# Optimal Network Based Targeting for Technology Adoption in Developing Countries

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## Motivation

- Low adoption of modern technologies in the agriculture of developing countries, especially in Sub-Saharan Africa (Bold et al., 2017).
- One of the key reasons: information constraints (Magruder, 2018).
- Social networks can help in easing the information constraints and increase technology adoption (Foster and Rosenzweig, 1995; Conley and Udry, 2010).
- What is the most effective way of using existing social ties to improve the adoption of a new technology?

# Motivation

- Existing literature argues that the answer depends on the underlying diffusion process:
  - Simple diffusion: targeting may not be needed (Akbarpour et al., 2020).
  - Complex diffusion: targeting seeds central to the network needed for effective diffusion (Beaman et al., 2021).
- **Assumption:** People are homogeneous in terms of their benefits from the new technology.
- Helps us to focus on a problem where the agents are trying to collectively learn the distribution of benefits common to all of them.
- There is still heterogeneity in adoption decision: explained by heterogeneous costs that require no social learning.

## Research Question

What happens to the most effective way of using existing social ties to improve the adoption of a new technology *if for some agents the new technology is more beneficial than the others?*

- Do the optimal network based targeting strategies change with respect to the degree of heterogeneity within the network?
- What are the policy concerns and recommendations in such scenario?

# Research Plan

- Theoretically model the scenario where agents are learning from each other about the benefits of a new technology, where benefits vary from one agent to another.
- Use simulations to characterize the outcomes of different targeting strategies in such scenario.
- Use existing data on the diffusion of pit planting in Malawi to validate the findings of the simulation results (with some assumptions).

# Preview of Results

- Simulations indicate that targeting central agents may not be optimal even under complex diffusion.
- In particular, the performance of such targeting strategy depends on the population level heterogeneity.
- Targeting early adopters works better if the population level heterogeneity is high.
- Reduced form results show support in favor of my hypotheses.

# Contributions to the Existing Literature

1. **Diffusion of information in developing economies:** providing evidence that the success of network-based targeting strategies depend on the population level heterogeneity.
2. **Population heterogeneity and social learning:** formalizing the scenario where agents learn from their network about a technology that is more beneficial to some of them than the others.
3. **Characterizing opinion leaders in diffusing new knowledge:** In the context of network-based targeting, provide answers based on population heterogeneity.

More Details on the Existing Literature

# Theoretical Framework

## Elements of the Model

- Two stage decision process: first learning, then adoption.
- Traditional technology has a sure payoff of $\pi^T$, where the new technology provides a payoff of $\pi^N(\omega_{it})$, $\omega_{it} \in \Omega$.
- Draws depend on the true distribution $p_i^*(\omega_{it})$ for household $i$: $p_i^* = \sum_{j \in \mathcal{I}} G_{ij} p_j^*$. Independent draws every period.
- The new technology is riskier than the traditional, with higher net expected benefits for some agents.
- Initially all households are uninformed $\Rightarrow$ $p_i^*$s are unknown.
- If uninformed, can become informed by putting effort $e_{it} \in \{0, 1\}$ at cost $\eta_i$.
- Agents are risk-neutral and myopic. They need to be informed before they adopt.

# Timeline

Assume the following timeline of decision making:

1. Every period, uninformed agent $i$ decide whether or not to get informed.
2. To decide, uninformed agents collect information on beliefs from their peers $j \in \mathcal{I}$. These beliefs $p_{jt-1}$ were formed in the last period. The uninformed agent $i$ uses DeGroot averaging to calculate $\hat{p}_{it} = \sum_{j \in \mathcal{I}} G_{ij} p_{jt-1}$ using these beliefs.
3. On the basis of $\hat{p}_{it}$, they decide whether or not to become informed.
4. If not informed ($e_{it} = 0$): $p_{it} = \hat{p}_{it}$, and next period they repeat from 1. If informed ($e_{it} = 1$): $p_i^*$ is known and adoption decisions are made on the basis of that. $p_{is} = p_i^* \ \forall s \geq t$.

# Adoption Decision

An agent's adoption decision is a two step process:

1. First they decide whether or not to get informed, based on the following rule:

$$e_{it} = \begin{cases} 1 \textit{ if } \int_{\omega_{it} \in \Omega} \hat{p}_{it}(\omega_{it}) \pi^N(\omega_{it}) - c_i - \pi^T \geq \eta_i \\ 0 \textit{ otherwise.} \end{cases}$$

   Only uninformed agents make this decision.

2. Conditional on being informed, they decide whether or not to adopt the new technology:

$$Adopt_{it} = \begin{cases} 1 \textit{ if } \int_{\omega_{it} \in \Omega} p_i^*(\omega_{it}) \pi^N(\omega_{it}) - c_i \geq \pi^T \\ 0 \textit{ otherwise.} \end{cases}$$

▸ Full Model

# Implications

- Let's simplify: $\Omega = \{\omega_H, \omega_L\}$ and $p^*_{iH} := p^*_i(\omega_H)$ is the true probability for household $i$.
- In step 2, conditional on being informed, the household will adopt the new technology iff:

$$p^*_{iH} \geq \frac{c_i + (\pi^T - \pi^N(\omega_L))}{(\pi^N(\omega_H) - \pi^N(\omega_L))} = \bar{p}^*_{iH}.$$

- In step 1 the household $i$ will choose to get informed at time $t$ iff:

$$p^H_{it} \geq \bar{p}^*_{iH} + \frac{\eta_i}{(\pi^N(\omega_H) - \pi^N(\omega_L))} = \bar{p}^*_{iH} + \bar{\eta}_i.$$

# Implications

- If information diffusion is efficient, people who should get informed:

$$p^*_{iH} \geq \bar{p}^*_{iH} + \bar{\eta}_i.$$

- Multiple possible equilibria: depends on the initial beliefs.
- What happens if when everyone is uninformed and $p^H_{it} \approx 0 \; \forall it$?
- How can network based targeting help?
- Who should be targeted?

# Simulations

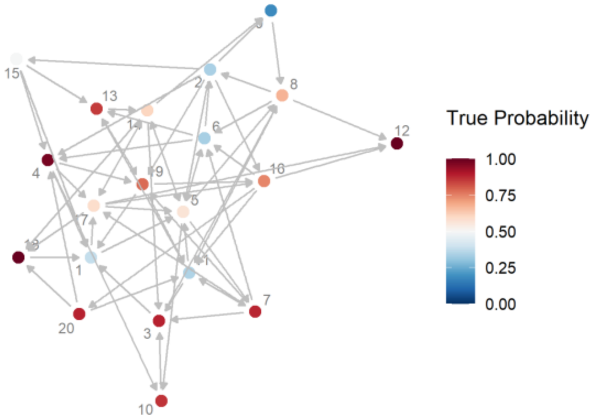



Figure 1: Distribution of True Probability within the network

# Illustrative example

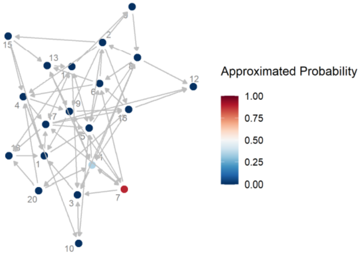



Figure 2: Seeding based on Centrality

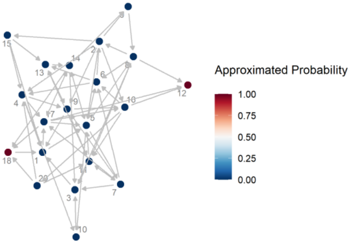



Figure 3: Seeding based on Probability

# Illustrative example

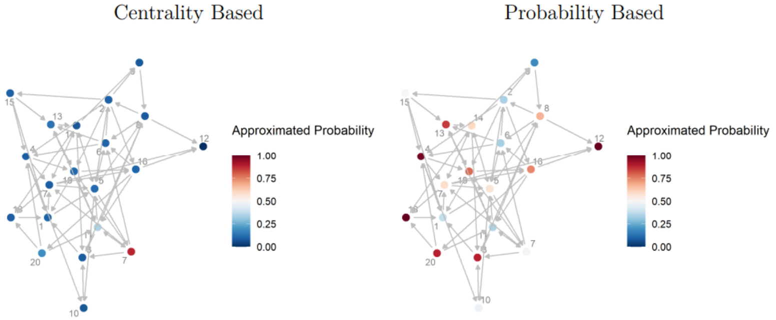



Figure 4: Performance of seeds after 10 periods

# Measuring Performance

The efficiency of a targeting strategy can be measured as:

$$\text{Targeting Efficiency} = \frac{\text{\% of informed households}}{\text{\% of informed households under full efficiency}}$$

- *% of informed households*: the fraction of households that choose to get informed within some periods of implementing the targeting strategy.
- *% of informed households under full efficiency*: is the fraction of households that should be informed under efficient diffusion of information.

# Simulation Results

Table 1: Simulation Results

| | | Level of Correlation | | | |
|---|---|---|---|---|---|
| Strategy | Statistic | Low | Medium | High | Perfect |
| Betweenness Centrality Based | Mean | 0.72 | 0.82 | 0.84 | 0.74 |
| | Variance | 0.17 | 0.10 | 0.09 | 0.08 |
| Probability Based | Mean | 0.94 | 0.81 | 0.76 | 0.72 |
| | Variance | 0.11 | 0.11 | 0.14 | 0.09 |
| | Observations | 200 | 197 | 192 | 200 |

*Notes:* Simulations on varying levels of correlation are all done for 200 networks, each containing 20 households. However, upon generation of the true probabilities, some networks may be dropped as they contained 0% of informed households under full efficiency.

▸ Robustness w.r.t different centrality measure ▸ Robustness w.r.t higher population

# Simulation Results

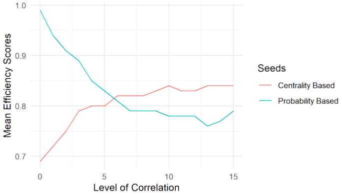



Figure 7: Mean efficiency scores over increasing levels of correlation

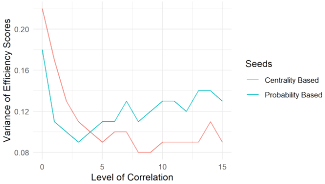



Figure 9: Variance of efficiency scores over increasing levels of correlation

# Empirical Analysis

# Hypotheses

The relative performance of centrality and probability based targeting strategies depend on the level of heterogeneity in a region. More specifically:

1. As the level of heterogeneity in terms of the applicability of a new technology $\uparrow$es, the performance of central seeds gets worse.
2. As the level of heterogeneity in terms of the applicability of a new technology $\uparrow$es, the performance of probability based seeds improves.

# Data

1. Replication data for Beaman, BenYishay, Magruder, and Mobarak, 2021 (henceforth, BBMM):

   - RCT to promote Pit Planting (PP) for Maize farmers in Malawi. Randomized information entry points at the village level.
   - Panel data contains information on adoption, demographics, and network characteristics. ▸ Timeline ▸ More Details

2. Agricultural Extension Services and Technology Adoption Survey (henceforth, AESTAS) data collected by International Food Policy Research Institute (IFPRI).

   - Nationally representative survey of farmers in Malawi.
   - Panel data contains information on adoption of different technologies and household demographics. ▸ More Details

# Identification

Using village level variations:

$$Y_{vt} = \beta_0 + \beta_1 Centrality_v + \beta_2 Probability_v + \beta_3 Het_v$$
$$+ \beta_4 Centrality_v \times Het_v + \beta_5 Probability_v \times Het_v + \lambda X_v + \zeta_t + \epsilon_{vt}$$

- $Y_{vt}$: adoption related outcome for village $v$ at time $t$ (excluding seeded households).
- $Centrality_v$: average centrality of the seeds for village $v$ at the baseline (information on centrality available in the data).
- $Probability_v$: average probability of adoption for the seeds for village $v$ at the baseline (not available in the data).
- $Het_v$: coefficient of variation (CV) of probability of adoption at the village level.

# Approximating Probability of Adoption

- How to calculate probability of adoption?
- Proxy for probability of adoption using predicted adoption and usage indices. Construction of Indices
- Calculate these indices at the baseline, conditional on some observable household demographics: number of adults and children, housing, livestock, and assets. Description of Variables
- Calculation uses estimates from following regressions using AESTAS data: $Adoption/Usage\ Index_{it} = f(X_{it}; \mu_{it})$. Results
- Based on a set of assumptions. All Assumptions

# Descriptive Statistics

Table 4: Baseline Village-level Sample Characteristics

| | Treatment Status | | | | |
|---|---|---|---|---|---|
| Variable | Benchmark | Complex | Simple | Geo | Overall |
| Adoption Rate (PP) | 0.018 | 0.030 | 0.029 | 0.029 | 0.026 |
| | (0.035) | (0.063) | ( 0.060) | (0.077) | (0.060) |
| Any Non-Seed Adopters (PP) | 0.300 | 0.340 | 0.320 | 0.420 | 0.345 |
| | (0.463) | (0.479) | (0.471) | (0.499) | (0.477) |
| Eigen-vector Centrality of Seeds† | 0.178 | 0.235 | 0.187 | 0.129 | 0.182 |
| | (0.090) | (0.077) | (0.096) | (0.090) | (0.096) |
| Predicted Adoption Index of Seeds‡ | 0.110 | 0.114 | 0.101 | 0.082 | 0.101 |
| | (0.034) | (0.036) | (0.041) | (0.025) | (0.036) |
| Predicted Usage Index of Seeds‡ | 0.184 | 0.186 | 0.172 | 0.158 | 0.175 |
| | (0.031) | (0.032) | (0.042) | (0.024) | (0.035) |
| CV of Predicted Adoption Index | 0.389 | 0.378 | 0.379 | 0.366 | 0.378 |
| | (0.069) | (0.077) | (0.075) | (0.062) | (0.071) |
| CV of Predicted Usage Index | 0.193 | 0.188 | 0.185 | 0.180 | 0.187 |
| | (0.039) | (0.040) | (0.037) | (0.033) | (0.038) |
| Observations | 50 | 50 | 50 | 50 | 200 |

*Notes:* † Contains 44 observations for the benchmark treatment group, 49 observations for the other treatment groups. ‡ Contains 48 observations for the complex treatment group. Seed level measures are calculated using the average of two seeds, whenever the information on both seeds are available. Otherwise they reflect the information for one seed. Coefficient of Variations (CV) are calculated at the village level for the whole village. Adoption Rate and Any Non-Seed Adopters are calculated excluding seed or shadow farmers in a village.

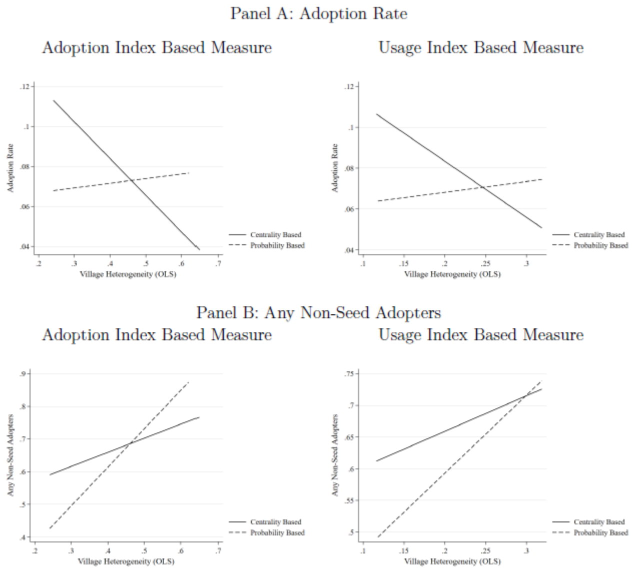



Figure 12: Outcomes for Different Seeding Strategies with respect to Village Heterogeneity

# Regression Results

Table 5: Village level Regression 1 of Adoption Outcomes (Pit Planting)

| Variables | Adoption Rate (1) | (2) | Any Non-Seed Adopters (3) | (4) |
|---|---|---|---|---|
| Eigen-vector Centrality of Seeds | 1.173** | 0.917* | 1.181 | 1.235 |
| (=*Centrality*$_v$) | (0.581) | (0.467) | (1.439) | (1.332) |
| Predicted Adoption Index of Seeds | -2.973** | -2.140 | -8.019** | -3.344 |
| (=*Probability*$_v$) | (1.467) | (1.318) | (3.257) | (3.233) |
| CV of Predicted Adoption Index | -0.296 | -0.157 | -0.928 | 0.506 |
| (=*Heterogeneity*$_v$) | (0.208) | (0.214) | (1.079) | (1.053) |
| $Centrality_v \times Heterogeneity_v$ | -2.625** | -2.131** | -2.851 | -3.299 |
| | (1.324) | (1.066) | (3.777) | (3.562) |
| $Probability_v \times Heterogeneity_v$ | 6.715** | 4.762* | 18.480*** | 7.562 |
| | (3.131) | (2.796) | (6.997) | (7.073) |
| Village-level Controls | No | Yes | No | Yes |
| Observations | 324 | 324 | 324 | 324 |
| R-squared | 0.080 | 0.180 | 0.049 | 0.169 |

*Notes:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. All regressions include a constant term and year fixed effects. Village-level controls include percentage of village using pit planting at baseline, percentage of village using compost at baseline, percentage of village using fertilizer at baseline, village size, the square of village size, and district fixed effects.

# Discussion

# Summary

- Focus on using network based interventions to improve technology adoption in developing countries.
- If the new technology has more benefits to some agents than the others and targeting is needed, who should we target?
- Through the lens of my theoretical model, simulations help me hypothesize that centrality (probability) based targeting perform worse (better) as the heterogeneity increase.
- Empirical results show support in favor of my hypotheses:
  - Village-level variations show that the +ve (-ve) effect of seeds' centrality (probability) on the adoption of pit planting decrease with increase in village-level heterogeneity. ▸ Robustness
  - Weaker evidences in favor of my hypotheses are found using the experimental variations in the data. ▸ Identification and Results

# Remarks

- Difficulty in targeting based on the probability of adoption.
- Use of additional data to predict adoption conditional on observable demographics.
- Better approach in disentangling the effects of centrality and probability of seeds.
- Importance of context in designing targeting strategies for technology adoption.
- Cost considerations? Is targeting optimal vs random seeding?

**Thank you!**

# Contributions to the Existing Literature

1. Diffusion of information in developing economies:
    - Network plays key role in improving diffusion (Foster and Rosenzweig,1995; Conley and Udry, 2010; Krishnan and Patnam, 2013).
    - Social networks can be used to improve technology adoption (Banerjee et al., 2013, 2019; Benyishay and Mobarak, 2019).
    - Underlying diffusion process is important in designing targeting strategies (Akbarpour et al., 2020; Beaman et al., 2021).

**Contribution:** Provide evidence (both theoretical and empirical) that the success of network-based targeting strategies depend on the population level heterogeneity.

# Contributions to the Existing Literature

2. Population heterogeneity and social learning:
    - People vary in terms of what they need to learn (Munshi, 2004; Tjernström ,2017) and how much they need to learn (Conley and Udry, 2010).
    - Existing models assume people to be homogeneous in terms of what they are learning (Acemoglu, Nedic, and Ozdaglar, 2008; Golub and Jackson, 2010; Banerjee et al., 2021).

**Contribution:** Formalize the scenario where agents learn from their network about a technology that is more beneficial to some of them than the others.

# Contributions to the Existing Literature

3. Characterizing opinion leaders in diffusing new knowledge:
    - Learning is more effective when the opinion leaders are in some way superior than their followers (Miller and Mobarak, 2015; Maertens, 2017).
    - Communicators that share a group identity with the farmers or face comparable agricultural conditions, does better job at convincing farmers to adopt a new technology (BenYishay and Mobarak, 2018).
    - Most effective opinion leaders are superior to the followers, but not excessively so (Feder and Savastano, 2006).

**Contribution:** Characterize opinion leaders in network-based targeting based on population heterogeneity.

◂ Back

# Theoretical Model

- Consider a two-stage decision process:
  - **Stage 1:** The agents decide whether or not to make an irreversible investment to learn about an available new technology.
  - **Stage 2:** Conditional on making that investment, in the second stage they decide whether to stick to a traditional technology, or adopt the new technology.
- Traditional technology has a sure payoff of $\pi^T$, where the new technology provides a payoff of $\pi^N(\omega_{it})$, $\omega_{it} \in \Omega$.
- $\omega_{it}$ is drawn independently at each period $t$ according to the true distribution $p_i^*(\omega_{it})$ for household $i$. Draws are not correlated over time within household and between households.

# Theoretical Model

- But, true distributions are positively correlated between households according to the existing network structure (more details below).
- $\forall it$, $\exists \omega_{it}, \omega'_{it} \in \Omega$ such that $\pi^N(\omega_{it}) \geq \pi^T \geq \pi^N(\omega'_{it})$.
- $\mathcal{I}$ denotes the set of all households.
- $\exists i, j \in \mathcal{I}$ such that $\int_{\omega_{it} \in \Omega} p_i^*(\omega_{it}) \pi^N(\omega_{it}) - c_i \geq \pi^T$ and $\int_{\omega_{jt} \in \Omega} p_j^*(\omega_{jt}) \pi^N(\omega_{jt}) - c_j \leq \pi^T$, with $c_i$ being the cost of new technology for household $i$.
- Initially all households are uninformed $\Rightarrow$ $p_i^*$s are unknown.
- The household $i$ has beliefs $p_{it}(\omega_{it})$ over the distribution of $\omega_{it}$ at period $t$.

# Theoretical Model

- At period $t$, uninformed agent $i$ has the option to become informed by putting effort $e_{it} \in \{0, 1\}$.
- If $e_{i\tau} = 1$, $e_{it} = 1 \ \forall t \geq \tau$.
- If $e_{it} = 1$, the agent learns the true distribution $p_i^*(\omega_{it})$ at cost $\eta_i$. The cost of learning is incurred the first time the agent gets informed only.
- If $e_{it} = 0$, no effort cost is incurred and the agent uses DeGroot averaging to approximate the true distribution.
- Let $G$ denote the $n \times n$ weighted, directed, and non-negative influence matrix ($n = |\mathcal{I}|$), where $G_{ij} \geq 0$ represents the weight $i$ places on $j$'s opinion (with $\sum_{j \in \mathcal{I}} G_{ij} = 1$).

# Theoretical Model

- Then $\hat{p}_{it} = \sum_{j \in \mathcal{I}} G_{ij} p_{jt-1}$ denotes household $i$'s approximation based on others' opinion following the DeGroot averaging.
- The true distributions are positively correlated between the households such that: $p_i^* = \sum_{j \in \mathcal{I}} G_{ij} p_j^*$.
- The belief of agent $i$ at period $t$:

$$p_{it}(\omega_{it}) = e_{it}(p_i^*(\omega_{it})) + (1 - e_{it})\hat{p}_{it}(\omega_{it}).$$

- Assume that agents need to be informed before they adopt: helps me explicitly capture the point when the agents stop seeking information from their peers.
- Assume the agents to be risk-neutral and myopic.

Back

# Simulation Robustness 1

Back

Table A1: Simulation Robustness (w.r.t different centrality measure)

| | | Level of Correlation | | | |
|---|---|---|---|---|---|
| Strategy | Statistic | Low | Medium | High | Perfect |
| Pagerank Centrality Based | Mean | 0.88 | 0.96 | 0.99 | 0.98 |
| | Variance | 0.17 | 0.05 | 0.04 | 0.01 |
| Probability Based | Mean | 0.94 | 0.81 | 0.76 | 0.72 |
| | Variance | 0.11 | 0.11 | 0.14 | 0.09 |
| | Observations | 200 | 197 | 192 | 200 |

*Notes:* Simulations on varying levels of correlation are all done for 200 networks, each containing 20 households. However, upon generation of the true probabilities, some networks may be dropped as they contained 0% of informed households under full efficiency.

# Simulation Robustness 2

◂ Back

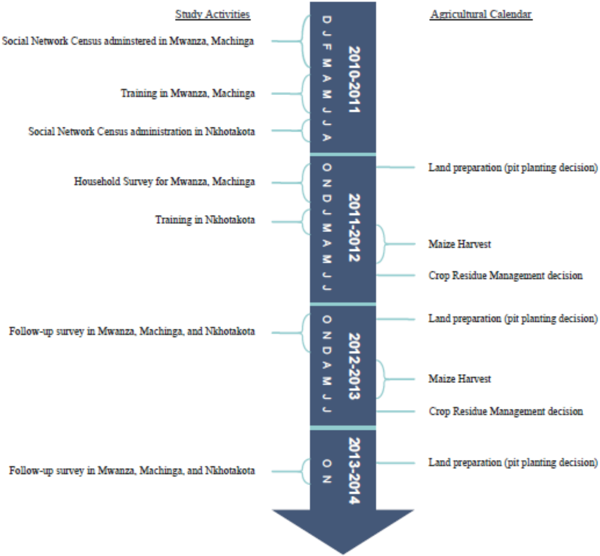
Table A2: Simulation Robustness (w.r.t different population)

| | | Level of Correlation | | | |
|---|---|---|---|---|---|
| Strategy | Statistic | Low | Medium | High | Perfect |
| Betweenness Centrality Based | Mean | 0.58 | 0.54 | 0.54 | 0.55 |
| | Variance | 0.20 | 0.13 | 0.13 | 0.14 |
| Probability Based | Mean | 1.04 | 0.55 | 0.52 | 0.59 |
| | Variance | 0.07 | 0.14 | 0.14 | 0.13 |
| | Observations | 200 | 200 | 200 | 200 |

*Notes:* Simulations on varying levels of correlation are all done for 200 networks, each containing 50 households. However, upon generation of the true probabilities, some networks may be dropped as they contained 0% of informed households under full efficiency.

# Timeline of BBMM

Back



# BBMM Replication Data

Back

- First collected the social network census data to elicit names of people each respondent consults when making agricultural decisions along with some other demographics.
- Used this responses with the village listing to identify links. Considered individuals linked if either party named each other or if they are part of the same household.
- Used simulations with the network information to identify seeds according to different diffusion processes to optimize diffusion after four periods.
- Randomly allocated villages to one of the four treatment groups and selected seeds for training based on that.
- Once the training is complete, randomly surveyed a panel of approximately 30 households per village, including all the seed and shadow farmers.

# AESTAS Data

◂ Back

- Objective was to monitor the *Lead Farmer* (LF) program in Malawi.
- Covers all districts of Malawi, except Likoma. Data collected in two waves: 2016 and 2018.
- Three types of interviews: Household, LF, and Community.
- Random sample of around 10 households were selected for interview from randomly selected sections within each district.
- Stratification was done based on whether or not the household had a LF.
- The same households were interviewed in the two waves with very small level of attrition (around 4%).
- For each household, both household head and their spouses were interviewed.

# Description of Key Demographic Variables

Back

- **Adults**: Number of adults in the household.
- **Children**: Number of children in the household.
- **Housing**: Standardized first principal component (PC). Includes information on materials walls are made of, roof materials, floor materials (0- Traditional, 1- Modern), and whether the household has a toilet (only in the BBMM sample).
- **Livestock**: Standardized first PC. Includes the number of sheep, goats, chickens, cows, pigs the household owns. The BBMM sample also includes number of guinea fowl and doves.
- **Assets**: Standardized first PC. Includes the number of bicycles, radios and cell phones the household owns.

# Approximating Probability of Adoption: All Assumptions

◂ Back

- **Assumption 1:** Adoption and Usage indices are good proxies for probability of adoption.
- **Assumption 2:** The variation in adoption and usage indices that can be captured by the observable demographics, are sufficient for my analysis. ▸ Actual and Predicted Variations
- **Assumption 3:** The mapping from the observable demographics to the adoption and usage indices are the same in the BBMM sample, as it is in the AESTAS sample.

▸ Sample Comparison

# Calculating Adoption and Usage Indices

Back

- **Adoption Index:** Uses self-reported adoption for a list of pre-determined technologies and practices. This covered both agricultural and food processing practices. Average of these set of dummy variables taken to calculate the index.
- **Usage Index:** Self-reported plot-level usage for a list of pre-determined agricultural technologies and practices. Average of these set of dummy variables taken to calculate the index.

# Sample Comparison

◂ Back

Table 2: Baseline Demographics Across Datasets

| | | Variables | | | | |
|---|---|---|---|---|---|---|
| Dataset | Statistic | Adults | Children | Housing | Livestock | Assets |
| AESTAS | Mean | 2.14 | 3.00 | -0.09 | -0.03 | -0.03 |
| | (SD) | (1.00) | (2.00) | (0.98) | (0.99) | (1.00) |
| | Median | 2.00 | 3.00 | -0.29 | -0.40 | -0.29 |
| | Skewness | 2.59 | 1.00 | 0.54 | 3.74 | 0.31 |
| | Kurtosis | 16.76 | 6.01 | 2.01 | 26.67 | 1.79 |
| | Observations | 2820 | 2820 | 2803 | 2820 | 2820 |
| BBMM | Mean | 2.36 | 2.77 | -0.02 | 0.02 | 0.09 |
| | (SD) | (0.95) | (1.86) | (0.99) | (1.02) | (1.03) |
| | Median | 2.00 | 3.00 | -0.24 | -0.31 | -0.10 |
| | Skewness | 1.21 | 0.76 | 2.48 | 4.64 | 1.24 |
| | Kurtosis | 5.43 | 4.43 | 8.70 | 35.03 | 5.64 |
| | Observations | 5384 | 5407 | 5382 | 5407 | 5407 |

*Notes:* The variables *Adults* and *Children* represent number of adults and children in a household, respectively. The variables *Housing*, *Livestock*, and *Assets* were standardized first principal components. More details available in the paper.

# Approximating Probabilities of Adoption

◂ Back

Table 3: OLS Regression Results for Adoption and Usage Indices

| | Adoption Index | | Usage Index | |
|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) |
| Adults | 0.008*** | 0.005** | 0.011*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Children | 0.003*** | 0.002 | 0.003*** | 0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Housing | 0.009*** | 0.007*** | 0.003 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Livestock | 0.010*** | 0.005* | 0.014*** | 0.009*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Assets | 0.024*** | 0.017*** | 0.020*** | 0.014*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Household Controls | No | Yes | No | Yes |
| Observations | 5610 | 5606 | 5610 | 5606 |
| R-squared | 0.096 | 0.149 | 0.085 | 0.123 |

*Notes:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the section level are in parentheses. All regressions use a constant term and sample weights. The variables *Adults* and *Children* represent number of adults and children in a household, respectively. The variables *Housing*, *Livestock*, and *Assets* were standardized first principal components.

# Approximating Probabilities of Adoption

◂ Back

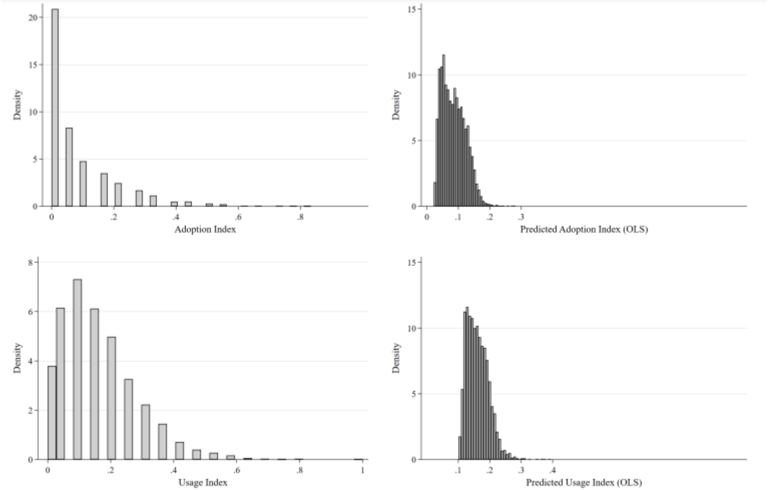



Figure 11: Actual and Predicted Adoption and Usage Indices

# Regression Results

## Table A1: Village level Regression 1 with Different Measure of Probability

| Variables | Adoption Rate (1) | (2) | Any Non-Seed Adopters (3) | (4) |
|---|---|---|---|---|
| Eigen-vector Centrality of Seeds | 0.999* | 0.817* | 0.984 | 1.067 |
| (=$Centrality_v$) | (0.565) | (0.480) | (1.302) | (1.191) |
| Predicted Usage Index of Seeds | -2.174 | -1.511 | -4.599 | -0.0836 |
| (=$Probability_v$) | (1.410) | (1.279) | (3.317) | (3.053) |
| CV of Predicted Usage Index | -1.091 | -0.631 | -2.549 | 2.142 |
| (=$Heterogeneity_v$) | (0.805) | (0.779) | (2.905) | (2.823) |
| $Centrality_v \times Heterogeneity_v$ | -4.481* | -3.936* | -4.874 | -5.907 |
| | (2.623) | (2.281) | (6.889) | (6.438) |
| $Probability_v \times Heterogeneity_v$ | 10.33* | 7.276 | 23.13 | 0.889 |
| | (6.160) | (5.623) | (14.19) | (13.40) |
| Village-level Controls | No | Yes | No | Yes |
| Observations | 324 | 324 | 324 | 324 |
| R-squared | 0.063 | 0.174 | 0.037 | 0.164 |

*Notes:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. All regressions include a constant term and year fixed effects. Village-level controls include percentage of village using pit planting at baseline, percentage of village using compost at baseline, percentage of village using fertilizer at baseline, village size, the square of village size, and district fixed effects.

# Regression Results

◂ Back

## Table A2: Village level Regression 1 with Different Measure of Centrality

| | Adoption Rate | | Any Non-Seed Adopters | |
|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) |
| Closeness Centrality of Seeds | 0.609** | 0.454* | 0.571 | 0.617 |
| (=$Centrality_v$) | (0.306) | (0.234) | (0.709) | (0.659) |
| Predicted Adoption Index of Seeds | -2.438** | -1.709 | -7.555** | -2.904 |
| (=$Probability_v$) | (1.230) | (1.134) | (3.201) | (3.152) |
| CV of Predicted Adoption Index | -0.0774 | -0.007 | -0.677 | 0.887 |
| (=$Heterogeneity_v$) | (0.214) | (0.202) | (1.196) | (1.158) |
| $Centrality_v \times Heterogeneity_v$ | -1.325* | -1.020* | -1.552 | -1.997 |
| | (0.716) | (0.558) | (1.896) | (1.823) |
| $Probability_v \times Heterogeneity_v$ | 5.610** | 3.814 | 17.55** | 6.849 |
| | (2.660) | (2.439) | (6.873) | (6.940) |
| Village-level Controls | No | Yes | No | Yes |
| Observations | 324 | 324 | 324 | 324 |
| R-squared | 0.087 | 0.179 | 0.048 | 0.170 |

*Notes:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. All regressions include a constant term and year fixed effects. Village-level controls include percentage of village using pit planting at baseline, percentage of village using compost at baseline, percentage of village using fertilizer at baseline, village size, the square of village size, and district fixed effects.

# Identification Using Experimental Variation

Back

$$Y_{vt} = \psi_0 + \begin{bmatrix} \psi_1 & \psi_2 \end{bmatrix} \begin{bmatrix} Centrality_v \\ Probability_v \end{bmatrix} + \psi_3 Het_v + \begin{bmatrix} 1 \\ Complex_v \\ Simple_v \\ Geo_v \end{bmatrix}' \Psi \begin{bmatrix} Centrality_v \\ Probability_v \end{bmatrix} Het_v + \gamma X_v + \rho_t + \eta_{vt}.$$

Effects are measured in terms of the Benchmark treatment:

- Same level of heterogeneity as the benchmark: $Y_{vt}$ $\uparrow$es with centrality and $\downarrow$es with probability.
- Less heterogeneous: seeds with higher centrality perform better and seeds with higher probability perform worse. No prediction for seeds with less centrality and probability.
- Higher heterogeneity: seeds with lower centrality perform better and seeds with lower probability perform worse. No prediction for seeds with more centrality and probability.

# Regression Results

## Table 6: Village level Regression 2 of Adoption Outcomes (Pit Planting)

| Variables | Adoption Rate (5) | (6) | Any Non-Seed Adopters (7) | (8) |
|---|---|---|---|---|
| Eigen-vector Centrality of Seeds | 0.775** | 0.633* | 1.704 | 1.638 |
| (= $Centrality_v$) | (0.377) | (0.366) | (1.538) | (1.477) |
| Predicted Adoption Index of Seeds | -2.362*** | -1.579* | -10.420*** | -5.947* |
| (= $Probability_v$) | (0.899) | (0.888) | (3.666) | (3.582) |
| CV of Predicted Adoption Index | -0.321 | -0.150 | -0.923 | 0.417 |
| (= $Heterogeneity_v$) | (0.267) | (0.262) | (1.087) | (1.058) |
| $Centrality_v \times Heterogeneity_v$ | -2.423** | -2.237** | -6.693 | -6.574 |
| | (1.045) | (1.008) | (4.258) | (4.064) |
| $Centrality_v \times Heterogeneity_v \times Complex$ | 0.657 | 0.665 | 4.328** | 3.756** |
| | (0.485) | (0.469) | (1.977) | (1.894) |
| $Centrality_v \times Heterogeneity_v \times Simple$ | 0.416 | 0.428 | 1.078 | 0.431 |
| | (0.499) | (0.484) | (2.033) | (1.953) |
| $Centrality_v \times Heterogeneity_v \times Geo$ | 2.026*** | 1.942*** | 0.103 | -0.070 |
| | (0.545) | (0.542) | (2.221) | (2.185) |
| $Probability_v \times Heterogeneity_v$ | 5.881*** | 4.104** | 22.970*** | 12.350 |
| | (2.040) | (2.019) | (8.314) | (8.142) |
| $Probability_v \times Heterogeneity_v \times Complex$ | -0.155 | -0.232 | -1.275 | -0.679 |
| | (0.851) | (0.823) | (3.469) | (3.320) |
| $Probability_v \times Heterogeneity_v \times Simple$ | -0.121 | -0.110 | 1.941 | 3.511 |
| | (0.887) | (0.862) | (3.617) | (3.476) |
| $Probability_v \times Heterogeneity_v \times Geo$ | -2.588*** | -2.562*** | -0.391 | 0.538 |
| | (0.949) | (0.932) | (3.870) | (3.759) |
| Village-level Controls | No | Yes | No | Yes |
| Observations | 324 | 324 | 324 | 324 |
| R-squared | 0.133 | 0.224 | 0.113 | 0.222 |

*Notes:* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. All regressions include a constant term and year fixed effects. Village-level controls include percentage of village using pit planting at baseline, percentage of village using compost at baseline, percentage of village using fertilizer at baseline, village size, the square of village size, and district fixed effects.