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ABSTRACT

Low adoption of agricultural technologies holds large productivity consequences for developing countries. Agricultural extension services counter information failures by deploying external agents to communicate with farmers. However, social networks are recognized as the most credible source of information about new technologies. We incorporate social learning in extension policy using a large-scale field experiment in which we communicate to farmers using different members of social networks. We show that communicator effort is susceptible to small performance incentives, and the social identity of the communicator influences learning and adoption. Farmers find communicators who face agricultural conditions and constraints most comparable to themselves to be the most persuasive. Incorporating communication dynamics can take the influential social learning literature in a more policy-relevant direction.

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1. Introduction

Many agricultural technologies with demonstrated productivity gains, such as timely fertilizer application, 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 a 'passive' form of social learning, implicitly assuming that farmers costlessly observe the field trials of their neighbors with little friction in the flow of information, and then update their expectations about the technology's profitability.

While the existence of social learning has been well established in the literature, a natural next question is whether policies to promote new technologies can be improved by leveraging the power of social influence. This paper explores such strategies using a randomized controlled

[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 2013, Bryan, Chowdhury and Mobarak 2014, 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 behavior of social contacts has been the perennial empirical challenge with which this literature has grappled (Manski 1993).

trial (RCT) in which we vary the dissemination method 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.

We first document that providing incentives to communicators affects the flow of information in these villages. This implies that when we try to use social influence to promote new technologies, the transmission of information from one farmer to another ceases to be automatic. Communicating with others and convincing them to adopt may require costly effort, while the benefits are external. Existing models of passive social learning (Foster and Rosenzweig 1995, Bardhan and Udry 1999, Munshi 2004) ignore communication (since agents automatically observe neighbors' actions), but taking the literature in this policy-relevant direction requires us to explore communication dynamics. 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 is consistent with results from both psychology (Briñol and Petty 2009, Fleming and Petty 2000) and economics (Munshi 2004) on the role of similarity between senders and receivers of information in persuading the latter to adopt specific behaviors.

We do not attempt to influence specific actions by peer farmers, but we document strategies they use. In addition to communication effort, incentives induce peer farmers to adopt the technology themselves, and this has a demonstration effect, similar to the existing social learning literature. Adoption subsequently increases yields, and the magnitudes suggest that implementing the incentive-based communication strategies was cost-effective.

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 2014; Banerjee et al. 2013; Beshears et al, 2011; Duflo and Saez 2003), job information (Beaman 2012; Magruder 2010), health inputs (Kremer and Miguel 2007, Godlonton and Thornton 2012, Oster and Thornton 2012; Miller and Mobarak 2014), 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). The medical literature has also studied the use of opinion leaders and documented the differential role of local as opposed to external leaders (Doumit et al 2007, Keating et al 2007, Kuo et al 1998, Locock et al 2001). 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, and Libai 2001; Kornish and Li 2010)

For policy, the results suggest that 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 neighbors.

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 neighbors - may be a promising approach.

We made experimental design choices to remain policy-relevant for ministries of agriculture around the world, and the different communication arms (peer versus lead farmers) and incentive sizes were chosen to be budget-neutral from the perspective of the agricultural extension department. In the process, we compare five "average-looking" peer farmers to one wealthy, atypical lead farmer across experimental cells. Peer farmers are therefore most effective per dollar spent (the policy relevant metric for the ministry) rather than per agent. This implies that multiple mechanisms could explain the differing performance of peer farmers – their identity, differing scale of the task, or the need for coordination across communicators. Using variation in village size and social network data on relationships between communicators and target farmers, we explore each of these mechanisms in turn, and find that the data are most consistent with communicator *identity* – insofar as it affects the agronomic relevance of the information being transmitted to target farmers - playing a central role. Even in the subset of villages where we can hold 'communicators per capita' constant, incentivized peer farmers (PFs) out-perform all other comparison groups. Furthermore, the incentive effects (comparing PFs with and without incentives) are not subject to any such concerns about multiple mechanisms.

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 Section 5. In Sections 6, 7, and 8, we test for alternative mechanisms underlying our results. We study the impacts on target farmers' yields and inputs in Section 9, and offer concluding remarks about policy implications in Section 10.

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 (World Bank 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, AEDOs 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 AEDO 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 AEDO 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.

Guidance given to AEDOs specified that LFs selected should have the following characteristics:

(A) Identified by the community as a "leader"

(B) Early adopter of technology

(C) Literate

(D) May have more resources at his/her disposal to aid technology adoption (oxcart, access to chemical fertilizers or pesticides, more land)

The selection process involved the AEDO convoking a meeting with 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, and was then asked to announce his choice to the village, to ensure that the community endorses the new lead farmer.

Guidance given to AEDOs specified that PFs selected should have the following characteristics:

(A) Thought of by the community as ordinary, average farmer

(B) Must be willing to try the new technology, but is not necessarily a progressive farmer

(C) Not necessarily literate

(D) Similar to average farmers in the village in terms of access to resources.

The selection process for PFs again involved the AEDO convoking and facilitating a meeting with village members. The first step was to identify the important social groups in the village. The directions given included (a) the meetings must be well attended (including by those who may work with the extension agent most often), and (b) 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). Meeting participants from each group nominated one representative, and the list was pared down to five in consultation with AEDOs and village leaders. The nominated peer farmers had to state that they understood their role and responsibilities. They were then presented to the village for endorsement.

Selecting both lead and peer farmers involved village meetings, consultation with leaders etc, and the approaches followed were not fundamentally different from each other. Furthermore, both lead and peer farmers were identified in *all* villages using the 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 AEDO 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 AEDOs to partner communicators), on the effort expended by these communicators, and their own adoption.

We collected baseline data on all communicators to assess how the characteristics of chosen LFs and PFs differed. Table 1 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 LFs and the general population in all of these dimensions, and they are slightly better off than the general population. The data therefore verifies proper implementation of the experimental design, and motivates a key aspect of the theoretical setup: that PFs are more similar to the target farmers than are LFs.

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 2 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 favorably: they are more highly rated in terms of trustworthiness and farming skills.[4]

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 similar 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 have somewhat greater

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

social stature than do PFs, but—partly as a result—have agricultural experiences that are further from those of the average respondent.

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 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 physical 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 AEDO) in order to preserve comparability to the treatment villages. The AEDOs 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 99 tests, we find differences that are significant at the 5% level, consistent with standard sampling differences; we find no significant differences across in baseline adoption rates across any of our treatment arms.

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 these experimental results first, before using variation in village size and in social network relationships to unpack the likely mechanisms at play. The data ultimately strongly support identity playing a central role, and the framework we present in section 3 highlights the role of identity in generating variation in performance across treatment cells.

The three different communication strategies were designed to be budget neutral from the perspective of the Ministry of Agriculture, so that the communication bundles represent useful comparisons, irrespective of the specific mechanisms at play. The AEDO receives the same salary across all arms. For the incentive treatments, each communicator type was to receive a specific award type (AEDOs 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. Finally, the incentive effects we document (comparing PFs with and without incentives or LFs with and without incentives) represent clean experimental estimates where the questions about multiple potential mechanisms are not relevant.

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 AEDO 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. Both the theory and the treatment effects we estimate suggest "similarity" between communicators and target farmers is a key mechanism at play, and our network data allows us to delve deeper to explore the dimensions in which identity and similarity are most relevant.

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 hand weeding or herbicide requirements may therefore increase. 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.[5] 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).

[5] 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.

The baseline levels of awareness and adoption of pit planting were quite limited in our sample. 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 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.[6] 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 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 $q_\theta = 1 - (k_\theta - k^*)^2$.[7]

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.

[6] 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.

[7] 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^*.

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:

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

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 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. We also collected information on all actual and shadow communicators' own technology adoption decisions.

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) 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 collected 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.[8] 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 favor of treatment villages (where they could win incentives), at the expense of control villages where they also should have been spending some time.

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

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.

During the first year, adoption is measured primarily using knowledge gains. 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[9] 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 3.

5. Empirical Results

5.1 Incentives and communicator retention of knowledge

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

The theory predicts that performance incentives increase communicators' own willingness to acquire the information presented, and relay the signal ($s_{x\theta}$) to their neighbors. To examine this prediction empirically, we test all communicators during the first follow-up survey on how 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.[10]

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. For ease of exposition, we run this regression separately for the two sub-samples of villages where incentives were or were not offered (results look the same when samples are combined and interaction terms between communicator type and incentives are used). 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 AEDOs, and assigned the task of communicating) do not perform as well as lead farmers without incentives, and their

[10] The shadow communicators are also statistically similar across treatment arms (e.g., shadow LFs in AEDO treatment villages are similar to shadow LFs in PF and control villages); these results are available on request.

performance is more comparable to shadow lead farmers who are not directly trained by AEDOs. 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.

5.2 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. 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.[11] 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 AEDOs (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.

5.3 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

[11] 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.[12] 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

[12] 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.

6. Alternative Mechanisms underlying the Peer Farmer Performance

Apart from the difference in identity, the peer and lead farmer treatments vary in a few other dimensions that could account for 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 lead to several alternative hypotheses that could explain various portions of our results: (1) scale effects from having five communicators rather than one; (2) non-linear effects of the incentives; (3) the joint-ness of the incentives could induce PFs to coordinate, collaborate, or otherwise influence one another to induce greater effort; (4) different wealth of LFs and PFs could induce differential response to the incentives; and (5) differing product market competition between LFs and PFs could similarly affect incentive-responsiveness.[14] We first

[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.

[14] These alternatives do not necessarily undermine what we learn from this experiment. The treatment arms were designed to be budget-neutral, and the superior PF performance per dollar spent contains valuable policy lessons.

explore these alternatives – for which we do not find strong support in the data – before delving deeper in the next section into the type of identity that matters most.

First, we consider whether variation in the number of communicators across the LF and PF arms can explain their relative performance. Any simple model that suggests that a larger number of communicators increases total effort or the precision of the information transmitted (a la Conley and Udry 2010) is unlikely to explain the data well, because PFs out-perform LFs in the incentive sample, while the converse is true in the non-incentive sample. Nevertheless, we can use natural variation in population size across our sample villages to directly control for such scale effects. Moreover, the random assignment of LF and PF communicators to villages of varying size creates an overlapping sub-sample where the communicators per capita are roughly constant across LF and PF villages. We can compare LF and PF performance in this sub-sample, holding scale constant.

Table 8 compares the adoption rate amongst target farmers across LF and PF villages, while directly controlling for scale effects using a measure of 'communicators per capita'. Communicators per capita does not have a significant effect on technology adoption, and our main finding continues to hold: when incentives are provided, the peer farmer based communication strategy leads to 18.4 percentage points greater technology adoption. Without incentives, there is zero difference in adoption between LF and PF villages, controlling for scale.

The last two columns re-examines these same questions for the subset of villages where the communicators-per-capita across LF and PF treatments overlapped on a common support (large PF villages combined with small LF villages). Incentivized PF villages experience 23 percentage point greater technology adoption than incentivized LF villages in this sub-sample. There is again a zero difference in the sub-sample without incentives. Taken together, all these results suggest that identity is a key mechanism underlying LF-PF differences even after controlling for scale effects.

Figure 3 looks directly at the effects of scale separately in the LF and PF villages with and without incentives, using variation in village size. Throughout, we find only very weak correlation of communicators per HH and adoption rates – and a negative correlation in the incentivized PF arm, which is associated with the largest rates of adoption.

Second, we consider whether non-linearities in our incentive offers could drive the differential effort and adoption effects that PFs exhibit relative to LFs. 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.[15] Recall that performance for purposes of our incentives was based on percentage point gains and not levels, and thus was independent of village size. We can 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 9. Columns 1 and 2 show that incentives for LFs do not affect adoption in 'small' villages with fewer than 65 households (the median in our sample) or even 50 households. In PF villages, however, we observe sizable effects of incentives even in 'large' villages with greater than 65 households (column 3) or 100 households (column 4).

It is also possible that the joint-ness of the incentives for PFs could induce teamwork or other peer effects among these groups. On the other hand, it could lead to 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 settings, joint incentives could lead individuals to coordinate and monitor one another. To test whether such joint-ness is driving the differential response of PFs, we compare villages where PFs were closely linked to one another at baseline to villages where PFs were not closely linked. We estimate:

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

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

The variable $PF\ Links_{vd}$ in this equation represents three different measures of the average likelihood that each PF is related to, in a group with, or talks daily with every other PF in the same village. These measures capture the share of strong bilateral relationships between PFs. In columns 5-7 of Table 9, 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.

As another alternative explanation for the differential responses of LFs and PFs to the incentives we provide, we consider whether the differences in wealth levels between LFs and PFs (typically associated with differing marginal utility from additional payments) are related to differing incentive-responsiveness. To do so, we control for the assigned communicators' housing conditions and educational attainment in estimating the effects of incentives on LFs and PFs. The results, shown in Appendix A6, indicate that within both LF and PF treatment arms, the effects of communicator wealth are larger in incentive villages rather than smaller. PFs continue to differentially respond to incentives, even after we control for the interaction of incentives and communicator wealth proxies. These results suggest differences in marginal utility are unlikely to drive our main results.

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 LFs and PFs 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. 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 1 and 2 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 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 10.

As there are five PFs in each village, our respondent-level measure of proximity is defined as the mean of the proximity to each of the PFs. The results are largely unchanged when we use maximum values (i.e., the respondent's relationship to the 'closest' PF), or median values.

The specifications in Table 10 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* or similar farm" to proxy for comparability. [16] 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. In other words, what types of target farmers are most convinced by the PF, and amongst what types of targets do incentives play the biggest role in enhancing the PFs success in persuasion? Table 11 shows results on the PF effect on technology adoption amongst different types of targets separately for incentive and non-incentive villages, and conducts a statistical test of differences across the two types of villages.[17]

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[16] This can be interpreted as the share of households who had larger farms than each PF, averaged over all of the PFs in the village. The variable is constructed based on respondents' perceived comparability with each PF. These perceptions are well correlated with actual relative farm sizes of respondents and PFs, which we also measured.

[17] 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

As before, similarity between target farmers and PFs is measured using the mean value of proximity, averaged across all five peer farmers.[18] There are two notable sets of results that emerge. The first, which is in some ways less interesting, is that immediate family members of the PF adopt regardless of whether an incentive was offered (see column 3). The second result is that the provision of incentives has a greater *marginal* effect on adoption amongst farmers who are more comparable to the PF in terms of land size and use of agricultural inputs. The first two columns show that when the PF is provided incentives and puts in more effort to convince others, target farmers with agricultural conditions similar to the PFs are the ones most likely to be persuaded. These results, coupled with our model's prediction on the types of communicators expected to respond to incentives, imply that agricultural comparability and relevance is a key determinant of success in communication.

The other columns show that peer farmers provided incentives are no more persuasive with their own extended family members, or those who are similar in terms of educational attainment or wealth or other socio-economic characteristics. There is a differential incentive response for group members, for whom the cost of communication might be lower. When we include all these characteristics simultaneously in a single regression, farm size similarity 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 suggest that agricultural comparability matters most. These findings are closely related to the Munshi (2004) result that heterogeneity in agricultural conditions impedes social learning. Munshi (2004) uses natural variation in rice growing conditions to derive this result, while we use direct reports from farmers on their bilateral comparability with communicators.

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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.

[18] As above, the results are qualitatively similar when considering the maximum values in linkages between a respondent across any of the five PFs, rather than the mean across all PFs.

8. Communication or demonstration?

We have shown that incentives induced peer farmers to put in more effort to communicate with others. It could have also induced more experimentation by the PFs on their own farms. This section explores whether PFs and LFs pursued such a 'demonstration' strategy, and then, whether communication effort or demonstration was crucial to persuading others.

Columns 1 and 6 of Table 12 show that the incentive treatment raised each communicator's propensity to adopt the assigned technology herself, and that this effect was stronger for PFs. The other columns in the table explore whether the communicators' use of the technology is correlated with others' use. We run OLS regressions (columns 2,3,7,8), and IV regressions (columns 4,5,9,10) where the randomized incentive treatments. Instrument for communicators' won adoption We control for other types of communicator effort (which also responded to incentives) directly in some specifications to check whether demonstration or communication effort was more successful in convincing others.

Lead farmers' own adoption is not robustly associated with others' adoption, especially when other aspects of LF effort are controlled for. LF demonstration does not appear to be important for the target farmers' decisions. In contrast, peer farmers' own experimentation with the technology appears crucial for convincing others to try. In both OLS and IV specifications, peer farmer demonstration has large and statistically significant effects on others' adoption, even after controlling for other dimensions of PF effort.

It is impossible to convincingly disentangle the informational channels in our setup, but these results are consistent with peer farmers not only relying on "soft" information to convince target farmers, but instead transmitting key information via their own actions. This suggests that PFs were not only teaching others about the methods to apply the technology, but also trying to signal its profitability. Our results on dissemination and learning are therefore closely related to the social learning literature (Foster and Rosenzweig 1995, Munshi 2004, Conley and Udry 2010) even though we pursued an active intervention strategy rather than rely on passive learning.

9. 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 we introduced (that impose new incentive and monitoring costs for the Malawi Ministry of Agriculture).

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 A7, 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 A7, 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 A8 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 A9, 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.[19] Continued use of pit planting among adopting households—or even expansion to additional households in these villages—would raise this ratio considerably.

10. Conclusions

Vast and important literatures across the social sciences have convincingly demonstrated that social learning is an important mechanism for the transmission of information and behaviors. Our experiment attempts to leverage these important insights for policy. In doing so, we document that communication dynamics between agents are important determinants of information dissemination. Social learning models can likely 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,

[19] We focus on yields and revenues rather than profits, because the increase in herbicide cost associated with pit planting is counter-balanced by the decrease in labor costs, and the cost side is awash.

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 AEDO 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). Many development, NGO and private sector marketing efforts rely on "opinion leader" based dissemination strategies (Miller and Mobarak 2014), including "early adopter" models favored by extension efforts, but these may result in lower levels of social learning and adoption than making 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.

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Figure 1: Intervention, Data Collection, and Agricultural Calendar

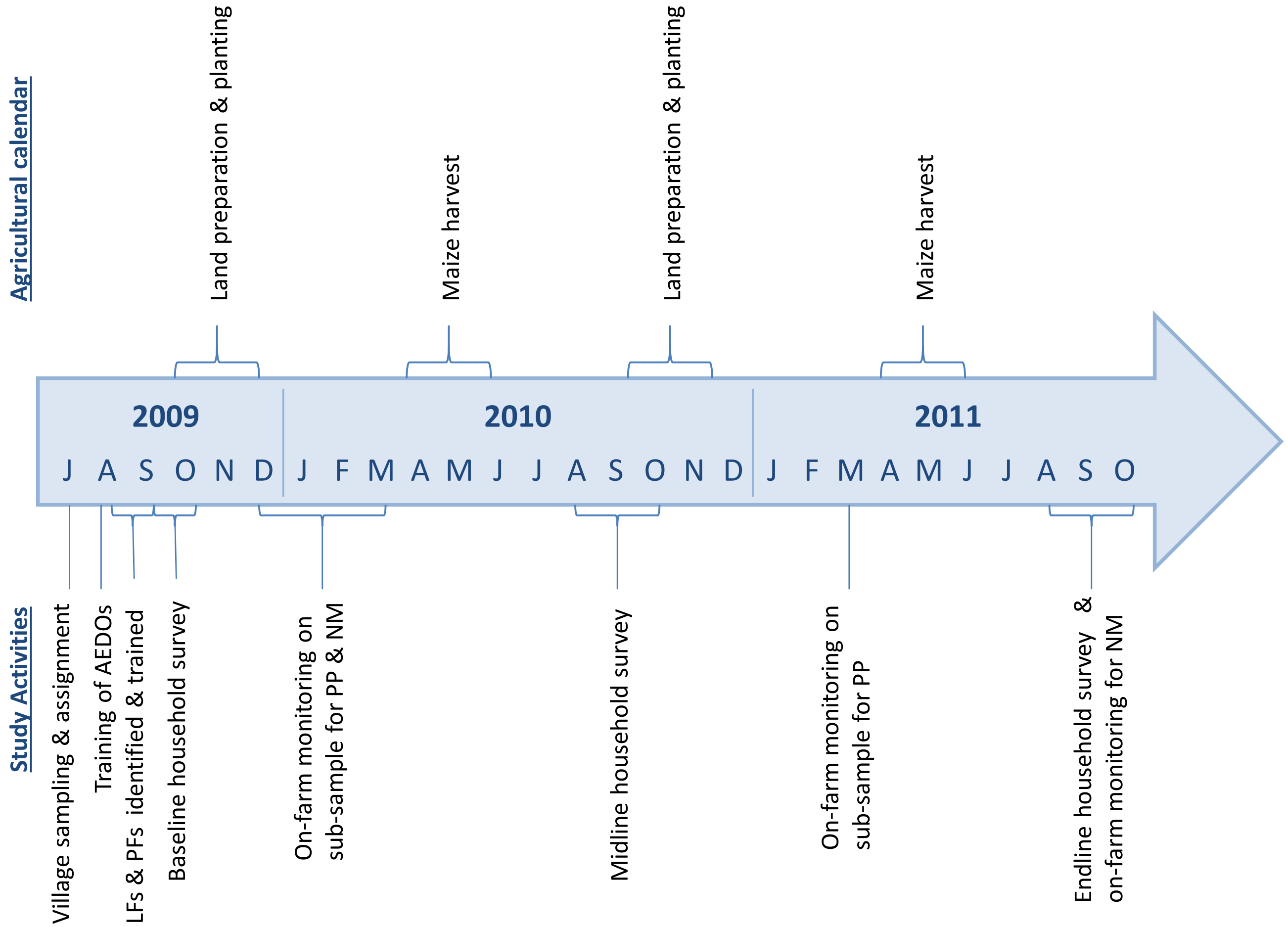


Figure 2: Treatment Arms

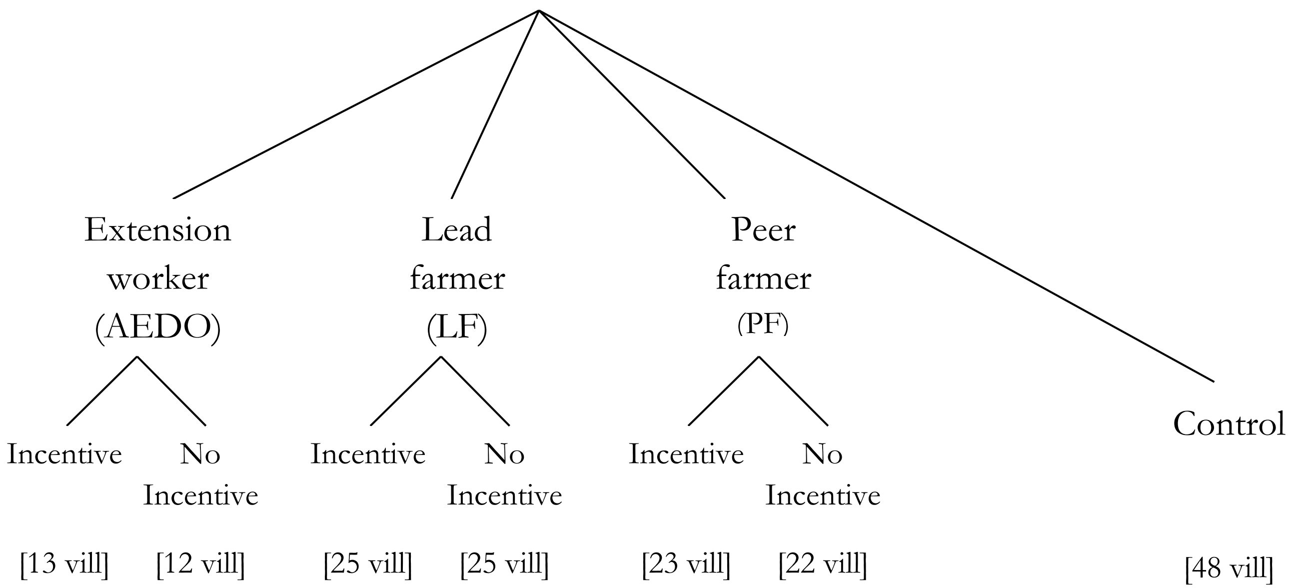
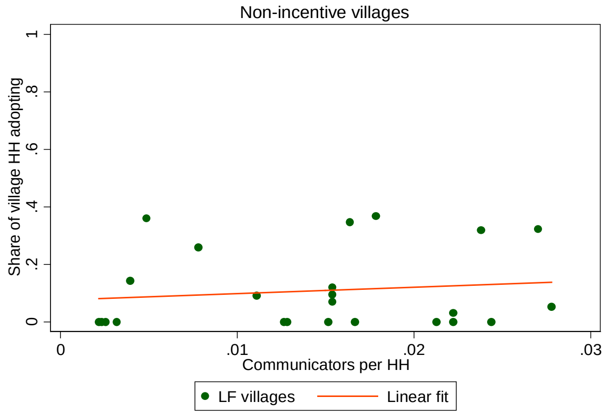
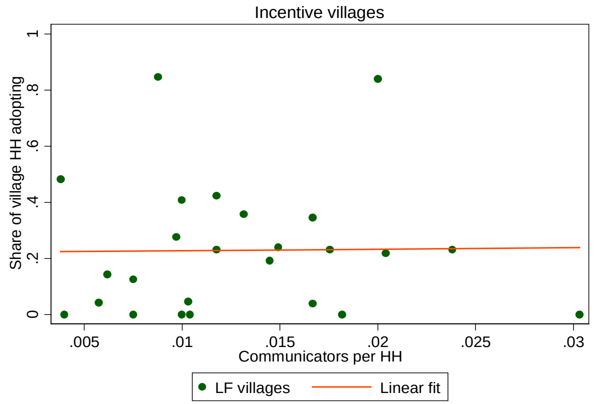


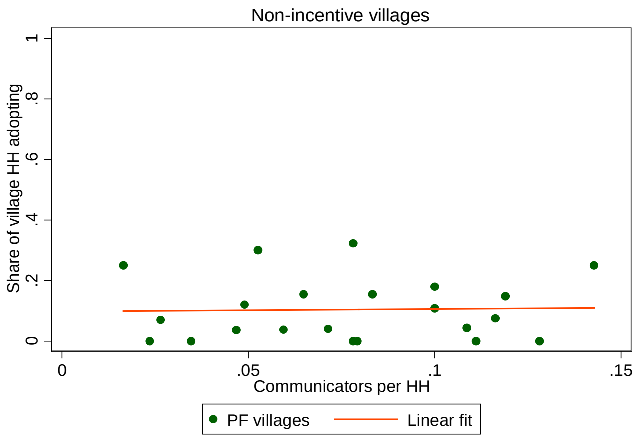
Figure 3: Share of village adopting technology vs. communicators per household

LF Villages





PF Villages



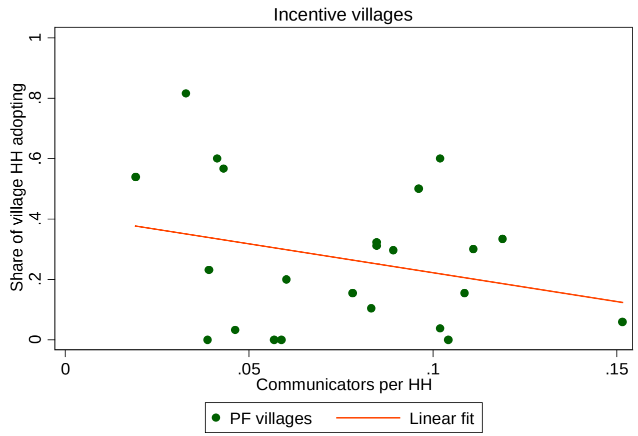


Table 1: Differences in demographics between communicators and the general population

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 2: 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]ɨ	3.58	3.45	0.134***
	(0.464)	(0.457)	(0.0587)
Farming skill rating [1-4]ɨ	2.88	2.71	0.175***
	(0.0798)	(0.0662)	(0.0600)

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

Table 3: 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 4: Knowledge Retention by Communicators (Acquiring and Sending A Signal in the Model)

	Dependent variable: Communicators' Knowledge scores			
	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)
Pit planting 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
Incentivized actual = Non-incentivized actual				
Mean of Dep. Var. for Shadow PFs	0.219	0.209	0.200	0.191
p-value for incentive = non-incentive				
Actual LF	0.451			
Actual PF	0.0375			

*** 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.

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

*** 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.

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)
Pit planting 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-value for incentive = non-incentive				
AEDO			0.064	0.026
LF			0.914	0.725
PF			0.025	0.023

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. 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.

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-value for incentive = non-incentive								
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

*** 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.

Table 8: Communicators per HH

	(1)	(2)	(3)	(4)
Dependent variable	Household adopted target technology in 2010/11 season			
Sample	All LF and PF villages		Common support	
Incentives?	Non-incentive	Incentive	Non-incentive	Incentive
PF village	-0.00232	0.184***	0.000882	0.232**
	(0.0466)	(0.0613)	(0.0433)	(0.106)
Communicators per HH	-0.318	-0.965	-3.379**	-5.633
	(0.573)	(0.969)	(1.501)	(5.246)
Pit planting district	-0.208***	-0.303***	-0.239***	-0.334***
	(0.0399)	(0.0379)	(0.0740)	(0.0668)
Observations	1,588	1,387	570	505
R-squared				
Mean of Dependent Var in LF	0.113	0.210	0.123	0.185
common support min	0.0526			

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered by village in parentheses. Cols 1-4 estimated via OLS; cols 5-8 estimated via probit, with average marginal effects shown. Common support sample (cols 3-4 and 7-8) is limited to villages where communicators per capita is between the minimum value for PF villages and the maximum value for LF villages.

Table 9: 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.

Table 10: Heterogeneity in PF-Incentive Effects Across Measures of Social Proximity

Dependent variable: Household adopted target technology in 2010/11 season	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	Full set of interaction terms
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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 or equal farm as respondent)	0.321***								0.363***
	(0.191)								(0.200)
PF treatment X mean(PF uses fewer or similar inputs as 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 11: Types of Target Farmers Persuaded by PFs with and without Incentives

	Dependent variable: Household adopted target technology in 2010/11 season							
	Agricultural comparability		Social Links				Poverty	
Baseline village mean of:	PF has smaller farm than respondent	PF uses same or fewer inputs than respondent	PF in immediate family	PF in extended family	PF in group with respondent	Respondent talks daily with PF	PF educational attainment	PF house has grass roof
Average marginal effect of characteristic for:								
Non-incentive villages	-0.143	-0.0504	0.430***	0.170	-0.00245	0.0853	0.001	0.005
	(0.186)	(0.134)	(0.258)	(0.107)	(0.127)	(0.107)	(0.015)	(0.079)
Incentive villages	0.240***	0.253***	0.410	0.0402	0.317***	0.134	-0.015	-0.008
	(0.0955)	(0.139)	(0.385)	(0.125)	(0.113)	(0.102)	(0.015)	(0.070)
p-value for incentive village X characteristic	*0.088*	*0.137*	*0.965*	*0.413*	*0.101*	*0.759*	*0.467*	*0.893*
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. Specifications include controls for 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 12: Communicator Adoption

Estimation:	OLS	OLS	OLS	IV	IV	OLS	OLS	OLS	IV	IV
Dependent variable:	Comm used tech (0/1)	Non-comm HH used tech				Comm used tech (share of PFs)	Non-comm HH used tech			
Communicator:	LF	LF	LF	LF	LF	PF	PF	PF	PF	PF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Communicator used technology		0.0838**	-0.0169	0.516	1.264		0.286***	0.237***	0.522***	0.590**
		(0.0406)	(0.0676)	(0.388)	(2.815)		(0.0551)	(0.0512)	(0.131)	(0.234)
Communicator knowledge score			0.104		-0.220			0.000206		-0.258
			(0.0714)		(0.704)			(0.0761)		(0.197)
Communicator held at least one activity			0.293*		-0.626			0.256***		0.125
			(0.156)		(2.070)			(0.0682)		(0.129)
Incentive village	0.211					0.409***				
	(0.130)					(0.0880)				
Pit Planting district	-0.578***	-0.215***	-0.305***	0.0438	0.542	-0.331***	-0.126***	-0.166***	-0.0709	0.0391
	(0.133)	(0.0429)	(0.0597)	(0.256)	(1.887)	(0.0825)	(0.0427)	(0.0559)	(0.0567)	(0.139)
Observations	1,132	1,132	1,007	1,132	1,007	1,415	1,415	1,415	1,415	1,415
R-squared	0.405	0.125	0.168	-	-	0.381	0.137	0.161	-	-

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

Characteristic	*p-value for ...*								
	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 used pit planting on at least one plotin 2008/9 [1]	0.609	0.730	0.778	0.329	0.767	0.461	0.858	0.113	0.378
Household used any composting in 2008/9 [2]	0.408	0.381	0.584	0.912	0.867	0.819	0.945	0.929	0.447
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

[1] Sample limited to pit planting districts; [2] Sample limited to composting districts; Sample in all other rows includes all districts. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by village in parentheses. All tests based on comparisons of means controlling for district fixed effects.

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

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix A6: Communicator wealth

Dependent variable	Household adopted target technology in 2010/11 season					
Sample	All LF and PF villages					
Incentives?	Non-incentive	Incentive	Non-incentive	Incentive	Non-incentive	Incentive
	(1)	(2)	(3)	(4)	(5)	(6)
PF village	-0.0330	0.111**	-0.0357	0.0727	-0.0161	0.0886*
	(0.0322)	(0.0443)	(0.0374)	(0.0609)	(0.0229)	(0.0509)
Communicator education			-0.0319***	-0.0255		
			(0.0116)	(0.0205)		
Communicator has grass roof					0.145***	0.0414
					(0.0414)	(0.0555)
Observations	1,588	1,387	1,588	1,387	1,588	1,387
Mean of Dependent Var in LF	0.113	0.210	0.113	0.210	0.113	0.210
p-value on PF village incentive = non-incentive		0.01		0.136		0.061
p-value on comm. char. incentive = non-incentive				0.783		0.139

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered by village in parentheses. All columns estimated via probit, with average marginal effects shown.

Appendix A7: 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 A8: 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 A9: 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 2nd stage coefficients with incentive village assignment as the instrument.