Causal Inference with Interference and Noncompliance in Two-Stage Randomized Controlled Trials

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Methodological Motivation: Two-stage RCTs

- Causal inference revolution over the last three decades
- The first half of this revolution $\rightsquigarrow$ no interference between units

- In social sciences, interference is the rule rather than the exception
- Significant methodological progress over the last decade
- Experimental solution: two-stage randomized controlled trials (Hudgens and Halloran, 2008)

- We consider interference, both from encouragement to treatment and from treatment to outcome, in the presence of noncompliance

Empirical Motivation: Indian Health Insurance Experiment

- What are the health and financial effects of expanding a national health insurance program?

- RSBY (Rashtriya Swasthya Bima Yojana) subsidizes health insurance for "below poverty line" (BPL) Indian households
- We conduct an RCT to evaluate the impact of expanding RSBY to non-poor (i.e., APL or above poverty line) households in Karnakata

- Does health insurance have spillover effects on non-beneficiaries?

Study Design

- Sample: 10,879 households in 435 villages
- Experimental conditions:
  - (A) opportunity to enroll in RSBY essentially for free
  - (B) No intervention
- Time line:
  1. September 2013 – February 2014: Baseline survey
  2. April – May 2015: Enrollment
  3. September 2016 – January 2017: Endline survey
- Two stage randomization:

Mechanisms	Village prop.	Treatment	Control
High	50%	80%	20%
Low	50%	40%	60%

Potential Outcomes Framework

- Individuals (households): $i = 1, 2, \dots, N$
- Blocks (villages): $j = 1, 2, \dots, J$
- Size of block j: n_j where $N = \sum_{j=1}^{J} n_j$

- Binary treatment assignment mechanism: $A_j \in \{0, 1\}$
- Binary encouragement to receive treatment: $Z_{ij} \in \{0, 1\}$
- Binary treatment indicator: $D_{ij} \in \{0, 1\}$
- Observed outcome: Y_{ij}

- Partial interference assumption: No interference across blocks
  - Potential treatment and outcome: $D_{ij}(\mathbf{z}_j)$ and $Y_{ij}(\mathbf{z}_j)$
  - Observed treatment and outcome: $D_{ij} = D_{ij}(\mathbf{Z}_j)$ and $Y_{ij} = Y_{ij}(\mathbf{Z}_j)$
- Number of potential values reduced from 2^N to 2^{n_j}

Intention-to-Treat Analysis: Causal Quantities of Interest

- Average outcome under the treatment $Z_{ij} = z$ and the assignment mechanism $A_j = a$:

$$\overline{Y}_{ij}(z, a) = \sum_{\mathbf{z}_{-i,j}} Y_{ij}(Z_{ij} = z, \mathbf{Z}_{-i,j} = \mathbf{z}_{-i,j}) \mathbb{P}_a(\mathbf{Z}_{-i,j} = \mathbf{z}_{-i,j} \mid Z_{ij} = z)$$

- Average direct effect of encouragement on outcome:

$$\text{ADE}^Y(a) = \frac{1}{N} \sum_{j=1}^{J} \sum_{i=1}^{n_j} \left\{ \overline{Y}_{ij}(1, a) - \overline{Y}_{ij}(0, a) \right\}$$

- Average spillover effect of encouragement on outcome:

$$\text{ASE}^Y(z) = \frac{1}{N} \sum_{j=1}^{J} \sum_{i=1}^{n_j} \left\{ \overline{Y}_{ij}(z, 1) - \overline{Y}_{ij}(z, 0) \right\}$$

- Horvitz-Thompson estimator for unbiased estimation

Complier Average Direct Effect

- Goal: Estimate the treatment effect rather than the ITT effect
- Use randomized encouragement as an instrument
  1. Monotonicity: $D_{ij}(1, \mathbf{z}_{-i,j}) \geq D_{ij}(0, \mathbf{z}_{-i,j})$ for any $\mathbf{z}_{-i,j}$
  2. Exclusion restriction: $Y_{ij}(\mathbf{z}_j, \mathbf{d}_j) = Y_{ij}(\mathbf{z}'_j, \mathbf{d}_j)$ for any $\mathbf{z}_j$ and $\mathbf{z}'_j$
- Compliers: $C_{ij}(\mathbf{z}_{-i,j}) \; = \; \mathbf{1}\{D_{ij}(1, \mathbf{z}_{-i,j}) = 1, D_{ij}(0, \mathbf{z}_{-i,j}) = 0\}$
- Complier average direct effect of encouragement (CADE(z, a)):

$$\frac{\sum_{j=1}^{J} \sum_{i=1}^{n_j} \{Y_{ij}(1, \mathbf{z}_{-i,j}) - Y_{ij}(0, \mathbf{z}_{-i,j})\} C_{ij}(\mathbf{z}_{-i,j}) \mathbb{P}_a(\mathbf{Z}_{-i,j} = \mathbf{z}_{-i,j} \mid Z_{ij} = z)}{\sum_{j=1}^{J} \sum_{i=1}^{n_j} C_{ij}(\mathbf{z}_{-i,j}) \mathbb{P}_a(\mathbf{Z}_{-i,j} = \mathbf{z}_{-i,j} \mid Z_{ij} = z)}$$

- We propose a consistent estimator of the CADE

Key Identification Assumption

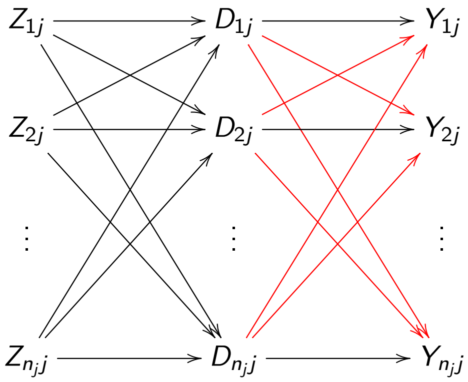
- Two causal mechanisms:
  - Z_{ij} affects Y_{ij} through D_{ij}
  - Z_{ij} affects Y_{ij} through $\mathbf{D}_{-i,j}$
- Idea: if Z_{ij} does not affect D_{ij}, it should not affect Y_{ij} through $\mathbf{D}_{-i,j}$

Assumption (Restricted Interference for Noncompliers)

If a unit has $D_{ij}(1, \mathbf{z}_{-i,j}) = D_{ij}(0, \mathbf{z}_{-i,j}) = d$ for any given $\mathbf{z}_{-i,j}$, it must also satisfy $Y_{ij}(d, \mathbf{D}_{-i,j}(Z_{ij} = 1, \mathbf{z}_{-i,j})) = Y_{ij}(d, \mathbf{D}_{-i,j}(Z_{ij} = 0, \mathbf{z}_{-i,j}))$

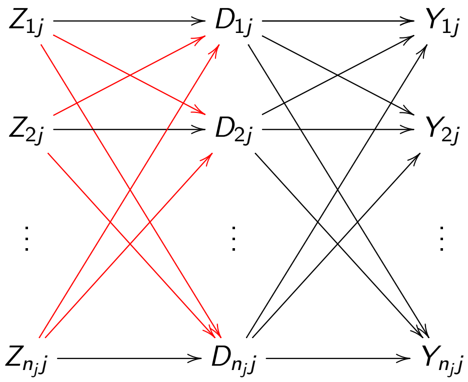
Scenario I: No Spillover Effect of the Treatment Receipt on the Outcome

$$Y_{ij}(d_{ij}, \mathbf{d}_{-i,j}) \;=\; Y_{ij}(d_{ij}, \mathbf{d}'_{-i,j})$$



Scenario II: No Spillover Effect of the Treatment Assignment on the Treatment Receipt

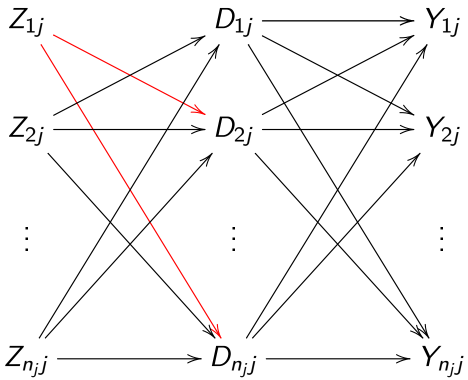
$D_{ij}(z_{ij}, \mathbf{z}_{-i,j}) \;=\; D_{ij}(z_{ij}, \mathbf{z}'_{-i,j})$ (Kang and Imbens, 2016)



Scenario III: Limited Spillover Effect of the Treatment Assignment on the Treatment Receipt

If $D_{ij}(1, \mathbf{z}_{-i,j}) = D_{ij}(0, \mathbf{z}_{-i,j})$ for any given $\mathbf{z}_{-i,j}$,

then $D_{i'j}(1, \mathbf{z}_{-i,j}) = D_{i'j}(0, \mathbf{z}_{-i,j})$ for all $i' \neq i$



Identification, Estimation, and Inference

1. Identification: monotonicity, exclusion restriction, restricted interference for noncompliers

$$\lim_{n_j \to \infty} \text{CADE}(z, a) = \lim_{n_j \to \infty} \frac{\text{ADE}^Y(a)}{\text{ADE}^D(a)}$$

2. Consistent estimation: additional restriction on interference (e.g., Savje et al.)

$$\frac{\widehat{\text{ADE}}^Y(a)}{\widehat{\text{ADE}}^D(a)} \xrightarrow{p} \lim_{n_j \to \infty, J \to \infty} \text{CADE}(z, a)$$

3. Randomization inference: stratified interference

Connection to the Two-stage Least Squares Estimator

- The model:

$$
\begin{aligned}
Y_{ij} &= \sum_{a=0}^{1} \alpha_a \mathbf{1}\{A_j = a\} + \sum_{a=0}^{1} \underbrace{\beta_a}_{\text{CADE}} D_{ij} \mathbf{1}\{A_j = a\} + \epsilon_{ij} \\
D_{ij} &= \sum_{a=0}^{1} \gamma_a \mathbf{1}\{A_j = a\} + \sum_{a=0}^{1} \underbrace{\delta_a}_{\text{ADE}} Z_{ij} \mathbf{1}\{A_j = a\} + \eta_{ij}
\end{aligned}
$$

- Weighted two-stage least squares estimator:

$$
w_{ij} = \frac{1}{\Pr(A_j) \Pr(Z_{ij} \mid A_j)}
$$

- Transforming the outcome and treatment: multiplying them by $n_j J/N$
- Randomization-based variance is equal to the weighted average of cluster-robust HC2 and individual-robust HC2 variances

Results: Indian Health Insurance Experiment

- A household is more likely to enroll in RSBY if a large number of households are given the opportunity

Average Spillover Effects	Treatment	Control
Individual-weighted	0.086 (s.e. = 0.053)	0.045 (s.e. = 0.028)
Block-weighted	0.044 (s.e. = 0.018)	0.031 (s.e. = 0.021)

- Households will use hospitals more if few households are given the opportunity

Complier Average Direct Effects	High	Low
Individual-weighted	−1649 (s.e. = 1061)	1984 (s.e. = 1215)
Block-weighted	−485 (s.e. = 1258)	3752 (s.e. = 1652)

Concluding Remarks

- In social science research,
  1. people interact with each other $\rightsquigarrow$ interference
  2. people don't follow instructions $\rightsquigarrow$ noncompliance

- Two-stage randomized controlled trials:
  1. randomize assignment mechanisms across clusters
  2. randomize treatment assignment within each cluster

- Our contributions:
  1. Identification condition for complier average direct effects
  2. Consistent estimator for CADE and its variance
  3. Connections to regression and instrumental variables
  4. Application to the India health insurance experiment
  5. Implementation as part of R package experiment

Send comments and suggestions to
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