Experimental Methods: Lecture 3

Spillover

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Road Map to Lecture 3

- Non-interference re-visited
- Spillover
- Design Case Studies
  - Uganda file festivals (Green et al)
  - Multiple Arms
  - Conjoint
  - Treatment Adaptive

Non-interference

- Permits us to ignore the potential outcomes that would arise if subject i were affected by the treatment of other subjects
- Formally, we reduce the schedule of potential outcomes $Y_i(\mathbf{d})$, where $\mathbf{d}$ describes all of the treatments administered to all subjects, to a much simpler schedule $Y_i(d)$, where d refers to the treatment administered to subject i.
- Implies that so long as a subject's treatment status remains constant, that subject's outcome is unaffected by the particular way in which treatments happened to be assigned to other subjects

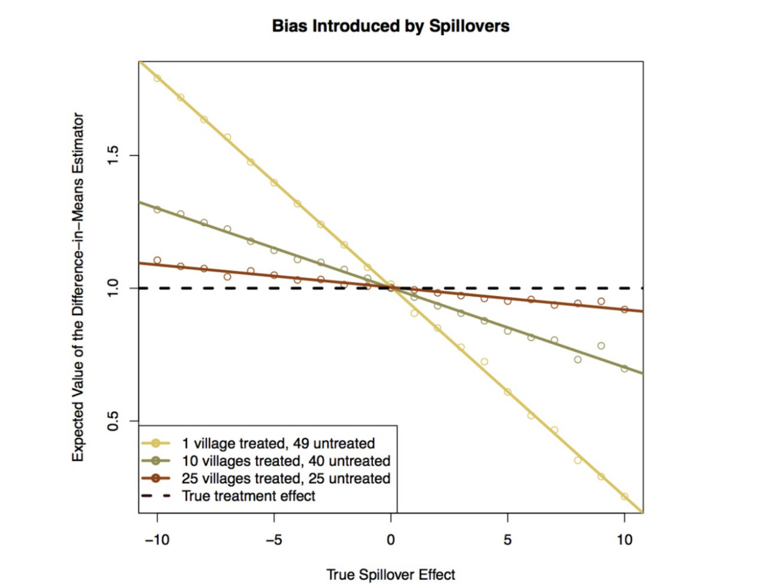
Non-interference violated

- Police patrols displace crime from treated to untreated areas
- Non-interference violated if your estimand is following:
    - Average potential outcome when a block is treated minus average potential outcome when no blocks are treated
- If police patrols displace crime from treated to untreated areas, observed outcomes in control will not be potential outcomes when no treatment administered anywhere
- Estimated ATE will tend to exaggerate the true ATE

Core assumptions violated?

- Public Health: Providing an infectious disease vaccine to some individuals may decrease the probability that nearby individuals become ill
- Politics: Election monitoring at some polling stations may displace fraud to neighboring polling stations
- Economics: Lowering the cost of production for one firm may change the market price faced by other firms
- Marketing: Advertisements displayed to one person may increase product recognition among her work colleagues

Spillover

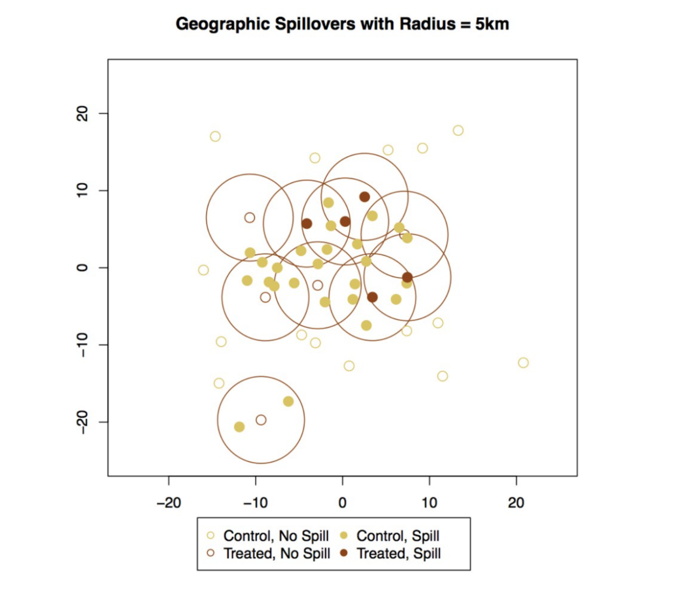


Bias Introduced by Spillovers
Expected Value of the Difference−in−Means Estimator
1.5
1.0
0.5
−10
−5
0
5
10
True Spillover Effect
1 village treated, 49 untreated
10 villages treated, 40 untreated
25 villages treated, 25 untreated
True treatment effect

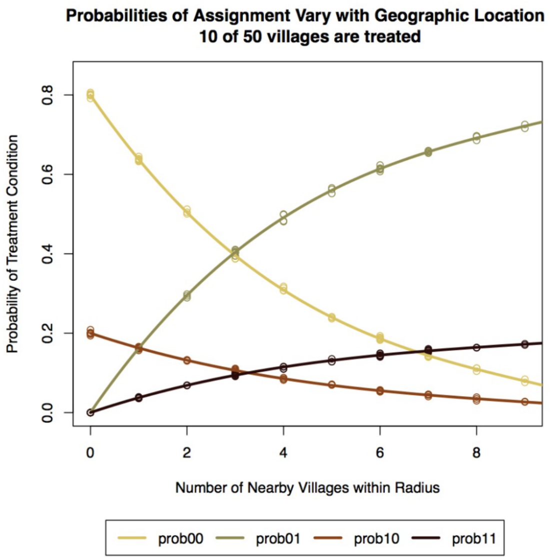
Estimating Spillover Effects

- $Y_{00} \equiv Y(Z_i = 0, Z_j = 0)$: Pure Control
- $Y_{10} \equiv Y(Z_i = 1, Z_j = 0)$: Directly treated, no spillover
- $Y_{01} \equiv Y(Z_i = 0, Z_j = 1)$: Untreated, with spillover
- $Y_{11} \equiv Y(Z_i = 1, Z_j = 1)$: Directly treated, with spillover
- We assume...
  - treatment assignments of non-neighboring units do not alter a unit's potential outcomes
  - model spillovers as a binary event: either some neighboring unit is treated, or not

Spillover


Geographic Spillovers with Radius = 5km
20
10
0
−10
−20
−20
−10
0
10
20
Control, No Spill
Control, Spill
Treated, No Spill
Treated, Spill

Spillover



Probabilities of Assignment Vary with Geographic Location
10 of 50 villages are treated
Probability of Treatment Condition
0.0
0.2
0.4
0.6
0.8
0
2
4
6
8
Number of Nearby Villages within Radius
prob00
prob01
prob10
prob11

```r
require(ggplot2)

# Define two helper functions
complete_ra <- function(N,m){
  assign <- ifelse(1:N %in% sample(1:N,m),1,0)
  return(assign)
}

get_condition <- function(assign, adjmat){
  exposure <-  adjmat %*% assign
  condition <- rep("00", length(assign))
  condition[assign==1 & exposure==0] <- "10"
  condition[assign==0 & exposure>0] <- "01"
  condition[assign==1 & exposure>0] <- "11"
  return(condition)
}
```

```r
N <- 50  # total units
m <- 10  # Number to be treated
# Generate adjacency matrix
set.seed(343)
coords <- matrix(rnorm(N*2)*10, ncol = 2)
distmat <- as.matrix(dist(coords))
true_adjmat <- 1 * (distmat<=5) # true radius = 5
diag(true_adjmat) <- 0

# Run simulation 10000 times
Z_mat <- replicate(10000, complete_ra(N = N, m = m)
    )
cond_mat <- apply(Z_mat, 2, get_condition, adjmat=
    true_adjmat)
# Calculate assignment probabilities
prob00 <- rowMeans(cond_mat=="00")
prob01 <- rowMeans(cond_mat=="01")
prob10 <- rowMeans(cond_mat=="10")
prob11 <- rowMeans(cond_mat=="11")
```

```
# calculate number of villages
vil_sum = rowSums(true_adjmat)
probs = cbind(prob00, prob01, prob10, prob11, vil_
    sum)
probs2 = as.data.frame(probs)
probs2 = as.matrix(probs2)
probs3 = rbind(probs2[,c(1,5)], probs2[,c(2,5)],
               probs2[,c(3,5)], probs2[,c(4,5)])
probs3 = as.data.frame(probs3)
probs3$ProbCat = c(rep("prob00",50), rep("prob01"
    ,50), rep("prob10",50), rep("prob11",50))
probs3$ProbCat = factor(probs3$ProbCat)
p = ggplot(probs3, aes(y = prob00, x=vil_sum))
p
p = p + geom_point()
p
p = p + geom_point(aes(colour = ProbCat))
p
p = p + labs(x = "Number␣of␣Nearby␣Villages␣within␣
    Radius")
```

Social processes that imply spillovers (from Greem)

- *Diffusion*: Interventions that convey information about commercial products or political causes may spread from individuals who receive the treatment to others who are nominally untreated.
- *Displacement*: Police interventions designed to suppress crime in one location may displace criminal activity to nearby locations.
- *Social comparison*: An intervention that offers housing assistance to a treatment group may change how the control group evaluates their own housing conditions.
- *Persistence and memory*: Within-subjects experiments, in which outcomes for a given unit are tracked over time, may involve "carryover" or "anticipation."

Why should we care about spillovers?

- Biased estimation of causal effects
  - Example: Understatement of average causal effects when an information treatment spreads to the control group
  - Example: Exaggeration of average causal effects when a crime prevention program causes displacement
- Mistaken policy inferences: Amplification of cumulative policy impact if the behavior encouraged by an intervention causes other individuals to change their behavior.
  - Example: Vaccine incentives to one individual encourages others to get vaccinated

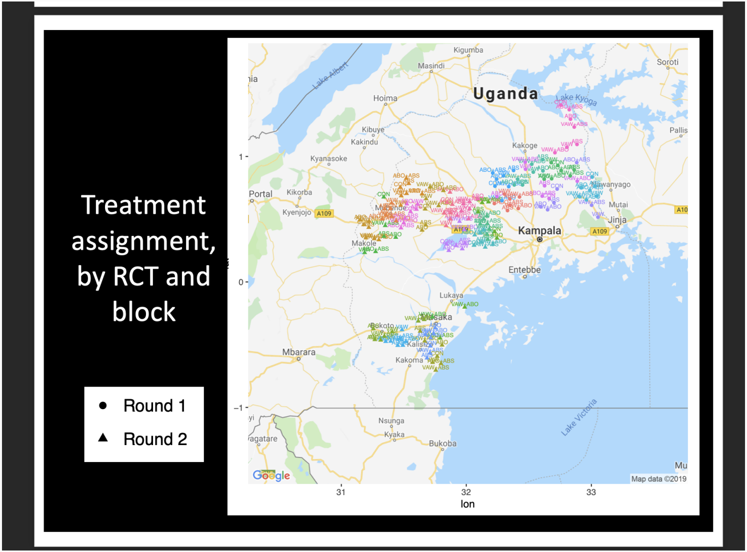
Designs to detect spillovers

- Simply measure outcomes for non-experimental units within social networks
    - Example: Spouses of those who receive health interventions (Fletcher and Marksteiner 2017 AEJ)
    - Extensions to placebo-control designs for media interventions involving noncompliance (Green et al. 2020 JRSS-A)
- Target specific nodes in a social network
    - Example: Bullying in 56 high schools (Paluck et al. 2016 PNAS)
    - Example: Encouraging subjects' neighbors or housemates to vote (Sinclair et al. 2012 AJPS)

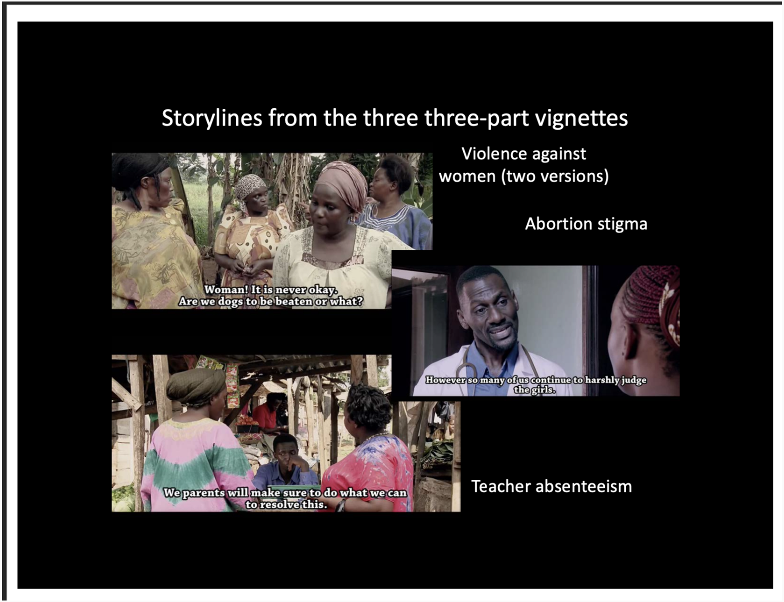
Design 1: Measure outcomes for non-experimental units within social networks

- Uganda film festival experiment: placebo-controlled messages during commercial breaks deployed in 168 rural villages
- Messages concerned violence against women, teacher absenteeism, or abortion stigma
- Surveys of random samples of villagers conducted 2 months later to measure outcomes
- Compare nonviewers in treatment or placebo villages in order to assess spillovers

Uganda Green et al



Uganda Green et al



Uganda Green et al

	Dependent variable:			
	Index of willingness to take action to counter intimate partner violence			
	Reached Directly	Reached Indirectly	Not Reached	Not Reached Directly
	(1)	(2)	(3)	(4)
VAW	0.046^{**}	0.004	-0.0002	0.003
	(0.015)	(0.012)	(0.014)	(0.010)
Control Mean	0.38	0.38	0.38	0.38
Vill. Means	0.38	0.37	0.37	0.38
Vill. SD	0.09	0.07	0.09	0.06
N Vill.	110	110	110	110
Block FE	Yes	Yes	Yes	Yes
Observations	1,154	2,441	1,918	4,359
Adjusted R^2	0.011	0.005	0.013	0.006
Notes:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Direct effects and spillovers from anti-VAW messages among all respondents in endline surveys following 2016 festival.

Coefficients estimated using the pre-registered least-squares regression, conditioning on block fixed-effects and an indicator for resampling. Standard errors are clustered at the village level. Two-tailed *p*-values are calculated by comparing the observed estimate to 2000 estimates simulated under the sharp null of no effects for all units by permuting the treatment assignment 2000 times.

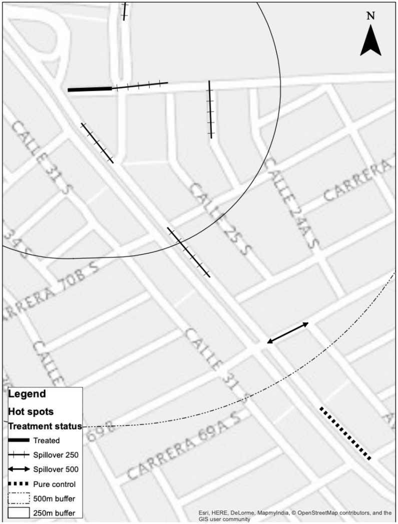
Design 2: Hot Spot Crime Experiment

Define potential outcomes:

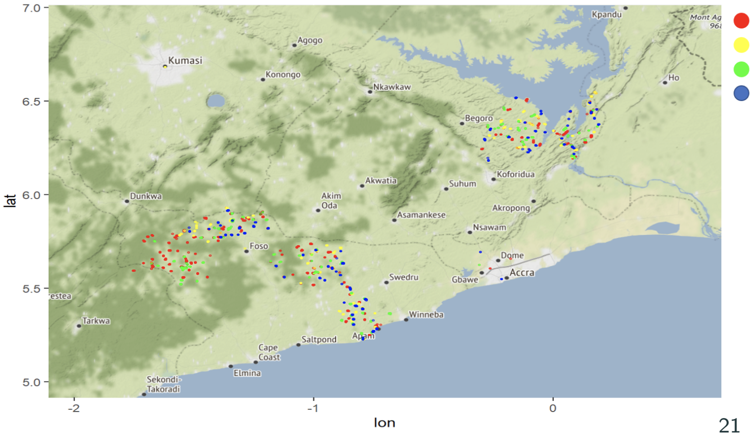
- directly treated
- proximal spillover
- distal spillover
- pure control

Design 2: Hot Spot Crime Experiment

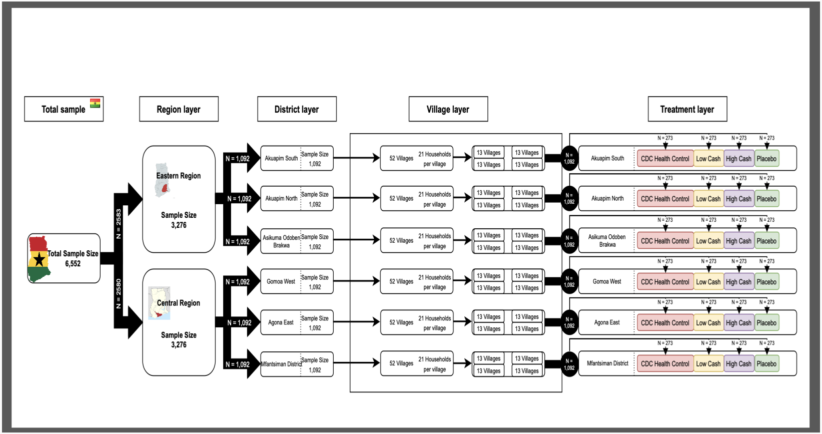
Figure 3: An example of assignment to the four treatment conditions



Geographic Treatment Mapping



Duch et al Ghana



Duch et al Ghana

Table 1: Financial Incentive Treatment Effects on Vaccinaion Intentiosn

	Dependent variable:		
	Intention to Vaccinate		
	(1)	(2)	(3)
Village Health	0.009		0.006
	(−0.022, 0.040)		(−0.039, 0.050)
Village High Cash	0.054***		0.031
	(0.023, 0.085)		(−0.015, 0.077)
Village Low Cash	0.064***		−0.025
	(0.032, 0.095)		(−0.065, 0.015)
Subject Health		0.015	0.010
		(−0.015, 0.046)	(−0.036, 0.057)
Subject Low Cash		0.119***	0.139***
		(0.090, 0.148)	(0.101, 0.177)
Subject High Cash		0.069***	0.039
		(0.039, 0.100)	(−0.009, 0.087)
Constant	0.720***	0.712***	0.711***
	(0.698, 0.742)	(0.696, 0.728)	(0.689, 0.733)
Observations	5,938	5,947	5,938
R^2	0.004	0.012	0.013
Adjusted R^2	0.004	0.011	0.012
Residual Std. Error	0.432 (df = 5934)	0.430 (df = 5943)	0.430 (df = 5931)
F Statistic	8.009*** (df = 3; 5934)	23.933*** (df = 3; 5943)	12.602*** (df = 6; 5931)
Note:			*p<0.1; **p<0.05; ***p<0.01

Homework Exercise Lecture 3

Prepare a simple R script illustrating how to incorporate the distance between control and treatment units in the estimation of treatment effects.