# Estimating Spillover effects in Smallholder Farmer Networks in Western Kenya

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### Context

- Majority(83%) of farms in the world are smallholder farms.
- In Sub-Saharan Africa, most of them are subsistence farms
- PlantVillage in Africa
  - Increase climate change resiliency
  - Tackle trans-continental crop pests and diseases.
- Goal is to introduce and increase Disease Management Behaviors (DMBs)

- Farmer organizations in Africa, specifically farmer groups in Kenya with LF and FFs.
- Most farmers are also accessible via SMS.
- Adoption of new technologies among farmers is generally slow and inhomogeneous but social channels help.
- Take advantage of these social networks to introduce and increase DMB adoption.

Preregistration at Open Science Framework https://doi.org/10.17605/OSF.IO/TXDP7 Does SMS messaging on DMBs have spillover effects and does it increase interest/adoption on farms?

- We hypothesize that there are spillover effects via social networks to SMS treatments.
- We hypothesise that larger the tie weight between farmers, the more likely they are to share and adopt methods.

### Farmer Group's Network



# Study Design

- 40 Farmer groups over 2 counties resulting in around 400 farmers
- First survey and network data collected from everyone
- Cluster Randomized Trial with rerandomization(Morgan & Rubin (2012))
  - Rerandomization allows the experimenter to improve covariate balance by pre-specifying a covariate balance criterion.
  - The balance criterion allows for blocking by county and takes into account individual and group level values.

### Treatments

- Treatment: Only LF receives treatment (SMS messaging)
- Control: LF and all FFs in farmer group receive treatment (SMS messaging)
- Treatment Unit is a single farmer group
- Measurement Unit is a single farmer in a group
  - Use of mulching in farm
  - Scouting for Fall Army Worm (FAW) in farm
  - Knowledge of Parasitoids to combat FAW

- Testing for interference at different tie thresholds: Bowers et al. (2013) testing framework
- Estimation via Exposure Mapping: Aronow and Sammi(2017)

# Bowers et al.(2013)

- "Fisherian" Randomization Test
- Framework for testing rather than estimation
- Write any causal model to transform potential outcome of one treatment vector z, y<sub>i,z</sub> to potential outcome for another treatment vector w, y<sub>i,w</sub>.

$$\mathcal{H}(y_{i,\mathbf{z}},\mathbf{w},\theta) = y_{i,\mathbf{w}} \tag{1}$$

- More specifically, potential outcome,  $y_z$  to uniformity trial,  $y_0$ .
- Uniformity Trial (Rosenbaum2007): All units receive the control condition, as if the experiment had not been carried out.

# Bowers et al.(2013) cont.

#### **Testing Framework**

- Causal model positing the form of interference. Could be theoretically motivated
- With hypothesized values of θ, use the model to map observed outcomes (y<sub>z</sub>) to the uniformity trial.
- Select a test statistic *T* that is effect increasing, i.e. is small when the treated and control distributions are similar and large if they diverge.
- Generate empirical distribution of T by sampling from  $Z \in \Omega$ .
- Estimate p-value.

#### Examples from the paper

- No interference, additive model:  $\mathcal{H}(y_{i,z}, \mathbf{0}, \tau) = y_{i,0} + z_i \tau$
- Direct + spillover from treated neighbours (multiplicative):  $\mathcal{H}(y_{i,z}, \mathbf{0}, \beta, \tau) = [\beta_0 + (1 - z_i)(1 - \beta_0)exp(-\tau_0^2 \mathbf{z}^T \mathbf{S})]^{-1} \mathbf{y}_z$

Our outcome data is binary.

logit  $p(x) = \beta_0 + \beta_1 dir + \beta_2 ind$ 

Sum of deviance residuals becomes our T and produce the empirical distribution of T by sampling from  $\mathbf{Z} \in \Omega$ .

### Use of Scouting



## **Use of Mulching**



### **Interest in Parasitoids**



- Re-weight/prioritise family ties.
- Check assumptions on LF's experiencing both direct and indirect effects
- Rewrite uniformity trial model



# **Exposure Mapping**



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