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Making networks work for policy

Evidence from agricultural technology adoption in Malawi

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Making networks work for policy: evidence from agricultural technology adoption in Malawi

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Summary

The slow adoption of agricultural technologies, particularly in Africa, is a persistent puzzle. Given that subsistence agriculture serves as the main income source for the majority of Africa's rural poor, interventions which increase the use of profitable agricultural technologies can have a major impact on development. One potential constraint to adoption of such technologies is lack of credible information. New technologies can diffuse through inter-personal ties; as social network members are often the most credible source of information. In order to increase adoption, we apply models of network theory on rich social network data from 200 villages in Malawi to identify seed farmers who would maximize technology adoption in theory. A randomized controlled trial, in collaboration with the Ministry of Agriculture and Food Security, compares theory-driven network targeting approaches to simpler, scalable strategies that either rely on a government extension worker or an easily measurable proxy for the network (geographic distance) to identify seed farmers. Adoption rates over three years are greater in villages that received the theory-based data intensive treatments.

To assess whether the theoretical predictions in diffusion models can help inform and improve public policy, we test whether training 'theoretically optimal' diffusion partners leads to greater adoption of a new technology. Selecting these partners required a social network census which we collected in 200 villages across three districts in Malawi. On those 200 networks, we simulated the optimal partners under different assumptions about the median threshold, determined who would be the best choices for that diffusion model, and gave their names to the Malawi Ministry of Agriculture and Food Security (MoAFS) extension workers for training on two types of conservation agriculture. The first, pit planting, is a practice largely unknown at base line, the second technique is crop residue management (CRM). We then trace adoption patterns in these villages over the next two to three seasons to test which sets of partners are most effective at getting farmers to adopt the new technology.

We benchmark the adoption in villages with our theoretically-optimal seeds against the status quo treatment where extension agents use local knowledge to select partners to train. Typically, this involves asking village leaders to nominate a pair of extension partners. Interventions that rely on local institutions may use a great deal of information in selecting these influential people, including their eagerness to try the new technology, their persuasiveness as communicators, and the trust other villagers have in their opinions. As such, our benchmark renders a strong test of diffusion theory: our theoretically-optimal partners were selected only by their position in the network, without the advantage of knowing characteristics available to extension workers choosing partners in benchmark villages.

We find that the data-intensive, theory-driven targeting of optimal seed farmers outperforms the simpler approaches to choosing seeds in terms of technology diffusion across the village over two or three years. Network theory-based targeting increases adoption by 3-4 percentage points more than relying on the extension worker, during the three-year period of the experiment when pit planting adoption grew from 0 per cent to about 10 per cent. The use of network theory therefore increased adoption by 30-40 per cent. The data also show that while physical proximity is not a great perfect proxy for social connections, even the low-cost geography-based targeting strategy generates some gains in adoption relative to the status quo benchmark. This strategy is much cheaper to implement than the theory-driven approaches, which suggests that developing methods to identify other low-cost proxies for social network structure would be a useful policy-relevant avenue for future research.

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Abbreviations and acronyms

AEDO	Agricultural Extension Development Officers
CRM	crop residue management
IPA	Innovations for Poverty Action
MoAFS	Ministry of Agriculture and Food Security, Malawi

1. Introduction

Low productivity in agriculture and environmentally-unsustainable farming challenges are pressing development challenges for many developing countries (Udry 2010). Technologies that would minimize adverse environmental effects and increase long-term yields exist, but have yet to be adopted on a wide scale. As such, the slow adoption of agricultural technologies is a persistent puzzle in development economics. One potential constraint to adoption is lack of credible information.

Social relationships are recognized as important vectors for information sharing through which farmers learn about, and are then convinced to adopt, new agricultural technologies (Griliches 1957; Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010). Scarce resources demand that many governmental programmes rely on this social diffusion to extend their reach: extension agents can rarely train every farmer that they are responsible for, and instead must rely on training a few dissemination partners and expecting social diffusion to reach the rest. As a result, programme efficacy will depend on how well-matched that programme is to the ambient social diffusion process, many aspects of which are both outside of the control of policy makers, and poorly understood.

This suggests that there may be room for improvement in programme design by optimizing the role that social diffusion will play following initial trainings. We used a large-scale field experiment in Malawi to evaluate whether integrating network theory on diffusion processes into extension provision, increases adoption of a new agricultural technology that improves yields for farmers in arid regions of Africa and investigate, what fraction of the gains from utilizing networks can be achieved by using a scalable, cost-effective proxy measure of a farmer's position in a social network. Lessons learned from this experiment are not limited to agricultural programmes. Large literatures in economics (Munshi 2004; Duflo and Saez 2003; Magruder 2010; Beaman 2012), finance (Beshears *et al*. 2013; Bursztyn *et al*. 2014), sociology (Rogers 1962), and medicine and public health (Coleman *et al*. 1957; Doumit *et al.* 2007) show that information and behaviour spread through interpersonal ties. As such, carefully-designed policies which utilize networks could help reduce the global under-adoption of some effective technologies.

There is a rich theoretical literature on diffusion processes (see Jackson 2008 Chapter 7 for a helpful review). For tractability, we refined our focus to a benchmark class of diffusion models: threshold models, where individuals adopt if they are connected to at least a threshold number of adopters (e.g. Granovetter 1978; Centola and Macy 2007; Acemoglu *et al.* 2011). We also tested treatments based on a single theoretically important and experimentally manipulable parameter: the identity of information seeds, that is, the relatively scarce individuals who are trained in the new technology, and from whom information may spread.[1] Within threshold diffusion models, the importance and identity of optimal seeds depends sharply on the threshold parameter. If individuals have a low threshold of adoption, the choice of seeds is not important for long-run adoption levels: if one connection is suitable

[1] One challenge in adapting theoretical results for this goal is that most key predictions in the theory literature on diffusion are derived for the implications of network structure (see Jackson 2008 Chapter 7). Yet, existing learning networks are predetermined and not experimentally manipulable. Moreover, it seems natural to expect that heterogeneity in underlying social structures reflects important heterogeneity in local conditions and institutions, particularly those related to the learning environment, raising concerns over validity of estimates which would leverage this variation.

to motivate adoption, then adoption diffuses quickly for most choices of seeds. Alternatively, it may be critical. If multiple connections are needed to encourage adoption, then many (and often most) potential seed pairings would yield no adoption at all.

To assess whether the theoretical predictions in diffusion models can help inform and improve public policy, we tested whether training theoretically-optimal diffusion partners leads to greater adoption of a new technology. Selecting these partners required a social network census which we collected in 200 villages in Malawi. On those 200 networks, we simulated the optimal partners under different assumptions about the median threshold, determined who would be the best choices for that diffusion model, and gave their names to the extension workers of the Ministry of Agriculture and Food Security, Malawi (MoAFS) for training. We then traced adoption patterns in these villages over the next two to three seasons to test which sets of partners are most effective at getting farmers to adopt the new technology.

We benchmarked the adoption in villages with our theoretically-optimal seeds against the status quo treatment where extension agents use local knowledge to select partners to train. Typically, this involved asking village leaders to nominate a pair of extension partners. As such, it resembled the treatment interventions in a number of recent studies which have used local institutions to identify influential people.[2] Interventions that rely on local institutions may use a great deal of information in selecting these influential people, including their eagerness to try the new technology, their persuasiveness as communicators, and the trust other villagers have in their opinions. As such, our benchmark rendered a strong test of diffusion theory: our theoretically-optimal partners were selected only by their position in the network, without the advantage of knowing characteristics available to extension workers choosing partners in benchmark villages.

The goal of our approach was not to yield a specific, actionable, and cost-effective mechanism for improving the efficiency of extension immediately. Rather, this research is foundational and serves as a first step to characterize the technological-diffusion process, and demonstrate that improvements to extension which select extension partners according to the diffusion process can lead to gains in take-up. This was a critical methodological choice for evaluations which would leverage social institutions to achieve particular outcomes: since social institutions are very context specific, a more straightforward evaluation of the efficacy of a particular social institution would not yield generalizable insights. Instead, as we will characterize the diffusion process, our policy recommendations will come in the form of attributes that knowledgeable local officials should be considering in deciding how to use the local institutional context to select partners and spread information. Subsequent research and experimentation will be needed to find cost-effective ways of determining the best partner farmers (through rapid surveys, elicitation of village leaders, etc.) given what we have learnt in this research about the fundamental diffusion process and the network position of farmers who maximize adoption given that diffusion process.

The report is organized as follows. We present the intervention design and implementation theory in Section 2. Project study context in terms of time and place is described in Sections

[2] Kremer *et al.* (2011) identifies and recruits 'ambassadors' to promote water chlorination in rural Kenya, Miller and Mobarak (2014) first markets improved cook stoves to 'opinion leaders' in Bangladeshi villages before marketing to others, Kim *et al.* (2014) promotes multi-vitamins and water chlorination through network nodes in Honduras, and BenYishay and Mobarak (2014) incentivizes 'lead farmers' and 'peer farmers' to partner with agricultural extension officers in Malawi.

3 and 4. Section 5 discusses all field activities, including data collection, intervention implementation and empirical strategy. Section 6 interprets the results, and Section 7 concludes the report with a discussion of policy implications.

2. Intervention and theory

We develop network-theory based strategies to disseminate information about new agricultural technologies in partnership with the MoAFS. The underlying theoretical basis for the network treatments is the linear threshold model (Granovetter 1978; Acemoglu *et al.* 2011). This model posits that an agent will adopt a new behaviour once the fraction of adopters amongst those he is connected to crosses a threshold. The model was originally designed to study a wide array of collective behaviour including riots, voting, migration, and new technology adoption. The underlying rationale for this formulation is either that the net benefits of adoption are a function of neighbours' adoption decisions (e.g. because the farmers expect to continue learning from each other's experiences on how to make best use of the technology), or because farmers need to hear about the new technology from multiple sources before they are persuaded to adopt.

2.1 Technologies

Since this study focuses on social network-based interventions, we needed to identify technologies where (a) the major adoption constraint is lack of information about the technology, and (b) net benefits of adoption are positive. Pit planting and CRM met these criteria and were chosen after extensive consultations with officials in MoAFS and World Bank. Preliminary results from a separate, ongoing study by BenYishay and Mobarak (2014) indicate that few Malawian farmers knew about pit planting in the driest regions of the country, where the returns to this practice are likely to be highest, suggesting that information dissemination about the technology was limited in our study areas. This may simply indicate that the technology is not appropriate for this setting, which is why people never bothered to learn about it. However, complementary data from the MoAFS and from the national agricultural census can help explain why it is information that might be lacking. The 2007 Malawi National Census of Agriculture and Livestock found that only 18 per cent of Malawian farmers attended any agricultural training, with less than 4 per cent receiving an on-farm visit from an extension officer. It was therefore plausible *ex ante* that information about even profitable and appropriate technologies may be lacking in rural Malawi.

Pit Planting

Maize farmers in Malawi traditionally plant in either flat land or after preparing ridges. Ridging has been shown to deplete soil fertility and decrease agricultural productivity overtime (Derpsch 2001, 2004). In contrast, pit planting, which is the main technology we train the seed farmers on, 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. The technique is practiced elsewhere in Africa, and has been shown to greatly enhance maize yields both in controlled trials and in field settings (BenYishay and Mobarak 2014). In Section 6.4 we offer further evidence on yield impacts in our sample of villages. This enhanced productivity is thought to derive from two mechanisms: (1) reduced tillage of topsoil, which allows nutrients to remain fixed in the soil rather than eroding, and (2) concentration of water around the plants, which aids in plant growth during poor rainfall conditions. The gains from the first mechanism over a counterfactual of continued ridging are thought to accumulate overtime, while the gains from the second are expected to accrue even in the very short run (greater water availability may improve plant growth even within hours). Studies of pit planting in southern Africa have found returns of 50 to 100 per cent for maize production (Haggblade and Tembo 2003) within the first year of production. Pit planting is also an effective method in reclaiming degraded land and harvesting water (Doumbia *et al.* 2005). Given the improved yield results, the decrease in soil erosion problems and the rehabilitation of degraded land, (Kadji *et al.* 2006) promotes greater investment in this technology.

Practicing pit planting may involve 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 up-front costs. However, land preparation becomes easier overtime, since pits should be excavated in the same places each year, and estimates suggest that land preparation time falls by 50 per cent within five years (Haggblade and Tembo 2003). The alternative land preparation method, ridging, is also labour intensive and new ridges are made every year. BenYishay and Mobarak (2014) show that the yield effects of pit planting are large in four other districts of Malawi, while the change in costs is negligible in comparison.

Crop residue management

Seed farmers were also trained in CRM, using a set of messages which largely focused on retention of crop residues in fields for use as mulch. Alternative practices commonly used by farmers include burning the crop residues in the fields or removing them for use as livestock feed and compost. The trainings emphasized the value of retaining crop residues as much to protect topsoil, reduce erosion, limit weed growth, and improve soil nutrient content and water retention. The trainings also addressed potential concerns about modifications in semi-arid areas (where there are fewer residues available), pest infestation, fire prevention, and alternative sources of livestock feed. There is little experimental evidence on the impacts of CRM on soil fertility, water retention, and yields in similar settings. Bationo and Mokwunye (1991) study the role of crop residue in alleviating soil fertility constraints to crop production in West Africa, and claim that the return of 'crop residue for soil fertility improvement cannot be overstressed.' Ouedraogo *et al.* (2001) find that the application of compost results in a significant increase in crop production—sorghum yield tripled—while also mitigating the negative effect of delayed sowing in Burkina Faso potentially leading to increased food availability. They however noted that in order for smallholder farmers to benefit from compost technology, efforts must be made to alleviate the socio-economic factors that are reducing adoption. Adediran *et al.* (2003) find that compost, from maize, weed biomass, and soybean residue, increases the yields of tomato and amaranth.

2.2 Experimental treatments

The study aims are addressed by comparing three different selection methods for 'seed farmers' on the following outcomes: adoption of pit planting at the village level; knowledge of pit planting (advantages, disadvantages and how to implement); and individual pit planting adoption and knowledge, as a function of distance to the seed farmer. Two seed farmers in each village were trained in the targeted technologies by MoAFS extension staff. Our experimental variation only changed the process by which the seed farmers were selected in each village, and all other aspects of the training remain the same. Within each district, we randomly assigned villages to one of the following three treatment arms (or seed farmer selection processes):

1. **Network treatment:** Network relationship data is collected and used to select optimal seed farmers based on network theory.[3]
2. **Geo treatment:** Network model is applied to an adjacency matrix where geographic proximity proxies for a network connection. Adjacency matrices describe a graph by representing which nodes (or individuals/households) are adjacent to which other nodes in the network. These are zero-one matrices i.e. they only have zeros and ones where one denotes a link (connection) between two nodes and zero otherwise.
3. **Status quo benchmark:** Extension worker selects the seed farmers.

Network treatment

The protocol to select the seed farmers in the network treatment villages was implemented as follows. We first collected network relationships data (described in detail in Section 5.3) on the census of households in each village before launching any field intervention activities. The social network structures observed in these data allowed us to construct network adjacency matrices for each of the 200 villages in our sample. Next we conducted technology diffusion simulations for all villages using these matrices. In these simulations, we found that when an individual is connected to at least τ individuals who adopted, he adopts[4]. We assumed that once an individual adopts, all other household members also adopt, since agricultural plots are held at the household level in Malawi. We ran the model for four periods, which corresponded to our data collection activities, in that, we surveyed the sample villages at baseline, and for up to three agricultural seasons after the interventions were implemented.

The final step to prepare for the experimental interventions was to choose the ‘optimal' partner farmers for each village as prescribed by the theoretical simulation randomly assigned to that village. To accomplish this, we picked a pair of individuals in the village and assigned them the role of seed farmers, and predicted the village adoption rate after four seasons under the theory assigned to that village[5]. We repeated this process for every other possible pair of seeds in the village, and ultimately selected the pair that yielded the highest average adoption rate.

Geo-treatment

In the geography (geo) treatment arm, the simulation steps were the same, except that we applied the procedure to a different adjacency matrix generated by making the assumption that two individuals are connected if their plots are located within 0.05 miles of each other in our geo-coded location data. We chose a radius of 0.05 miles because this characterization produced similar values for network degree measures in our villages, as using the actual network connections measures.

[3] Note that this treatment was cross-randomized into two subgroups: simple contagion (λ=1) and complex contagion (λ=2). See Appendix A for more details.
[4] Each individual in the village draws a random adoption threshold τ from the data, which is normally distributed N (λ, 0.5) but truncated to be strictly positive.
[5] Given the randomness built in to the model, we simulate the model 2,000 times and create a measure of the average adoption rate induced by these two seeds.

Status-quo benchmark

The third group is the status-quo benchmark, where Agriculture Extension Development Officers (AEDOs) were asked to select two seed farmers as they normally would. The specific criterion in the benchmark treatment was as follows: extension agents were informed to select lead farmers according to their usual protocol. Discussions with the MoAFS suggest that extension agents are trained to use a community meeting to select lead farmers, but may not always follow this method in practice. The process was a black box to us, but we felt a benchmark where extension agents work within their current *de facto* framework was by far the most relevant one for the comparisons we wanted to draw here.

Comparing the adoption performance of network theory-based targeting against this benchmark constitutes a meaningful and challenging test for the network treatment. In principle, the AEDOs could use valuable information not available to researchers, such as the individual's social stature or motivation to take on the role, to select highly effective seed farmers. It is not clear that the theory-driven diffusion strategies would outperform this treatment. Another option would have been to randomly select seed farmers from the population, but that would have constituted a weaker test. Furthermore, allowing extension staff to select the seeds is what the MoAFS and other policymakers would normally do, so this is the most relevant counter-factual.

Shadow seeds

Note that each of the three seed farmer selection strategies can be applied to any one of the 200 villages to identify who the optimal seed farmers would be under any given treatment (e.g. we could identify the optimal geo-treatment seed farmer in a village assigned to the status quo benchmark). In fact, we identified these counter-factual optimal farmers for all our villages and labeled them 'shadow seeds' associated with each of the other three treatments. This is very useful for analysis, because in any regression where we examine decisions made by the actual seed farmers to understand who they are and the attributes they possess, the shadow seeds form the relevant comparison group. When we report effects on the broader village population, we exclude both the actual and the shadow seeds from those samples.

3. Study context

Our experiment took place in 200 villages randomly sampled from three Malawian districts with largely semi-arid climates: Machinga, Mwanza and Nkhotakota. Villages per district are based on relative district population size with 58 villages in Nkhotakota, 112 in Machinga and 30 in Mwanza. These districts were selected in close collaboration with MoAFS, and as such, our study received full support of Ministry affiliates at the study site. Our sample was randomly selected from the universe of households in the 200 study villages and was therefore representative of the study site population. All three districts are predominantly rural, and the majority of the population farms maize. This is largely representative of the national demographics as well. Approximately 84 per cent of Malawi's population lives in rural areas (World Bank 2015), and agricultural production in these areas is dominated by maize: more than 60 per cent of the population's calorie consumption derives from maize, 97per cent of farmers grow maize, and over half of households grow no other crop (Lea and Hanmer 2009). Malawi is one of several African countries that have unexploited opportunities for greater maize yields (Udry 2010). Technology adoption and productivity in maize is thus directly tied to welfare in these areas. Estimates of national maize yields may vary considerably across sources. National maize yields in Malawi averaged 2.2 metric tons per hectare between 2011 and 2013 according to the FAO (FAO 2015). The World Development Report in 2008 reports the average national yields were just over 1 metric ton per ha. In our study areas, farmers reported yields of close to 1 metric ton per ha. There is variation across our three districts in the average size of total landholdings: 1.7 acres per household in Machinga, 2 in Mwanza and 2.5 acres in Nkhotakota. However, maize yields are pretty consistently similar across the three districts.

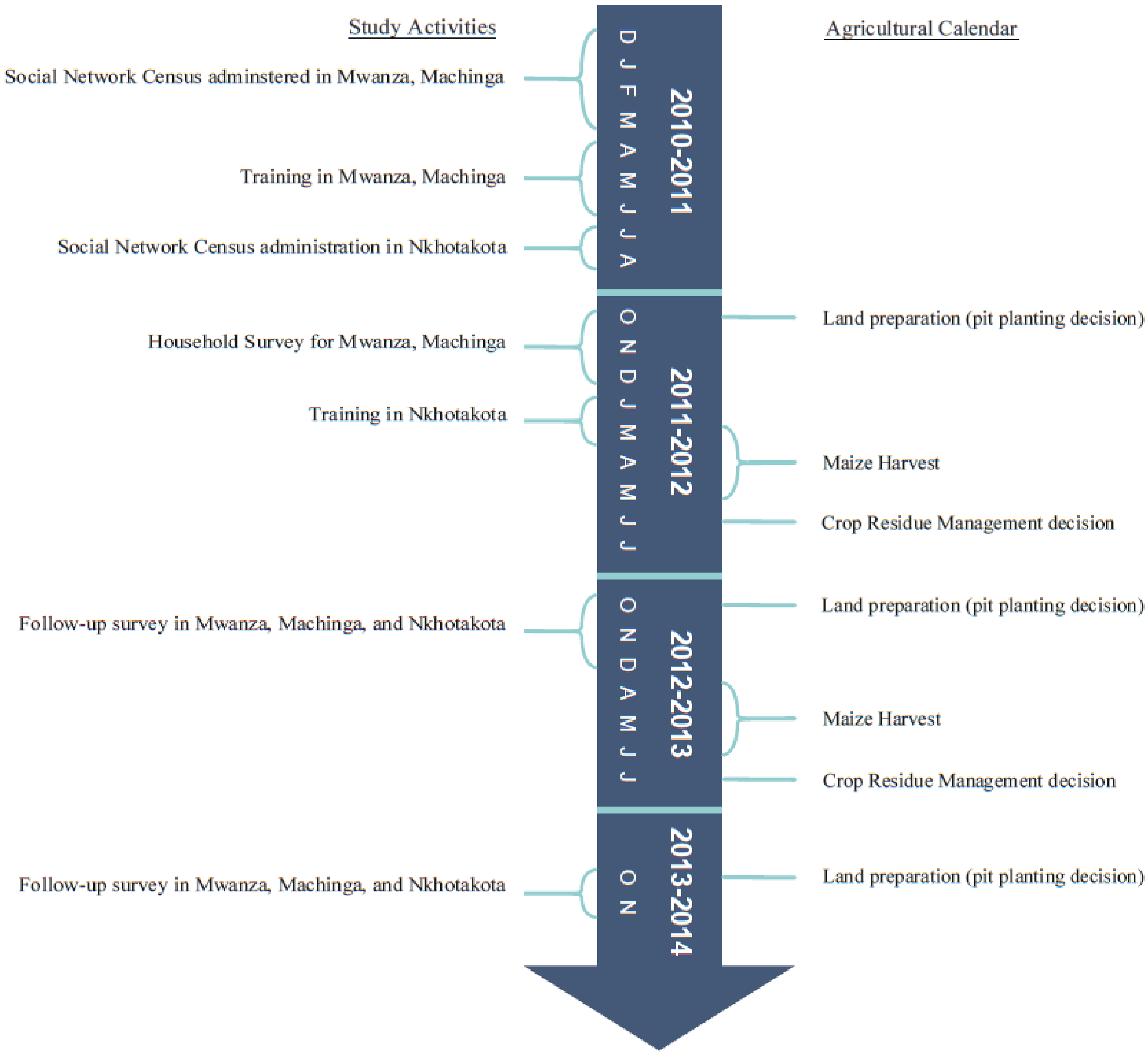
The existing agricultural extension system in Malawi relies on AEDOs who are employed by the MoAFS. Many AEDOs are responsible for upwards of 30-50 villages, which implies that direct contacts are sparse. According to the 2006/2007 Malawi National Agricultural and Livestock Census, only 18 per cent of farmers report participating in any type of extension activity. Against this backdrop of staff shortages, incorporating social learning in the diffusion process may be a cost-effective way to improve the effectiveness of extension.

4. Timeline

The field activities for this project began in December 2010 with the social network census. Due to funding delays, the social network could not be completed in all three districts before the 2010-2011 rainy season. Completion of the census in the districts of Mwanza and Machinga was prioritized, as these districts cover a large part of the sample and were accessible before the rains came. The social network census for our third study district, Nkhotakota, began in July 2011. As such, data on three agricultural seasons was collected in Machinga and Mwanza, while only two seasons are captured in Nkhotakota.

Seed farmer trainings took place in April-June of 2011 for Machinga and Mwanza districts, and January-March of 2012 for Nkhotakota. Survey rounds were conducted in Machinga and Mwanza in October-December of 2011, 2012 and 2013, and in Nkhotakota in OctoberDecember of 2012 and 2013. A graphic depiction of the study timeline can be seen in Figure 1.

Figure 1. Project timeline



5. Evaluation: design, methods and implementation

5.1 Sample selection

Our sample of 200 villages was randomly divided across treatment arms: 100 network treatment[6], 50 geo treatment villages, and 50 benchmark status quo villages. While villages may have been expecting to receive programming from MoAFS, none of the villages were aware that the study contributed to the selection of seed farmers. Randomization was conducted by the research team using Stata, a statistical software program, after the baseline data collection. Randomization was stratified based on per cent of village using compost at baseline, per cent village using fertilizer at baseline, and per cent of village using pit planting at baseline.

We aimed to have 30 observations per village in our final sample. For village-level outcomes (like mean adoption), this would allow us to detect an effect size of 0.6 standard deviations at the 95 per cent level with 84 per cent probability. Assuming that mean adoption is 20 per cent, we would be able to capture a 4.4 percentage point difference in adoption at the village level.

For individual level outcomes (such as individual adoption, information, etc.), this number was sufficient to capture a small (0.2 of a standard deviation) effect with 86 per cent likelihood, assuming a moderate (rho = .075) intra-cluster correlation. It is worth noting that social network effects on changes in agricultural behaviour in other contexts have found much larger effects than this (e.g. Conley and Udry 2010).

The social network census attempted to capture all households in each village. There was no eligibility criteria for the subsample of households selected for the follow-up surveys; all households were eligible to be randomly selected. Table 1 shows overall sample sizes in each of the different categories.

Table 1: Sample sizes

	Villages	Seeds trained	Seeds in 2012-2013 sample	Shadows trained	Shadow farmers surveyed in 2012-2013	Farmers surveyed in 2012-2013
Simple	50	100	88	200	154	1,198
Complex	50	100	98	200	150	1,159
Geo	50	100	93	200	160	1,148
Benchmark	50	100	89	200	240	1,123

5.2 Training of seed farmers

Note that the intervention in our study is the selection of seed farmers, and the actual training programme for seed farmers did not vary across treatment groups. After we produced the lists of seed farmers for each village using the procedures described above, technology training for the selected seed farmers was conducted for all study villages. We provided AEDOs with two seed farmer names for each village in experimental arms one and two, and then replacement names if either of the first two refused to participate. Refusal was uncommon. Seed farmers in each village were trained by the AEDO assigned to their

[6] As mentioned above, the network treatment group was cross-randomized into simple and complex treatments.

village. The AEDOs themselves were first trained in groups by staff from the Ministry's Department of Land Conservation. Specifically, the training was designed by MoAFS and was led by two technical experts from the regional Agriculture Development Division. The following week the AEDOs conducted seed farmer trainings, and they were aware they were participating in a study regarding seed farmer selection. Each seed farmer was invited to attend a one-day training session on both pit planting (the primary focus) and CRM. Farmer trainings were monitored by an IPA staff member using a three-pronged approach: randomly observing farmer trainings, back checks with farmers for unobserved trainings, and collection of basic worksheets from all AEDOs upon completion of their trainings. Farmer training took two to three months to complete in each district, as shown in Figure 1, and did not vary in content for the duration of the study.

Following the training of seed farmers by AEDOs, all seed farmers were also informed that they would receive a small in-kind gift (valued at US$8) if they themselves adopted pit planting in the first year (and that the gift would be given only in the first year). The gift was given at the time of follow up data collection and adoption was verified on the farm by the enumerator. There was no gift or incentive offered or provided on the basis of others' adoption in the village. Incentives were provided only to seed farmers, in exchange for them adopting pit planting. The incentives were used to guarantee high(er) adoption rates among those trained. Even with training, lead farmers may not adopt new technologies, particularly technologies like pit planting which require a major change in practice. Without the incentives, there would presumably have been a much lower adoption rate by seed farmers, guaranteeing that there would be little dissemination of information into the village. IPA enumerators conducted household visits to verify adoption after the first year before the seed farmer was given the in-kind gift. Enumerators travelled with a lead farmer to each of his/her plots and verified whether the farmer had adopted pit planting and how the farmer used the crop residues. If planting pits were present, the enumerator measured the dimensions of the pits and counted their frequency to determine whether the specifications matched the recommendations of the agriculture office.

5.3 Data

Data collection was conducted in partnership with IPA. Ethical approval for all research activities was provided by the institutional review boards at Massachusetts Institute of Technology and Northwestern University.

Programming in Blaise

All surveys were conducted on net books using Blaise, a software program for computer-assisted personal interviews. This method of data collection has several distinct advantages: survey skips are written into the programming code and occur automatically, each question has a specified value type and range that reduces data collection mistakes, and all enumerators have to answer each question that is displayed so questions cannot be accidentally skipped. In addition, the data can be analyzed in real time to correct problematic questions or to uncover challenges enumerators are having, which can be corrected through retraining.

Computer data collection has an added advantage when conducting a social network census. After the listing data is collected from a village, the program dynamically creates a comprehensive list of all adults in the village and assigns unique IDs. The list is then imported onto the net books for use during the household and individual surveys in the same village. The net books with a complete list of villagers allow the surveys to use that information to find social connections between the respondent and those they talk to about agriculture and farming technologies. Enumerators are able to use a search function within the programme to identify and verify individuals named in the questionnaire modules. This eliminates mistakes that may occur when using IDs hand-written onto questionnaires.

Enumerator training and data collection

IPA recruited, tested, and trained enumerators and field supervisors in the districts of Mwanza, Nkhotakota and Machinga. Each enumerator applicant was assessed based on a combination of local knowledge and survey experience, with the goal of creating important synergies within the survey teams. Selected enumerators underwent a weeklong rigorous training session which included protocols for approaching respondents, obtaining informed consent, asking survey questions, entering data in net books, and dealing with obstacles commonly encountered in the field. All surveys were piloted in villages near the study sample to test the efficacy of the questions and to refine the survey design. All survey instruments were drafted in English and translated into Chichewa, the most commonly spoken language in Malawi. The survey was also back-translated into English to ensure complex phrasing was accurately described in Chichewa. Additionally, the survey was translated into Yao, a language spoken in very remote areas of Machinga district bordering Mozambique, to ensure all respondents would be able to easily participate.

Social network census data

As mentioned above, targeting based on different network characteristics—including relational statistics of these networks—requires relatively complete information on network relationships within the village (Chandrasekhar and Lewis 2011). To collect this data, our field teams listed all adults in each of our sample villages and created a database with all adult names and household structures for each village. Specifically, the census was divided into two parts: a village-listing exercise and individual household visits. In the listing exercise, enumerators travelled to each village in the study sample and created lists of all households in a given village. All households then received an individual household visit where a general household questionnaire was administered in addition to individual male and female questionnaires. For each household, a roster of all household member names, nicknames, maiden names, genders, relationships, and ages was completed. Net book computers were used by the field teams to identify links in real-time. While the field team attempted to interview one man and one woman in each household, in practice we reached more than 80 per cent of households participating in the census in every sample village. Enumerators returned to households several times to ensure that all available households were surveyed. In total, enumerators interviewed a sample of 18,926 respondents from 15,049 households.

The main focus of the social network census was to elicit the names of people each respondent consults when making agricultural decisions. General information on household composition, socioeconomic characteristics of the household, general agriculture information, and work group membership was also collected. The individual questionnaires asked about agricultural contacts several ways: first by asking in general terms about farmers with whom they discuss agriculture and whom they are in agricultural work groups with. To probe more deeply, we also asked them to recall over the last five years if they had: (i) changed planting practices, (ii) tried a new variety of seed, for any crop, (iii) tried a new way of composting, (iv) changed the amount of fertilizer being used for any crop, or (v) tried a new crop, such as paprika, tobacco, soya, cotton, or sugar cane, or (vi) started using some other new agricultural technology. If they responded affirmatively, we asked respondents to name individuals they knew had previously used the technique in the past and whether they had consulted these individuals. Finally we asked them if they discussed farming with any relatives, fellow church or mosque members, or farmers whose fields they pass by on a regular basis. We also elicited contacts with whom they share food and close friends, though we do not use these types of connections in generating our adjacency matrices as they may not be relevant for agricultural conversations. These responses were matched to the village listing to identify links.

Sample household survey sata

Follow-up household surveys were conducted in the months following the seed farmer training. Survey data was collected on farming techniques, input use, yields, assets, and other characteristics for a sample of approximately 5,600 households in the 200 sample villages. Respondents were asked to answer questions related to household agricultural production during the last rainy season; for example: crops grown, how much land they put under the different crops and their yield. The questionnaire contained a section on questions specifically on crop management practices for maize. Data was also collected through on-farm monitoring visits in a subset of the villages. The farm visits gave us concrete data on rates of adoption and adherence to the recommendations for the target technologies.

Enumerators attempted to survey all seed and shadow farmers in each village, as well as a random sample of 24 other individuals, for a total of 30 households in each village.[7] In villages with fewer than 30 households, all households were surveyed. No additional inclusion or exclusion criteria were used. The initial rounds referenced agricultural production in the preceding year—thus capturing some baseline characteristics—as well as current knowledge of the technologies, which could reflect the effects of training. Since the data was collected at the start of a given agricultural season, we observe three adoption decisions for pit planting for farmers in Mwanza and Machinga, and two decisions for farmers in Nkhotakota. Since CRM decisions are made the end of an agricultural season after harvest, we observed CRM decisions for two agricultural seasons in Mwanza and Machinga, and one in Nkhotakota. Data was collected by enumerators via paper survey. Following the completion of field work, survey data was double-entered electronically by a team of experienced IPA data entry operators using the software CSPro. The data was error-checked by a senior data entry supervisor and was also independently audited, where the error rate was shown to be 0.016 per cent, well below IPA's maximum allowable error rate for entered data.

Rainfall data

We obtained daily precipitation data over 9 km grid cells from aWhere (2014). aWhere's weather data are assembled from ground meteorological stations and orbiting weather satellites, with daily precipitation data derived from Colorado State University's near-real time implementation of a high resolution, global, satellite precipitation product. The data product is a multi-sensor combination of several satellite passive microwave precipitation algorithms available in near-real time from the National Oceanic and Atmospheric Administration, which is then processed using a 3-D spline interpolation. Using these data, we constructed seasonal total precipitation at each village location.

[7] In Simple, Complex and Geo villages there were 6 (2x3) seed and shadow farmers to interview, while in Benchmark villages there were 8 (2x4) seeds and shadows, so we randomly selected among shadow farmers.

5.4 Empirical strategy

The randomization protocol allows for a very simple empirical strategy. Some of our main results will look at an outcome y on a series of indicator variables for whether an individual *i* resides in a village *j* which was assigned to a network or geographic targeting strategy. The excluded category will be the benchmark villages.

$$y_{ijt} = \alpha + \beta_1 Network + \beta_2 Geographic + X_j \gamma + \epsilon_{ijt}$$

Where Network = 1 if individual *i* lives in a village *j* which was assigned to the network contagion targeting strategy and 0 otherwise. Since this is randomly assigned, we can interpret β_1 as the causal effect of the targeting strategy on individual *i*'s outcome y. Also included in the specification are the X_j control variables. These are stratification controls (per cent of village using compost at baseline; per cent village using fertilizer at baseline, per cent of village using pit planting at baseline); village size and its square; and district fixed effects. Standard errors are clustered at the village level. The outcomes we analyze at the individual-level include the randomization check, the characteristics of seed and shadow farmers, the adoption decisions of seed and shadow farmers, crop yields and conversations about pit planting. These are found in Tables 2-7. These regressions are done separately year by year.

We also do a very similar regression using data aggregated to the village level in Tables 89 which look at pit planting adoption among all non-seed farmers. The specification is therefore:

$$y_{jt} = \alpha + \beta_1 Network + \beta_2 Geographic + X_j \gamma + \epsilon_{jt}$$

As before, the X_j control variables are stratification controls (per cent of village using compost at baseline; per cent village using fertilizer at baseline, per cent of village using pit planting at baseline); village size and its square; and district fixed effects. Standard errors are clustered at the village level.

In order to look at individual-level adoption decisions among individuals who were not seeds we use the following specification:

$$Y_{ij} = \alpha + \beta_1 TSeeds + \beta_2 Network + \beta_3 Geo + \theta_j + \varepsilon_{ijt}$$

Where β_1 is the only coefficient of interest, since $TSeeds$ is an indicator for the respondent being directly connected to at least one trained seed farmer. The variable $Network = 1$ indicates that the household is connected to at least one 'network seed' and Geo is 1 if the household is connected to at least one geo seed. To illustrate, we compare, say, two farmers who are both connected to exactly two 'network seeds', but where one farmer is in a village randomly assigned to the 'network contagion' treatment (so that his connections were actually trained on the technology), while the other was not. We interpret the effects of variables associated with β_2 and β_3 as those of control variables that capture the respondent's overall network position with respect to the (actual and shadow) seed farmer links (which is endogenous), and these coefficients are omitted from the table presenting the results.[8] This specification constrains the effect of being connected to trained seeds to be the same across targeting treatments. The specification results are presented in Table 10.

6. Results

6.1 Qualitative data analysis

Participatory rural communication appraisal (PRCA) tools and focus group discussions were used to collect qualitative data from four of the sample villages. This allowed for a more in-depth perspective/investigation on the influence of farmers' social networks in order to understand whether the use of seed farmers and their social networks is an effective way of facilitating technology uptake in recognition of other attempts that are existent, for instance, extension workers and farmer field schools. Participation was based on the number of people who were able and willing with attendance ranging from 6 to 11. The qualitative data was used to help interpret and contextualize statistical findings and anomalous data from the quantitative analysis. Since the qualitative analysis was done with a very small subsample of the villages, results must be interpreted with caution.

Ranking and mapping was used to identify the flow of agricultural information in the villages. All the villages ranked either the extension worker or the extension partner/seed farmer as the most important source of agricultural information. This makes extension partners and community social networks very important. They however pointed out that extension workers are not readily available due to the distance it takes to travel to their homes and the high extension worker to community members' ratio. Three of the villages ranked extension partner or seed farmers and friends as the ones they most frequently consult or meet for agricultural information. Participants mentioned that they rely on the hard-working and progressive farmers and their friends to receive agricultural information and advice. Social networks therefore seem to have greater leverage in influencing technology adoption.

Extension partners were also asked to evaluate the economic feasibility of the new conservation techniques against their conventional ridge tillage in terms of time, labour, capital and land usage. Preliminary qualitative analysis revealed that pit planting improved crop yields in most villages supporting what was found in the quantitative data. Qualitative research highlighted difficulties faced by farmers who adopted the new technology (e.g. weed and bug control), shedding light on reasons why some villages may have performed more poorly than others. It was revealed that the new technologies have more intensive start-up costs in terms of time and labour, though adopters found these costs to be worthwhile in the long run. Adopters additionally noted that the success of the new technology may also be linked to when in the growing season the technology is introduced. Trends such as these helped inform and shape the quantitative data analysis. The qualitative data was also used to inform broader policy recommendations based on the quantitative findings. For example, the preliminary qualitative report results suggested that there was misinformation in the community about why certain seed farmers were selected,

[8] For example, $1Simple$ indicates that the respondent is directly connected to one simple seed while $2Simple$ says that the respondent has connections to two simple seeds. $1Complex$, $2Complex$, $1Geo$ and $2Geo$ are analogously defined for complex seeds and geo seeds respectively.

which may not have been fully revealed in the quantitative analysis. While seed farmers stood as influencers of technology adoption, it was also a new technology to them and they would need ongoing support from the extension workers. However, if the extension workers felt undermined in the process of selecting these seed farmers, the requisite technical support might be challenging to provide. Future policy implementation should better engage the extension workers on why partner farmers were selected. Community members also pointed out they would adopt the technology after first observing their friends field; reiterating the influence of field trials/demonstrations and learning from an adopter in your social network when new technologies are introduced. Issues such as these, which could play an important role in scale-up and programme expansion, will supplement the conclusions reached through the quantitative randomised controlled trial.

6.2 Balance

Table 2 shows a balance check table for key variables in the analysis. The treatment and control groups were compared to ensure there were no significant differences. Overall, households in the treatment and control villages were similar. However, there are significant differences between the control and network on farm size and housing at the 1 per cent and 5 per cent level respectively whilst for livestock there is a difference between control and geo at the 5 per cent level. This is a reasonable number of characteristics to differ statistically, given the large number of tests displayed in Table 2, and that a certain per cent will be statistically significant by chance.

We made no assumptions about other technologies and in fact at inception we thought there would be significant differences in the threshold number of contacts based on technical characteristics. This is why we trained in two different technologies. However, we see little evidence that the second technology (CRM) resulted in any behavioural change at all. This may be because farmers were already adopting similar methods at the time of training. We would anticipate that our results would extrapolate best to contexts where technological adoption requires a major change in established practices, and where there are no credit constraints to adoption.

Table 2: Randomization check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Housing[1]	Assets[1]	Livestock[1]	Used fertilizer	Basal fertilizer (kg)	Top dressing fertilizer (kg)	Pit planting	Number of adults	Number of children (<5)	Farm size (acres)
Benchmark	-0.179	-1.093	-0.178	-0.001	60.490	71.230	0.000	2.309	1.201	1.676
	(0.277)	(0.185)	(0.200)	(0.002)	(14.560)	(15.940)	(0.001)	(0.077)	(0.074)	(0.251)
Network Partners	-0.429	-1.201	-0.230	-0.001	60.240	68.870	0.000	2.301	1.227	1.476
	(0.295)	(0.188)	(0.208)	(0.002)	(15.200)	(16.290)	(0.001)	(0.079)	(0.072)	(0.256)
Geo	-0.314	-1.183	-0.320	0.000	58.850	68.580	0.000	2.296	1.220	1.605
	(0.325)	(0.198)	(0.202)	(0.002)	(14.380)	(16.620)	(0.001)	(0.079)	(0.072)	(0.268)
Observations	15,080	15,347	15,347	15,065	11,221	11,331	15,070	15,095	15,081	15,074
R-squared	0.014	0.019	0.015	0.815	0.127	0.178	0.104	0.861	0.548	0.354
Control = Network	0.023	0.083	0.448	0.533	0.944	0.427	0.975	0.774	0.276	0.005
Control = Geo	0.481	0.223	0.045	0.550	0.643	0.434	0.694	0.725	0.453	0.471
Network = Geo	0.560	0.798	0.077	0.147	0.701	0.919	0.548	0.883	0.776	0.160
Joint	0.072	0.202	0.074	0.304	0.884	0.677	0.828	0.935	0.542	0.017

Note

[1] Housing, assets and livestock variables are indices constructed from a principle components analysis.

Table 3: Seed and shadow characteristics by optimal treatment

	Wealth Measures		Social Network Measures			
	Farm Size	Total Index (PCA)	Degree	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment						
Network	-0.098	0.216	1.837*	123.292**	0.005*	0.088**
	(0.18)	(0.22)	(1.00)	(58.90)	(0.00)	(0.04)
Geo	-0.622***	-0.769***	-3.750***	-94.787	0.005*	-0.146***
	(0.19)	(0.23)	(1.04)	(61.53)	(0.00)	(0.04)
p-values						
Network= Geo	0.000	0.000	0.000	0.000	0.882	0.000
N	1,242	1,242	1,270	1,270	1,270	1,270
Mean of Benchmark Partners	2.07	0.651	13.9	171	0.005	0.546
SD of Benchmark Partners	2.98	1.7	6.81	345	0.007	0.294

Notes

1 The sample includes all seeds and shadows. The sample frame includes 100 benchmark farmers (two partners in 50 villages), as we only observe benchmark farmers in benchmark treatment villages, and six additional partner farmers (two simple partners, two complex partners, and two geo partners) in all 200 villages.

2 Betweenness centrality is derived from the number of shortest paths between individuals in a network. Closeness centrality measures the average social distance from each individual to every other individual in the network. Eigenvector centrality measures how an individual is well-connected to parts of the network with the greatest connectivity. Individuals with higher eigenvector scores are connected to a lot of other individuals that are themselves well-connected etc.

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

6.3 Characteristics of seed farmers

The experimental design allowed extension workers to choose any seed farmer they wanted in the benchmark treatment, and this may have sometimes coincided with the network theory - targeted seeds. However, the treatment arms generated different types of seed farmers in general. It also generated different clustering patterns.

Table 3 compares the seed farmers chosen in the three different experimental arms in terms of observables such as wealth and land size from our survey data, and in terms of centrality measures computed from our social network census data. The most striking pattern in Table 3 is that the seeds selected under the geographic treatment are much poorer than other seeds. This is because many households live on their farm land in Malawi. Therefore households who are geographically closer to other people also have less land. These households are also poorer in terms of other assets. Therefore while the idea of using geography as a proxy for one's network may be intuitive, the implications of geographic centrality may be highly context-specific. We also computed that seed farmers selected through the network treatment are the most 'central' across all measures of network centrality. Seed farmers in this group have almost two more direct connections to others in the village than the seed farmers chosen by the extension workers. Seeds in the network treatment also possess the highest betweenness, which implies that they are important players in the communication paths in these villages.

6.4 Do seed farmers adopt the technology themselves?

Table 4 and Figure 2 show that the interventions increased the likelihood that the seed farmers themselves adopted the technologies. The sample is restricted to seed and shadow farmers only, so this specification captures the causal effect of the intervention, and not differences in adoption across farmers at different positions within the network. In Table 4, columns (1)-(3) focus on pit planting whilst columns (4)-(5) focus on CRM. Seed farmers trained in the technology adopted at about a 30 per cent rate in all three years. This means that they are 17-26 percentage points more likely to adopt than comparable shadows across all three years, who adopt at a 6-13 per cent rate across years, so this represents a large increase. These results indicate that seed farmer adoption rates are constant, whilst control farmers have increasing adoption rates and should not be misinterpreted as seed farmers abandoning pit planting. As a result, the difference between seed farmers and control farmers is decreasing. This is strong evidence that farmers find this technology valuable, which is in line with our yield results.

We provided an in-kind incentive for the seed to adopt pit planting in the first year but not thereafter. The persistent adoption gap suggests that the seeds who tried out pit planting found the technology to be profitable. We never provided the seeds any incentive to adopt CRM, but the trained farmers were 13 percentage points more likely to use CRM in the first year. CRM was a much better-known technology to begin with, with 33 per cent of shadows practicing it in the first year. CRM adoption dropped in the second year among both actual seeds and the shadows. These results are consistent with the observation that pit planting is a newer and unknown technology for which information constraints were probably more relevant. Pit planting adoption among those trained was also persistent, which suggests that the seed farmers found the method useful. In contrast, CRM take up did not persist, which could mean that the technology was not well suited for these farmers. This makes analysis of network effects on CRM adoption more complicated, because some of the messages that got passed between farmers may have been 'do not adopt', and adoption propensity among others in the village may not be the right outcome variable.

Figure 2: Training partner farmers on pit planting increases adoption

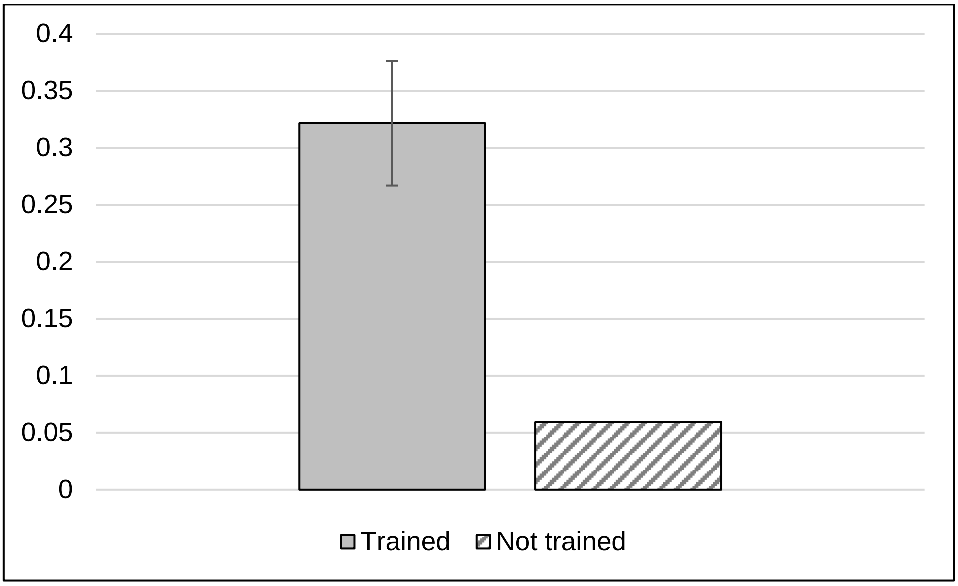


Table 4: Seeds versus counterfactual farmers

	Adopted Pit Planting			Adopted CRM	
	(1)	(2)	(3)	(4)	(5)
Seed	0.262 ***	0.221 ***	0.169 ***	0.130 ***	0.061 ***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
N	972	961	692	972	661
Mean	0.059	0.089	0.129	0.329	0.241
Season	1	2	3	1	2

Notes

[1] Also included are village fixed effects. Sample includes only seed and counterfactual seed farmers. Standard errors are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 restricts the sample to only seed farmers who were trained (and drops all shadows) to examine whether adoption behaviour varies across the three types of seeds in the experimental arms. Columns (1)-(3) show that there are no differences in adoption propensities across the three types of seeds. This is perhaps striking because AEDOs could have screened partner farmers in benchmark villages based on their interest in using the new technology. Columns (4)-(5) show that there are no significant differences in adoption in season 1 for CRM adoption. The negative coefficients in Table 5 indicate a lower adoption rate than the benchmark treatment (all coefficients are relative to the excluded group), though these differences are not statistically different from zero.

Table 5: Seed farmers' adoption of technologies

	Adopted Pit Planting			Adopted CRM	
	(1)	(2)	(3)	(4)	(5)
Network treatment	-0.025	0.082	0.083	0.053	-0.108
	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)
Geo treatment	-0.105	-0.057	-0.033	0.000	-0.101
	(0.08)	(0.07)	(0.08)	(0.08)	(0.10)
N	342	330	247	342	232
Mean	0.346	0.269	0.246	0.432	0.382
Network = Geographic	0.254	0.029	0.105	0.401	0.929
Season	1	2	3	1	2

Notes

[1] Also included are stratification controls (per cent of village using compost at baseline; per cent village using fertilizer at baseline, per cent of village using pit planting at baseline); village size and its square; and district fixed effects. Only seed farmers are included. Standard errors are clustered at the village level.
*** p < 0.01, ** p < 0.05, * p < 0.1.

6.5 Effect of technology adoption on crop yields

We collected data on maize yields in our follow-up surveys, and we use this to show that the technologies we promoted led to an increase in productivity (Table 6). We further used rainfall variation to study heterogeneity in the yield gains, because pit planting is more productive under arid conditions. This allows us to establish that the information about pit planting that diffused through the networks was likely positive on an average. This in turn would allow us to interpret more adoption of pit planting as a signal of greater information diffusion.

We compared seed farmers to shadow farmers to study yield effects, exploiting the randomization in the experimental design. In an intent-to-treat specification, maize yields among seed farmers (who were both trained on the technologies and promised a small reward to adopt) are 11.5 per cent greater than the yields experienced by the comparable shadows. The second column of Table 6 examines the heterogeneity in this yield effect across rainfall states, because pit planting is designed to increase yields under arid conditions, when soil moisture retention in the pit is most important. This specification allows a linear interaction with rainfall, and indicates that the relative productivity on the seed farmers' plots, compared to shadow farmers, is decreasing with precipitation. The benefits of adopting pit planting are highest in low rainfall states. To put the effect size in perspective, the returns to pit planting are as large as the yield increase from moving from the bottom quintile of rain to the fourth quintile. A concern with pit planting is that too much rainfall could cause water-logging in the pits. In our data, the returns to pit planting are zero – not negative – at the top quintile of rain. The heterogeneity results strongly suggest that the yield increases for seed farmers comes from adoption of pit planting.

We report the local average treatment effect using an IV regression in the third column in which we instrument pit planting adoption with an indicator for being randomly assigned the role of the actual seed farmer who gets trained and incentivized to adopt (rather than a shadow). In this specification, pit planting adoption is associated with a 47.5 per cent increase in maize yield.

Table 6: Yields

	(1)	(2)	(3)
Estimation	OLS	OLS	IV
Adopted PP			0.475**
			(0.206)
Seed	0.115**	0.457***	
	(0.050)	(0.127)	
Total precipitation over season (mm)		0.084***	
		(0.032)	
Seed X total precipitation		-0.144***	
		(0.048)	
Observations	1,460	1,460	1,460

Notes

[1] All columns include district and season FE and controls for total farm size, village size, and village baseline usage of fertilizer, composting and pit planting. Robust standard errors clustered by village in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.6 Seeds farmers' interactions with other villagers

Thus far we have documented that the seed farmers trained on the technologies are more likely to adopt the technology themselves, realize some productivity gains from pit planting and persist with adoption, and that some types of seeds are more network central than others. Next we investigate whether these seed farmers assigned a communication role exert any effort to disseminate information about pit planting to their neighbours in the village.

Table 7 uses data collected in 2011 and 2012 on conversations about pit planting that all respondents had with others in the village. Each respondent was asked questions about seven other individuals in their village, whether they knew them, and what they had discussed. The seven individuals included the two seed farmers, some randomly selected shadow farmers, and a random sample of other village residents.[9] The empirical challenge with documenting more conversations with the seeds trained on the technologies is that these seeds were chosen to be network central, and such individuals would have more conversations with others regardless of our experimental treatments.

[9] In Nkhotakota, the definition of the boundaries of the village is not uniformly agreed upon. In some cases, the extension workers selected seed farmers from outside of the geographic area that our listing exercise defined as a village. We have limited information about connections between individuals in the village and the seed farmers in such cases.

We instead exploit the random variation in the experiment, and compare conversations with the (say) network treatment seeds who were assigned the communication role by our intervention to communication with the (network treatment) shadows in other villages who are observably similar, and who would have been the communicator had those comparison villages been assigned to the network treatment. In other words, we test whether a potential seed being trained on pit planting increases the likelihood that he talks to others about pit planting.

Table 7: Conversations about pit planting

	With Network Partner	With Geo Partner
	(1)	(2)
Network treatment	0.073***	0.002
	(0.018)	(0.008)
Geo treatment	0.007	0.031**
	(0.014)	(0.016)
N	3,349	3,718
mean	0.051	0.018
SD	0.220	0.133
Test: Network = Geo	0.000	0.038
Season	1	1

Notes

[1] Sample excludes seed and shadow farmers. We only collected this data in 2011-2012 and therefore this analysis is restricted to Mwanza and Machinga.

Table 7 shows that the experiment did induce the seed farmers to discuss pit planting with fellow villagers. Column (1) shows that there are more discussions with the network seed compared to the benchmark villages (7.3 percentage points). This represents a large increase over the mean value (5.1) in the benchmark villages. Column (2) shows, analogously, increases in conversations about pit planting with the geo farmer in Geo villages (3.1 percentage points). In summary, the seed farmers trained in the pit planting method discussed the technology with others in his village as a result of our treatment.

6.7 Does social network-based targeting increase adoption?

The Granovetter (1978) and Acemoglu *et al.* (2011) threshold model of network diffusion suggests that to maximize technology adoption, information or other inducements to adopt should be targeted to key individuals within a network. The first step in our programme evaluation therefore examines whether threshold-model inspired network-based targeting improves the adoption rate of a seemingly productive, welfare-enhancing technology. Table 8 and Figures 3 and 4 focus on pit planting adoption, because our analyses of seed behaviour and yield effects indicate that the experiment induced persistent adoption of only pit planting among seeds, and the seeds experienced higher yields by practicing pit planting.[10]

[10] Adoption patterns for CRM are presented in Appendix B.

Table 8: Aggregate pit planting adoption

	Adoption Rate for non-seeds			Number of non-seed adopters			Any non-seed adopters		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Network Treatment	0.012	0.034**	0.023	0.200	1.783**	1.375	0.047	0.225***	0.276***
	(0.009)	(0.014)	(0.021)	(0.496)	(0.723)	(1.186)	(0.078)	(0.084)	(0.094)
Geo Treatment	0.019	0.041	0.016	0.439	0.639	-0.665	0.125	0.108	0.218**
	(0.014)	(0.026)	(0.030)	(0.587)	(0.727)	(1.055)	(0.095)	(0.095)	(0.109)
N	200	200	141	200	200	141	200	200	141
Mean Benchmark	0.021	0.041	0.076	1.15	1.82	4.01	0.300	0.420	0.514
SD of Benchmark	0.040	0.080	0.108	3.42	3.48	6.19	0.463	0.499	0.507
P value of test: Network = Geo	0.597	0.765	0.763	0.640	0.167	0.062	0.364	0.145	0.513
Season	1	2	3	1	2	3	1	2	3

Notes

[1] Network partners are villages where seeds were selected using the threshold model and the social network data. Geographic partners refers to villages where seeds were selected using the threshold model, but where links were proxied by geographic distance instead of direct solicitation of social network links. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[2] Columns (4)-(6) include sample weights for village size.

[3] Also included are stratification controls as listed in Table 5. Seed and shadow farmers are excluded.

[4] Test: Network = Geographic shows the p- value of the test of whether the effect of the network partners treatment is different from the geographic partner treatment.

[5] Season refers to the number of seasons following the training of seed farmers. Season one is 2010 in Mwanza and Machinga, and 2011 in Nkhotakota. Columns (3), (6) and (9) use data from villages in Mwanza and Machinga as we have three seasons of data only for those two districts.

Table 9: Aggregate pit planting adoption if less than median baseline familiarity with pit planting (<0.0432 ever tried)

	Adoption rate for non-seeds			Number of non-seed adopters			Any non-seed adopters		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Network Treatment	0.013	0.039*	0.061**	1.161**	2.670*	3.663**	0.104	0.208	0.394***
	(0.011)	(0.023)	(0.027)	(0.571)	(1.350)	(1.518)	(0.108)	(0.130)	(0.122)
Geo Treatment	-0.006	0.022	0.048	-0.061	0.371	1.606	0.033	0.048	0.355**
	(0.010)	(0.029)	(0.033)	(0.516)	(1.200)	(1.560)	(0.130)	(0.144)	(0.151)
N	99	99	82	99	99	82	99	99	82
Mean Benchmark	0.020	0.040	0.053	0.589	1.86	2.86	0.250	0.458	0.450
SD of Benchmark	0.039	0.093	0.093	1.18	3.84	5.46	0.442	0.509	0.510
P- value of test: Network = Geo	0.054*	0.513	0.679	0.065*	0.120	0.254	0.554	0.158	0.758
Season	1	2	3	1	2	3	1	2	3

Notes

[1] Network partners are villages where seeds were selected using the threshold model and the social network data. Geographic partners refers to villages where seeds were selected using the threshold model, but where links were proxied by geographic distance instead of direct solicitation of social network links.

[2] Columns (4)-(6) include sample weights for village size.

[3] Also included are stratification controls as listed in Table 5. Seed and shadow farmers are excluded.

[4] Test: Network = Geo shows the p value of the test of whether the effect of the network partners treatment is different from the geographic partner treatment.

[5] Season refers to the number of seasons following the training of seed farmers. Season one is 2010 in Mwanza and Machinga, and 2011 in Nkhotakota. Columns (3), (6) and (9) use data from villages in Mwanza and Machinga as we have three seasons of data only for those two districts.

Figure 3: Adoption rates across network, geo and benchmark partner villages

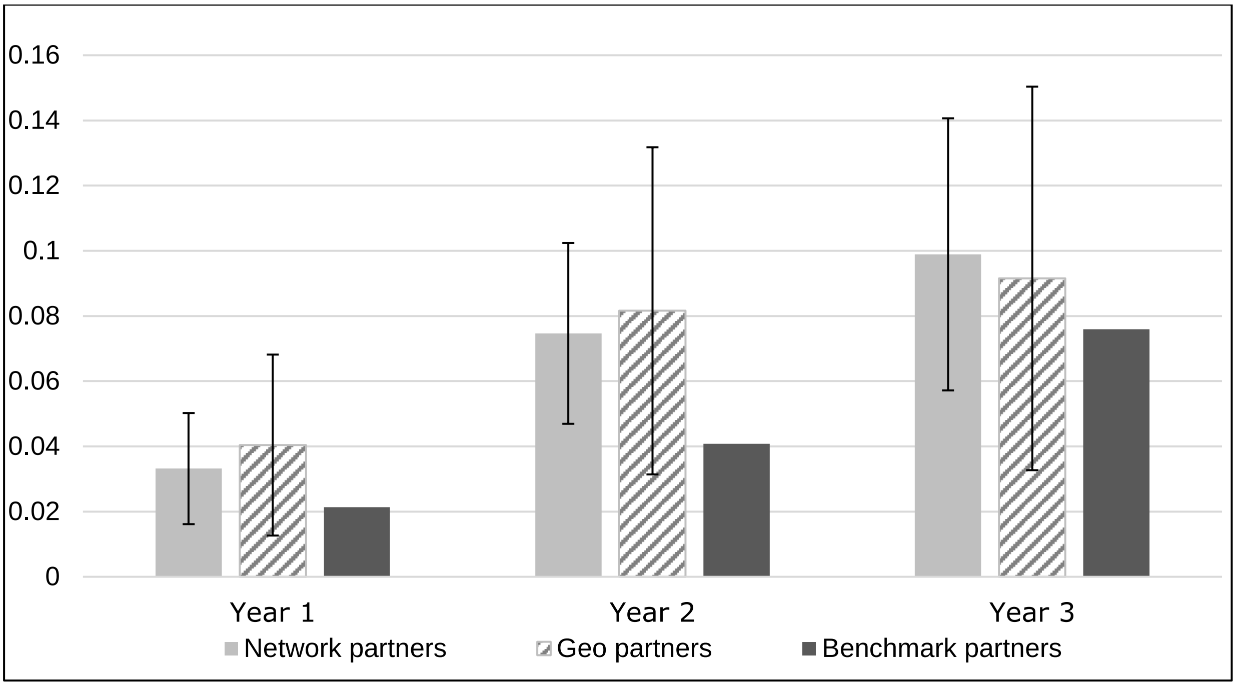
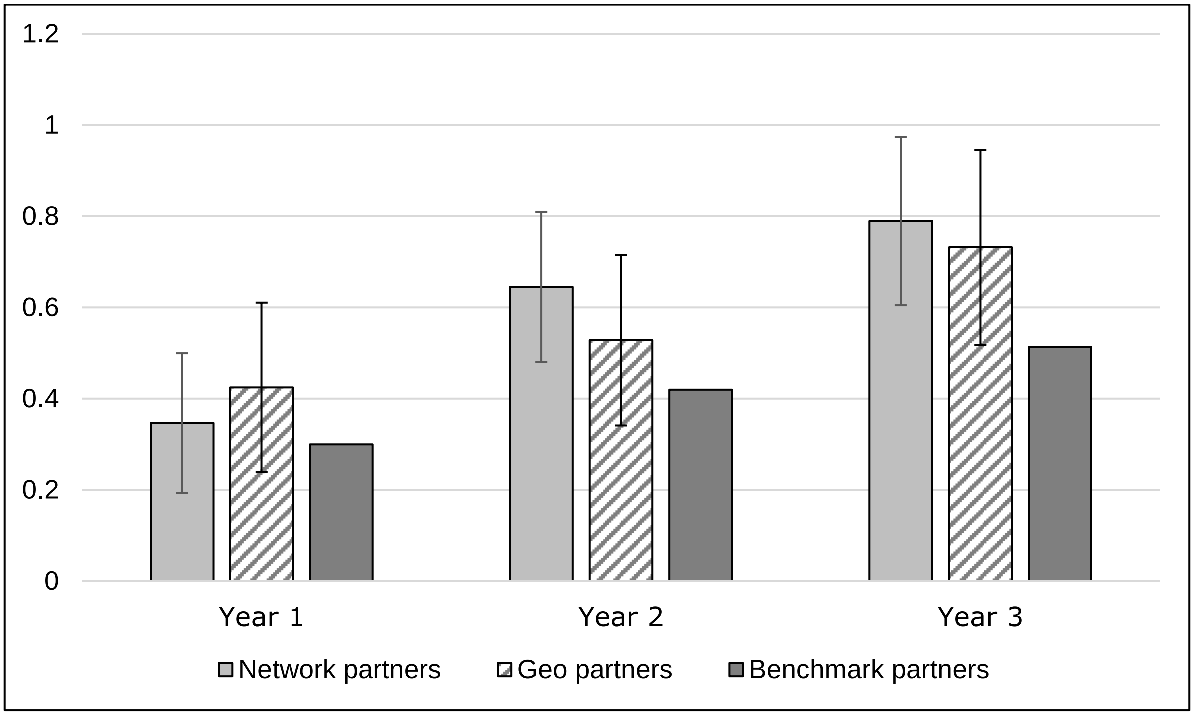


Figure 4: Any adoption in the village (excluding trained partners)



We compare the pit planting adoption rates in all three seasons between villages where social network-based targeting was implemented, against the benchmark villages where AEDOs chose the seeds, and villages in which geographic proximity was used as a proxy for network connections.

The dependent variables measure adoption propensities in the village computed using only farmers who are neither seeds nor potential seeds (i.e. the shadow farmers). We captured adoption in three ways: the adoption rate in the village (columns (1)-(3)), the total number of adopters (columns (4)-(6)), and an indicator for whether there was any adoption (columns (7)-(9)). The latter serves as an indicator for longer-term adoption: if there was no new adoption by season three (as happened in 46 per cent of control villages in Mwanza and Machinga), there is little prospect for continued adoption of pit planting.

We see no differences in the village-level adoption rate of pit planting in the first season– when information likely rested only with the seed farmers. In season two, however, villages where information was targeted to farmers based on the threshold model simulations achieved a higher level of adoption of pit planting, by 3.4 percentage points, than in benchmark villages. Since the adoption rate was only 4 per cent in the benchmark case, this constituted an 83 per cent increase in adoption rates over villages where AEDOs selected seeds. These benchmark villages experienced a significant increase in the adoption rate between seasons two and three (7.6 per cent compared to 4.1 per cent). The adoption rate remained 2.3 percentage points higher in villages where social network-based targeting was applied, but this gap is not statistically different. We see a very similar pattern when we use the number of adopters rather than the adoption rate as our dependent variable: there is no difference in season one, a significant increase in season two (1.78 additional adopters, doubling the 1.8 adopters on average in benchmark villages), and a qualitatively similar magnitude but imprecisely estimated difference in season three (1.38 additional adopters over the 4 adopters in benchmark villages).

In columns (7)-(9), we again see differences across treatments during season one in an indicator for any adoption outside of the seeds directly trained by the Ministry. In season two, only 42 per cent of benchmark villages had at least one adopter (among our randomly selected sample). This went up to 65 per cent in the network theory-targeted villages, a difference which is significant with 99 per cent confidence. In season three, 51 per cent of benchmark villages had some adoption while network theory-based targeting achieved at least some adoption in 79 per cent of all villages. A key difference between the benchmark and the use of the threshold model is thus on the extensive margin, i.e., whether targeting leads to any diffusion at all. Since we do not observe any differential adoption of pit planting in network theory targeted versus benchmark villages in season one, it's not that the threshold model simulations were successful in selecting seeds who were inherently smarter or better with the technology; it's more likely that the theory-driven, data-intensive treatments affected the diffusion process itself. The theoretical simulations had also suggested that differences in diffusion rates would become apparent in the second or third periods.

Table 9 shows the adoption patterns in the subsample of respondents who had less than the median baseline familiarity with pit planting. The trends observed in the full sample largely hold true for this group as well. In season two, we saw a significant increase in the village-level adoption rate of pit planting in network treatment villages. This continued in season 3, in which the adoption rate was 6.1 percentage points higher than that found in benchmark villages (5.3 per cent). The difference in season 3 adoption rates is significant in this subgroup while the difference was positive, but not statistically significant, in the full sample, indicating that the network treatment was more effective in farmers unfamiliar with pit planting. In columns (4)-(6) we also see the stronger treatment affect: the subgroup of farmers with lower baseline pit planting knowledge had significantly more adopters in treatment villages compared to benchmark villages over all three seasons (compared to season 2 only in Table 8).

6.8 Is geographic proximity a good proxy for social connectedness?

While we find that network theory-based targeting statistically increases pit planting adoption, the small absolute value of that increase is not necessarily cost effective, since the procedure is data intensive, and eliciting social network connections in each village is expensive. Whilst conducting the study, we anticipated this drawback of the network theory-driven approach, and therefore included the geography-based treatment arm, which is more feasible for government extension agencies to replicate and scale.

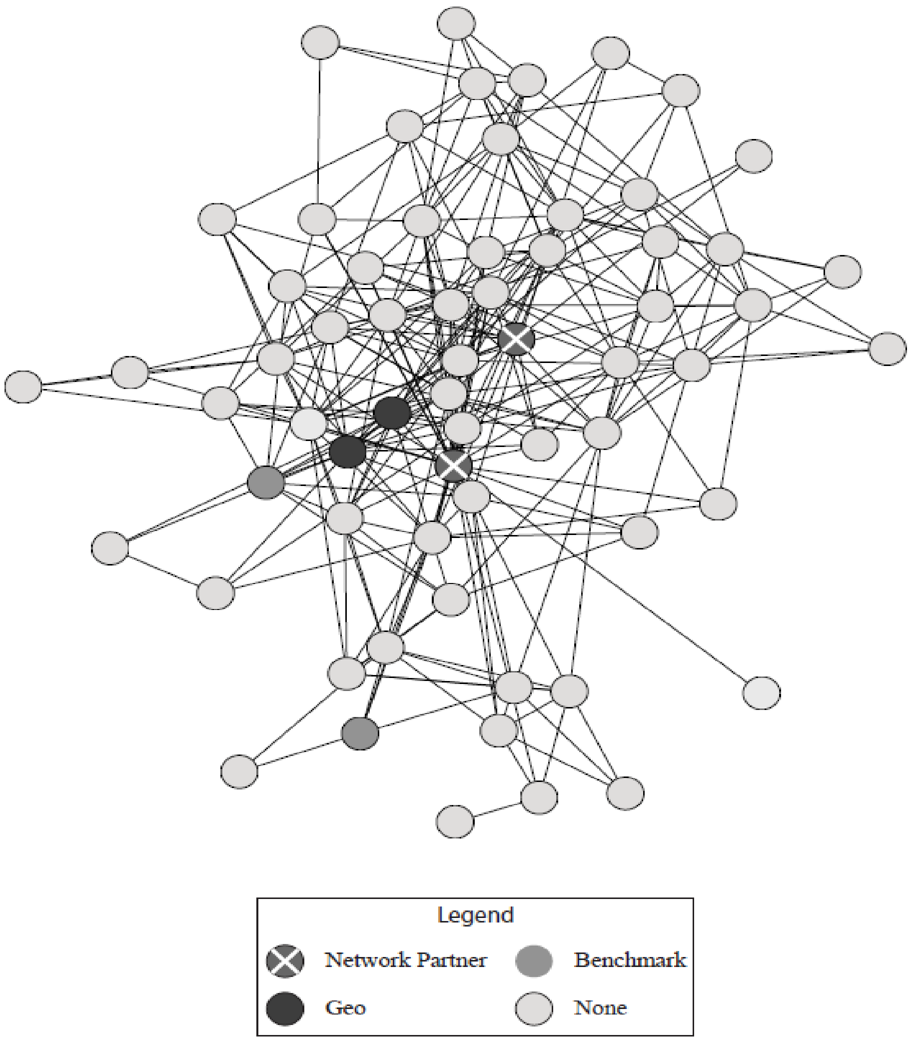
Table 8 provides some suggestive evidence that the geography proxy may be able to provide some of the gains in adoption observed under targeting using social network theory, particularly in the medium run. For the adoption rate, the geo effects are similar in size to the network- theory treatment effects, but less precise. We cannot reject that the geo treatment is the same as the benchmark villages, nor statistically-different than the network villages. The geo treatment does not perform as well as the theory-based treatments in generating a larger number of non-seed adopters. The point estimate in season three was smaller and statistically different from the network-theory villages (p =.06). In terms of the extensive margin of any adoption in the village, the geo treatment villages exhibited a statistically significant 22 percentage point increase in adoption by season three relative to benchmark villages, and this gain is statistically similar to using the data intensive, theory-driven procedures to target.

Figure 5 provides some insights into the underlying reasons for these differences. The figure is a representation of the social network in one village in our sample. Each circle in Figure 5 represents a node in the network (in this case, that means a household in the village), and the lines connecting the circles indicate households who are socially connected as measured by our survey. Households who are very central to the network, i.e., those who have many connections and connections to other important households in the network, are displayed as being in the center of the network. The figure shows where seeds for the network treatment (both simple and complex), geo treatment, and benchmark treatment are located within the village social networks from our data. The network partners are quite central. The benchmark seeds are not very central nor are they share many friends in common[11].

The geo-seed farmers are on average much poorer, and Figure 5 shows that they are often in more remote locations in the network of social connections (consistent with Table 3 showing that they have lower eigenvector centrality values) than Network partners. The geo seeds are still connected to a few others (since their selection process employed a simulation based on a contagion model); therefore there was some diffusion to their geographic neighbours, which leads to the observed increase in the extensive margin. However, since these seeds are not well connected, overall there is a slower pace of diffusion (e.g., to their secondary connections) than in the case where (dense) social network relationships are used to select seed farmers as in the Network partners case.

[11] In this particular village, the benchmark seeds are less central than the geo seeds. Table 3 shows that this is not a typical case, but there is a lot more variation in how the extension workers chose benchmark farmers than there is in how network and geo partners were chosen.

Figure 5: Network maps of seed and shadow farmers



6.9 Individual level-analysis

The diffusion process we observe in Tables 8 and 9 should start out among individuals close to the seeds and then percolate through the rest of the network. We therefore look to see if individuals who are directly connected to trained seed farmers have higher knowledge of pit planting and higher adoption rates. Table 10 compares individuals connected to one or two trained seeds to those who are not connected to any. However, since network position was clearly endogenous, we controlled for whether an individual was connected to a network or geo (actual or shadow) seeds irrespective of whether those connections were trained on the new technologies. We are therefore controlling for the respondent's network position, and only using variation generated by the experiment. To illustrate, we compare, say, two farmers who are both connected to exactly two simple seeds, but where one farmer is in a village randomly assigned to the network treatment (so that his connections were actually trained on the technology), while the other was not. The specification was formally discussed in Section 5.4.

Table 10: Individual-level analysis of pit planting decisions

	Season 1		Season 2		Season 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Adopted PP	Heard of PP	Adopted PP	Heard of PP	Adopted PP	Heard of PP
Connections to at least 1 seed	-0.006 (0.012)	0.022 (0.028)	0.034** (0.017)	0.009 (0.033)	0.010 (0.019)	0.055 (0.040)
N	3,220	3,184	2,986	3,445	2,286	2,361
Mean of Excluded Group	0.023	0.206	0.050	0.269	0.058	0.378
SD of Excluded Group	0.149	0.405	0.219	0.444	0.235	0.485

Notes

[1] Sample excludes seed and shadow farmers in all villages, and excludes benchmark villages. Seed farmers are either network or geo (no benchmark farmers included).

[2] Additional controls include indicators for the respondent being connected to: at least one network partner, at least one geo partner.

[3] Also included are village fixed effects.

[4] The excluded group is comprised of individuals with no connections to a seed farmer.

In season one we see no effect of the information targeting on adoption among individuals directly connected to at least one seed, relative to those with no connections. However, column (3) shows that in Season 2 the training did lead to more adoption among those directly connected to seeds. A household with at least one direct connection to trained seeds are 3.4 percentage points more likely to adopt in the second season than those with no connections. Given that people with no connections to seeds adopt at a 5 per cent rate, this is a 68 per cent increase. By Season 3, however, we no longer see differences in either adoption or knowledge. This may be because the diffusion process had progressed to individuals further from the seeds by the third year. Looking at the means, we observe that both the adoption rate and awareness of pit planting has increased among individuals with no direct contacts (to 5.8 per cent and 37.8 per cent respectively), thus eroding the difference between direct and indirect contacts as information spreads further out from the seeds over time. In summary, analysis using individual-level data demonstrates that the increases in village adoption that we observed in Table 8 are driven by individuals who are initially close to the trained seeds.

7. Discussion and policy implications

We used a large-scale field experiment in Malawi to evaluate whether integrating network theory on diffusion processes into extension provision increases adoption of a new agricultural technology that improves yields for farmers in arid regions of Africa. The focus of this experiment was not to pilot a mechanism for identifying extension partners in the field but rather to characterize the diffusion process, and document that an explicit consideration of the diffusion process can yield a higher take-up rate. This is useful for the policy makers who can use the results to understand the potential impact of social networks in helping spread technology: having characterized the diffusion process, policy makers can consider how best to use the local institutions to take advantage of networks in diffusion.

We documented that the data-intensive, theory-driven targeting of optimal seed farmers out-performs the simpler approaches to choosing seeds in terms of technology diffusion across the village over two or three years. Network-theory based targeting increases adoption by 3-4 percentage points more than relying on the extension worker, during the three-year period of the experiment when technology adoption grew from 0 per cent to about 10 per cent. The use of theory-based procedures to identify seeds leads to a 50 per cent greater likelihood that at least one other person in the village adopts. These large relative gains in diffusion are not at all obvious ex-ante, because the extension worker may have chosen seeds to optimize on useful personality traits such as diligence, stature, credibility or interest in participation, all of which are either unobservable to the researcher, or not used as inputs in the simulation of contagion models. The results suggest that simply changing who is trained in a village on a technology on the basis of social network theory can increase the adoption of new technologies compared to the Ministry's existing extension strategy.

The data also show that while physical proximity is not always a perfect proxy for social connections, even the low-cost geography-based targeting strategy generates some gains in adoption relative to the status quo benchmark. This strategy is much cheaper to implement than the theory-driven approaches, which suggest that developing methods to identify other low-cost proxies for social network structure should be pursued in order to make network-based targeting more policy relevant and scalable. Banerjee *et al.* (2014) have shown that in India a simple question like 'if we want to spread information about a new loan product to everyone in your village, to whom do you suggest we speak?' is successful in identifying individuals with high eigenvector centrality and diffusion centrality. It is also striking that this does not appear to be the process that government extension workers in Malawi follow, even when they are given complete freedom to select seeds. The AEDO- selected seed farmers exhibited lower eigenvector centrality than the seeds selected through our network-based simulations.

Given that we have successfully characterized the diffusion of pit planting, our research suggests several relevant actions for extension policy. First, in contexts like this one, extension agents will want to select partners using a mechanism which guarantees multiple sources of information in the same region of the network. This means certainly that multiple seed farmers will need to be trained in a particular village, and ideally that they would be selected to be seed farmers who share many contacts. For example, identifying a salient group within the village and asking that group to nominate a pair of potential extension partners may be successful.

Appendix A: Simple versus complex contagion

We employed two different versions of the threshold model in different arms of our experiment to gain insight on the specific structure of the threshold and associated patterns of diffusion. The first version called 'simple contagion' postulated that each individual needs to know only one other household who has adopted the technology in order to be convinced to adopt herself. Centola and Macy (2007) show that some types of products – such as information about job opportunities - spread through simple contagion. However, other behaviour may require multiple sources of information before they are adopted, and we explore this using a complex contagion model in a second arm of our experiment. Centola (2010) provides empirical evidence that complex contagion is relevant for health behaviour. While this literature has focused on identifying the ideal network structures for maximizing diffusion, we instead applied these models in a field experiment to understand how to target information within a network in order to best exploit the pre-existing social network architecture of villages in Malawi.

A full discussion of both the theoretical predictions of the simple vs complex contagion models and the corresponding empirical results can be found in the academic paper Beaman *et al.* (2014).

Appendix B: Aggregate CRM adoption

	Adoption Rate for non-seeds		Number of non-seed Adopters	
	(1)	(2)	(3)	(4)
Network Treatment	-0.013	-0.021	0.541	-0.410
	(0.025)	(0.022)	(1.645)	(1.503)
Geo Treatment	-0.001	-0.042	-0.226	-2.066
	(0.032)	(0.029)	(1.674)	(1.641)
N	200	141	200	141
Mean of Benchmark	0.308	0.227	14	12.1
SD of Benchmark	0.217	0.105	12.1	11.1
P value of test: Network = Geo	0.688	0.468	0.624	0.315
Season	1	2	1	2

Notes

[1] Network partners are villages where seeds were selected using the threshold model and the social network data. Geographic partners refers to villages where seeds were selected using the threshold model, but where links were proxied by geographic distance instead of direct solicitation of social network links.

[2] Also included are stratification controls as listed in Table 5. Seed and shadow farmers are excluded.

[3] Test: Network = Geographic shows the p- value of the test of whether the effect of the network partners treatment is different from the geographic partner treatment.

[4] Season refers to the number of seasons following the training of seed farmers. Season 1 is 2010 in Mwanza and Machinga, and 2011 in Nkhotakota. Columns (2) and (4) include only villages in Mwanza and Machinga as we have three seasons of data only for those two districts.

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Subsistence agriculture serves as the main source of income for the majority of Africa's rural poor. However, the rate of adoption of technologies that can increase agricultural profits remains slow. One potential constraint is the lack of credible information. This study tests the impact of training diffusion partners chosen using a theory-based selection approach and whether it leads to greater adoption of new agricultural technologies. The findings suggest that changing who is trained on a technology by using social network theory can increase adoption rates among farmers. Researchers also found that low-cost geographic targeting increased adoption. It was also cheaper than theory-based targeting.

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