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Social Learning and Incentives for Experimentation and Communication

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Low adoption of agricultural technologies holds large productivity consequences for developing countries. Many countries hire agricultural extension agents to communicate with farmers about new technologies, even though a large academic literature has established that information from social networks is a key determinant of product adoption. 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 own adoption and effort are susceptible to small performance incentives, and the social identity of the communicator influences others' learning and adoption. Farmers appear most convinced by communicators who share a group identity with them, or who face comparable agricultural conditions. Exploring the incentives for injection points in social networks to experiment with and communicate about new technologies can take the influential social learning literature in a more policy-relevant direction.

Key words: Social learning, Technology adoption, Agriculture, Peer effects.

JEL Codes: O33, O13, Q16

1. INTRODUCTION

Many agricultural technologies with demonstrated productivity gains, such as timely fertilizer application, improved seed varieties, and composting, have not been widely adopted in developing countries, and in Sub-Saharan Africa in particular (Udry, 2010; Duflo *et al*., 2011). 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

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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 neighbours with little friction in the flow of information, and then update their expectations about the technology's profitability. Now that the importance of social learning has been established, a natural next question is whether the power of social influence can be leveraged to promote new technologies.

Our study explores whether we can cost-effectively improve new technology adoption by involving farmers closer to the target population as promoters, and by providing them incentives to experiment with the technology and communicate this information to others. We do this through a randomized control trial (RCT) in which we vary the dissemination method for two new technologies for maize farming across 120 villages in Malawi. In each village, we randomly assign the role of main communicator about the new technology to either (1) a government-employed extension worker, (2) a "lead farmer" (LF) who is educated and able to sustain experimentation costs, or (3) five "peer farmers" (PFs) 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 small performance-based incentives in the experimental design.[3]

We first document that providing incentives to communicators affects the flow of information in these villages. Without incentives, PFs and LFs rarely adopt the technologies themselves, and largely do not communicate information about the technologies to target farmers. As a result, target farmers do not know more about the technologies or adopt them at higher rates than in control communities. In contrast, when incentivized, PFs experiment at higher rates and communicate information to other farmers, who subsequently adopt the technology themselves. There is greater diffusion of knowledge and adoption by target farmers when PFs are incentivized, especially for the more novel of the two technologies. LF responsiveness to incentives are much more muted.

1. Other deterrents examined by the literature recently include imperfections in credit markets (Croppenstedt *et al*., 2003; Crepon *et al*., 2015), insurance markets (Cole *et al*., 2013; Bryan *et al*., 2014; Karlan *et al*., 2015), land rights (Goldstein and Udry, 2008; Ali *et al*., 2011), and output markets (Ashraf *et al*., 2009). Jack (2013) offers a careful review of this literature.

2. Distinguishing peer effects from incidental correlations in the behaviour of social contacts has been the perennial empirical challenge with which this literature has grappled (Manski, 1993). A growing literature shows that social relationships are an important vector for the spread of information in a variety of contexts, including educational choices (Bobonis and Finan, 2009; Carrell and Hoekstra, 2010; De Giorgi *et al*., 2010; Duflo *et al*., 2011; Garlick, 2012), financial decisions (Duflo and Saez, 2003; Banerjee *et al*., 2013; Burzstyn *et al.*, 2014; Beshears *et al*., 2015), job information (Magruder, 2010; Beaman, 2012), health inputs (Kremer and Miguel, 2007; Godlonton and Thornton, 2012; Oster and Thornton, 2012; Miller and Mobarak, 2015), energy choices (Alcott, 2011) and doctors prescribing drugs (Coleman *et al*., 1957; Iyengar *et al*., 2011).

3. Our work relates to recent studies that promote new technologies through network "injection points": Kremer *et al*., 2011; Ashraf *et al*., 2014; Leonard and Vasilaky, 2016; Beaman *et al*., 2015. A literature in medicine has explored the role of opinion leaders in changing behavior (Kuo *et al*., 1998; Locock *et al*., 2001; Doumit *et al*., 2007; Keating *et al*., 2007). A marketing literature explores conditions under which incentives stimulate word-of-mouth referrals (Biyalogorsky *et al*., 2001; Kornish and Li, 2010). Also related, more broadly, is the lengthy literature on the effects of performance-based incentives on the production of public goods, reviewed by Bowles and Polania-Reyes (2012).

These incentive results imply that when we try to use social influence to promote new technologies, experimentation and transmission of information to others cease to be automatic. This is a crucial difference between the passive social learning documented by Griliches (1957) and others (in which some farmers experiment with technologies on their own, neighbours learn by observing them, and ideas slowly diffuse), and the social diffusion of a new technology we try to "activate" via a policy intervention. Diffusion through an external intervention appears to follow a different process, and may require us to pay more careful attention to early adopters' incentives for experimentation and for communicating information to others. When we provide peer farmers small incentives to communicate, we observe a brand new technology move from essentially zero market penetration to about 10–14% usage within two agricultural seasons.

We provide an informal conceptual framework that explains (1) why incentives matter in this setting, and (2) why PFs may react more strongly to incentives.[4] The framework generates auxiliary testable predictions that allow us to delve deeper into the questions of communicator and target farmer characteristics that lead to faster adoption. The greater effectiveness of PFs that we document could stem from their greater social or physical proximity to target farmers, but our data indicate that similarity in farm size and input use, and common group membership, matter more. Farmers appear to be most convinced by the advice of others who face agricultural conditions that are comparable to the conditions they face themselves.[5] We do not attempt to influence specific actions by PFs, but we document strategies they use. Incentives induce PFs to both expend communication effort and adopt the technology themselves, and the latter has a demonstration effect.

For policy, our results suggest that social learning can be harnessed to cost-effectively improve public agricultural extension services. Adoption of our targeted technologies increased maize yields substantially, making the incentive-based communication strategies cost-effective. More broadly, while large numbers of extension workers are employed in developing countries (Anderson and Feder, 2007), the impact of these services have largely been disappointing: the use of modern varieties of seeds, fertilizer, and other agricultural inputs has remained relatively stagnant and unresponsive to extension efforts in sub-Saharan Africa (Udry, 2010; Krishnan and Patnam, 2013). These deficiencies can often be traced back to a lack of qualified personnel and insufficient extension resources,[6] suggesting that leveraging pre-existing social networks may be a particularly powerful and cost-effective way to address these failures.

This article is structured as follows: Section 2 describes the context and experimental design. Section 3 presents a conceptual framework for social learning with endogenous communication. The data are described in Section 4 and empirical results presented in Section 5. We test for alternative mechanisms underlying our results in Sections 6 and 7. We study the impacts on target farmers' yields and inputs in Section 8, and offer concluding remarks about policy implications in Section 9.

4. Our work 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.

5. This is consistent with the results from both psychology (Fleming and Petty, 2000; Briñol and Petty, 2009) and economics (Munshi, 2004) on the role of similarity between senders and receivers of information in persuading the latter to adopt specific behaviours.

6. Approximately half of government extension positions remain unfilled in Malawi, and each extension worker in our sample is responsible for 2,450 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.

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.[7] 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 LF 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 LF 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 (unlike lead farmers) and geographically dispersed throughout the village.

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) LF — supported by AEDO.
(c) 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). Supplementary 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".

7. 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).

(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 convening a meeting with community members to identify a short list of potential LFs. 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 LF.

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 convening and facilitating a meeting with village members. The first step was to identify the important social groups in the village. The directions given included (1) the meetings must be well attended (including by those who may work with the extension agent most often), and (2) 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 PFs had to state that they understood their role and responsibilities. They were then presented to the village for endorsement.

Selecting both LFs and PFs involved village meetings, consultation with leaders etc, and the approaches followed were not fundamentally different from each other. Furthermore, both LFs and PFs were identified in *all* villages using the selection processes described above. However, in the villages randomly assigned to the LF (PF) treatment arm, only the selected LF (set of PFs) was 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 LFs and PFs 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 LFs and PFs to each other and to the rest of our sample (of non-communicator maize farmers who are the intended "recipients" of the messages). LFs are indeed better educated and cultivate more land than both the general population and those chosen as PFs. Differences between LFs and PFs are also substantial but not statistically significant. Thirty percent of PFs are women, while no LFs are. PFs generally fall between LFs and the general population in all 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 our framework: that PFs are more similar to the target farmers than are LFs.

TABLE 1
Differences in demographics between communicators and the general population

Characteristic	Non-communicators	PFs	LFs	*p*-value LF = PF	*p*-value non-comm = PF
Person is female*	0.338	0.308	0	0.000	0.489
	(0.0113)	(0.0441)	0		
Household head is male	0.738	0.704	0.938	0.000	0.312
	(0.0163)	(0.0326)	(0.0264)		
Household head age	41.65	43.15	38.44	0.164	0.0757
	(0.383)	(0.905)	(2.985)		
Household head's highest level of education completed (levels: 1–8)	3.366	3.698	4.000	0.205	0.00127
	(0.0861)	(0.115)	(0.225)		
House walls are made of burnt bricks	0.446	0.513	0.629	0.173	0.0315
	(0.0249)	(0.0440)	(0.0854)		
House roof is made of grass	0.744	0.652	0.660	0.921	0.00546
	(0.0188)	(0.0341)	(0.0715)		
Number of animals owned by the household	1.320	1.586	1.567	0.916	0.00351
	(0.0570)	(0.100)	(0.173)		
Number of assets owned by household	4.788	5.393	5.639	0.623	0.000527
	(0.144)	(0.214)	(0.478)		
Own farm is household's primary income source	0.819	0.872	0.876	0.955	0.00715
	(0.0169)	(0.0215)	(0.0776)		
Total household cultivated land 2008–09 (hectares)	0.982	1.071	1.333	0.151	0.0336
	(0.0216)	(0.0463)	(0.181)		

Notes: Standard errors clustered by village in parenthesis. * Denotes share of female respondents in baseline round. Share of female respondents is 34% in midline round. In endline round, additional effort was expended to ensure greater gender balance in respondents, with 56% of respondents being women. Controlling for gender of the respondent in the regressions does not affect any of the results.

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. Using first-order links for analysis, we find that LFs are more central in social networks than the average PF. Respondents are significantly more likely to be related to LFs and to talk more regularly with LFs than to each of the PFs individually. At the same time, respondents are more likely to be related to at least one of the PFs and to talk regularly with one of the PFs than with the LF. In other words, the five PFs in a village will jointly have more links than the one LF, but a one-to-one comparison suggests that LFs possess more links. Villagers perceive LFs more favourably: they are more highly rated in terms of trustworthiness and farming skills.[8] A total of 21% of villagers report having discussed farming topics with an LF at least several times in the previous year; only 13% of villagers have done so with the average PF, and 9% of villagers have done so for the average non-LF/PF.

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, 41.7% of respondents consider the average PF in their village to have a farm size similar to their own (compared to 32.6% for LFs), while 25.6% consider the average PF uses the same or fewer inputs on her farm (21.2% for LF). Thus, LFs have somewhat greater social stature than do PFs, but—partly as a result—have agricultural experiences that are further from those of the average respondent.

The LF and PF treatment arms vary the number of communicator farmers engaged (1 LF versus 5 PFs) in addition to their identity. We try to disentangle communicator group size effects

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

TABLE 2
Differences in social links, perceptions & comparability between communicators

Communicator	LF	PF (mean)	LF - PF
Related to respondent	0.502	0.450	0.0433***
	(0.0277)	(0.0261)	(0.00850)
Immediate family of respondent	0.213	0.106	0.107***
	(0.0170)	(0.0108)	(0.0148)
Talk daily with respondent	0.158	0.137	0.0207***
	(0.0178)	(0.0154)	(0.00642)
Group together with respondent	0.130	0.124	0.00584
	(0.0129)	(0.0121)	(0.00694)
Communicator uses same or fewer inputs than respondent	0.212	0.256	−0.0440***
	(0.0187)	(0.0154)	(0.0118)
Communicator's farm is same or smaller than respondent	0.326	0.417	−0.0912***
	(0.0234)	(0.0162)	(0.0169)
Trustworthiness rating [1–4]ł	3.228	3.080	0.148***
	(0.0631)	(0.0444)	(0.0509)
Farming skill rating [1–4]ł	3.183	3.038	0.145**
	(0.0577)	(0.0446)	(0.0542)

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

from those related to identity using within-arm variation in the number of communicators per target farmer in the village, intra-group relationships among PFs, etc, as described below.

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 effects on *other*, recipient farmers in the village, not the communicators' own adoption. 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 programme, 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. Supplementary 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.

In addition to inducing communicators to exert effort, the incentives may have had a signaling value that directed communicators towards the specific aspects on which they should focus. We attempted to minimize this by not disclosing exam questions (or even topics) to avoid encouraging over-focusing on these details, and by ensuring that exam questions covered various aspects of the technologies.

The training of AEDOs was conducted in August of 2009, using a 3-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

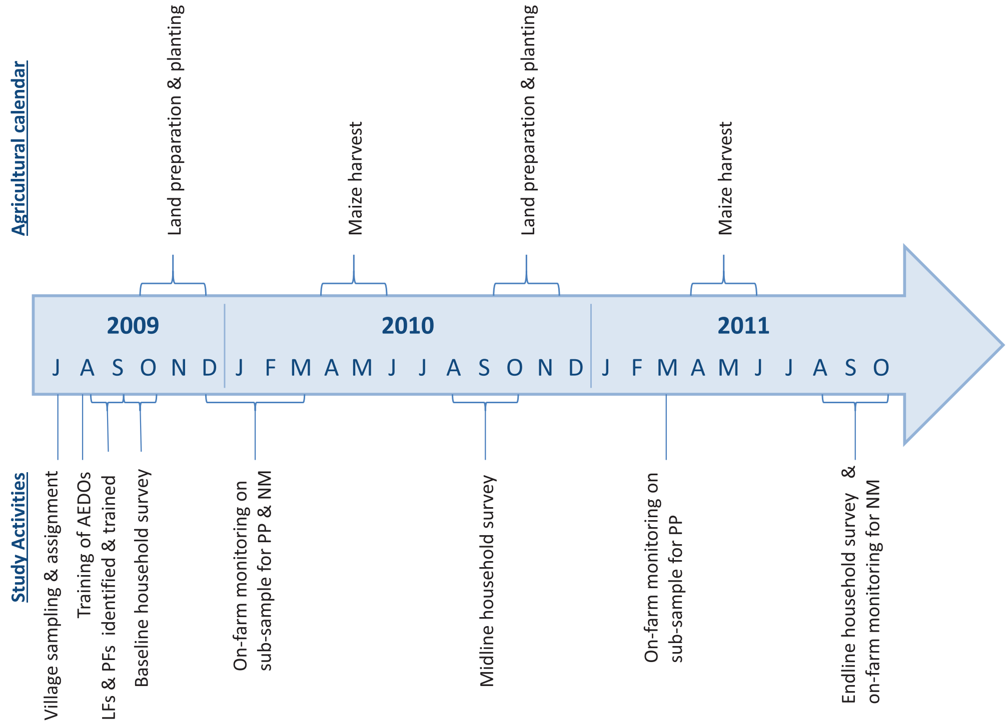

FIGURE 1
Intervention, data collection, and agricultural calendar.

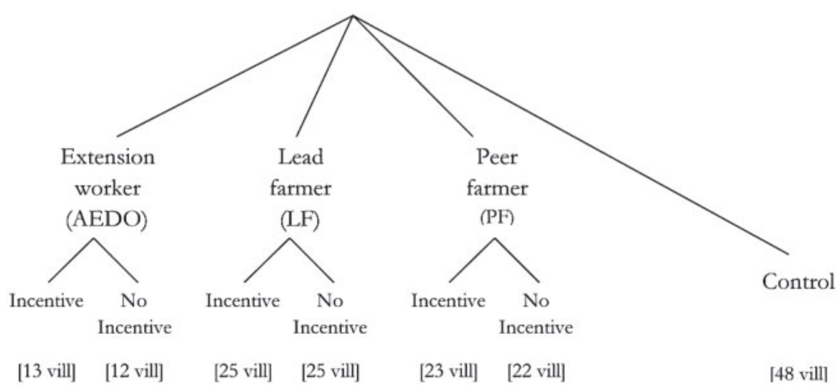

FIGURE 2
Treatment arms.

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 forty-eight 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.

Supplementary 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 25 out of 231 tests, we find differences that are significant at the 5% level; these differences rarely occur for the same treatment arm comparison over different variables. We find significant differences in only 3 out of 42 comparisons of 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 versus 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, LFs received a large bag of fertilizer, and PFs 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 PF 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 trade-off 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 not 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 LFs generally command higher social status and respect, while PFs may enjoy greater credibility because they are closer to other villagers in social, financial, or agricultural technology space. It is therefore not obvious ex-ante which of the three strategies would perform best.

2.4. *Gender reservation of communicators*

The data we use from the 120 villages were part of a larger 168-village experiment in which we reserved the communicator role for women in an additional 48 PF and LF villages. All analysis in this article completely excludes those forty-eight villages.[9] Supplementary Appendix A4 expands on our experimental design to show the excluded villages in which gender reservation was assigned.

2.5. *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. Supplementary 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% 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 labour-intensive task with potentially large upfront 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.[10] 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 Supplementary 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 *et al*., 1999). 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).

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 $\pm$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 per cent 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.

9. Further details on the gender experiment are provided in BenYishay *et al*. (2016), which examines the effects of the gender reservation. In all data used in this article, no guidance on the gender of the communicators was provided. Nonetheless, we control for the gender of the communicators in regressions we run in this article.

10. 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.

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.[11] We begin with the observation that the suitability of the technologies we promote to each individual farmer is uncertain.[12] This is because returns to the technology depend on specific farmer characteristics that may differ across farmers: For example, pit planting imposes labour and pesticide costs, and farmers who are credit constrained may be able to use less labour and pesticides. Composting requires a mode to transport the prepared compost to the field; farmers who own carts or who can borrow or rent them thus experience higher returns than those who do not. Pit planting appears to generate the greatest benefits for farmers on flat rather than sloped lands, and farmers need to learn this. Implementing a new technology may require skill or broader human capital, and farmers may be uncertain about the returns to adoption at their own skill level. In summary, all these forms of heterogeneity makes the net returns to a specific farmer unknown ex ante. They also suggest that it is easier to learn from other farmers who face similar constraints and agricultural conditions.

Training provided by a communicator allows farmers to learn about these returns. Experimentation by the communicator (that neighbouring farmers can observe) provides further evidence on the technology under the specific conditions that the communicator faces. This may be more informative to the farmer receiving the message if he faces input costs, market and soil conditions more similar to the communicator.

Communicators must decide whether to expend time and effort to communicate information about the technology to other farmers in his village. This is where our framework differs from existing models in the social learning literature, in which all other farmers automatically observe (possibly with some error) any one farmer's choice, and they therefore automatically benefit from others' experimentation. In contrast, we consider the decision to communicate to be an endogenous choice.

Communication effectiveness depends on the proximity or similarity of the informed communicator to the target farmer. Proximity or similarity of characteristics can be interpreted

11. A more formal framework from an earlier version of the article, along with all data, replication files and Supplementary Appendix Material for this article can be found at http://faculty.som.yale.edu/mushfiqmobarak/research.html

12. While we focus on uncertainty about suitability of the technology for the individual farmer, an alternative interpretation would examine uncertainty about the implementation details of the technology (*e.g.* how wide to dig the pits). The latter interpretation is less consistent with our full set of results, especially the advantage PFs have over LFs in generating knowledge and adoption gains; the greater similarity of PFs to others would not necessarily give them an advantage in communicating these technical details.

in different ways: geographic proximity, social similarity, or agronomic relevance (*e.g.* similar farm size, similar access to inputs and similar constraints). One sensible interpretation of this proximity is that it shapes how relevant the communicator information is to the recipient farmer's agricultural decision-making.

A communicator's own experimentation with the technology adds a further signal that is complementary to verbal communication (at the extreme, villagers may ignore any message they receive from a communicator who does not invest in learning about the technology by experimenting themselves). Farmers who receive communication update their beliefs about the returns from the technology under their own conditions. They obtain more precise estimates of the expected returns when the communicator is more proximate to them and when she exerts more effort in communication. In the standard target input model that is used in the social learning literature (Bardhan and Udry, 1999), this would imply that a farmer's expected payoff from using the new technology increases in his proximity to an informed communicator and the precision of the communication received.

3.1. *Incentives for communicators*

We now consider how the interventions in the experiment would affect communicator and other (recipient) farmer behaviour. Communicators in our experiment receive "target incentives", which is a payoff if a certain mass of farmers in her village adopt the new technology. The incentive provides a reason for the communicator to incur the cost of acquiring and transmitting information. If the distribution of farmers is single-peaked, then communicators in the most populated part of the distribution of characteristics (who are most similar to the largest number of other farmers), would find it easiest to convince a sufficient number of farmers to win the incentive. Therefore, communicators in the central part of the distribution would respond most strongly to such incentives. Communicators in the under-populated part of the distribution may not find it worthwhile to communicate at all, because reaching the incentive target may require too much effort. In other words, LFs in our experimental design (who are "a-typical" in a village) may not respond to incentives at all, or at best, should be less responsive than PFs.

Furthermore, undertaking costly transmission of knowledge is useless to the communicator if receivers ignore the message. Incentives therefore provide a reason for the communicator to experiment herself, even though the incentives were not explicitly conditioned on own experimentation. Effective communication thus consists of two parts: experimenting with, and acquiring information about the new technology, and then making an effort to transmit that information to others. In some settings, experimentation could be the only required form of communication. The verbal communication part is likely more important for cases like ours, where the technology is entirely new, and the communicator actually needs to teach target farmers *how to* use a new technology. For classes of technologies where no such teaching or learning is required, input choices and yield/profit outcomes are easily observable, and heterogeneity in agricultural conditions across farmers is limited, then experimentation (*i.e.* actions rather than words) may be the only form of communication that is necessary.

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 key theoretical concepts to our data. In our framework, 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, and experiment with the technology himself as the empirical counterparts 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, and experiment with the technology. For this analysis, we compare the actions of the LFS or PFs to these shadow communicators.

Second, whether communicators choose to transmit signals to others 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. As our framework highlights, experimentation is also a form of communication, so we collected data on adoption by assigned LFs and PFs.

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: They were paid based on knowledge gains in the first year, and actual adoption in the second year.

We make the following predictions for our empirical setting:

1. Incentives increase communicators' own willingness to learn about, and experiment with the technology.
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. Given our method for selecting partner (LFs or PFs), this implies that PFs, 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 in terms of their own learning, experimentation, and communication efforts. LFs may or may not respond to incentives.
3. The technology adoption rate by recipient farmers should also be most responsive to incentives in the PF villages, since PFs were explicitly chosen to be, on average, closer to target farmers. Recipient farmers would be less responsive in the LF arm.

It is important to note that there are mechanisms outside the framework highlighted above 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 120 sample villages, in addition to surveys of the actual and shadow LFs and PFs in these villages (a total sample of 3,720 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 753 households to directly observe land preparation and any evidence of composting.[13] 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 that fall under the jurisdiction of the same AEDOs in charge of a few of the treatment villages, so that we can study whether there was any displacement of AEDO effort in favour of treatment villages (where they could win incentives), at the expense of control villages where they also should have been spending some time.

The following year (2010–11), we conducted another round of on-farm monitoring of pit planting practices in thirty-four villages. 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 twenty-five 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.

Supplementary Appendix A5 shows attrition rates and attritor characteristics across treatment arms. Attritors are defined as baseline households who were sampled for re-interview but were not successfully re-interviewed. While attrition rates were higher during the endline survey in some treatment cells, the composition of attritors did not meaningfully vary across these cells.

During the first year, adoption is measured primarily using knowledge gain. Knowledge is measured using a score capturing each respondent's accuracy in specifying the key features of the 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 Supplementary 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 (plots are typically prepared using a uniform method in rural Malawi), or the existence of at least one compost heap prepared by the household. We directly observe the use of pit planting 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. *Communicator adoption and retention of knowledge*

Our framework suggests that performance incentives should increase communicators' own willingness to acquire the information presented, experiment with the technology themselves,

13. Budget constraints prevented us from conducting this monitoring on all sample farms.

TABLE 3
Summary statistics

Variable	Mean	SD	Min	Max	*N*
Technology knowledge and use					
Knowledge score on targeted technology at midline	0.153	0.270	0	1	3,125
Household used targeted technology at end line	0.160	0.367	0	1	3,256
Only treatment villages					
Assigned communicator held at least one activity at midline	0.560	0.497	0	1	1,966
Only pit planting districts					
Household used pit planting at end line	0.039	0.194	0	1	1,606
Only composting districts					
Household produced compost at end line	0.039	0.194	0	1	1,606
Household head characteristics					
Male	0.701	0.458	0	1	2,883
Age	42.2	16.6	0	91	2,664
Education level (1–8)	3.349	1.452	1	8	2,871
Household wall material					
Mud and poles	0.054	0.227	0	1	2,895
Unburned bricks	0.306	0.461	0	1	2,895
Compacted earth	0.159	0.366	0	1	2,895
Burned bricks	0.444	0.497	0	1	2,895
Household roof material					
Grass	0.748	0.434	0	1	2,895
Iron	0.221	0.415	0	1	2,895
Primary water source in dry season					
River	0.086	0.280	0	1	2,895
Unprotected well	0.059	0.235	0	1	2,895
Protected well	0.133	0.339	0	1	2,895
Communal tap	0.093	0.291	0	1	2,895
Borehole	0.589	0.492	0	1	2,895
Assets and income					
Number of animals owned by HH	1.290	1.120	0	7	2,895
Number of assets owned by HH	4.755	2.274	0	17	2,895
Own farm is primary source of income	0.809	0.393	0	1	2,895
HH derives income from *ganyu* (paid labour on others' farms)	0.487	0.500	0	1	2,895
HH derives income from business	0.398	0.490	0	1	2,895
HH member has taken out a loan	0.060	0.237	0	1	2,895

and relay the signal to their neighbours. 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. We create a knowledge score based on communicators' performance in these tests (Supplementary Appendix A2). We also collect data on whether the communicators adopt the technologies themselves.

We created these scores and adoption outcomes 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" PFs and shadow LFs 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. Supplementary Appendix A6 verifies that the actual and shadow communicators are statistically similar in terms of their baseline demographic and economic characteristics.[14]

14. 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).

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

$$knowledge/adopt_{cvd} = \alpha + \beta_1 shadow\ LF_{cvd} + \beta_2 actual\ LF_{cvd} + \beta_3 actual\ PF_{cvd} + Z_{cvd}\Gamma + \nu \text{Gender}_{vd} + D_d + \varepsilon_{cvd}.$$

The subscripts denote communicator $c$residing in village $v$in district d, Z_{cvd} is a matrix of individual -level controls, Gender_{vd} is the village female share of communicators, 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.[15] In Table 4 we report results with and without individual controls and district fixed effects.

Those chosen as LFs (who are richer and more educated, as we have seen) generally perform better on the tests compared to those chosen as PFs. LFs are also more likely than PFs to adopt the technology. Without incentives, actual PFs (who are trained by the AEDOs, and assigned the task of communicating) do not perform as well as LFs without incentives, and their test performance and adoption rates are more comparable to shadow LFs who are not directly trained by AEDOs. Their adoption rates are not statistically distinguishable from that of shadow PFs. In summary, PFs do not appear to retain knowledge about new technologies when they are not provided incentives, and they do not adopt the technologies themselves.

When incentives are introduced, we observe the strongest improvements in knowledge scores and in adoption rates for PFs. With incentives, PFs are just as knowledgeable about the technologies as the actual LFs with incentives. The first four columns of Table 4 indicate that incentives improve PFs' knowledge scores by about 20 percentage points, which represents a 90% increase in knowledge scores relative to shadow PFs. This incentive effect for PFs is both quantitatively and statistically significant (with a p-value of 0.002, comparing columns 1 and 3). Incentives increase LF knowledge scores by about five percentage points, but this is not a statistically significant increase.

Incentives increase PFs' own adoption rates by over 60 percentage points. This represents a quadrupling of the adoption rate relative to shadow PFs. In contrast, LFs are not responsive to the incentives at all.

In summary, incentives increase PFs' own willingness to learn about the technology (*i.e.* acquire and send a signal) and adopt it themselves. The adoption results suggest, consistent with our framework, that it makes sense for the communicators who are "closer" to the target farmers to learn about the new technology, experiment with it, and use it as a "demonstration strategy" only when incentives are added.

5.2. *Communicator effort*

Next, we test whether communicators make a greater effort to communicate and transmit knowledge to other farmers 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

15. We verified that the main results look the same when samples are combined and interaction terms between communicator type and incentives are used.

TABLE 4
Knowledge retention and adoption by communicators

	Dependent variable: communicators' knowledge scores				Dependent variable: communicators' own adoption			
	Unincentivized communicators		Incentivized communicators		Unincentivized communicators		Incentivized communicators	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shadow LF	0.0843*	0.0739*	0.0696*	0.0649*	−0.125	−0.153*	0.00998	−0.0185
	(0.0433)	(0.0409)	(0.0388)	(0.0384)	(0.0764)	(0.0835)	(0.0683)	(0.0765)
Actual LF assigned to Communication	0.220**	0.222**	0.263***	0.267***	0.451***	0.436***	0.394***	0.374***
	(0.105)	(0.0937)	(0.0811)	(0.0841)	(0.138)	(0.146)	(0.113)	(0.107)
Actual PF assigned to communication	0.00286	−0.0227	0.204***	0.193***	−0.107	−0.152**	0.551***	0.505***
	(0.0324)	(0.0397)	(0.0528)	(0.0585)	(0.0673)	(0.0704)	(0.0808)	(0.0860)
Pit planting district	0.326***		0.322***		−0.267***		−0.422***	
	(0.0411)		(0.0372)		(0.0678)		(0.0620)	
Communicator is female	−0.0203	−0.0224	0.00419	0.00767	0.0884	0.0835	0.0222	0.0234
	(0.0313)	(0.0305)	(0.0312)	(0.0322)	(0.0637)	(0.0582)	(0.0464)	(0.0442)
District FE	N	Y	N	Y	N	Y	N	Y
Additional baseline controls	N	Y	N	Y	N	Y	N	Y
Observations	473	473	438	438	356	356	306	306
R^2	0.276	0.308	0.316	0.327	0.182	0.230	0.353	0.369
p-values for								
Actual LF = Actual PF	0.0466	0.0142	0.542	0.472	8.83e-05	0.000108	0.268	0.376
Actual LF = Shadow LF	0.235	0.142	0.0354	0.0335	0.000117	0.000363	0.00441	0.00504
Mean of Dep. Var. for Shadow PFs	0.219	0.219	0.188	0.188	0.232	0.232	0.218	0.218
p-value for incentive = non-incentive								
Actual LF			0.895				0.922	
Actual PF			0.002				0.000	

Notes: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Standard errors clustered by village in parentheses. Excluded group is shadow PF. Additional baseline controls in columns 2, 4, 6, and 8 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. Knowledge scores include zero scores for respondents who answered that they were not aware of the technology.

TABLE 5
Communicator effort to transmit knowledge

	Dependent variable: designated communicator held at least one activity			
	Unincentivized communicators		Incentivized communicators	
	(1)	(2)	(3)	(4)
AEDO treatment	0.496***	0.274	0.691***	0.544***
	(0.0504)	(0.166)	(0.0644)	(0.167)
LF treatment	0.565***	0.413**	0.738***	0.602***
	(0.0716)	(0.177)	(0.0645)	(0.149)
PF treatment	0.391***	0.163	0.812***	0.674***
	(0.0938)	(0.159)	(0.0598)	(0.178)
Communicator is female	−0.0249	0.0445	−0.0743*	−0.0349
	(0.0480)	(0.0802)	(0.0375)	(0.0617)
Pit planting dummy	Y	–	Y	–
District FE	N	Y	N	Y
Additional baseline controls	N	Y	N	Y
Observations	1,068	914	898	801
R^2	0.517	0.578	0.641	0.677
p-values for				
AEDO = LF	0.361	0.106	0.558	0.411
AEDO = PF	0.238	0.182	0.102	0.124
LF = PF	0.100	0.00457	0.339	0.430
p-value for incentive = non-incentive				
AEDO			0.210	0.103
LF			0.563	0.794
PF			0.00433	0.00133

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

the assigned communicator held such an activity. We use the following specification:

$$effort_{ivd} = \beta_1 AEDO_{ivd} + \beta_2 LF_{ivd} + \beta_3 PF_{ivd} + Z_{ivd}\Gamma + \nu \text{Gender}_{vd} + D_d + \varepsilon_{ivd},$$

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, LFs exert more effort than either PFs or AEDOs, but the coefficients are statistically comparable. When incentives are provided (columns 3 and 4), PFs are the communicators most likely to hold activities. PFs put substantially (and statistically significantly, $p<0.01$) more effort with incentives, and the PF-incentive effect is significantly larger than it is for other communicators, consistent with our framework.[16] PF effort more than

16. 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.

doubles when incentives are added. In all, 67–81% of all respondents attend a dissemination activity when PFs with incentives are the assigned extension partner. In contrast, the increase in effort from LFs is not as large, and not statistically distinguishable from no change (*p*-value of 0.10 or 0.21). Thus we continue to see 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.[17]

We also test whether the increased effort by communicators in response to the incentives leads them to send signals to recipient farmers who are more dissimilar from them. As Supplementary Appendix A8 shows, the interacted effect of incentives and similarity in farm size with each recipient farmer on effort by PFs (as reported by that recipient farmer) is not statistically different from zero, suggesting incentives do not simply lead PFs to target farmers who are similar to them, consistent with our framework.

Finally, it is possible that communicators may have employed additional strategies (beyond communication) to encourage adoption among other farmers, such as by sharing inputs with them or providing unpaid labor on their farms. In Supplementary Appendix A9, we do not see any evidence of such alternative strategies being employed by PFs, under either incentivized or non-incentivized arms. If anything, incentivized PFs appear less likely to share fertilizer with other households).

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

$$\begin{aligned} knowledge_{ivd} = & \alpha + \beta_1 AEDO_{ivd} + \beta_2 LF_{ivd} \\ & + \beta_3 PF_{ivd} + Z_{ivd}\Gamma + \nu \text{Gender}_{\text{vd}} + D_d + \varepsilon_{ivd}. \end{aligned}$$

The average value of the knowledge score index is 0.1 in the pure control villages, which is the omitted category in the regression. In our treatments without incentives, that index increases by 0.18–0.21 in AEDO villages, by 0.16–0.17 in LF villages, and it does not change at all in PF villages. In other words, when PFs are not provided incentives, other farmers in the village do not seem to learn anything about the new technologies. When incentives are added, however, (columns 3 and 4), knowledge scores increase by most in PF villages. The knowledge scores double in PF-incentive villages relative to pure control villages.[18] The effect of incentives on

17. Results are also similar for other forms of communication beyond holding special events. Supplementary Appendix A7 shows that recipient farmers in incentivized PF villages are differentially more likely to report having discussed farming with the actual PFs than the shadow PFs in control villages—a difference not observed for non-incentivized PF villages. The fact that communication increases does imply that our intervention imposes on the communicators' time, but we do not have the data to fully account for these time costs.

18. 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).

TABLE 6
Knowledge after one season among target farmers

	Dependent variable: knowledge scores in household survey			
	Unincentivized communicators		Incentivized communicators	
AEDO treatment	0.212***	0.178***	0.0636**	0.0587**
	(0.0582)	(0.0443)	(0.0253)	(0.0232)
LF treatment	0.172***	0.161***	0.0527	0.0658
	(0.0533)	(0.0446)	(0.0404)	(0.0451)
PF treatment	0.0233	0.00485	0.103***	0.0903**
	(0.0265)	(0.0303)	(0.0386)	(0.0415)
Pit planting district	0.180***		0.188***	
	(0.0322)		(0.0239)	
Female share of communicators	0.0621	0.120	−0.0435	0.00229
	(0.108)	(0.0749)	(0.0932)	(0.0781)
District FE	N	Y	N	Y
Additional baseline controls	N	Y	N	Y
Observations	2,227	1,947	2,057	1,834
R^2	0.215	0.290	0.175	0.209
p-values for				
AEDO = LF	0.563	0.751	0.817	0.893
AEDO = PF	0.00635	0.00297	0.318	0.486
LF = PF	0.00818	0.00115	0.297	0.639
Mean of Dep. Var. for Control Villages	0.0977	0.0968	0.0977	0.0968
Mean of Dep. Var. for AEDO Villages	0.308	0.318	0.134	0.138
p-value for incentive = non-incentive				
AEDO			0.0180	0.0115
LF			0.0391	0.0666
PF			0.0786	0.134

Notes: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. 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.

PFs is statistically significant (p-value $=0.08$). The extra effort expended by PFs in incentive villages (that we documented earlier) results in greater knowledge transmission, and this is all consistent with our 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.[19] We use the following specification:

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

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

19. In Supplementary Appendix A10, we replicate our results using continuous outcome measures (such as the amount of compost produced by the HH); our findings are largely unchanged.

villages), because adoption rates for the two technologies were very different at 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 thirty-four 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 2.9 pp higher in AEDO villages, and 2 pp higher in LF villages compared to controls, while they are 3 pp lower in PF villages (column 1). When incentives are added, adoption is 0, 7, and 14 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 relative to adoption in AEDO villages (0.03). The incentive effect in PF villages (the move from -3 to 14 pp) is both statistically significant (p-value < 0.0001) and dramatically larger than the effect of incentives among the other communicators. In addition, in the sample of villages where incentives were provided, pit planting adoption is statistically significantly greater when PFs are assigned as communicators rather than LF or AEDO.

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 (14.9 pp), and this incentive effect in PF villages is statistically significant (p-value $= 0.075$), and almost identical in magnitude as when we study self-reported adoption data. The differential response to incentives also exists when we assess target farmers' plans for adoption in the following season (columns 5 and 6). In all, 28% of target farmers in PF villages planned to adopt the following year, which indicates that the technology is becoming more popular and growing.

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 14.4%, 14.9%, and 27.7% through self-reports, on-farm-monitoring, or future plans, respectively) all represent meaningful gains relative to baseline and relative to the pure control group. These adoption gains are comparable to the diffusion rates for hybrid corn observed in Iowa and other Midwestern states of the U.S. during the 1930s and 1940s, in the periods soon after the introduction of that technology (Griliches, 1957).

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 12.6, 27.5, and 39.1 pp higher in AEDO, LF, and PF villages with incentives, respectively, compared to our control villages. The incentive effect in peer farmer villages is highly statistically significant (p-value <0.000). The PF-incentive effect is also significantly larger than the LF-incentive effect. These effect sizes are also quite dramatic given baseline adoption levels of any type of compost of only 24%. Parallel to the communicator knowledge retention and communicator effort results, we see a differentially stronger response to incentives among PFs, *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. Importantly for policy, adoption in PF-incentive villages is much higher than in the "status-quo" treatment for the Malawi Ministry of agriculture (un-incentivized AEDO villages).

6. ALTERNATIVE MECHANISMS UNDERLYING THE PEER FARMER PERFORMANCE

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

TABLE 7

Adoption after two seasons among target famers

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 (1)	Incentive (2)	Non-incentive (3)	Incentive (4)	Non-incentive (5)	Incentive (6)	Non-incentive (7)	Incentive (8)
AEDO treatment	0.0286*	0.000887	0.102***	−0.0358	0.106**	−0.00940	−0.00353	0.226**
	(0.0159)	(0.0166)	(0.00286)	(0.0461)	(0.0408)	(0.0314)	(0.0682)	(0.111)
LF treatment	0.0217**	0.0665*	0.0303***	0.147*	0.0376	0.0716	−0.0203	0.275***
	(0.00878)	(0.0377)	(0.00415)	(0.0743)	(0.0531)	(0.0682)	(0.0837)	(0.0909)
PF treatment	−0.0278***	0.144***	−0.0171*	0.149	−0.00842	0.277***	−0.0471	0.391***
	(0.00881)	(0.0387)	(0.00763)	(0.0947)	(0.0556)	(0.0735)	(0.0714)	(0.0697)
Female share of communicators	0.0929***	0.0948**	0.114***	0.0731	−0.0505	0.0981	0.0481	−0.0300
	(0.0314)	(0.0412)	(0.0172)	(0.196)	(0.0862)	(0.123)	(0.111)	(0.228)
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,185	1,188	215	282	1,185	1,188	1,178	866
p-values for								
AEDO = LF *p*-value	0.708	0.138	0.000	0.0873	0.224	0.320	0.871	0.723
AEDO = PF *p*-value	0.00312	0.000740	0.000	0.0905	0.0914	$9.62e-05$	0.621	0.191
LF = PF *p*-value	0.000367	0.182	0.000	0.986	0.518	0.0494	0.736	0.318
Mean of Dep. Var. for Control Villages	0.00782	0.00782	0	0	0.0821	0.0821	0.241	0.241
Mean of Dep. Var. for AEDO Villages	0.0520	0.0250	0.083	0	0.214	0.108	0.198	0.443
p-value for incentive = non-incentive								
AEDO	0.396		0.546		0.0297		0.0553	
LF	0.211		0.331		0.952		0.00147	
PF		0.0000		0.0750		0.0000		0.0000

Notes: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. All columns report OLS effects. Standard errors clustered by village in parentheses. Excluded group is control villages. Columns 3 and 4 use the random subsamples of households in PP villages for which direct observation was conducted (sample sizes are limited because it was expensive to do the direct observation. We allocated a larger sample size to incentive villages in order to validate the self-report data on the basis of which incentives were awarded).

to rate their assigned communicators' honesty, skill and agricultural knowledge in the midline survey. Using these data, Supplementary Appendix A11 shows that incentives do not undermine communicators' credibility. Target farmers appreciate PFs' extra effort in incentive villages, and rate them as *more* knowledgeable and honest. LFs, whose effort is not responsive to incentives, do not receive similar recognition, but are not penalized either.

Apart from the difference in identity, the PF and LF 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.[20] We first explore these alternatives — for which by and large we do not find strong support in the data — before delving deeper in the next section into why identity matters, and the dimensions of identity that matter most.

First, we consider whether variation in the number of communicators across the LF and PF arms can explain their relative performance. Simple explanations such as "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 our data well, because PFs out-perform LFs in the incentive sample, while the converse is generally true in the non-incentive sample. Nevertheless, we can use natural variation in population size across our sample villages to understand scale effects. Figure 3 looks at the effects of "communicators per capita" (which varies within the set of PF villages and within the set of LF villages due to variation in village size) on adoption rates. The correlation between communicators per capita and adoption rates is quite weak in both PF villages and in LF villages. For example, correlation is weakly positive in non-incentive villages, and negative in PF-incentive villages. Thus, there is little evidence that communicator scale predicts adoption rates, and no evidence that this effect is more pronounced in the incentivized arms.

A related possibility is that five PFs are jointly more representative of the distribution of farmers than the one LF (beyond the fact that each PF is on average more similar to other farmers in the village). To assess whether this is driving our results, we investigate whether the effect of incentives on adoption in PF villages varies with the distribution of farm size across PFs.[21] Supplementary Appendix A12 shows that incentives increase adoption in PF villages, and that there is no systematic heterogeneity in this effect across different villages with different distributions of PF landownership. Interaction terms between the incentive treatment and different moments of land distribution (standard deviation, range or mean absolute deviation from mean) are never significant.

Having multiple communicators in the PF arm creates opportunities for collaboration and coordination of promotion activities across PFs. There is some indication in the data that this might be happening: incentives increase the likelihood that four PFs jointly host a technology training session. However, there is little indication that this led to greater technology adoption

20. 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 still contains valuable policy lessons.

21. We focus on the distribution of landownership because (we will show in Section 7 that) PFs are most successful in convincing farmers who are proximate to them in terms of their landownership.

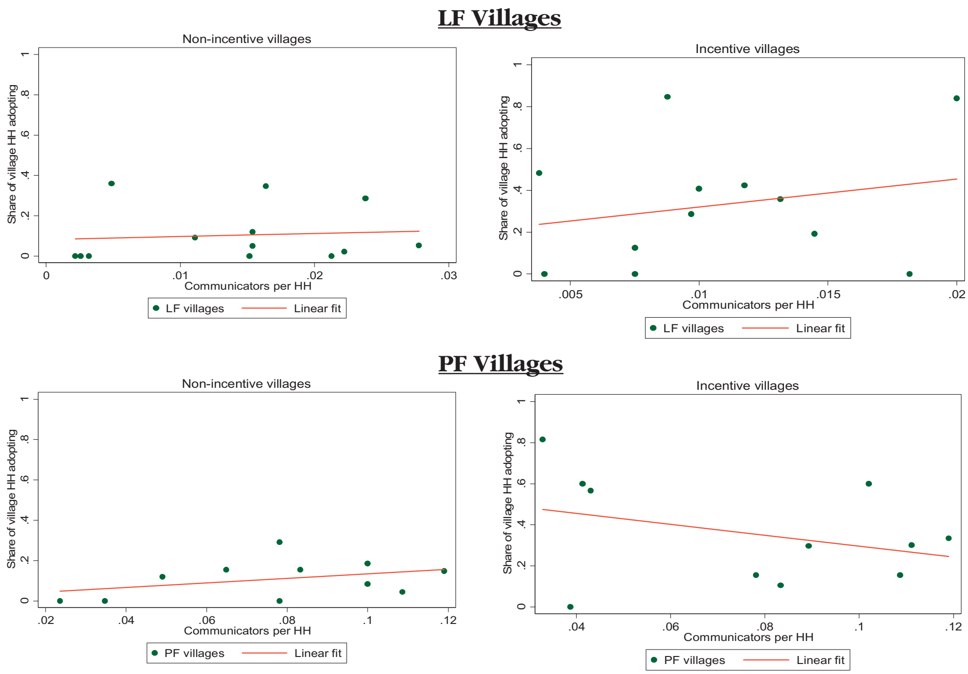

FIGURE 3

Communication per HH.

among other farmers. In Supplementary Appendix A13, multiple PFs jointly leading the training results in a much smaller effect on pit planting or composting adoption than the main effect of offering incentives to those communicators. Thus, coordination and cooperation between PFs could be a relevant channel, but does not appear to be the main channel by which the PF-incentive treatment fostered technology adoption.

Beyond scale effects, we now 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.[22] 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 1–3 of Table 8. Column 1 shows that incentives for LFs has a 36 percentage point effect on adoption in "small" villages with fewer than 65 households (the median in our sample). In contrast, PFs respond to incentives more strongly even in "large" villages with greater than 65 households (50 percentage points in column 3) or 100 households (56 percentage points column 4). Non-linearity considerations therefore do not eliminate the incentive-response gap between PFs and LFs.

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

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

TABLE 8
Testing alternative hypotheses

Alternative hypothesis:	Dependent variable: Household adopted target technology in 2010–11 season Non-linearity of incentives			Jointness of incentives		
	LF villages with ≤65 hh (1)	PF vill. with > 65 hhs (2)	PF vill. with > 100 hs (3)	PFs related to one another (4)	PFs in group with another (5)	PFs talk daily with one another (6)
Average marginal effect of						
Incentive village	0.358***	0.503***	0.558***			
	(0.0686)	(0.123)	(0.131)			
Incentive village @ 25th percentile of PF links			0.425***	0.361***	0.330***	
			(0.0425)	(0.0528)	(0.0660)	
Incentive village @ 75th percentile of PF links			0.334***	0.389***	0.400***	
			(0.0498)	(0.0407)	(0.0601)	
p-value for incentive @ 25th pct = incentive @ 75th pct				0.121	0.642	0.488
Mean of Dep. Var. in LF Non-incentive Villages	0.13					
Mean of Dep. Var. in PF Non-incentive Villages		0.137	0.120	0.133	0.133	0.133
Observations	330	121	95	665	665	665

Notes: ***$p<0.01$, **$p<0.05$, *$p<0.1$. Estimates shown are average marginal effects from probit regression: adopt = f(β incentive+λ pitplanting+γ female share of comms). Sample includes all non-communicator households. Standard errors clustered by village in parentheses. All regressions control for female share of communicators.

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:

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

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 4–6 of Table 8, we present the mean marginal effects of the incentive treatment at both the 25th and 75th percentiles of the PF links measures. Effects at the 25th percentile are not statistically different than those at the 75th percentile. Moreover, even in villages where PFs are not particularly well-connected at baseline, the presence of incentives dramatically improves outcomes, and increases adoption by 33–43 percentage points. These results suggest that the joint-ness of incentives is not likely to account for the entirety of 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. Results 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 PFs 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. PFs, 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 conceptual framework is silent about the specific dimension of proximity that matters. 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 9.

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.[23] The specifications in Table 9 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 PFs on average, so we use measures such as "PF has *smaller* or similar farm" to proxy for comparability.[24] Whether we control for the interaction terms individually or jointly, the factors

23. Supplementary Appendix A14 repeats these specifications using the maximum value of the connection (*i.e.* whether the respondent is connected to *any* PF) rather than the average value of connection to the five PFs. The results become smaller in magnitude and less likely to be statistically significant. This suggests, related to our discussion of mechanisms in the previous section, that the five PFs combined having access to a broader social network is unlikely to be the mechanism driving the PF treatment effects.

24. 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.

TABLE 9

Heterogeneity in PF-incentive effects across measures of social proximity

Interaction term being tested: Dependent variable in all specifications: household adopted target technology in 2010–11 season	PF has smaller farm than respondent (1)	PF uses same or fewer inputs than respondent (2)	PF educational attainment (3)	PF house has grass roof (4)	PF in immediate family (5)	PF in extended family (6)	PF in group with respondent (7)	PF talks daily with respondent (8)	Full set of interactions (9)
AEDO treatment	0.0859*	0.0794	0.0708	0.0648	0.0799*	0.0761	0.0990*	0.0757	0.0872*
	(0.0486)	(0.0488)	(0.0481)	(0.0486)	(0.0454)	(0.0463)	(0.0517)	(0.0457)	(0.0513)
LF treatment	0.129**	0.126**	0.156***	0.140***	0.122**	0.130***	0.131**	0.145**	0.157**
	(0.0519)	(0.0549)	(0.0530)	(0.0525)	(0.0487)	(0.0483)	(0.0529)	(0.0563)	(0.0642)
PF treatment	0.152*	0.115	0.340**	0.359***	0.168***	0.190***	0.0875*	0.233***	0.121
	(0.0816)	(0.0941)	(0.163)	(0.135)	(0.0449)	(0.0667)	(0.0512)	(0.0628)	(0.160)
PF treatment X mean(PF has smaller or equal farm as respondent)	0.203								−0.350
	(0.245)								(0.344)
PF treatment X mean(PF uses fewer or similar inputs as respondent)		0.287							0.842**
		(0.317)							(0.372)
PF treatment X mean(PF education)			−0.0298						−0.0445
			(0.0490)						(0.0422)
PF treatment X mean(PF grass roof)				−0.203					0.0227
				(0.173)					(0.140)
PF treatment X mean(PF in respondent's immediate family)					0.936*				−0.439
					(0.475)				(0.849)
PF treatment X mean(PF in respondent's extended family)						0.0960			0.170
						(0.139)			(0.144)
PF treatment X mean(PF in group with respondent)							0.988***		1.020*
							(0.349)		(0.569)
PF treatment X mean(PF talks daily with respondent)								−0.236	−0.659*
								(0.283)	(0.331)
Observations	1,647	1,647	1,625	1,625	1,647	1,647	1,647	1,647	1,625
R^2	0.273	0.275	0.285	0.282	0.277	0.272	0.279	0.274	0.303

Notes: 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. Estimates are from the following specification: adopt$=\alpha+\beta$ AEDO $+\lambda$ LF$+\gamma$ PF$+\tau$Proximity$+\mu$PF*Proximity$+\gamma$ female share comm$+\Gamma$X+D_district$+\varepsilon$. All regressions thus control for district FE and the same set of control variables as in prior tables (including female share of communicators). 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.

that emerge as quantitatively (and statistically) most significant are: (1) comparability in terms of land size, and (2) whether the PF and the targets share membership in the same group (such as a church group). PFs with incentives whose land size is most comparable to others in their village are significantly (39 percentage points) more likely to convince target farmers to adopt. PFs with larger immediate or extended family networks are not differentially more successful, nor are PFs who had engaged in frequent social interactions at baseline (prior to the introduction of these interventions).

Second, we examine whether the incentive-response of the PFs varies across different types of target farmer households. In other words, what types of target farmers are most convinced by the PF, and among what types of targets do incentives play the biggest role in enhancing the PFs success in persuasion? Table 10 shows results on the PF effect on technology adoption among different types of targets separately for incentive and non-incentive villages, and conducts a statistical test of differences across the two types of villages.[25]

As before, similarity between target farmers and PFs is measured using the mean value of proximity, averaged across all five PFs. 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, although standard errors are large given the small sample (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. The *p*-values of the differences between incentive and non-incentive arms are around 0.12–0.13. These results, coupled with our prediction on the types of communicators expected to respond to incentives, provide suggestive evidence that agricultural comparability and relevance is a key determinant of success in communication. There is also a differential incentive response for group members, for whom the cost of communication might be lower.

In summary, while our conceptual framework does not provide specific guidance on the type of proximity that lead PFs 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.

8. EFFECTS OF TECHNOLOGY ADOPTION ON YIELDS AND INPUT USE

We collect detailed data on yield, revenues, labour, 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 labour costs, and those need to be accounted for to

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

TABLE 10
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 hast 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	−0.157	−0.136	−0.183	−0.0444	−0.00688	−0.0169	−0.0166	0.0761
	(0.336)	(0.198)	(0.175)	(0.173)	(0.317)	(0.220)	(0.0186)	(0.0783)
Incentive villages	0.262**	0.282	1.056***	0.423**	0.833***	0.513*	−0.0236	−0.113
	(0.128)	(0.214)	(0.369)	(0.183)	(0.233)	(0.273)	(0.0494)	(0.185)
p-value for incentive village X characteristic	*0.2*	*0.043*	*0.001*	*0.046*	*0.035*	*0.113*	*0.893*	*0.334*
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Female share of communicators control	Y	Y	Y	Y	Y	Y	Y	Y
Household baseline controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	530	530	530	530	530	530	530	530
When included jointly...	*p*-value							
PF has smaller farm than respondent	0.200							
PF uses same or fewer inputs than respondent	0.0426							
PF educational attainment	0.893							
PF house has grass roof	0.334							

Notes: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. 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 also 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.

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 labour use recorded in the endline survey. In Supplementary Appendix A15, 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 95$^{\text{th}}$ 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 55 kg/ha, or 3% of the baseline mean yield of 1678 kg/ha in this sample. Given differences in adoption of pit planting of 17% in response to PF incentives (Table 7), we estimate a treatment effect on the treated (TOT) of 19%. 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 230 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 stronger evidence of yield gains. In column 4 of Supplementary Appendix A15, we find an ITT of 1,014 kg/ha due to PF incentives that is statistically significant (50% increase in mean yields). Conditioning on baseline yields in column 5, we find similar effects. Finally, our IV regressions indicate quite large effects of actual adoption of upwards of 2,134 kg/ha, equivalent to 105% of baseline yields. These effects are quite large but not out of line with estimates in fertilizer-scarce environments.

Supplementary Appendix A16 examines whether pit planting affected farmers' input use. Farmers are much more likely to use manure 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 tool, herbicide, basal, or top dress fertilizer usage.

In Supplementary Appendix A17, we assess the impacts of pit planting on the total labour hours devoted to land preparation, planting, fertilizer application, weeding, and harvesting. Our surveys very carefully collect detailed data on labour 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 19 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 smaller reductions in fertilizer application, planting, and harvesting, and noisy impacts weeding hours due to incentives. In total, we find an ITT reduction of 32 hours across all labour categories in the prior season, equal to roughly 20% of total hours. This reduction considerably 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 fertilizer use across incentive treatments. We also do not find any evidence of labour 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 17 pp for pit planting and 43 pp for composting, the programme costs are US$100 per household adopting pit planting and US$39.70 per household adopting composting. Our estimated yield gains from pit planting adoption suggest that each treated household gained US$14 (this is the ITT estimate of 55 kg of maize, priced at 2011 harvest-period maize prices and foreign exchange rates) in the first year. This yields a benefit/cost ratio of 0.83 in the first year.[26] Continued use of pit planting among adopting households—or even expansion to additional households in these villages—would raise this ratio considerably. If we take the household reports of "plan to use" pit planting the following year (Table 7) at face value, the benefit-cost ratio easily exceeds unity. The yield gains from composting are dramatically larger (our ITT estimate equates to $258), generating a benefit/cost ratio of 15:1 in the first year alone.

9. 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 behaviours. Our experiment attempts to leverage this insight for policy. In doing so, we document that incentives for injection points within a social network to do the initial experimentation, and communication dynamics between agents are important determinants of information dissemination, especially when we attempt to "activate" social learning via intervention to speed up technology diffusion. Social learning models can likely be enriched by studying the incentives that govern whether (and how) people experiment with new technologies and communicate about them with their peers. Such an approach would also make the social learning and peer effects documented by economists in a variety of contexts more policy-relevant. As this experiment shows, agricultural extension services can be improved by incorporating social learning in communication strategies.

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

The fact that incentives matter and social transmission is not always automatic may help reconcile divergent findings in the literature on the existence of social learning (*e.g.* Conley and Udry, 2010 versus Duflo *et al*., 2011). Many development, NGO and private sector marketing efforts rely on "opinion leader" based dissemination strategies (Miller and Mobarak, 2015), including "early adopter" models favoured by extension efforts. In our setting, the LF approach results in lower levels of social learning and adoption than providing incentives to PFs 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, which we are pursuing in follow-up work (Beaman *et al*., 2015). 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.

26. We focus on yields and revenues rather than profits, because we do not observe an increase in purchased inputs.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

REFERENCES

ALCOTT H. (2011), "Social Norms and Energy Conservation", *Journal of Public Economics*, **95**, 1082–1095.

ALI D., DEININGER K., and GOLDSTEIN M. (2011), "Environmental and Gender Impacts of Land Tenure Regularization in Africa: Pilot evidence from Rwanda" (World Bank Policy Research Working Paper 5765).

ANDERSON J. and FEDER G. (2007), "Agricultural Extension", *Handbook of Agricultural Economics*, **3**, 2343–2378.

ASHRAF N., BANDIERA O., and JACK K. (2014), "No Margin, No Mission? A Field Experiment on Incentives for Pro-Social Tasks", *Journal of Public Economics*, **120**, 1–17.

ASHRAF N., GINÉ X., and KARLAN D. (2009), "Finding Missing Markets (and a Disturbing Epilogue): Evidence from An Export Crop Adoption and Marketing Intervention in Kenya", *American Journal of Agricultural Economics*, **91**, 973–990.

BANDIERA O. and RASUL I. (2006), "Social Networks and Technology Adoption in Northern Mozambíque", *The Economic Journal*, **116**, 869–902.

BANERJEE A., CHANDRASEKHAR A. G., DUFLO E. *ET AL.* (2013), "The Diffusion of Microfinance", *Science*, **341**, doi: 10.1126/science.1236498.

BARDHAN P. and UDRY C. (1999), *Development Microeconomics* (Oxford University Press, Oxford).

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

BEAMAN L., BENYISHAY A., Magruder J. *ET AL.* (2015), "Can Network Theory based Targeting Increase Technology Adoption?" (Working Paper, Yale University).

BESHEARS J., CHOI J. J., LAIBSON D. *ET AL.* (2015), "The Effect of Providing Peer Information on Retirement Savings Decisions", *Journal of Finance*, **70**, 1161–1201.

BIYALOGORSKY E., GERSTNER E., and LIBAI B. (2001), "Customer Referral Management: Optimal Reward Programs", *Marketing Science*, **20**, 82–95.

BOWLES S. and POLANIA-REYES S. (2012), "Economic Incentives and Social Preferences: Substitutes or Complements?", *Journal of Economic Literature*, **50**, 368–425.

BRIÑOL P. and PETTY R. E. (2009), "Persuasion: Insights from the Self-Validation Hypothesis", *Advances in Experimental Social Psychology*, **41**, 69–118.

Bryan G., CHOWDHURY S., and MOBARAK S. (2014), "Under-Investment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh", *Econometrica*, **82**, 1671–1748.

CARRELL S. E. and HOEKSTRA M. L. (2010), "Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids", *American Economic Journal: Applied Economics*, **2**, 211–228.

COLE S., GINÉ X., and VICKERY J. (2013), "Barriers to Household Risk Management: Evidence from India", *American Economic Journal: Applied Economics*, **5**, 104–135.

COLEMAN, J., KATZ E., and MENZEL H. (1957), "The Diffusion of an Innovation Among Physicians", *Sociometry*, **20**, 253–270.

CONLEY T. and UDRY C. (2010), "Learning about a New Technology", *American Economic Review*, **100**, 35–69.

CREPON B., DEVOTO F., DUFLO E. *ET AL.* (2015), "Impact of Microcredit in Rural Areas of Morocco: Evidence from a Randomized Evaluation", *American Economic Journal: Applied Economics*, **7**, 123–150.

CROPPENSTEDT A., DEMEKE M., and MESCHI M. (2003), "Technology Adoption in the Presence of Constraints: The Case of Fertilizer Demand in Ethiopia", *Review of Development Economics*, **7**, 58–70.

DE GIORGI G., PELLIZZARI M., and Redaelli S. (2010), "Identification of Social Interactions through Partially Overlapping Peer Groups", *American Economic Journal: Applied Economics*, **2**, 241–275.

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

————. (2004), "History of Crop Production, With and Without Tillage", *Leading Edge*, **3**, 150–154.

DEWATRIPONT M. and TIROLE J. (2005), "Modes of Communication", *Journal of Political Economy*, **113**, 1217–1238.
DOUMIT G., GATTELLARI M., GRIMSHAW J. *ET AL.* (2007), "Local Opinion Leaders: Effects on Professional Practice and Health Care Outcomes", *Cochrane Database Syst. Rev.* **1**, CD000125.
DUFLO E., DUPAS P., and KREMER M. (2011), "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya", *American Economic Review*, **101**, 1739–1774.
DUFLO E., KREMER M., and ROBINSON J. (2011), "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya", *American Economic Review*, **101**, 2350–2390.
DUFLO E. and SAEZ E. (2003), "The Role of Information and Social Interactions in Retirement Plans Decisions: Evidence from a Randomized Experiment", *Quarterly Journal of Economics*, **118**, 815–842.
FLEMING M. and PETTY R. E. (2000), "Identity and Persuasion: An Elaboration Likelihood Approach", in D. Terry and M. Hogg (eds.) *Attitudes, Behavior, and Social Context: The Role of Norms and Group Membership*, Mahwah, NJ: Lawrence Erlbaum Associates Publishers, 171–199.
FOSTER A. and ROSENZWEIG M. (1995), "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture", *Journal of Political Economy*, **103**, 1176–1209.
GARLICK R. (2012), "Academic Peer Effects with Different Group Assignment Policies", (U. of Michigan mimeo).
GODLONTON S. and THORNTON R. (2012), "Peer Effects in Learning HIV Results", *Journal of Development Economics*, **97**, 118–129.
GOLDSTEIN M. and UDRY C. (2008), "The Profits of Power: Land Rights and Agricultural Investment in Ghana", *Journal of Political Economy*, **116**, 981–1022.
GRILICHES Z. (1957), "Hybrid Corn: An Exploration in the Economics of Technical Change", *Econometrica*, **25**, 501–522.
HAGGBLADE S. and TEMBO G. (2003), "Conservation Farming in Zambia" (International Food Policy Research Institute EPTD Discussion Paper #108).
IYENGAR R., VAN DEN BULTE C., and VALENTE T. W. (2011), "Opinion Leadership and Social Contagion in New Product Diffusion", *Marketing Science*, **30**, 195–212.
JACK B. K. (2013). "Constraints on the Adoption of Agricultural Technologies in Developing Countries" (Literature review, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley)).
KARLAN D., OSEI R., OSEI-AKOTO I. *ET AL.* (2015), "Agricultural Decisions after Relaxing Credit and Risk Constraints", *The Quarterly Journal of Economics*, **129**, 597–652.
KEATING N. L., AYANIAN J. Z., CLEARY P. D. *ET AL.* (2007), "Factors Affecting Influential Discussions Among Physicians: A Social Network Analysis of a Primary Care Practice", *J. Gen. Intern. Med.*, **22**, 794–798.
KORNISH L. J. and LI Q. (2010), Optimal Referral Bonuses with Asymmetric Information: Firm-Offered and Interpersonal Incentives", *Marketing Science*, **29**, 108–121.
KREMER M. and MIGUEL E. (2007), "The Illusion of Sustainability", *Quarterly Journal of Economics*, **112**, 1007–1065.
KREMER M., MIGUEL E., MULLAINATHAN S. *ET AL.* (2011), "Social Engineering: Evidence from a Suite of Take-up Experiments in Kenya" (Mimeo, UC Berkeley).
KRISHNAN P. and PATNAM, M. (2013), "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?", *American Journal of Agricultural Economics*, **95**, 308–327.
KUO D., GIFFORD D. R., and STEIN M. D. (1998), "Curbside Consultation Practices and Attitudes among Primary Care Physicians and Medical Subspecialists", *J. Amer. Med. Assoc.*, **280**, 905–909.
LEA N. and HANMER L. (2009), "Constraints to Growth in Malawi" (World Bank Policy Research Working Paper No. 5097).
LEONARD K. and VASILAKY K. (2016), "As Good as the Networks They Keep? Improving Farmers' Social Networks via Randomized Information Exchange in Rural Uganda", *Economic Development and Cultural Change*, **66**.
LOCOCK L., DOPSON S., CHAMBERS D. *ET AL.* (2001), "Understanding the Role of Opinion Leaders in Improving Clinical Effectiveness", *Social Science & Medicine*, **53**, 745–757.
MAGRUDER J. (2010) "Intergenerational Networks, Unemployment, and Inequality in South Africa", *American Economic Journal: Applied Economics*, **2**, 62–85.
MANSKI C. (1993), "Identification of Endogenous Social Effects: The Reflection Problem", *The Review of Economic Studies*, **60**, 531–542.
MILLER G. and MOBARAK A. M. (2015), "Learning about New Technologies through Social Networks: Experimental Evidence on Non-Traditional Stoves in Rural Bangladesh", *Marketing Science*, **34**, 480–499.
MUNSHI K. (2004), "Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution", *Journal of Development Economics*, **73**, 185–215.
MWATO I. L., MKANDAWIRE A. B. C. and MUGHOGHO S. K. (1999), "Combined Inputs of Crop Residues and Fertilizer for Smallholder Maize Production in Southern Malawi", *African Crop Science Journal* **7**, 365–373.
NKHUZENJE H. (2003), "Contribution of Promiscuous and Specific Soybean Variety Residues to Soil Fertility Improvement and Maize Yield under Smallholder Farms in Zomba District, Southern Malawi" (Thesis submitted in partial fulfilment of the requirements of Master of Science degree in agronomy (Soil science)).
NYIRONGO J., MUGHOGHO S., and KUMWENDA J. (1999), "Soil Fertility Studies with Compost and Igneous Phosphate Rock Amendments in Malawi", *African Crop Science Journal*, **7**, 415–422.
OSTER E. and THORNTON R. (2012), "Determinants of Technology Adoption: Private Value and Peer Effects in Menstrual Cup Take-Up", *Journal of the European Economic Association*, **10**, 1263–1293.
ROGERS E. M. (1962), *Diffusion of Innovations* (New York, NY: The Free Press).
SANCHEZ P. A. (2002), "Soil fertility and hunger in Africa", *Science*, **295**, 2019–2020.

STOORVOGEL J. J., SMALING E. M. A. and JANSSEN B. H. (1993) "Calculating Soil Nutrient Balances in Africa at Different Scales. I. Supranational Scale", *Fertilizer Research*, **35**, 227–235.

UDRY C. (2010), "The Economics of Agriculture in Africa: Notes Toward a Research Program", *African Journal of Agricultural and Resource Economics*. **5**, 284–299.

World Bank (2008), *World Development Report 2008: Agriculture for Development* (Washington, DC: The World Bank).

World Bank (2011), *World Development Indicators* (Washington, DC: World Bank).