Communicating with Farmers through Social Networks

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Abstract

Adoption of agricultural technologies remains surprisingly low in many African countries, despite productivity gains demonstrated in laboratory or field trials. Theoretical and empirical studies in economics and sociology argue that social networks are the most persuasive source of information about new products and behaviors, but governments in developing countries continue to rely on extension services – usually a set of external agents – to communicate with farmers about new technologies. We conduct a field experiment with the Malawi Ministry of Agriculture where extension workers are partnered with key members of social networks to teach farmers about two agricultural technologies. These agents are sometimes provided performance incentives. We find that the provision of small incentives to communicators matters a lot for generating learning and adoption, which suggests that communication dynamics not captured in existing theories of social learning in agriculture (which typically assume automatic transmission of knowledge) are important. We delve into the details of knowledge transmission, and find that the identities of the communicator and the receiver and the nature of their relationship are important, and their actions and effort are susceptible to small financial incentives. It is most productive to incentivize communicators who are most similar to the target farmers.

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1. Introduction

Adoption of key agricultural technologies remains low in many African countries, despite large demonstrated gains from technologies such as efficient and timely fertilizer application, organic composting, and reduced tillage planting techniques. Recent work by Conley and Udry (2010) indicates that social learning about these technologies may play an important role in their adoption, as farmers update their expectations of a technology's profitability based on the experiences of other farmers under similar conditions to their own. Other studies—most notably Duflo, Kremer and Robinson (2011)—find little evidence of this social learning when these technologies are promoted by external organizations. This is consistent with a meta-study by Waddington et al (2012) that finds very weak social effects from farmer training in field school settings. Why these contrasting results arise represents a crucial puzzle in understanding whether social learning can be harnessed to increase the adoption of key technologies.

To address this puzzle, we ask whether the extent of learning depends on the identity, incentives, and effort of the individuals to whom this knowledge is first disseminated. Specifically, we pose two key questions: (1) Does the extent of this learning vary when the information is disseminated by individuals of different social stature? (2) Can relatively small differences in incentives for dissemination of these technologies generate significant differences in social learning? More broadly, we seek to understand whether social learning be harnessed to cost-effectively increase the adoption of key technologies.

To answer these questions, we utilize a field experiment in which agricultural extension workers and individual farmers in Malawi were trained on a technology and, in some cases, incentivized to disseminate this information to other farmers. The experiment varied the social position and gender of the individual farmers trained and designated as primary communicators. While "lead" farmers who are better educated and better able to sustain experimentation costs might transmit technical information about our targeted technologies, messages delivered by "peer" farmers who are more representative of the general population may be more trusted or more applicable to the recipient's own conditions. To test whether these farmer communicators can effectively transmit knowledge and increase adoption—and whether the relative social positions of these communicators matters—we randomly varied the assigned main communicator in each of 168 villages. These individuals were trained in November of 2009; we examine the knowledge of the targeted practices among a random sample of other farmers in the communicators' villages in June-August of 2010, as well as the usage of these practices in June-October of 2011. To identify communication patterns that result from this exogenous introduction of the information, our experiment includes a set of detailed questions on each farmer's relationships with the designated communicators and a random subsample of other farmers in her village.

Conley and Udry (2010) show the effect of informational links between early adopters and other farmers, but this need not be the optimal dissemination path to maximize a technology's adoption. We describe the pattern of communication in village social networks that result when information is introduced to an exogenously determined household type. Understanding this variation in communication patterns resulting from varying types of communicator types is important if the frequency and credence of communication varies across individuals of different stature or other characteristics. We therefore track this information flow across farmers to different genders, poverty status and education levels.

We also recognize that, as in the provision of many public or quasi-public goods, social learning is often heightened when communicators receive incentives to do so. Such incentives may increase the communicators' effort level but, if they are widely known, may also undermine his credibility. We test which of these effects dominates by providing incentives to a randomized subset of communicators for raising knowledge and adoption among others in their village.

This work builds on several other related strands of literature. The literature on agricultural technology adoption decisions is a lengthy one, tracing back at least to Grilliches (1957). Empirical estimation of peer effects in this literature has been a perennial challenge, as correlation among social contacts is difficult to distinguish from actual communication and decisional linkage—the reflection problem highlighted by Manski (1993). More recently, Foster and Rosenzweig (1995) and Munshi (2004) highlight the role of heterogeneity in spurring social learning, as farmers with larger land holdings experiment and generate knowledge spillovers for poorer neighbours.

Beyond agriculture, a growing literature has shown that social relationships are an important vector for the spread of information in a variety of contexts, including job information (e.g., Beaman 2011, Magruder 2009), deworming (Miguel and Kremer 2007), HIV testing (Godlonton and Thornton 2009), and menstruation cup use (Oster and Thornton 2009). Recognizing the potential for peer-based promotion implied by these networks, a number of papers have also examined the impact of promoters or ambassadors who are meant to be more representative of and better connected to the general population in which the behavioural change or technology adoption is anticipated (e.g., Kremer et al 2009).

Our work also aims to make a direct policy contribution by identifying the extent to which traditional agricultural extension services can be cost-effectively supplemented through existing social networks. As many as 400,000 extension workers are currently employed in developing countries, primarily by governments who have seen extension as the primary mechanism for raising agricultural productivity (Anderson and Feder 2007). As Anderson and Feder (2007) note, this may "well be the largest institutional development effort the world has ever known." However, the impact of these efforts has been mixed at best: A recent synthetic review by Waddington et al (2011) of farmer field schools—one of the leading models of extension—finds that such schools can raise the yields of the relatively small number of participants but do not translate into broader productivity improvements among other village members, and thus are unlikely to meet cost-effectiveness benchmarks.

Moreover, the state of the sector in many developing countries leaves much to be desired, with insufficient funding and qualified personnel. Unofficial estimates in Malawi place the share of public extension positions that are filled at approximately 50%, with each extension worker in our sample 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 is a vital challenge for governments of many developing countries.

This paper is laid out as follows: in section 2, we discuss the context of agricultural learning in Malawi. We next lay out our study design in section 3, and detail the technologies disseminated in section 4. We discuss our data collection efforts in section 5, and assess the characteristics of the communicators in section 6. In section 7, we lay out our results on knowledge gains after one agricultural season, and parse out the effects along the information transmission path in section 8. We detail our findings on adoption in section 9. Finally, we conclude in section 10.

2. Context

Our experiment takes place in eight districts across Malawi[1]. Approximately 80% of Malawi's population lives in rural areas and agriculture accounts 31% of Malawi's GDP (WDI 2011). Agricultural production and policy is dominated by maize.[2] 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 recently been subject to extensive policy attention.

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

Partly in response to this shortage, MoAFS had begun encouraging its AEDOs to select and partner with "lead farmers" in each village, as these farmers would reduce AEDOs workload by training other farmers in some of the technologies and topics for which AEDOs would otherwise be responsible. Lead farmers (LFs) are selected by an AEDO in consultation with a community (sometimes by election among a shortlist of candidates

[1] The study districts are: Balaka, Chikwawa, Dedza, Mchinji, Mzimba, Neno, Rumphi, and Zomba.
[2] 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).

identified by an AEDO). MoAFS guidance to AEDOs for selecting LFs indicates that they should be progressive, well-educated farmers known to be early adopters of technologies.

No formal MoAFS guidance existed on the use of other types of partner farmers to extend an AEDO's reach (or reduce his workload), particularly not on the use of a more representative set of farmers to do so.

Our study tests the effectiveness of these extension worker and lead farmer-based channels for disseminating knowledge and adoption of pit planting and composting. We also assess the effectiveness of an alternative farmer-led dissemination channel: 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. Study Design

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

(a) AEDO only
(b) LF (supported by AEDO)
(c) PFs (supported by AEDO)

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

For the LF treatment arm, the following guidance was given to AEDOs for the selection of LFs:

1. The AEDO convokes a meeting with local leaders and community members to identify a short list of potential lead farmers.

2. The AEDO selects one of the farmers on the short list to be the lead farmer, in consultation with village leaders.

3. The AEDO announces his choice to the village, to be sure that the community will endorse the new lead farmer.

The following guidance was given for the selection of five PFs:

1. The AEDO convokes and facilitates a meeting with all village members to identify five farmers that represent different social groups in the village, and who are willing to try out the new technology. The meetings must be well attended, many different farmers must attend (including by those who may work with the extension agent most often), and there should be representatives from all the different social groups in the village (males, females, elders, adolescents, people from different clubs or church groups, etc).
2. Participants at the meeting identify the different important social groups in the village, and each group nominates one representative. From the group of people nominated as potential peer farmers, meeting participants working together with the AEDO and village leaders to narrow the group down to five, while ensuring that the five represent different groups.
3. The farmers nominated by the community agree that they understand their role and responsibility as a peer farmer, and they are presented to the village for endorsement.

The second treatment type involved random assignment into the following groups:

(a) Additional incentives for performance
(b) No additional incentives for performance (beyond private incentives of communicator)

We defined performance in terms of village-wide knowledge gains in the first year of the program and adoption gains in the second year. In the first year of the program, each communicator 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. Each communicator type was to receive a specific award type (extension officers received bicycles, lead farmers received a large bag of fertilizer, and peer farmers each received a package of legume seeds), but the maximum total value of rewards for each village was specified as 12,000 MWK (roughly US$80). Where no additional incentives are provided, communicators face their own private incentives for communication.

Our study sample includes 168 villages that were randomly assigned villages into one of four primary communication arms: (1) Extension worker [AEDO] (25 villages,), (2) lead farmer [LF] (50 villages), (3) peer farmers [PF] (45 villages), and (4) control (48 villages). Each of the three communicator arms was then further assigned into incentives-based groups, with 50% of villages assigned to the additional incentive group (or 50%+1, in the case of non-integer group sizes). In our control group, extension workers continued to operate as they normally would, but with no additional training on pit planting or composting. Our treatment arms are described in Figure 1.[3]

[3] In a separate study, we introduced cross-cutting treatments that vary the gender of the LF and PFs assigned to each village.

4. Technologies Disseminated

The intervention we study involves the promotion of two technologies aimed at improving maize yields: pit planting and "Chinese composting". Pit planting involves planting seeds in a shallow pit in the ground, serving as an effective strategy to retain moisture for the plant while minimizing soil disturbance. Appendix A1 describes the technique specifications as disseminated. In contrast to pit planting, ridging has been the conventional method of land preparation in Malawi, in part because it was compulsory under the Hastings Kamuzu Banda regime (Banda 2007). However, ridging depletes soil fertility in tropical areas, and has created a decrease in 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. Pit planting does involve additional costs compared to ridging; as only a small portion of the surface is tilled, extensive hand weeding or herbicide application is required. 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).

Once maize crops are harvested, crop residues can serve as useful materials for compost manure and mulch (again, described in further detail in Appendix A1). 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 (Mughogo 1992, Stoorvogel, Smaling and Janssen 1993). Studies of compost application in Malawi—the country of focus of this project—indicate soil fertility improvements and substantial returns on maize plots (Mughogho 1992, Nalivata 1998, Sakala 1998, Mwato et al 1999, Nyirongo et al 1999, Mhango 2002, Nkhuzenje 2003, Kumwenda and Gilbert 2003).

Despite the large returns observed in other studies from these technologies, the baseline levels of awareness and adoption in our sample were quite limited. Pit planting is a relatively new technology in Malawi, and only 12% of respondents in our control villages had heard of the technology at baseline. Many 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% around the recommended dimensions), and only 11% knew the correct amount of manure to apply per pit. Partly as a result, only 1% of the respondents at baseline reported having ever used pit planting, and the share of respondents who had reported pit planting with specifications close to the recommended guidelines (i.e., within 25% of the correct dimensions) was not statistically different from zero.

Moreover, knowledge of pit planting was cited as the most frequent reason for non-adoption: 85% 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: 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 (with similar shares of respondents knowing the length of time until maturity and that the compost should be keep moist). Other features of composting were more broadly known at baseline (it should be stored covered and under shade and applied to the field prior to planting), likely because these are common to other types of compost as well.

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 (rather, 62% of adopters had used pit composting, 31% had used Chimato, 7% Bokashi, and 4% liquid composting methods). Adoption of Chinese composting was not statistically different from zero at baseline.

The profitability of pit planting and Chinese composting vary substantially with agroclimactic factors: pit planting is appropriate in dryer 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.

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 these partner farmer trainings. Incentive-based performance awards were assessed on the basis of the midline survey and endline surveys (discussed below), and awards were provided shortly after these survey data became available.

5. 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, as well as the actual and shadow LF and PFs in these villages (a total sample of 5,208 respondents). We subsequently conducted on-farm monitoring of PP and NM practices later in the 2009-2010 agricultural season among a sample of 1,400 households.[4] At the conclusion of the 2009-2010 season, we conducted a midline survey wave that rotated a share of the sample households within each village to avoid monitoring biases. In this follow-up survey, we interviewed the primary agricultural decision-maker in the household, as well as his or her spouse (with each interview conducted separately). During the 2010-2011 season, we conducted one round of on-farm monitoring of PP practices in 34 villages. Finally, we conducted a second follow-up household survey

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

round in July-October 2011, again interviewing the primary agricultural decision-maker and spouse in 25 household in the village, as well as the LF and PF households.

In order to compare the effects of the intervention on farmers with varying degree of linkage to the primary communicator, we identify comparable individuals to lead and peer farmers in villages where these were not designated as primary communicator types. In treatment villages, AEDOs identified partner farmers whom they would have selected had those assignments been implemented ("shadow" LFs and PFs). In control villages, the survey team identified these "shadow" LFs and PFs in collaboration with village leaders.

We consider two primary outcome measures: (1) knowledge of the targeted technology, and (2) adoption of the technology on a farmer's plot. Our measure of knowledge is a score capturing each household respondent's accuracy in specifying the key features of the relevant technology promoted in her district. For pit planting, this score captures the length, width, and depth of each pit ($\pm 25\%$), the number of seeds to be planted in it, the quantity of compost 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. Many respondents reported never having heard of these technologies; these respondents received scores of 0 in our main analysis data.

Our primary measures of adoption are the use of PP on at least one household plot[5] or the existence of at least one compost heap prepared by the household. We observe the use of PP during on-farm monitoring, which largely validates the survey responses.

6. Empirical Results: Communicator characteristics

We begin by assessing whether the communicators selected via the varied methods do in fact differ in key characteristics. A comparison of the baseline characteristics of lead and peer farmers in Table 1A indicates that lead farmers are indeed better educated, less poor, and able to sustain larger family sizes than is the general population. Peer farmers are closer to the general population in all of these dimensions, although they are still somewhat better off than the sample means. Actual and shadow communicators are generally quite comparable.[6]

In Table 1B, we compare the social network links and perceptions of lead and peer farmers. Considering first-order social links at baseline, LFs are more central in such networks than are PFs: we find that respondents are slightly more likely to be related to LFs, be members of a joint group with LFs, and to talk more regularly with LFs. Perceptions of LFs are generally more favourable than those of PFs. Assessing differences in perceptions at

[5] Households in Malawi typically prepare the land for an entire plot in using a uniform method (i.e., pit planting, ridging, etc.)

[6] While actual lead farmers are somewhat more likely to have finished 5 or more years of education than are shadow lead farmers, this difference is not statistically significant.

midline among our control sample,[7] we find that LFs are more highly rated in terms of agricultural knowledge, honesty, and work effort. Not surprisingly, PFs are more likely to be considered as comparable to the respondent in terms of farm size and input use. At baseline, 44.7% of respondents consider the average PF in their village to have a farm size of equal or similar size to their own (compared to 33.1% for the LF in their village), while 38.3% consider the average PF uses the same or fewer inputs on her farm (28.5% for LF). Thus, LFs have greater social stature than do PFs, but—partly as a result—have farm experiences that are further from those of the mean respondent.

7. Knowledge results

Assessing knowledge gains after one agricultural season, we divide our primary results, presented in Table 3, into those in the subsamples with un-incentivized and incentivized communicators. In the un-incentivized subsample, extension workers raise knowledge scores by approximately 17 percentage points relative to the control group and lead farmers raise these scores by 8 percentage points. The effect of assignment to the peer farmer treatment, on the other hand, is very small and not statistically significant different from zero. These effects are stable when accounting for the gender and household head role of each respondent (column 2).

Comparing these results to those in the subsample with incentivized communicators (columns 3-4), one immediately notes that *incentives matter*. The rank ordering of communicator types by effect size is reversed: peer farmers perform the best, with knowledge scores 12 pp higher than the control group, while lead farmer villages see scores that are slightly more than 6.5 pp higher and extension workers approximately 5 pp higher. These differences for PFs and AEDOs are statistically distinguishable at the 5% confidence level (when tested by interacting the individual communicator type with the incentives treatment dummy in the full sample).

8. Information Transmission

There are two steps in the information transmission pathway we study: (1) from the trainers to the communicators, and (2) from the communicators to other farmers. Differences among communicators could arise in either step: Communicators may be retaining different amounts of information about these technologies, as well as differing in their ability, effort and credibility to transmit messages about these technologies to other farmers.

To assess the role of the first step in this pathway, we compare the knowledge levels of actual and shadow lead and peer farmers, who were also administered the same knowledge questions as part of the household survey. In this sample of communicators, we find the pattern of effects mirrors that among the pattern among the general population (Table 4).

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

The omitted group in these specifications is shadow PF (i.e., PFs not assigned to actual communication). Shadow LFs perform somewhat better than shadow PFs (6 pp higher in the unincentivized sample, and 8 pp higher in the incentivized sample). More notably, PFs assigned to actual communication in the incentivized sample perform 16 pp higher than do shadow PFs and 13 pp higher than actual PFs in unincentivized villages. These results indicate that the communicators' own learning and retention plays a key role in the information dissemination process.

We also test whether the scores of these communicators capture much of the explanatory power of the treatment variables by including these scores in our main estimations using our full sample of respondents. The results, displayed in Table 5, indeed suggest that communicator's own knowledge levels are important determinants of others farmers' knowledge levels. In the un-incentivized sample, the treatment effect of lead farmers disappears when the knowledge level of lead farmers in lead farmer treatment villages is included (interacting the knowledge level of all lead farmers—including both actual and shadow lead farmers—with a village's assignment to lead farmer treatment). The effect of this lead farmer knowledge interaction term is positive and of a reasonable magnitude, but its standard error is too large to be statistically significant. In the incentivized sample, the treatment effect of peer farmers also falls dramatically when the knowledge score of peer farmers in peer farmer-assigned villages is introduced. The coefficient on this score is large and indicates that the treatment effects of incentivized peer farmers are likely arising from these communicators' own higher levels of knowledge retention.

We also investigate whether the communicators differ in their effort to communicate their knowledge to other farmers. Rather than rely on self-reported communicator activities, we use questions from our household survey on whether a sample farmer participated in any activity led by communicators of different types. These activities include demonstration days, and group trainings. We construct a dummy variable indicating whether the respondent participated in *any* activity led by a communicator of the type assigned to her village. In Table 5, we show the results of a probit estimation of this probability in our treatment sample (the omitted treatment type is thus unincentivized PF). Our results are generally consistent with the reduced form effects of treatment type on farmer knowledge. Farmers are much more likely to have attended an activity organized by an unincentivized AEDO than an unincentivized PF. When facing incentives, the order is once again reversed, where farmers are four times more likely to have attended a PF activity than an AEDO activity, and twice as likely to have attended a PF activity than a LF-organized one. Interestingly, the incentives do *not* reduce the effort level of AEDOs – the effect of incentives is insignificant but not negative, suggesting that incentives may weaken AEDO outcomes through other channels. On the whole, these findings suggest that *both* steps in the information transmission pathway appear to be important—communicators differ in both their acquisition and retention of knowledge and in their efforts to transmit this knowledge to others.

Finally, even when communicators exert effort, the presence of incentives may undermine the credibility of their messages, in particular if these incentives are tied to the beliefs and/or knowledge of the receivers. To assess whether the introduction of heightened incentives for information transmission affect communicators' credibility, we use questions from our follow-up survey on respondents' perceptions of the communicators' characteristics. These questions asked each respondent to rate LFs and PFs' honesty, agricultural knowledge, and diligence (phrased as "hard working") on a scale from 1 to 4 (with higher scores indicating more positive perceptions). We hypothesize that if incentives undermine communicators' credibility, these communicators may be rated as having differentially lower honesty levels (relative to other characteristics).

We test this hypothesis in Table 7 by regressing the honesty and agricultural knowledge ratings of the assigned communicator in our treatment sample on the presence of incentives. In columns 1 and 3, we see that incentives do not significantly affect LF honesty ratings, but significantly raise the honesty ratings of PFs. This is true even when we control for mean ratings of non-assigned communicators (in columns 2 and 4). Moreover, these effects are quite consistent with those on knowledge ratings (columns 5-8), with significance patterns and coefficient magnitudes that are quite close. These results are consistent with an explanation in which incentives increase PF effort levels and thus contact between PFs and other farmers. Inasmuch as greater contact induces more favourable perceptions of a communicator, this may be true of a variety of characteristics, including honesty. The similarity between the results for honesty and knowledge indicates that the incentives do not appear to substantially undermine communicator credibility.

We further investigate whether incentives do in fact change social interactions in a manner consistent with these broad perceptions changes. In Table 8, we employ a linear probability model to regress whether a respondent speaks with their assigned communicator at least once a week (columns 1-2) or walks past the communicator's house regularly (columns 3-4). In both instances, respondents report much greater interaction with incentivized PFs than unincentivized ones, helping explain our findings that perceptions of PFs improve when the latter are incentivized.

9. Adoption Results

While knowledge of the technologies is required for their adoption, it is clearly not sufficient. As previously described, liquidity and insurance constraints might prevent households from adopting technologies known to be profitable, as might behavioural constraints. We therefore investigate whether the varied treatments led to differential adoption in the second agricultural season after the initial trainings took place.

In Table 9, we assess the changes in the unincentivized sample using linear probability models. We begin by assessing reported awareness for pit planting (columns 1-2) and composting (column 3). We find that the AEDO treatment raised awareness of PP significantly, but decreased awareness of composting (although the latter estimate is noisy and insignificant). Consistent with these patterns, we find that the AEDO treatment raised the usage of PP by 4.3 pp (column 5, based on survey responses) and 3.4 pp (column 6, based on on-farm monitoring). As with awareness of composting, the AEDO treatment appears to have *lowered* usage of composting by almost 10 pp.

The unincentivized LF and PF treatments appear to have had similarly ambiguous results. Neither treatment raised knowledge of PP significantly. Awareness of composting is significantly higher in LF-assigned villages than in the control villages, but PF villages are not statistically different from the controls. Considering adoption next, we find that the LF treatment raised adoption of PP by an insignificantly small amount based on survey responses – although on-farm monitoring indicates that these gains are significant and as large as 6.3 pp. The effect on composting usage is 4 pp, although it is not significant. In the case of PFs, the gains in survey-based usage of PP are 2 pp, but usage of composting is not significantly different from zero (in fact, the coefficient estimate is -4.8 pp). Thus, we find only small effects in the unincentivized treatments that are sensitive to measurement and vary substantially for the two technologies.

Moving to the incentivized treatments (in Table 10), we find starkly different results from those in the unincentivized cases. All treatments significantly raised awareness of PP: AEDO villages experienced a gain of 9 pp, LF villages a 10 pp gain, and PF villages a 27 pp gain. Awareness of composting also rose dramatically, with gains of 25 pp (AEDO), 19 pp (LF), and 29 pp (PF). These gains are particularly notable for PF villages, which saw no significant gains in either technology in the unincentivized sample.

Despite the gains in awareness of PP in AEDO villages, we find no significant gains in adoption (based on either survey or monitoring). This may be related to the historical experience in Malawian agricultural extension, in which the government mandated compulsory ridging. Messages from official government sources recommending alternatives to ridging may therefore generate substantial dissonance. AEDO treatment villages do see dramatic gains in composting usage of 22 pp – more than 100% higher than is adoption in control villages.

We find that the LF treatment does generate gains in both PP (3 pp) and composting (15 pp). The effects on PP adoption are quite similar when measured using survey responses and monitoring (although standard errors based on the latter measures are larger). Notably, we find that PF villages experience large and significant gains in both PP (9 pp) and composting (27 pp). These are the largest gains in usage of either technology experienced under any of our treatment arms, and are particularly dramatic relative to the low usage of PP (0.7 %) and composting (20%) in our control villages.

Thus, we find that the impacts on adoption rates two seasons after the initial trainings are broadly consistent with those on knowledge gains in the first season after the training. While AEDOs working alone can raise knowledge and usage of some technologies in certain settings, these effects are not consistent and quite sensitive to the presence of incentives. When AEDOs work with LFs, small gains in knowledge and usage accrue, that may be somewhat strengthened by the use of incentives. When AEDOs work with PFs, however, the results can either be dramatic (large and highly significant) or disappointing (small and largely insignificant), largely based on the existence of performance incentives.

Finally, we investigate why incentives so drastically alter the impacts of PFs. Recall that PFs differ from LFs in a number of dimensions, and that their primary advantage appears to be their comparability to other farmers. This comparability may reduce the marginal cost of dissemination for these farmers, as they generate information that is more relevant to other farmers. At the same time, they may well face higher costs in learning and retaining information about the technologies than do LFs, who are better educated and more experienced with newer farming techniques. If learning costs are independent of the number of the number of other farmers trained by the communicator, they act as a fixed cost and generate increasing returns to scale. Thus, with higher fixed costs and lower marginal costs, PFs may experience returns to scale that are more pronounced than do LFs. As a result, PFs may respond differentially to incentives, as these allow them to reach their (higher) minimum scale.

We test whether these characteristics (comparability, learning costs) do in fact lead to greater responsiveness among PFs to the presence of incentives. We estimate whether PFs who exhibit these characteristics at baseline are differentially likely to raise adoption rates when incentivized. To do so, we use our main non-communicator sample of PF treatment villages, and interact the incentive treatment with the average characteristics among the PFs in the respondent's village. The results are displayed in Table 11 and Table 12. These show that villages where the average PF is rated as having a smaller farm than average respondent generally have lower adoption rates when the PFs are not incentivized (columns 1-2). However, the interaction term of this PF characteristic and incentives is positive and highly significant. In fact, the incentive treatment itself is not significant once we include this interaction term, suggesting that much of the impact of the incentives is concentrated in the subsample of "particularly comparable PF" villages.

When we proxy comparability in terms of larger farm sizes (i.e., less comparable) and input usage (columns 3-6), we find coefficients on the interaction of incentives and comparability that are largely consistent with our explanation, although statistical significance is weaker in these instances.

We assess whether PFs who face higher learning costs differentially respond to the incentive treatment. We proxy learning costs with a PF's level of education. In columns 7 and 8 of Table 11, we interact the incentive treatment with the share of PFs in a village who completed only primary education or less. We find that the adoption of PP is indeed greater in villages where this share of less educated PFs is higher and where these PFs are eligible for incentives. We also find a positive coefficient on this interaction term in our composting adoption regression, but this coefficient is not statistically significant.

We also consider whether other characteristics lead PFs to experience lower marginal costs for disseminating adoption and thus to differentially respond to incentives in the presence of fixed learning costs. One possibility is that poorer farmers have a lower opportunity cost for their time, and as a result experience lower marginal costs of dissemination. We therefore test whether the poverty of the average PF in a village—proxied by their roof and wall construction materials and the presence of a radio in the household—interacts with the the incentive treatment. The results, displayed in columns 1-6 of Table 12, show little evidence of such an interaction.

Finally, we also consider whether greater social links at baseline may allow for lower marginal costs of dissemination. We note that LFs on average have higher numbers of first order links than does the average PF in a village (see **Error! Reference source not found.**), but it remains possible that some feature of the PF social link distribution is different from that of LFs, and generates lower marginal costs for dissemination. We thus test whether the incentive effect is concentrated in villages where the average degree of social connection to PFs is particularly high. Interacting the incentive treatment and this measure of PFs' familial, group, and frequent communication links (Table 11, columns 7-12), we find no statistically significant effects for these interactions. That is, unlike comparability, average first-order social links do not appear to induce PFs to differentially respond to incentives.

While these baseline characteristics are themselves not experimentally assigned—and thus may be correlated with other omitted variables—the pattern of results is consistent with our explanation of the differential responsiveness of PFs to the incentive treatment.

10. Conclusions

Our study explicitly tests the extent to which policymakers can use social learning to expand the spread of new technologies, with particular emphasis on the social stature and incentives faced by partner farmers. We find that volunteer farmers who are relatively representative of the general population can generate knowledge gains that are as high as those of professional agricultural extension staff when they face externally provided incentives to do so. While a full cost effectiveness analysis is beyond the scope of this study, the cost of providing these incentives is certainly small relative to the cost of having an extension worker to regularly visit a given village. This suggests that effort by such volunteer farmers could well be a suitable substitute for additional extension worker labor.

Our results help reconcile divergent findings in the literature on the existence of social learning. In the absence of external incentives, we find that some progressive leaders do undertake some efforts to learn about and even teach others, and some limited social learning results—consistent with Conley and Udry (2010). On the other hand, when a representative group of farmers receives training but faces only limited incentives to disseminate them, little learning and social adoption results (a la Duflo, Kremer and Robinson 2011). Moreover, we find that "early adopter" models favoured by many extension efforts may result in lower levels of social learning and adoption than would efforts that make use incentivized peer farmers.

Our study also raises a number of crucial related questions. Firstly, is adopting the targeted pit planting and composting techniques indeed profitable for most of our sample farmers, whose implementation of these techniques and access to complementary inputs may well vary from those on demonstration plots or those examined in prior studies? Moreover, what share of observed non-adoption is rational, i.e., on the part of many farmers for whom profitability of doing so is negative? Future work utilizing detailed agricultural revenues and plot-level costs collected in a second follow-on survey will help shed light on these issues.

A second important question is how this social learning varies within a village based on farmers' baseline connections to LFs and PFs. Understanding these communication patterns may help to further refine the partner selection process. For example, PFs who are particularly well-connected to other farmers may be the most influential, but the definition of "well-connected" can vary depending on the specific social network model one adopts. In a follow-on field experiment, we aim to assess whether models of simple or complex contagion are better able to predict such influential PFs. A related question is whether such models can be based on geographic proximity rather than self-reported social links, which are more costly to accurately determine at scale. Carefully identifying a subset of PFs who are most influential and who can be easily identified would provide policymakers with a refined tool for extending the use of new technologies that can raise yields while reducing pressures on scarce land and other ecological resources.

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Figure 1: Treatment Arms

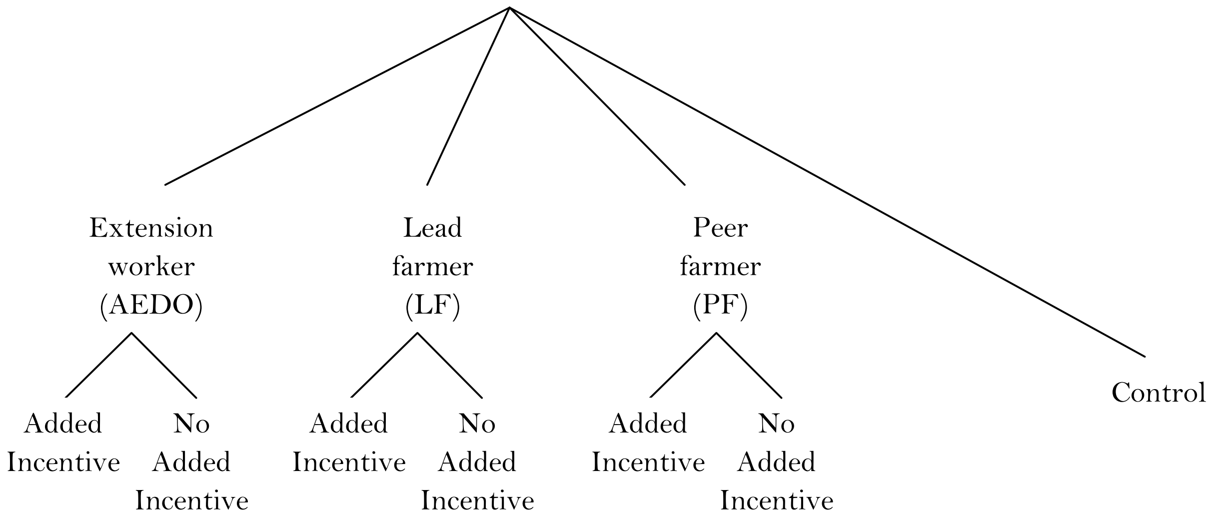

Table 1: Differences in demographics between communicators and the general population

	Non-communicator households	LFs		PFs		Difference between		
		Actual	"Shadow"	Actual	"Shadow"	Non-communicator & LFs	Non-communicator & PFs	PFs & LFs
Household has grass roof	79.1%	64.0%	67.6%	73.6%	75.6%	12.63% ***	4.18% **	8.45% **
Respondent education > year 5	45.6%	76.3%	64.3%	54.5%	55.8%	-22.8% ***	-9.1% ***	-13.1% ***
Household size	4.6 [2.123]	5.489 [2.376]	5.548 [2.149]	5.174 [2.145]	5.153 [1.974]	-0.93 ***	-0.60 ***	-0.37 *
Respondent age	41.5 [16.8]	41.2 [14.1]	42.2 [13.3]	40.2 [14.2]	41.4 [14]	-0.4	0.5	-0.9

Table 2: Differences in social links, perceptions, and comparability between communicators

Communicator	LF	PF (mean)	LF - PF (mean)
Related to respondent	0.514	0.466	0.048
Immediate family of respondent	0.131	0.107	0.024
Talk daily with respondent	0.217	0.189	0.027
Group together with respondent	0.177	0.147	0.030
Communicator uses same or fewer inputs than respondent	0.285	0.383	-0.098
Communicator's farm is same or smaller than respondent	0.331	0.447	-0.117
Honesty rating [1-4]*	3.58	3.35	0.23
Agricultural knowledge rating [1-4]*	3.41	3.05	0.36

* Measured at midline (sample includes only control villages)

Table 3: Knowledge scores after one year (zeros included)

	Unincentivized communicators		Incentivized communicators	
	(1)	(2)	(3)	(4)
AEDO treatment	0.165***	0.166***	0.0529***	0.0555***
	(0.0467)	(0.0449)	(0.0244)	(0.0236)
LF treatment	0.0795***	0.0798***	0.0652***	0.0655***
	(0.0285)	(0.0279)	(0.0238)	(0.0234)
PF treatment	0.0278	0.0241	0.118***	0.118***
	(0.0247)	(0.0248)	(0.0325)	(0.0324)
Male HH head respondent		0.00866		0.0422
		(0.0267)		(0.0263)
Female HH head respondent		-0.0604***		-0.0198
		(0.0283)		(0.0274)
Female Non-HH head respondent		-0.0113		0.0149
		(0.0257)		(0.0274)
CF District	0.193***	0.193***	0.210***	0.210***
	(0.0226)	(0.0222)	(0.0200)	(0.0198)
Constant	-0.00780	0.00394	-0.0163	-0.0380
	(0.0132)	(0.0261)	(0.0126)	(0.0265)
Observations	2,601	2,601	2,664	2,664
R-squared	0.194	0.207	0.218	0.230
F-test1 AEDO = LF	2.892	3.136	0.204	0.144
Prob>F1	0.0919	0.0794	0.652	0.705
F-test2 AEDO = PF	7.543	8.568	3.542	3.308
Prob>F2	0.00707	0.00418	0.0625	0.0717

*** p<0.1, ** p<0.05, * p<0.01. Standard errors clustered by village in parentheses. Excluded group is Male Non-HH Head in control villages in NM districts

Table 4: Knowledge scores among communicators

	1	2	3	4
	Unincentivized communicators		Incentivized communicators	
Respondent is shadow LF	0.0591	0.0394	0.0794***	0.0903***
	(0.0398)	(0.0423)	(0.0344)	(0.0340)
Respondent is LF assigned to	0.0430	0.192***	0.0937	0.152***
actual communication	(0.0658)	(0.0921)	(0.0567)	(0.0789)
Respondent is PF assigned to	0.0215	-0.0355	0.155***	0.132***
actual communication	(0.0571)	(0.0574)	(0.0576)	(0.0633)
Village assigned to Female LF		0.00939		0.133***
		(0.0819)		(0.0553)
Village assigned to Female PF		0.114		0.115
		(0.0936)		(0.104)
Respondent is actual LF * Female		-0.256***		-0.210***
		(0.105)		(0.0970)
Respondent is actual PF * Female		0.00747		-0.00162
		(0.0795)		(0.0970)
Village assigned to CF	0.319***	0.312***	0.357***	0.362***
	(0.0470)	(0.0481)	(0.0419)	(0.0413)
Constant	0.0775***	0.0803***	0.0480	0.0156
	(0.0372)	(0.0453)	(0.0313)	(0.0374)
Observations	450	450	444	444
R-squared	0.208	0.225	0.274	0.296
LF = PF (p-value	0.821		0.475	

Table 5: Communicator knowledge effect on other farmers' knowledge

	Un-incentivized communicators		Incentivized communicators	
	1	2	3	4
AEDO treatment	0.165***	0.114***	0.0529***	0.0498
	(0.0467)	(0.0506)	(0.0244)	(0.0367)
LF treatment	0.0795***	0.0227	0.0652***	0.0553***
	(0.0285)	(0.0330)	(0.0238)	(0.0310)
PF treatment	0.0278	0.00875	0.118***	0.0212
	(0.0247)	(0.0312)	(0.0325)	(0.0364)
Village assigned to CF	0.193***	0.0875***	0.210***	0.147***
	(0.0226)	(0.0360)	(0.0200)	(0.0314)
LF Knowledge		0.0426		0.0512
		(0.0645)		(0.0731)
PF Knowledge		0.302***		0.122
		(0.108)		(0.0821)
LF treatment x LF knowledge		0.0895		-0.0288
		(0.0823)		(0.0671)
PF treatment x PF knowledge		-0.0109		0.169***
		(0.111)		(0.0789)
Constant	-0.00780	-0.0210	-0.0163	-0.0319
	(0.0132)	(0.0254)	(0.0126)	(0.0279)
Observations	2,601	1,514	2,664	1,567
R-squared	0.194	0.265	0.218	0.267

Table 6: Communicator Effort

	Prob(Respondent participated in communicator-led activity)		
	[1]	[2]	[3]
AEDO treatment	0.142***	0.147***	0.149***
	(0.0593)	(0.0583)	(0.0593)
LF treatment	0.0515	0.0553	0.0498
	(0.0801)	(0.0803)	(0.0785)
Incentives x AEDO	0.0693	0.0680	0.0619
	(0.0575)	(0.0561)	(0.0565)
Incentives x LF	0.149***	0.149***	0.154***
	(0.0785)	(0.0788)	(0.0771)
Incentives x PF	0.283***	0.287***	0.294***
	(0.0694)	(0.0699)	(0.0679)
Male HH head respondent		-0.00950	-0.0422
		(0.0551)	(0.0561)
Female HH head respondent		-0.0840	-0.0869
		(0.0608)	(0.0611)
Female Non-HH head respondent		0.0303	0.00949
		(0.0617)	(0.0611)
Household has grass roof			-0.0232
			(0.0266)
Respondent education > year 5			0.0808***
			(0.0237)
Village assigned to CF	-0.0153	-0.0167	-0.0167
	(0.0461)	(0.0462)	(0.0451)
Observations	2,962	2,962	2,725
P-value AEDO = LF	0.188	0.177	0.139
P-value AEDO = PF	0.0163**	0.0120**	0.0119**
P-value LF = PF	0.520	0.491	0.526
P-value AEDO + Incent = LF	0.0350**	0.0364**	0.0276**
P-value AEDO +Incent = PF	0.00153***	0.00139***	0.00118***
P-value AEDO + Incent = LF + Incent	0.876	0.884	0.919
P-value AEDO + Incent = PF + Incent	0.294	0.291	0.208
P-value LF = PF + Incent	0.00208***	0.00199***	0.000745***
P-value LF + Incent = PF	0.00491***	0.00465***	0.00416***
P-value LF + Incent = PF + Incent	0.247	0.248	0.202
P-value AEDO = PF + Incent	0.0170**	0.0147**	0.0127**
P-value AEDO = LF + Incent	0.341	0.341	0.377

Table 7: Perceptions of Communicators

	Honesty				Agricultural Knowledge			
	LF		PF		LF		PF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Incentives	0.0624	-0.0266	0.225***	0.177***	0.142	0.0271	0.309***	0.210***
	(0.0926)	(0.0745)	(0.0819)	(0.0619)	(0.119)	(0.104)	(0.0951)	(0.0733)
Rating of PF honesty (mean)		0.582***				0.604***		
		(0.0644)				(0.0657)		
Rating of LF honesty				0.629***				0.623***
				(0.0339)				(0.0300)
Village assigned to CF	-0.162***	-0.118	-0.123	-0.0222	-0.184	-0.103	-0.163***	0.0242
	(0.0901)	(0.0716)	(0.0807)	(0.0601)	(0.117)	(0.0936)	(0.0971)	(0.0711)
Household has grass roof	-0.103***	-0.0950***	0.0499	0.1000	-0.144***	-0.132***	-0.0546	-0.0380
	(0.0458)	(0.0354)	(0.0725)	(0.0679)	(0.0656)	(0.0580)	(0.0677)	(0.0603)
Age of respondent	-6.04e-05	-0.00134	0.000921	-9.38e-05	-0.00106	-0.000131	0.00399***	0.00284***
	(0.00112)	(0.000930)	(0.00153)	(0.00120)	(0.00182)	(0.00151)	(0.00201)	(0.00137)
Constant	3.669***	1.867***	2.977***	0.766***	3.478***	1.692***	2.485***	0.507***
	(0.196)	(0.258)	(0.177)	(0.152)	(0.240)	(0.224)	(0.181)	(0.134)
Observations	853	834	745	687	812	783	724	663
R-squared	0.018	0.346	0.025	0.412	0.025	0.354	0.037	0.441

Table 8: Changing Social Interactions

	(1)	(2)	(3)	(4)
Dependent variable	Talk to communicator	Talk to communicator	Walks by communicator's house	Walks by communicator's house
Sample	Non-incentive	Incentive	Non-incentive	Incentive
AEDO treatment	0.234***	0.285***	0.0577	0.117***
	(0.0723)	(0.0526)	(0.0760)	(0.0513)
LF treatment	0.176***	0.226***	0.00868	0.0743
	(0.0458)	(0.0394)	(0.0505)	(0.0454)
PF treatment	0.117***	0.339***	0.0627	0.139***
	(0.0495)	(0.0449)	(0.0497)	(0.0504)
Observations	2,109	2,222	2,109	2,222

Table 9: Awareness and adoption after 2 years

	Non-incentive villages					
	(1)	(2)	(3)	(5)	(6)	(7)
Dependent variable	Heard of PP	Know enough to use PP	Heard of NM	Used PP	Used PP - OFM	Used NM
AEDO treatment	0.216***	0.189***	-0.0916	0.0429***	0.0336	-0.0946***
	(0.0462)	(0.0442)	(0.0678)	(0.0174)	(0.0214)	(0.0446)
LF treatment	0.0643	0.0439	0.131***	0.0110	0.0628***	0.0406
	(0.0577)	(0.0415)	(0.0655)	(0.00794)	(0.0349)	(0.0521)
PF treatment	0.0372	0.0387	0.0536	0.0193***	0.0280	-0.0475
	(0.0508)	(0.0403)	(0.0596)	(0.0115)	(0.0484)	(0.0447)
Constant	0.254***	0.111***	0.456***	0.00712***	0.0220	0.195***
	(0.0262)	(0.0213)	(0.0511)	(0.00288)	(0.0214)	(0.0342)
Observations	1,516	1,516	1,367	1,516	208	1,367
R-squared	0.023	0.028	0.017	0.011	0.015	0.011
AEDO = LF (p-value)	0.0210	0.00799	0.000559	0.0937	0.309	0.00749
AEDO = PF (p-value)	0.00308	0.00528	0.00962	0.254	0.900	0.251

Table 10: Awareness and adoption after 2 years

	Incentive villages					
	(1)	(2)	(3)	(5)	(6)	(7)
Dependent variable	Heard of PP	Know enough to use PP	Heard of NM	Used PP	Used PP - OFM	Used NM
AEDO treatment	0.0873***	0.0593***	0.251***	-0.00144	0.0307	0.218***
	(0.0311)	(0.0353)	(0.0761)	(0.00605)	(0.0310)	(0.0935)
LF treatment	0.0994***	0.111***	0.191***	0.0321***	0.0276	0.150***
	(0.0465)	(0.0407)	(0.0695)	(0.0150)	(0.0383)	(0.0654)
PF treatment	0.268***	0.264***	0.285***	0.0940***	0.0950***	0.273***
	(0.0426)	(0.0396)	(0.0654)	(0.0221)	(0.0395)	(0.0741)
Constant	0.254***	0.111***	0.456***	0.00712***	0.0220	0.195***
	(0.0262)	(0.0213)	(0.0511)	(0.00288)	(0.0209)	(0.0342)
Observations	1,619	1,619	1,393	1,619	344	1,393
R-squared	0.052	0.071	0.057	0.043	0.023	0.052
AEDO = LF (p-value)	0.775	0.251	0.422	0.0363	0.939	0.512
AEDO = PF (p-value)	1.17e-05	1.87e-05	0.626	8.63e-05	0.125	0.619

Table 11: PF Response to Incentives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Comparability						Education	
PF baseline characteristic	Communicator has smaller farm than respondent		Communicator has larger farm than respondent		Communicator uses same or fewer inputs than respondent		Communicator education primary or less	
Technology	Used PP	Used NM	Used PP	Used NM	Used PP	Used NM	Used PP	Used NM
Incentive treatment	-0.00312	-0.00568	0.126***	0.594***	0.0235	-0.0342	0.00387	0.273***
	(0.0432)	(0.131)	(0.0636)	(0.306)	(0.0599)	(0.150)	(0.0261)	(0.137)
Communicator characteristic	-0.08***	-0.46***	-0.0246	-0.0921	0.0880	-0.0786	-0.0231	0.0313
	(0.0215)	(0.201)	(0.0699)	(0.396)	(0.0796)	(0.169)	(0.0187)	(0.0604)
Incentive X characteristic	0.198***	1.080***	-0.105	-0.512	0.0998	0.871***	0.141***	0.0823
	(0.0811)	(0.311)	(0.125)	(0.486)	(0.115)	(0.323)	(0.0354)	(0.149)
Observations	662	584	662	584	662	584	662	584
R-squared	0.023	0.152	0.022	0.144	0.029	0.152	0.051	0.129

Sample is PF-assigned villages. Omitted category is unincentivized treatment.

Table 12: PF Response to Incentives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Poverty						Social links					
PF baseline characteristic	Grass roof		Walls made of cheapest materials		HH has no radio		Related to communicator		In group with communicator		Talk daily with communicator	
Technology	Used PP	Used NM	Used PP	Used NM	Used PP	Used NM	Used PP	Use NM	Used PP	Use NM	Used PP	Used NM
Incentive treatment	0.0196	0.464***	0.0596***	0.359***	0.0371	0.319***	0.0728	0.417***	0.098***	0.155	0.061***	0.365***
	(0.0568)	(0.139)	(0.0329)	(0.0834)	(0.0434)	(0.150)	(0.0545)	(0.120)	(0.0370)	(0.106)	(0.0339)	(0.0942)
Communicator characteristic	-0.0746***	0.189	-0.00688	0.0884	0.00991	0.0140	0.00279	-0.0137	0.00398	0.0731	-0.0747	0.0416
	(0.0385)	(0.132)	(0.0344)	(0.0622)	(0.0831)	(0.175)	(0.0490)	(0.110)	(0.0688)	(0.158)	(0.0470)	(0.106)
Incentive X characteristic	0.0768	-0.184	0.0699	-0.113	0.127	-0.00110	0.00673	-0.302	-0.122	0.872	0.0801	-0.311
	(0.0748)	(0.173)	(0.0636)	(0.115)	(0.109)	(0.282)	(0.108)	(0.320)	(0.131)	(0.525)	(0.0803)	(0.695)
Observations	662	584	662	584	662	584	662	584	662	584	662	584
R-squared	0.019	0.126	0.022	0.125	0.032	0.122	0.018	0.134	0.021	0.148	0.019	0.124

Sample is PF-assigned villages. Omitted category is unincentivized treatment.

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