

# Interference

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Rubin (1978)

SUTVA 2: No interference between units.

Does  $A$ 's assignment affect  $B$ 's potential outcomes?

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- ▶ Other common examples?

# Examples of Interference in Field Experiments

Gerber and Green (2012)

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- ▶ Contagion
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- ▶ Deterrence
- ▶ Persistence
- ▶ Memory

## Bias under Interference

Agent	Y if MaryH	Y if PeterH	Y if LimorH	Y if NobodyH
Mary	100	50	70	70
Peter	50	50	50	50
Limor	90	50	90	90
Mean	80	50	70	70

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- ▶  $\bar{Y}_{\text{None}} = 70$ .
- ▶ Calc TEs relative to  $\bar{Y}_{\text{None}}$  (“uniformity”)

## Bias under Interference: Uniformity Trial

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► True uniformity ATE:  $\frac{(100-70)+(50-50)+(90-90)}{3} = 10$

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# Notation

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$$\begin{aligned} Y_i(z_i, \mathbf{z}) &\stackrel{?}{=} Y_i(z_i, \mathbf{z}') \\ Y_1(1, (1, 0, 0, 1, \dots)) &\stackrel{?}{=} Y_1(1, (1, 1, 0, 0, \dots)) \\ Y_0(0, (0, 0, 0, 1, \dots)) &\stackrel{?}{=} Y_0(0, (0, 1, 0, 0, \dots)) \end{aligned}$$

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Under balanced random assignment, **no** interference, naive diff in means has expectation

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which is *unbiased* for ATE.

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- ▶ Multilevel experiments can help estimate these effects
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- ▶ “Detecting Spillover Effects: Design and Analysis of Multilevel Experiments”, Sinclair, McConnell, and Green (2012)

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- ▶ assign clients in “some client letters” preparers to letters/no letters

# Diagnosis of Potential Interference

## 1. Block:

```
data(x100)
block.out <- block(data = x100, groups = "g",
                  id.vars = c("id"),
                  block.vars = c("b1", "b2"))
```

## 2. Assign:

```
assg.out <- assignment(block.out, seed = 157)
```



# Diagnosis of Potential Interference

Diagnose interference after assignment (1D, Lindsay et al. (2001))

## 3. Diagnose:

```
diagnose(assg.out, data = x100, id.vars = "id",  
         suspect.var = "b1", suspect.range = c(0, 5))
```

```
##  
## Units differing by at least 0 and no  
## more than 5 on b1:  
##  
## Group: a  
##      Unit 1  Unit 2  Difference  
## 1  1073    1098         0  
## 2  1002    1036         1  
## 3  1016    1060         1  
## 4  1039    1076         3  
##  
## Group: b
```

## Further Examination of Design

### 4. Get block IDs:

```
createBlockIDs(assg.out, data = x100, id.var = "id")
```

```
##      [1] 29 17 14  5 17 33 35 10 21 41 39 45 32 49 36 12 18
##     [26]  6 37 31  4 11 20 16 47 28 48 12 23 18  2 19 48 14
##     [51] 32 11 40 15 29  8 23  1  9 13  3 24 26 28  3 50  5
##     [76]  2 25 25 26 43 16 46 35  1 44 45 50 37  7 30 10 38
```

## Further Examination of Design

### 5. Get balance:

```
assg2xBalance(assg.out, x100, id.var = "id",  
              bal.vars = c("b1", "b2"))
```

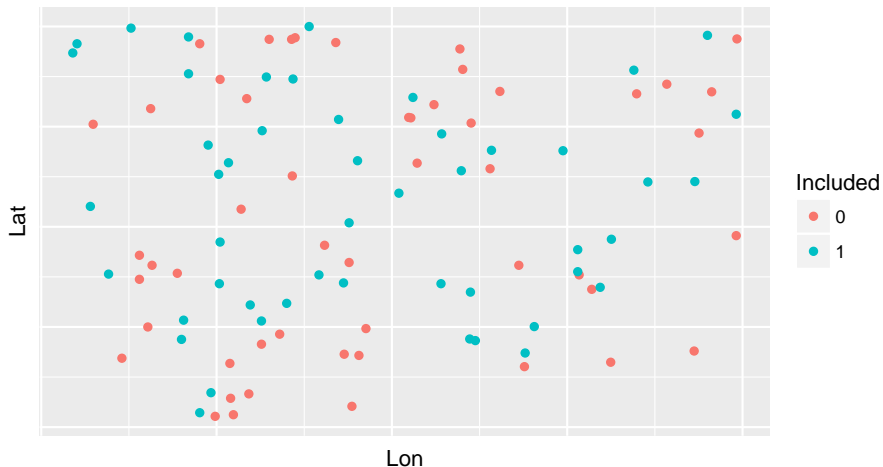
```
## $Group1  
##      strata():   unstrat  
##      stat      Treatment Control adj.diff std.diff      z  
## vars  
## b1              -23.7      0.0      -23.7      -0.08      -0.  
## b2              28.6      0.0      28.6      0.10      0.  
## ---Overall Test---  
##           chisquare df p.value  
## unstrat      0.161  2  0.922  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.'  
##  
## $Group2  
##      strata():   unstrat
```

# Avoiding Potential Interference due to Proximity

Are units too near each other?

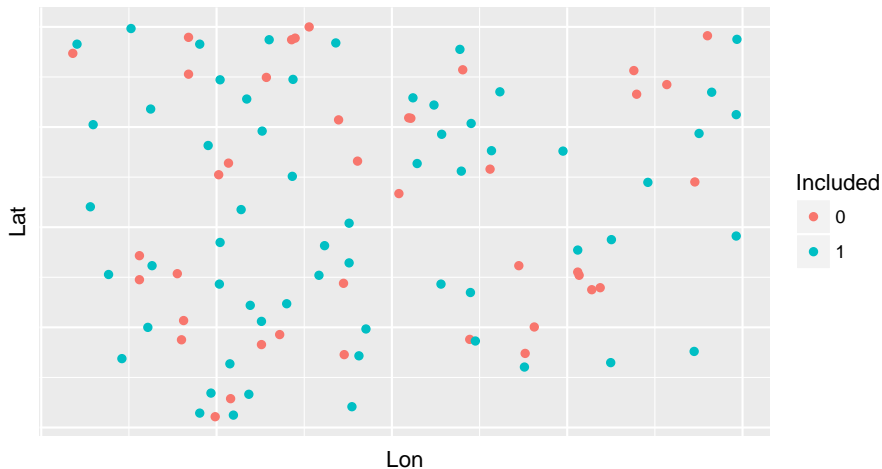
# Avoiding Potential Interference due to Proximity

Are units too near each other?



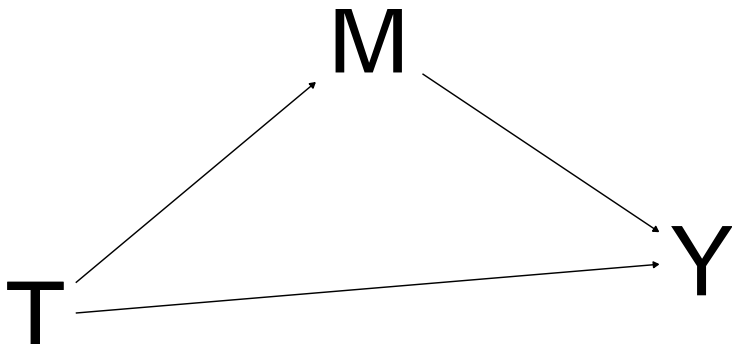
# Avoiding Potential Interference due to Proximity

3000 iterations, max min distance:



# Estimating Direct and Indirect Effects

- Different to mediation *direct*, *indirect* effects



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Think of this as different problem

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Think of this as different problem

- ▶ (Though, “effect of treatment through others” works?)
- ▶ (Common concept, but not really a mediating *variable*)

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		Total	Cases	Risk per 1,000 population	Total	Cases	Risk per 1,000 population
>50%	22,394	12,541	16	1.27	6,082	9	1.47
41–50%	24,159	11,513	26	2.26	5,801	27	4.65
36–40%	24,583	10,772	17	1.58	5,503	26	4.72
28–35%	25,059	8,883	22	2.48	4,429	26	5.87
<28%	24,954	5,627	15	2.66	2,852	20	7.01

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- ▶ Overall effect:  $35/8479 - 25/18623 = 2.79/1000$

# Estimating Direct and Indirect Effects

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Designing the randomized experiment:

Table 2. Illustrative example of a two-stage randomized placebo-controlled vaccine trial based on data from Ali et al. (2005)

Group $i$	Group assignment $S_i$	Vaccine recipients ( $Z_{ij} = 1$ )		Placebo recipients ( $Z_{ij} = 0$ )	
		Total $\sum_j Z_{ij}$	Cases $\sum_j Z_{ij} Y_{ij}(\mathbf{Z}_i)$	Total $\sum_j (1 - Z_{ij})$	Cases $\sum_j (1 - Z_{ij}) Y_{ij}(\mathbf{Z}_i)$
1	1	12,541	16	12,541	18
2	1	11,513	26	11,513	54
3	0	10,772	17	25,134	119
4	0	8,883	22	20,727	122
5	0	5,627	15	13,130	92

NOTE: Group assignment  $S_i = 1$  (0) corresponds to 50% (30%) vaccine coverage.

## Hudgens and Halloran (2008) (on Ali 2005)

Table 3. Estimates of population average direct, indirect, total, and overall effects per 1,000 individuals per year for data in Table 2

Effect	Parameter	Estimate	Estimated variance
Direct	$\overline{CE}^D(\psi)$	1.30	.856
Direct	$\overline{CE}^D(\phi)$	3.64	.178
Indirect	$\overline{CE}^I(\phi, \psi)$	2.81	3.079
Total	$\overline{CE}^T(\phi, \psi)$	4.11	.672
Overall	$\overline{CE}^O(\phi, \psi)$	2.37	1.430

- ▶  $\psi$ : 50% coverage
- ▶  $\phi$ : 30% coverage

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Ichino and Schündeln (2012) in Ghana

Design:

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- ▶ Where election observers are sent, smaller registration irregularities
- ▶ In nearby control areas, *larger* irregularities

If interference, diff-in-means estimator (or regression coef)

- ▶ is **not** unbiased for ATE
- ▶ is difference:

$(\text{ITT for Tr group}) - (\text{indirect/spillover effect on Co group})$

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- ▶ if news raises anxiety in HH, irrelevant if I saw news

Next: Causal Forests

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