Online Appendix for Can Network Theory-based Targeting Increase Technology Adoption?

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A.1. Technical Details of Simulation Methods

To identify our seed partners, we used the social network census of households in all study villages. The social network structures observed in these data allow us to construct network adjacency matrices for each of the 200 villages. Next, we conduct technology diffusion simulations for all villages using these matrices, where each individual in the village draws an adoption threshold τ from the data, which is normally distributed[1] $N(\lambda, 0.5)$ but truncated to be strictly positive. We conduct simulations with $\lambda=1$ and $\lambda=2$ in all villages to evaluate simple and complex contagion respectively.

In the simulations, when an individual is connected to at least τ individuals who are informed, she becomes informed in the next period. Once an individual is informed, we assume that all other household members are immediately also informed. We also assume that becoming informed is an absorbing state. As seed farmers are trained by extension agents, we assume all assigned seed farmers become informed.

We run the model for four periods.[2] Given the randomness built into the model, we simulate the model 2000 times for each potential pair of seeds in the village, and create a measure of the average information rate induced by each pair. We designate the pair that yields the highest average three-

[1] Heterogeneity in the model comes from variation across individuals in the net benefits realized by adopting pit planting. This affects the threshold number of connections an individual would need to have in order to get enough signals to be induced to adopt.

[2] We collected data for up to three agricultural seasons ("years") after the interventions were implemented, so our theoretical set-up largely matches our empirical research design. With knowledge of the value of λ, a policymaker could use the model to maximize adoption over any timeframe they cared about, either more short-term or more long-term.

period information rate in our simulations as the two "*optimal seeds*" for each village for that particular model (simple contagion, λ=1 or complex contagion, λ=2). Armed with the identities of the optimal seeds under each model, we then randomly assign different villages in the sample to the treatment arms. Optimal seeds identified through the complex contagion (λ=2) simulation are trained in villages that were randomly assigned to treatment 1. Optimal seeds identified through the simple contagion (λ=1) simulation are trained in the randomly chosen villages assigned to treatment 2.

To determine seeds for villages in the Geo treatment arm, the simulation steps are the same as in the complex contagion case, except that we apply the procedure to a different adjacency matrix. To capture the idea that geography may be an easy way to capture key features of a social network, we generate an alternative adjacency matrix 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 produces similar values for network degree measures in our villages as using the actual network connections measures.

A.2. Effect of technology adoption on crop yields

In order to estimate the returns of adopting the new technologies on yields, we compare seed farmers to shadow farmers. Online Appendix Table A4 demonstrates that there were large differences in adoption rates between seeds and shadow farmers. To estimate the impact of adoption on yields, we estimate an ITT specification exploiting that random difference in take-up:

$$y_{ivt} = \beta Seed_{ivt} + \gamma X_v + \delta_t + \epsilon_{ivt} \qquad (1)$$

where y_{ivt} is log maize yields for farmer *i* in village *v* at time *t*, $Seed_{ivt}$ is an indicator for being the selected seed farmer, X_v are control variables used during the re-randomization routine (see notes in Table 2), village size, village size squared, district fixed effects plus baseline land size. δ_t are year dummies. We use data from years 2 and 3. In the intent-to-treat specification in Online Appendix Table A1, column (1), maize yields among seed farmers are 13% greater than the yields experienced by the shadow seeds. The fact that the technologies we promoted led to an increase in output strongly suggests that the information about pit planting that diffused through the networks was likely positive on average.

Since only about 30% of seeds adopted pit planting, we also report the local average treatment effect using an IV regression in column (2) in which we instrument pit planting adoption with an indicator for being randomly assigned as the seed (rather than a shadow). In this specification, pit planting adoption is associated with a 44% increase in maize yield. However, we cannot rule out that CRM adoption also increased yields, potentially violating the exclusion restriction in the IV estimation.[3]

A.3. Adoption rates among seeds (compared to shadow farmers)

Online Appendix Table A4 compares the technology adoption behavior of seed farmers to shadow farmers. We focus on this sub-sample because shadow farmers act as the correct experimental counter-factual for the seed farmers to capture the causal effect of the intervention, removing any bias due to the seeds' position within their networks. We estimate the following equation, and Panel A displays the results:

$$y_{ivt} = \beta Seed_{ivt} + \delta_v + \epsilon_{ivt} \qquad (1)$$

where the dependent variable is an indicator for adoption, and δ_v are village fixed effects. Column (1) shows that trained seeds are 52% more likely in year 1 to know how to pit plant than shadow farmers. Columns (4)-(6) show that seed farmers who are trained on pit planting adopt at a rate of 31-32% in all three years, compared to the low 5% adoption rate of shadow farmers in year 1.

[3] We also cannot rule out any labor or other input use response to training which may have positively contributed to yields. Changes in other inputs makes it impossible for us to say that the yields increases map directly into increases in profits.

Panel B of Online Appendix Table A4 restricts the sample to only seed farmers (and drops all shadow farmers) and compares knowledge and adoption among seeds across the four experimental arms as follows:

$$y_{ivt} = \beta_0 + \beta_1 Simple_v + \beta_2 Complex_v + \beta_3 Geo_v + \delta X_v + \epsilon_{ivt} \qquad (2)$$

where X_v include the re-randomization controls (listed in table notes), village size, the square of village size, and district fixed effects. Standard errors are clustered at the village level. Column (1) shows that in the first year, Benchmark seeds are most likely to say they know how to pit plant, while all other seeds are similar. The extension agents evidently chose seed farmers carefully to ensure that their chosen extension partners receive the initial training from them. However, in years 2 and 3, familiarity between Benchmark, Simple and Complex seeds converge and have similar levels of familiarity with pit planting, though knowledge is declining over time. Geo seeds continue to display lower familiarity in subsequent years.

Column (4) shows that there are no differences in adoption propensities across the four types of seeds in the first year. This implies that it is unlikely that any observed differences in village-wide adoption patterns across the four treatment arms, that we will examine later, are driven by initial adoption differences inside the sub-sample of seed farmers. Columns (5) and (6) show that seed farmers in simple contagion villages become relatively more likely over time to adopt the technology. This could be due to the technology diffusion process, or in other words, a consequence of the experiment. Columns (7)-(8) show that there are no significant differences in adoption in years 1 or 2 for crop residue management.

A.4. Conversation frequency and adoption cascades

AMS establish that random seeding is sufficient to generate an adoption cascade when $CD > 1$, where C refers to the probability that a conversation takes place on a given link and D represents the mean degree in the network. Our experimental evidence found that at least 5% of randomly selected respondents were having conversations with seeds due to the training in each year. To map this number to the CD framework, we first suppose that mean degree (the average number of contacts that a person has) is stable over time, so that the mean degree of trained seed partners is the same at the follow-up as in our listing (indeed, in results available from the authors, we demonstrate that whether a respondent reports knowing a seed or shadow farmer at follow-up is the same regardless of whether the seed was actually trained or not).

In our data, the mean village has 77 respondents (households), 2 of whom are seeds. Thus, when we document that training induced at least 5% of respondents to have conversations about pit planting with seeds, we establish that at least 3.75 households per village had a conversation with a seed farmer (3.75 = 0.05*75). Based on Table 1, the mean degree of seeds is 11.63; thus, we expect that seeds have a conversation with 32% of their connections. In other words, the 5% lower bound on conversations about pit planting suggests that $C \approx 0.32$.

Mean degree among farmer households in our study villages is about 7. Thus, in our data $CD > 7 * 0.32 = 2.24$, where the greater than inequality is due to the fact that the 5% of experimentally exogenous conversations is a very restrictive lower bound. In other words, using this bounding exercise, we are confident that $CD > 1$ and so adoption cascades should take place with random seeding.

A.5. Micro-foundation of threshold model

We develop this micro-foundation by extending a framework presented in Banerjee et al. (2016) (hence: BBCM). One key insight in BBCM is that the majority of members of a social network may not have access to *any* useful signal when they are confronted with an entirely new technology. Thus, there are two parts to the learning problem for new technologies: acquiring a signal in the first place (becoming informed) which may be costly, and forming a revised belief on the profitability of the new technology based on the signals received from informed connections. Optimizing farmers adopt a new technology only if their beliefs change, and they are convinced by others that this would be more profitable than alternatives.[4]

There are three key phases of decision-making in our model: (1) the farmer has to decide whether to acquire information[5], (2) she has to combine the new information with her priors, and (3) she then decides whether to adopt the new technology. We will present and solve the model backwards, starting with the third phase.

The farmer will choose to adopt the new technology in phase 3 if she believes that adoption will be profitable. Suppose farmer *j* knows the technology will cost her c_j to adopt and believes the new technology has either profit $\bar{\pi}$ or $\underline{\pi}$ $(\underline{\pi} < c_j < \bar{\pi})$.[6] Since the technology is new and farmer *j* is initially uninformed, she has a uniform prior as to whether the technology is profitable or not. She can aggregate signals given by her connections to update her prior and make an informed adoption decision.

We adopt the same learning environment modeled in BBCM: first, informed farmer *i* disseminates a binary signal, $x_i \in \{\underline{\pi}, \bar{\pi}\}$, which is accurate with probability $\alpha > \frac{1}{2}$. Uninformed farmers do not disseminate a signal. Second, farmers follow DeGroot learning (DeMarzo et al. 2003).

[4] A very different micro-foundation for a similar model is explored in Jackson and Storms (2019). In that model, thresholds become relevant as individuals face greater payoffs from conforming to the behavior of their connections. Since coordination incentives for smallholder adoption of new agricultural technologies seem likely to be low, we pursue instead a model based on learning and individual optimization.

[5] There is a growing literature on how agents decide whether to seek out information. Banerjee et al. (2019a) – which builds on theoretical work by Chandrasekhar, Golub and Yang (2019) – demonstrate in the context of India's demonetization that some agents choose to remain uninformed in order to avoid shame. BenYishay et al. (2020) show that agents may choose not to receive agricultural information if the sender is a woman.

[6] Here for simplicity we follow BBCM in assuming that the distribution of profits is binary and known. In practice, there will be uncertainty over a wider range of profits due to the potential performance of the technology under different agroclimatic conditions and different weather realizations. While posterior distributions will be much more complicated under more realistic depictions of uncertainty, the key intuition driving the threshold model will be unchanged.

DeGroot learning can be interpreted as a boundedly rational version of Bayes learning, and suggests that farmers aggregate signals from their connections without attempting to calculate the inherent correlation structure between those signals. That is, if farmer *j* sees a signal of $\bar{\pi}$ from both farmers *i* and *k*, she interprets that as two positive signals without decomposing the likelihood that farmer *i* and *k* are disseminating information obtained from the same source.[7] Once farmers have observed signals from their informed connections, they aggregate those signals via Bayes' rule.

This framework suggests the following for the second phase of the farmer's learning problem: suppose farmer *j* has D_j informed contacts. If farmer *j* decides to learn about the new technology from her informed contacts, and if *H* of those contacts provide the signal $x = \bar{\pi}$, then the farmer's posterior probability that $\pi = \bar{\pi}$ is given by[8]

$$E_j[\pi = \bar{\pi}] = \frac{\alpha^{2H-D_j}}{\alpha^{2H-D_j} + (1-\alpha)^{2H-D_j}}$$

Denote $\tilde{\bar{\pi}} = \bar{\pi} - \underline{\pi}$ and $\tilde{c_j} = c_j - \underline{\pi}$. With that posterior, the farmer would adopt the technology if

$$\frac{\tilde{c}_j}{\tilde{\bar{\pi}}} \leq \frac{\alpha^{2H-D_j}}{\alpha^{2H-D_j} + (1-\alpha)^{2H-D_j}} \leq \frac{\alpha^{D_j}}{\alpha^{D_j} + (1-\alpha)^{D_j}} \qquad (1)$$

This model highlights a potential challenge to diffusing new technologies: when few other farmers are informed, then there is a ceiling on how much a new farmer's priors would move even if they receive unanimously positive signals from the informed. At early stages in the diffusion process, D_j may be small for most farmers.

Last, we consider the first phase of the farmer's learning problem, which is her decision to acquire signals and become informed. Here, we depart from BBCM to suggest that there may be a

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[7] Chandrasekhar, Larreguy and Xandri (2020) provide laboratory evidence in support of DeGroot learning over Bayes learning in India. Additional citations in favor of this boundedly-rational approximation can be found in BBCM.

[8] A simple proof is given in BBCM.

small cost to receiving a signal η. This cost could be interpreted as "shoe leather" costs of acquiring information (which are not necessarily trivial in villages in rural Malawi as households may be fairly far apart), or as stigma from seeking information (e.g. Banerjee et al. 2019a).

Thus, the farmer *j* with informed degree D_j has an objective given by

$$\max_{d \le D_j} \sum_{h \le d} \frac{1}{2} \left(\left[\alpha^h (1-\alpha)^{d-h} (\overline{\pi} - c_j) + (1-\alpha)^h \alpha^{d-h} (\underline{\pi} - c_j) \right] \left(I \left(\frac{\alpha^{2h-d}}{\alpha^{2h-d} + (1-\alpha^{2h-d})} > \frac{\tilde{c}}{\tilde{\tilde{\pi}}} \right) \right) \right) - \eta d$$

When $\eta = 0$, the dynamics of learning are explored by BBCM. However, when $\eta > 0$ the dynamics are slightly different. In that case (for small η), farmers will only become informed if

$$\frac{\alpha^{D_j}}{\alpha^{D_j} + (1-\alpha)^{D_j}} > \frac{\tilde{c}_j}{\tilde{\tilde{\pi}}} \tag{2}$$

In other words, farmers only choose to seek information if they have a large enough number of informed connections, such that it is possible that an informed decision would lead them to adopt. In this case (and for small η), farmers will choose to seek information when they have only one informed connection if

$$\frac{\alpha}{\alpha + (1-\alpha)} > \frac{\tilde{c}_j}{\tilde{\tilde{\pi}}} \tag{3}$$

In general, they will choose to become informed with λ informed connections if

$$\frac{\alpha^{\lambda}}{\alpha^{\lambda} + (1-\alpha)^{\lambda}} > \frac{\tilde{c}_j}{\tilde{\tilde{\pi}}} \tag{4}$$

This implies that farmers choose to become informed about new technologies if expectations about the net benefits of technology are high (i.e., low costs and high potential gains), or if signals from individual other farmers are highly accurate. Under certain parameter values, just a single informed contact may be sufficient to induce farmers to seek information. That is the diffusion process that Centola and Macy (2007) refer to as a "simple contagion." They demonstrate that some types of information – for example, job opportunities – spread in this way. On the other hand, if the expected upside of the technology is more modest relative to costs, or if signals from other farmers have low accuracy, then farmers may only be persuaded to seek information when there is sufficient information to be gained from their network.[9] In that case, for many farmers the lowest λ satisfying equation (4) may be larger than 1, and information diffusion follows a process termed "complex contagion" in the literature.[10]

Our interpretation of the microeconomics of the threshold theory is that the thresholds result from an underlying process of farmers deciding *whether* to learn, given their information environment. This motivates an experimental design in which we seed new information in a network to improve the overall information environment, which can change incentives to learn and jump-start the technology diffusion process.

Given that the econometrician is unlikely to observe signal accuracy (α), the threshold required for adoption of a specific new technology is an empirical question. As a numerical example, consider a technology with 30% potential returns (so that $\tilde{\tilde{\pi}} = 1.3\ \tilde{c}_J$). If signals are more than 77% accurate, farmers will choose to become informed if they have a single informed connection, and diffusion will follow a simple contagion. If signal accuracy falls in the range of 65-77% accurate, then farmers will only become informed if they have 2 informed connections, and learning will follow a complex contagion. If signals are less than 65% accurate, then farmers will need at least 3 informed connections to make an adoption decision. In general, agents will face higher thresholds in contexts

[9] Though not explicitly considered here, minimal thresholds for learning will also be higher if η (the cost of information acquisition) is larger.

[10] Several theory papers have explored the implications of this model. In contrast to the "strength of weak ties" in labor markets proposed by Granovetter (1978), strong ties may be important for the diffusion of behaviors that require reinforcement from multiple peers. Centola (2010) provides experimental evidence that health behaviors diffuse more quickly through networks where links are clustered, consistent with complex contagion. Acemoglu et al. (2011) highlights that when contagion is complex, highly clustered communities will need a seed placed in the community in order to induce adoption. Finally, Monsted et al. (2017) provide experimental evidence generated by twitter-bots that twitter hashtag retweets follow a process which more closely resembles complex than simple contagion.

where signals are noisier, a point with implications for external validity which we return to in the concluding remarks.

Model predictions and implications for the experiment

The micro-foundation of the threshold model suggests that the model would need to be tested using the diffusion of a truly new technology, where would-be adopters are *ex ante* uninformed about the technology and face an important adoption decision. A corollary is that the threshold model should fit the data better in locations where the technology is more novel. A good empirical setting to test the model is also one in which agents are receiving noisy signals from the network.

If thresholds exist and are above one, then seeding the network with multiple sources of information who are clustered in the same part of the network will achieve very different diffusion patterns than seeding the network with the same number of information sources spread more diffusely. Our experimental design will take advantage of this insight. When thresholds are above one, the information environment only induces learning when initial nodes share some connections, which we test using micro data on technology diffusion patterns.

The model highlights that farmers will become informed when they have sufficiently many informed contacts. However, conditional on being informed, they will only adopt the technology if the realization of signals from their connections are sufficiently positive. These two facts suggest two different tests of the model.

PREDICTION 1: If most farmers in a village have a threshold $\bar{\lambda}$, then people who are connected to at least $\bar{\lambda}$ informed farmers should become informed themselves.

PREDICTION 2: Adoption should increase most strongly among farmers who have high net benefits of adoption, who would adopt with a broader range of received signals.[11]

[11] For clarity, the model assumed that the potential net benefits of production were known to the farmer before deciding whether to become informed about the technology. In practice, farmers may or may not be aware that their private net

A.6. Simulation of cost-effective targeting strategies

For our simulations, we suppose that our extension agent starts with a random sample of candidate respondents, and is able to screen out individuals with less than 2 connections. We suppose the extension agent starts with a list of 2-10 randomly selected farmers.

Starting from that random sample of farmers, we solicit each farmer's connections and calculate each random farmer's degree. We then focus on 6 candidate targeting strategies:

A. Trains two randomly selected people from that list (used as a benchmark)
B. Trains the two highest degree people from that list
C. Select two random friends of the highest degree person from that list
D. Trains the two highest degree connections of the highest degree farmer from the random sample (requires interviewing all connections of the highest degree respondent to determine their degree)
E. Selects two farmers from that list at random; interviews two of their connections (selected at random) and trains two of the connections' connections[12]
F. Trains the highest degree respondent and one of his connections (at random).

For each of these five candidate strategies, we simulate adoption rates after 4 rounds of simulations against the seeds chosen by our Complex treatment. We find that Strategy A, selecting two farmers at random, achieves 57% of the adoption produced by the Complex treatment. We can then view the other targeting strategies in terms of their performance above the random benchmark. Strategy B is identical to random selection with only 2 initial interviews, and so similarly generates

benefits to adoption are high before becoming informed. Only when a farmer is *ex ante* aware that she has relatively high net benefits will we see greater adoption associated with a greater propensity to become informed.

[12] This "friends of friends" approach to identifying central people was inspired by Feld (1991), Christakis and Fowler (2010), and Kim et al. (2015), who note that randomly selected connections tend to be more central than randomly selected nodes in a network. We again assume that the extension agent is able to screen out potential trainees with less than two total connections.

57% adoption; however, as the extension agent interviews more people to identify these high degree individuals it performs somewhat better, achieving 70% of the complex contagion adoption with 10 total interviews. Strategies C and D both leverage the highest degree respondent from the initial random sample. These perform the best out of the strategies we consider. Strategy C achieves 73% of the optimized adoption with just two total interviews, which increases modestly to 76% of the optimized adoption as the number of interviews grows to 10 to better identify a high degree individual. Strategy D, our best performing strategy, achieves 84% of the optimized adoption with 2 initial interviews (necessitating 8 total interviews as the connections are interviewed), and up to 90% of the optimized adoption with 8 initial interviews (and 13 total interviews). Strategy E requires a total of 4 interviews, and achieves 69% of the optimized adoption. Strategy F achieves 60% of the optimized adoption with 2 interviews, and up to 67% of optimized adoption with up to 10 interviews.

Clearly the most effective strategies are those that identify a high degree farmer and train her connections. Given the nature of the complex contagion learning process, the intuition is clear: training two high degree friends of someone who is high degree means that three people with many connections in the same part of the network will become informed. With clustered networks, it is likely that others will as well.

Figure A1: Project Timeline

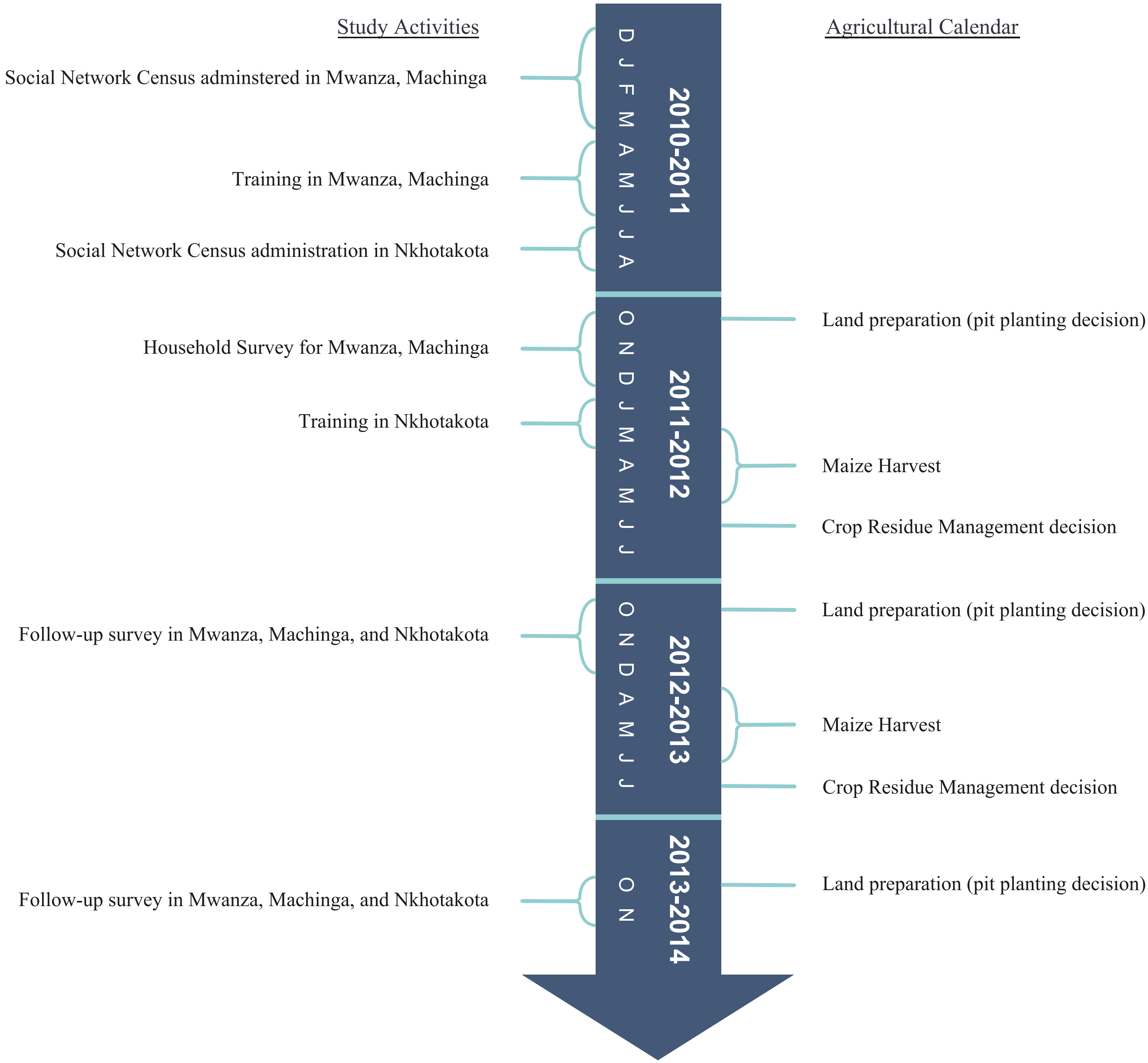

Table A1: Agricultural Yields of Seeds Relative to Shadow (Counterfactual) Farmers

	Log of Agricultural Yields	
	(1)	(2)
Seed	0.126	
	(0.061)	
Adopted Pit Planting		0.443
		(0.210)
N	959	959
Mean of Shadows		
Year	2,3	2,3

Notes

1 Sample includes only seed and shadow farmers. Benchmark villages are excluded.

2 Agricultural yields were winsorized. The specification also controls for total farm size; controls used in the re-randomization routine (percent of village using compost at baseline; percent village using fertilizer at baseline; percent of village using pit planting at baseline); village size and its square; and district and year fixed effects. Standard errors are clustered at the village level.

Table A2: Characteristics of the Seeds Chosen by Each Treatment Arm

	Farm Size	Wealth Index (PCA)
	(1)	(2)
Treatment arm:		
Complex Contagion	-0.037	0.380
	(0.19)	(0.23)
Simple Contagion	-0.152	0.113
	(0.19)	(0.23)
Geographic	-0.614	-0.740
	(0.19)	(0.23)
P-values for Tests of Equality in Seed Characteristics		
Simple = Complex	0.335	0.067
Complex = Geographic	0.000	0.000
Simple = Complex = Geographic	0.000	0.000
N	1248	1248
Mean Value for Seeds in Benchmark Treatment (omitted category)	2.06	0.626
SD for Seeds in Benchmark Treatment	2.97	1.7

Notes

1 The sample includes all seeds and shadows. The sample frame includes 100 Benchmark farmers (2 partners in 50 villages), as we only observe Benchmark farmers in Benchmark treatment villages, and up to 6 additional partner farmers (2 Simple partners, 2 Complex partners, and 2 Geo partners) in all 200 villages.

2 Benchmark treatment seeds are the reference category.

Table A3: Distribution of Distance to Partner Farmers

	(1)	(2)	(3)	(4)
Path Distance to Closest Partner	Simple Partner	Complex Partner	Geo Partner	Benchmark Seed
1	38%	42%	24%	33%
2	50%	41%	46%	44%
3	9%	10%	20%	14%
4 +	4%	6%	10%	9%
N	4856	4856	4856	922

Notes

1 The data in this analysis includes respondents in our household surveys, linked to the social network census to capture their connections - direct and indirect - to the partner (or seed) farmers. Seed and shadow farmers are themsevles removed, as well as the 6.5% of households in our sample (419) with zero measured connections.

2 In columns (1)-(3), connections to both seeds and shadow farmers are analyzied, while in column (4) we only look at connections to the Benchmark seed in Benchmark villages.

Table A4: Seed Knowledge and Adoption

	Knows How to Pit Plant			Adopts Pit Planting			Adopts CRM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Seeds	0.518	0.367	0.245	0.258	0.230	0.182	0.137	0.047
	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Years	1	2	3	1	2	3	1	2
N	659	735	503	686	672	489	686	467
Mean of Shadows	0.165	0.187	0.291	0.0541	0.0929	0.139	0.32	0.207
SD of Shadows	0.371	0.39	0.455	0.227	0.291	0.347	0.467	0.406
Panel B								
Simple diffusion	-0.133	-0.067	0.108	-0.006	0.129	0.176	0.078	-0.097
	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)	(0.08)	(0.09)
Complex diffusion	-0.120	-0.058	0.007	-0.020	0.002	0.037	-0.001	-0.077
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)
Geographic	-0.193	-0.255	-0.150	-0.095	-0.064	-0.003	-0.011	-0.075
	(0.07)	(0.07)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)	(0.10)
Years	1	2	3	1	2	3	1	2
N	343	383	264	353	352	259	353	243
Mean of Benchmark	0.824	0.653	0.547	0.337	0.276	0.238	0.442	0.339
SD of Benchmark	0.383	0.479	0.502	0.476	0.45	0.429	0.5	0.478
p-value for tests of equality in adoption rates across treatment cells:								
Simple = Complex	0.872	0.904	0.242	0.862	0.077	0.108	0.311	0.808
Complex = Geographic	0.377	0.016	0.111	0.36	0.358	0.625	0.886	0.977
Joint test of 3 treatments	0.472	0.021	0.011	0.252	0.008	0.049	0.235	0.795

Notes

1 In Panel A, all columns compare seed farmers to shadow farmers. Village fixed effects are included, and standard errors are clustered at the village level.

2 In Panel B, the sample includes only seed farmers, and the reference group is Benchmark seed farmers. The specification also includes controls which were used in the re-randomization routine (percent of village using compost at baseline; percent village using fertilizer at baseline; percent of village using pit planting at baseline); village size and its square; and district fixed effects. Standard errors are clustered at the village level.

Table A5: Test of Balance across Randomized Treatment Arms

	Complex	Simple	Geo	Benchmark	N	p-value of joint test
	(1)	(2)	(3)	(4)	(5)	(6)
Housing (pca)	-0.036	-0.160	0.022	0.107	14000	0.057
	(0.09)	(0.05)	(0.21)	(0.08)		
Assets (pca)	-0.035	-0.060	-0.040	-0.003	14300	0.880
	(0.05)	(0.07)	(0.06)	(0.08)		
Livestock (pca)	0.026	0.012	-0.087	0.010	14300	0.223
	(0.06)	(0.06)	(0.04)	(0.06)		
Basal fertiliser (kg)	53.113	51.978	50.917	50.937	10400	0.971
	(3.14)	(4.78)	(3.17)	(2.25)		
Top dressing fertiliser (kg)	49.488	49.822	50.278	52.168	10500	0.779
	(2.05)	(3.33)	(2.53)	(2.01)		
# of Adults	2.316	2.305	2.299	2.299	14000	0.975
	(0.02)	(0.02)	(0.03)	(0.02)		
# of Children	2.650	2.617	2.619	2.587	14300	0.751
	(0.05)	(0.04)	(0.05)	(0.04)		
Farm size (acres)	1.676	1.624	1.764	1.798	14000	0.071
	(0.06)	(0.08)	(0.09)	(0.08)		
Own land	0.907	0.904	0.903	0.913	14300	0.932
	(0.01)	(0.01)	(0.02)	(0.01)		
Yields	290	304	304	300	13400	0.852
	(21.65)	(18.63)	(20.71)	(25.59)		
Provided Ganyu	0.250	0.254	0.242	0.234	14000	0.635
	(0.02)	(0.01)	(0.02)	(0.02)		
Used Ganyu	0.134	0.123	0.150	0.140	14000	0.124
	(0.01)	(0.01)	(0.01)	(0.01)		

Notes

1 Housing, assets and livestock in the first three set of rows are pca scores. Housing includes information on: materials walls are made of, roof materials, floor materials and whether the household has a toilet. Assets includes the number of bicycles, radios and cell phones the household owns. Livestock is an index including the number of sheep, goats, chickens, cows, pigs, guinea fowl, and doves.

2 Columns (1)-(4) give the means and standard errors of the variable listed in the title column in each of the treatment arms. The seeds and the shadow seeds are excluded from the sample. The data is from the social network census.

3 Column (6) shows the p-value of a joint test of significance of all treatment arms. Also included in the specification used for the test are controls used in the re-randomization routine (percent of village using compost at baseline; percent village using fertilizer at baseline; percent of village using pit planting at baseline) and district fixed effects. Standard errors are clustered at the village level.

4 Ganyu is the term used in Malawi for hired wage labor on the farm.

Table A6: Village Level Adoption Outcomes for Crop Residue Management (CRM)

	Any Non-Seed Adopters	Adoption Rate
	(1)	(2)
Complex Diffusion Treatment	-0.064	-0.026
	(0.060)	(0.027)
Simple Diffusion Treatment	-0.083	-0.037
	(0.062)	(0.027)
Geographic treatment	-0.152	-0.054
	(0.070)	(0.029)
Year	2	2
N	141	141
Mean of Benchmark Treatment (omitted category)	0.971	0.204
SD of Benchmark	0.169	0.109
p -values for tests of equality of coefficients…		
Test: Simple = Complex	0.794	0.680
Test: Complex = Geo	0.258	0.366
Test: Simple = Geo	0.336	0.583

Notes

1 The "Any non-seed adopters" indicator in columns (1) excludes seed farmers. The adoption rate in column (2) include all randomly sampled farmers, excluding seed and shadow farmers.

2 Analysis restricted to data from Mwanza and Machinga.

3 All columns include controls used in the re-randomization routine (percent of village using compost at baseline; percent village using fertilizer at baseline; percent of village using pit planting at baseline); village size and its square; and district fixed effects. Standard errors are clustered at the village level.