to select a lead farmer.
  - Introduction to the concept of peer farmer. As this concept was developed by DAES and the study research team, this was a new topic for all the AEDOs.
- Day 2
  - Classroom explanation of conservation farming / nutrient management technologies, with specific discussion of pit planting/Chinese composting.
  - Hands-on training in pit planting /Chinese composting using the demonstration plots at the Training Centres.
- Day 3
  - Visits to farmers who had adopted pit planting / Chinese composting to discuss the experience
  - Explanation to each AEDO of the specific village assignment, whether he/she was to work with a lead or peer farmer in the village, and whether there were any gender requirements for the extension partner.

Training of Extension Partners (Lead and Peer Farmers)

At the training, AEDOs were assigned to select lead and peer farmers in the target villages by the end of August. Although AEDOs were told to work primarily with either a lead or peer farmer (or neither, depending on assigned communication strategy), they were asked to identify one lead farmer and five peer farmers in all villages in order for data collection about social networks to be complete and unbiased. In control villages, "shadow" lead and peer farmers (six representatives of different social networks in the village) were identified through village focus groups facilitated by the field supervisors of the data collection teams, for accurate comparison of social networks. As soon as the lead and peer farmers were identified, their names were reported back to the District office of the Ministry of Agriculture and Food Security, to ensure that those households were all sampled in the baseline survey.

The AEDOs assigned to work with either lead farmers or peer farmers trained those individuals in their home villages during the month of September. Typically, the training lasted for half of a day and involved an explanation of the new technology as well as a practical demonstration. The AEDOs then made follow-ups with the lead and peer farmers over the next few months, often assisting them to set up demonstration plots on their own fields.

Appendix A2: Technical Specifications of Pit Planting and Nutrient Management

Specifications for Pit Planting

Pit planting is a conservation farming technology that increases a soil's capacity for storing water while at the same time allowing for minimum soil disturbance. This is because when planting pits are excavated in a field, they may be used for at least two seasons before farmers have to reshape the pits. Planting pits enable farmers to use small quantities of water and manure very efficiently, and are cost and time efficient (although labor to construct the pits can be a constraint). Pits are ideal in areas where rainfall is limited.

The following are the guidelines for pit planting that the project will employ. These guidelines were developed by the MoAFS Department of Land Resources Management.

Step 1: Site Selection

Identify a plot with relatively moderate slopes. If possible the site should be secure from livestock to protect the crop residues.

Step 2: Land Preparation

Mark out the pit position using a rope, and excavate the pits following the recommended dimensions (as shown in the table below). These should be dug along the contour. The soil should be placed on the down slope side. Stones may be placed on the upslope side of the pit to help control run off, but this is optional. If available, crop residues from the previous harvest should be retained in the field so there is maximum ground cover.

Pit dimension and spacing:

Spacing between pits	70cm
Spacing between rows	75cm
Depth	15cm
Length	30cm
Width	15cm

At this spacing, there will be 15,850 pits per hectare (158 pits per 0.1ha). Where rainfall is limited, pits can be made deeper and wider to make maximum use of rainwater.

Step 3: Planting, Manure and Fertilizer Application

The pit can be planted to maize crop at the spacing below:

Crop	Seeds/pit	Plants/ha
Maize	2	56,000

It is recommended that farmers apply 2 handfuls of manure in each pit. Two weeks before rainfall, apply manure and cover the pit with earth. If basal fertilizer is available, it can also be applied at the same time. When manure has been applied, the pits should be covered with soil. A shallow depression should still remain on top.

If top dressing is available, it should be applied when the maize is kneed high. In some areas, it may be after 21 days. Use the local area recommendations to calculate the right amount to be applied (refer to the *Guide to Agricultural Production in Malawi*).

Step 4: Weed Control and Pest Management

The pits must be kept free of weeds at all times. Weed as soon as the weeds appear and just before harvesting. This will reduce the amount of weeds in the following season. Use of herbicides to control weeds is optional.

Step 5: Harvesting

Remove the crop. Cut plants at base, leaving stems and leaves on the soil. The roots should not be uprooted; they should be left to decompose within the pit.

Increasing the Efficiency of the Pits

It is important to realize that the use of these pits alone will not produce the highest yields. For best results:

- Always incorporate crop residues, leaving a minimum of 30% of crop residue on the field.
- Apply manure generously.
- Protect crops from weeds, pests, and diseases.
- Always plant with the first productive rains.
- Grow crops in rotation; at least 30% of the cropped land should be planted to legumes.

Guidelines for Nutrient Management

Below are the guidelines to the nutrient management strategy the project will employ. These guidelines were developed by the MoAFS Department of Agricultural Research.

Step 1: Materials for Making Compost

The following materials are appropriate for making compost:

- Leguminous crop residues (Ground-nuts and Soyabean)
- Fresh leaves of leguminous trees
- Chopped maize stover (about 6 inches long)
- Animal or Chicken manure (Optional)

Mix three parts of leguminous biomass (crop residues and/or fresh leaves) to two parts maize stover

Step 2: Composting method

Put a layer of legume crop residue followed by a layer of stover then a layer of green leaves of legume tree repeat making the layers until the heap is 120 cm high. After constructing a set of three layers add 5 liters of water to moisten the materials.

After constructing the heap smear the wet earth around the heap covering the biomass. The materials should be kept moist throughout the composting period. After 60 days the manure is ready, remove the manure and keep them under shade

Step 3: Application method

Apply the manure at least two weeks before planting. Apply 3 kg of manure applied per 10 m ridge. Split open the ridge about 4 cm deep, spread the manure on the open ridge then bury the manure thus reconstituting the ridge.

Step 4: Planting

At the rain onset plant maize, one maize seed per planting hole on the ridge at a distance of 25 cm between planting holes.

Step 5: Use of Inorganic Fertilizer (optional, depends on availability)

- Use 23:21:0+4S for basal dressing. Apply fertilizer as dollop; make a hole about 3 cm deep between the maize planting hills.
- Apply 60 kg N/ha of 23:21:0+4S at a rate 2g per hole (cups to be calibrated to measure 2 g fertilizer).
- Apply the inorganic fertilizer one (1) week after maize germination

Knowledge Questions Administered in Household Surveys

Pit Planting	
Knowledge Question	***Correct answer (acceptable range)***
How far apart should the planting pits be?	70 cm (52.5 cm – 87.5 cm)
How deep should planting pits be?	20 cm (15 cm – 25 cm)
How wide should planting pits be?	30 cm (22.5 cm – 37.5 cm)
How long should planting pits be?	30 cm (22.5 cm – 37.5 cm)
How many maize seeds should be planted in each pit?	4
Should manure be applied?	Yes
How much manure should be applied?	2 double handfuls
After harvest what *should* be done with the stovers?	Maize plants cut off at base, leave roots to decompose in pit, stems and leaves used to cover the soil.

Chinese Compost	
Knowledge Question	***Correct answer (acceptable range)***
What materials should be used for Chinese composting?	leguminous crop residues, fresh leaves of leguminous trees, maize stoves, chicken or livestock manure
How much time should Chinese compost be let mature?	60 days (48 – 72 days)
How should Chinese compost be kept while it is maturing?	in a covered heap
Should it be kept in the sun or the shade?	Shade
Should it be kept moist or dry?	Moist
When should Chinese compost be applied to the field?	at least 2 weeks before planting

Appendix A3: Balance Tests

	p-value for ...								
Characteristic	***AEDO = LF***	***AEDO = PF***	***AEDO = Control***	***LF = PF***	***LF = Control***	***PF = Control***	***AEDO Incentives = Non-incentives***	***LF Incentives = Non-incentives***	***PF Incentives = Non-incentives***
Household head is male	0.538	0.375	0.702	0.0790*	0.799	0.165	0.924	0.188	0.68
Household head age	0.672	0.384	0.476	0.0818*	0.136	0.783	0.461	0.979	0.812
Household head's highest level of education completed (levels: 1-8)	0.428	0.504	0.0919*	0.847	0.202	0.153	0.5	0.435	0.284
House walls are made of burnt bricks	0.987	0.386	0.478	0.239	0.337	0.0527*	0.309	0.003***	0.712
House roof is made of grass	0.925	0.803	0.531	0.637	0.476	0.239	0.91	0.292	0.0819*
Number of animals owned by the household	0.927	0.476	0.812	0.475	0.704	0.309	0.685	0.118	0.167
Number of assets owned by household	0.0577*	0.391	0.336	0.202	0.341	0.846	0.547	0.953	0.175
Own farm is household's primary income source	0.588	0.246	0.958	0.0237**	0.461	0.152	0.833	0.329	0.0455**
Total household cultivated land 2008/09 (hectares)	0.18	0.0977*	0.581	0.633	0.516	0.32	0.878	0.906	0.947

Appendix A4: Differences in demographics between actual and shadow communicators

	LFs			PFs		
Characteristic	**Actual**	**Shadow**	**p-value**	**Actual**	**Shadow**	**p-value**
Household head is male	0.913	0.935	0.68	0.756	0.762	0.91
	(0.0449)	(0.0273)		(0.0434)	(0.0310)	
Household head age	40	41.33	0.75	41.07	43.85	0.23
	(3.381)	(2.436)		(2.089)	(0.929)	
Household head's highest level of education completed (levels: 1-8)	4.348	4.311	0.92	3.967	3.745	0.51
	(0.159)	(0.338)		(0.320)	(0.0979)	
House walls are made of burnt bricks	0.543	0.673	0.37	0.453	0.575	0.21
	(0.113)	(0.0900)		(0.0870)	(0.0449)	
House roof is made of grass	0.547	0.560	0.84	0.630	0.664	0.81
	(0.0813)	(0.0400)		(0.107)	(0.0815)	
Number of animals owned by the household	1.761	1.785	0.94	1.762	1.640	0.57
	(0.167)	(0.263)		(0.189)	(0.0985)	
Number of assets owned by household	5.457	5.879	0.56	5.287	5.564	0.43
	(0.451)	(0.562)		(0.253)	(0.239)	
Own farm is household's primary income source	0.935	0.888	0.57	0.729	0.873	0.19
	(0.0387)	(0.0727)		(0.107)	(0.0218)	
Total household cultivated land 2008/09 (hectares)	1.384	1.316	0.77	0.929	1.125	0.04
	(0.166)	(0.160)		(0.0830)	(0.0475)	

Standard errors clustered by village in parenthesis

Appendix A5: Perceptions of Communicators

	Honesty		Agricultural Knowledge	
	LF	PF	LF	PF
Incentives	0.0624	0.225***	0.142	0.309***
	(0.0926)	(0.0819)	(0.119)	(0.0951)
Village assigned to CF	-0.162***	-0.123	-0.184	-0.163***
	(0.0901)	(0.0807)	(0.117)	(0.0971)
Household has grass roof	-0.103***	0.0499	-0.144***	-0.0546
	(0.0458)	(0.0725)	(0.0656)	(0.0677)
Age of respondent	-0.0000604	0.000921	-0.00106	0.00399***
	(0.00112)	(0.00153)	(0.00182)	(0.00201)
Constant	3.669***	2.977***	3.478***	2.485***
	(0.196)	(0.177)	(0.24)	(0.181)
Observations	853	745	812	724
R-squared	0.018	0.025	0.025	0.037

Appendix A6: Yields after two years in PF villages

	Dependent variable: Household maize yield in 2010/11 season (winsorized at 95%)					
Technology	Pit Planting			Composting		
Estimation	ITT	ITT	IV	ITT	ITT	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive villages	298.1***	178.8***		66.11	38.18	
	(46.81)	(65.99)		(113.5)	(118.3)	
Baseline maize yield (winsorized at 95%)		0.107***	0.118		0.0633***	0.0658
		(0.0297)	(0.0695)		(0.0366)	(0.0385)
HH used pit planting on any maize plot for the 2010/11 season			5,020			
			(6,646)			
HH produced any compost during the 2010/11 rainy season						143.1
						(438.5)
Observations	425	358	358	532	432	432
R-squared	0.306	0.306		0.145	0.169	
Mean baseline yield		1678			1945	
Implied impact over baseline	17.8%	10.7%	299.3%	7.4%	3.4%	2.0%

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by village in parentheses. Sample is limited to PF villages. Columns 1, 2, 4, and 5 show results from OLS estimation. Columns 3 and 6 show instrumental variable regressions, where incentive eligibility instruments for technology adoption.

Appendix A7: Input Use and Pit Planting in PF villages

	Dependent variable: use of each input on any household plot											
	Used tool for land preparation		Used herbicide		Intercropped		Used manure		Used basal fertilizer		Used top dress fertilizer	
	ITT	IV	ITT	IV	ITT	IV	ITT	IV	ITT	IV	ITT	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Incentive village	0.112***		0.150***		0.170***		0.0773		0.0385		0.0720	
	(0.0469)		(0.0331)		(0.0480)		(0.0842)		(0.0509)		(0.0513)	
HH used pit planting in 2010/11 season		1.698		1.887		1.874		0.988		0.560		0.977
		(1.225)		(1.357)		(1.169)		(0.615)		(0.821)		(0.953)
District FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Regression	Probit	2SLS	Probit	2SLS	Probit	2SLS	Probit	2SLS	Probit	2SLS	Probit	2SLS
Observations	765	765	765	765	765	765	765	765	765	765	765	765
Mean of Dep. Var. In Non-incentive PF Villages	0.768		0.0134		0.117		0.132		0.582		0.587	

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses, clustered by village. Sample is all non-communicator HHs in PF villages where PP was promoted. ITT columns show average marginal effects from probit regressions. IV columns show 2nd stage coefficients with incentive village assignment as the instrument.

Appendix A8: Labor and Pit Planting in PF villages

	Dependent variable is total number of hours on all HH plots devoted to each type of labor											
Type of labor	Land preparation		Fertilizer Application		Planting		Weeding		Harvesting		Total	
	ITT	IV	ITT	IV	ITT	IV	ITT	IV	ITT	IV	ITT	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Incentive village	-6.474		-1.104***		-2.753		-0.192		-1.986***		-14.35***	
	(4.970)		(0.625)		(4.618)		(1.773)		(0.633)		(6.768)	
HH used pit planting on maize plot		-99.61***		-16.41		-38.35		-5.019		-299.0		-214.9***
		(56.46)		(11.84)		(46.90)		(43.95)		(1,489)		(108.2)
District FEs?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Observations	629	629	629	629	619	619	563	563	386	386	630	630
Mean of Dep. Var. In Non-incentive PF Villages	50		9.9		52		19		10.9		141	

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses, clustered by village. Sample is all non-communicator HHs in PF villages where PP was promoted. ITT columns show OLS coefficients. Instrumental variable columns show 2[nd] stage coefficients with incentive village assignment as the instrument.