Spillover Effects in Cluster Randomized Trials with Noncompliance

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Outline

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  - Motivation: School-wide deworming treatment in Kenya with noncompliance.

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  - Goal: Investigate what happens when considering spillover effects in CRTs with noncompliance.

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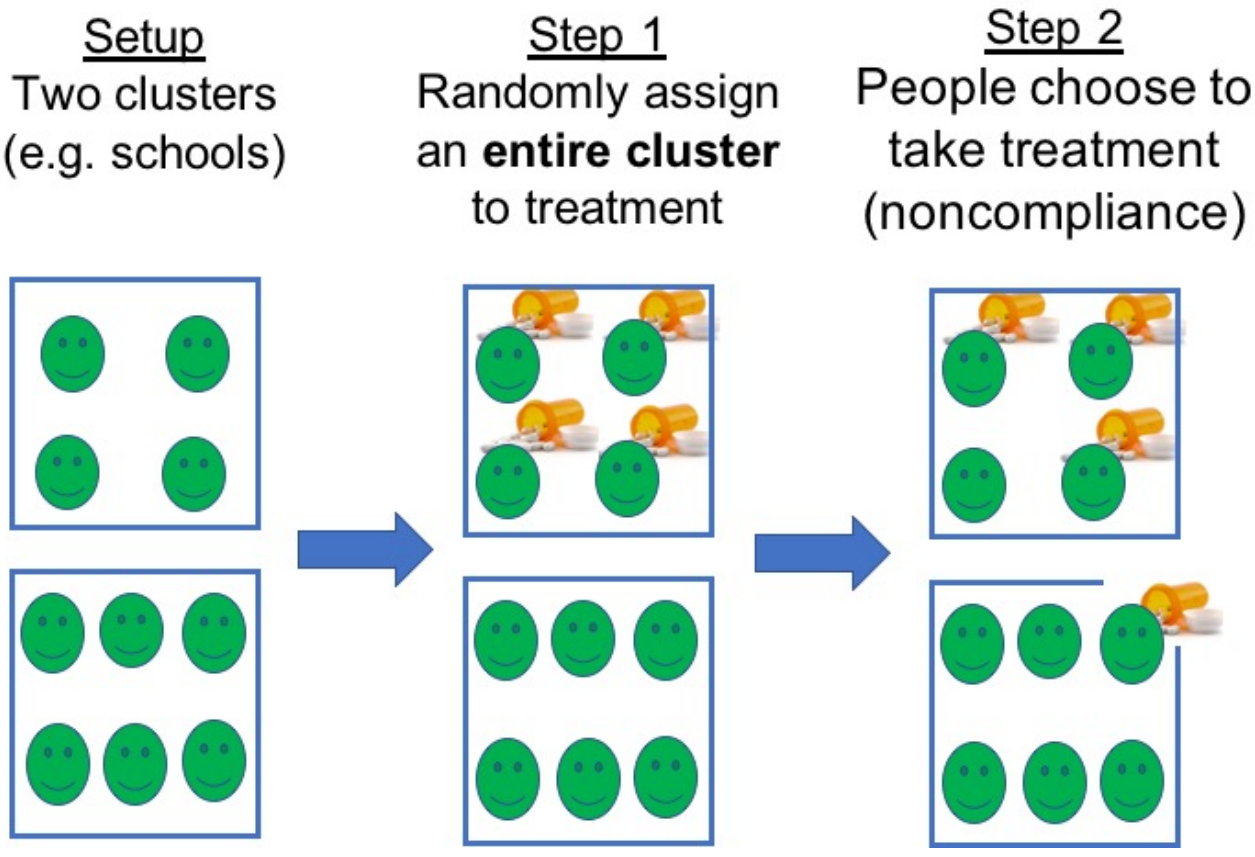

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2. Estimate the **number of compliers** by diff-in-means: $\widehat{\mathrm{N}}^{\mathrm{CO}}$
3. Take the ratio: $\widehat{\mathrm{CACE}} = \frac{\widehat{\mathrm{ITT}}}{\widehat{\mathrm{N}}^{\mathrm{CO}}}$, "IV/Wald estimator" or "TSLS"

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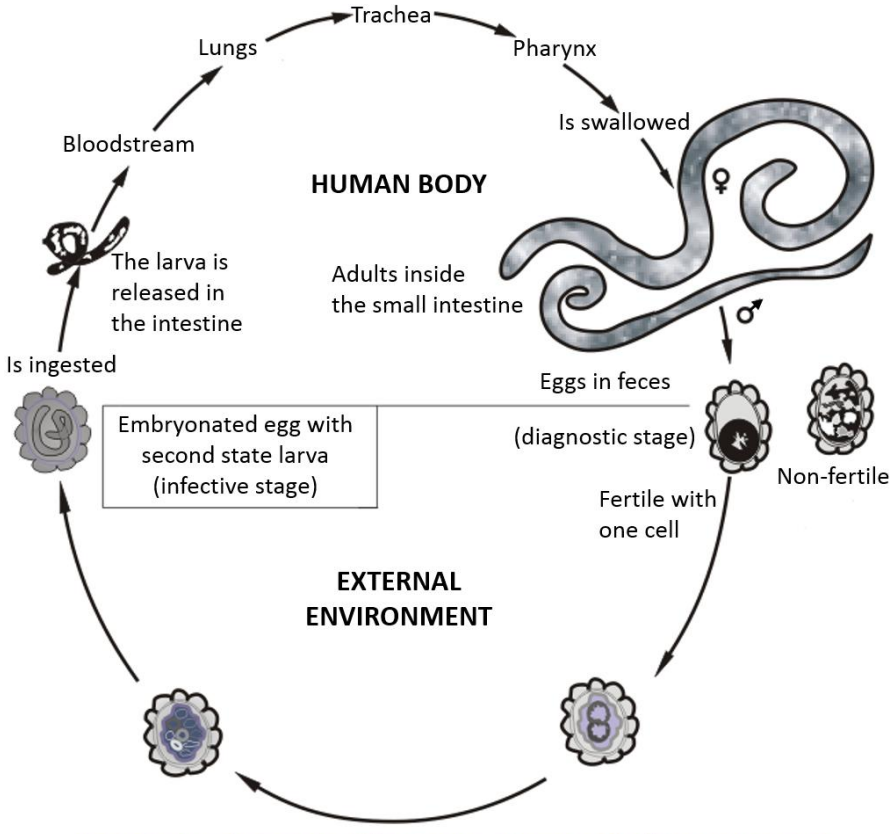

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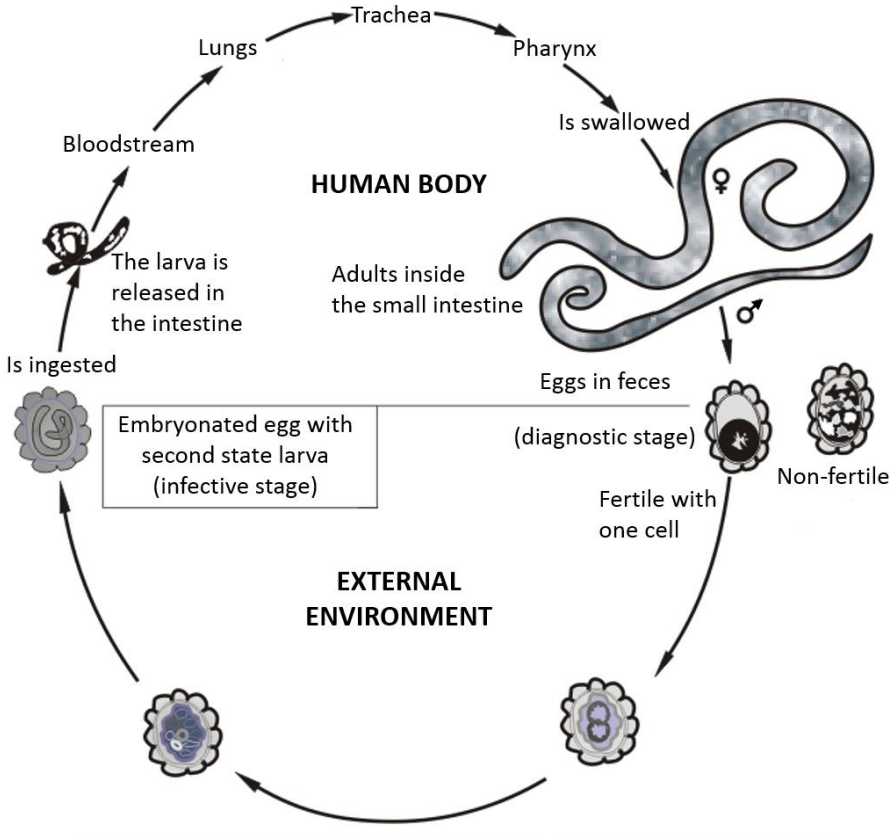

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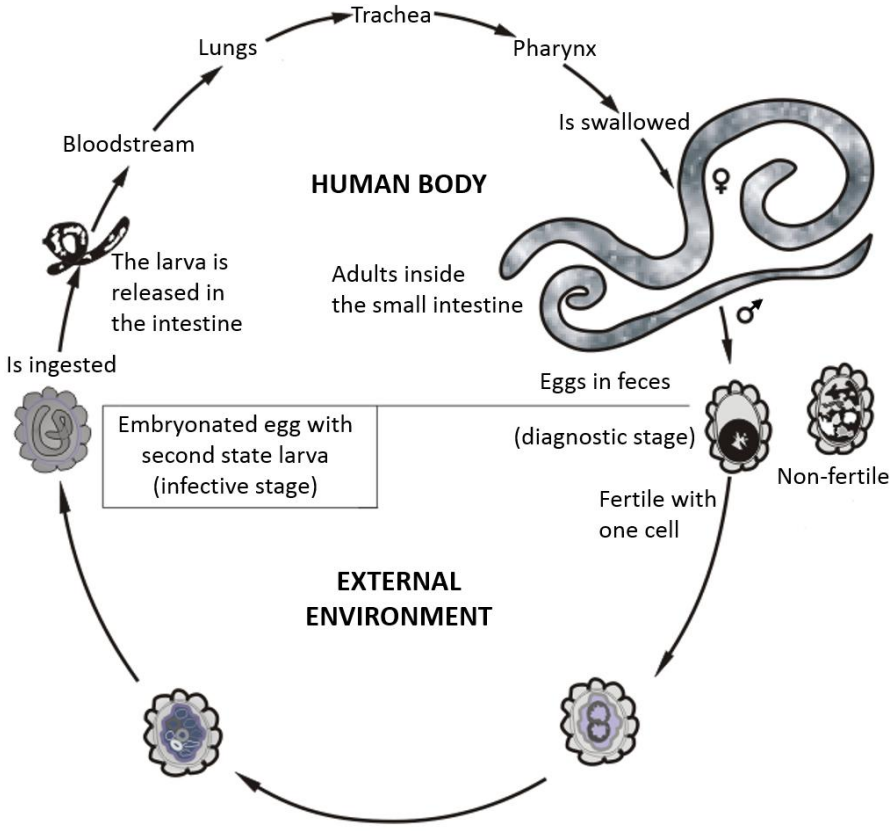

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- Primary School Deworming Project **(PSDP)** was a public health intervention to reduce infection of intestinal helminths among schoolchildren.

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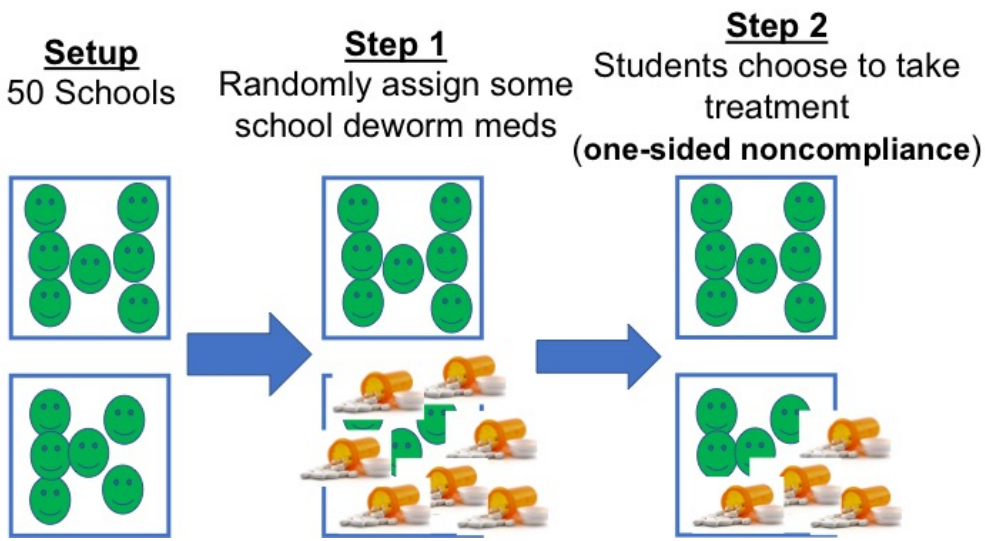

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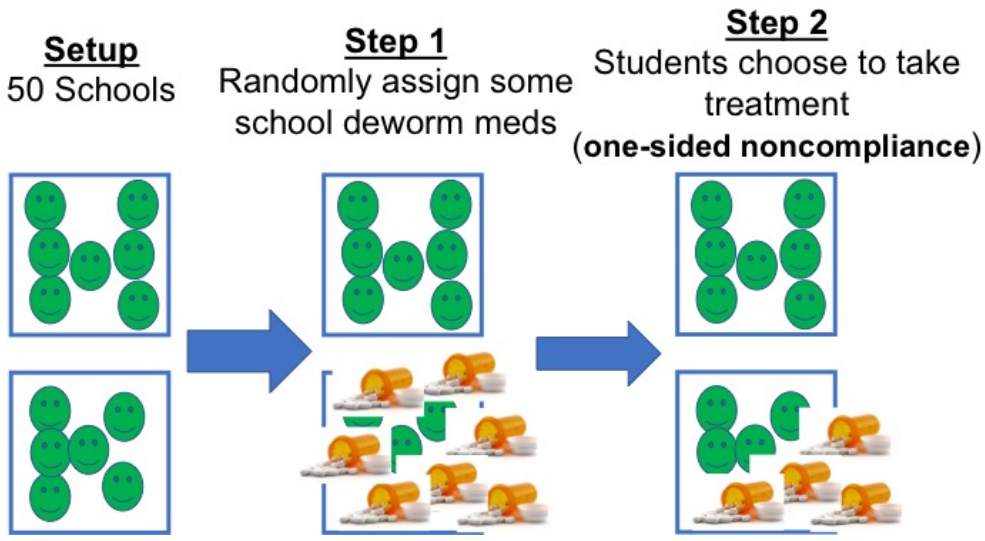

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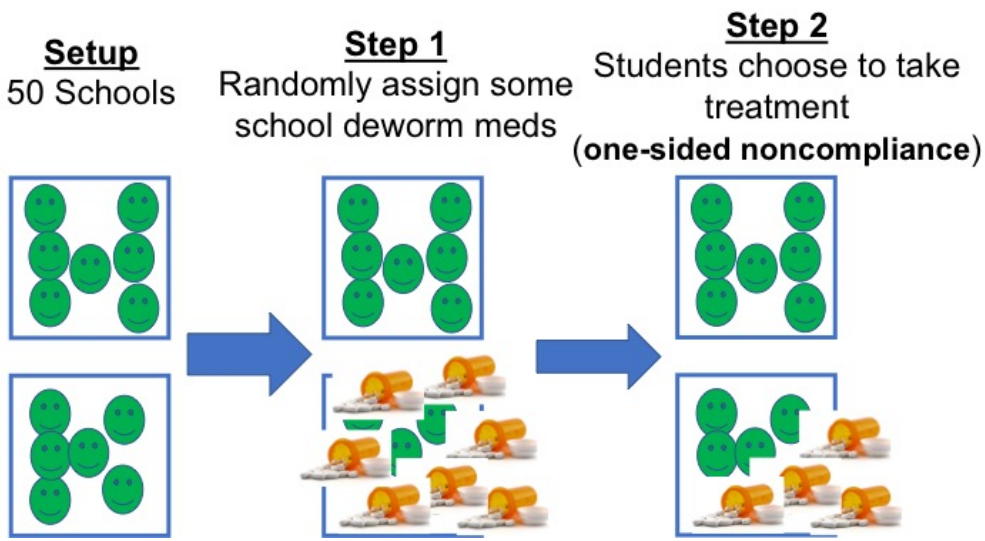

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  5. $\widehat{\text{CATE}} = -0.41$; taking meds reduced infection (on avg.) by **41%** among compliers)

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Thus, there could be a direct and indirect effect of treatment.

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- That is, we assume no spillovers across clusters.
- Noncompliance opens the door for spillovers within clusters, since not all units in each cluster are exposed.

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- Q3: What can we **learn** from CRT data, specifically to understand network causal effects?

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- **Defiers (DF)**: Systematically defy treatment offer.

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2. IV strength (i.e. compliance to treatment) and subgroup effects
   - If IV is strong (i.e. many COs), IV estimator $\approx$ $\left[\begin{smallmatrix}\text{Total Effect}\\ \text{Among COs}\end{smallmatrix}\right]$
   - If IV is weak (i.e. few COs), IV estimator $\approx$ $\left[\begin{smallmatrix}\text{Spillover Effects}\\ \text{Among NTs and ATs}\end{smallmatrix}\right]$

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1. Main Point: CRTs, as a design, are **generally inadequate** to study spillover effects when noncompliance is present
   - Fix 1: Make more assumptions
   - Fix 2: Create "robust" designs (e.g. peer encouragement designs?)

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- Result 3: Point-wise, permutation-based inference for bounds are possible.

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- You plug in these estimates to min/max bounds.
- They are consistent if (i) cluster sizes are bounded, (ii) IV isn't weak, (iii) (essentially) $\mathrm{TE}^{\mathrm{CO}}$ and $\mathrm{PE}^{\mathrm{NT}}$ are stable in asymptopia.

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Note 1: One-sided noncompliance; students in control clusters can't take meds even if they wanted to.
Note 2: Both noncompliance and interference plausible.

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	Point Est.	Uncertainty
Compliance rate (i.e. % COs)	82%	95% CI (71%, 93%)
Standard IV method (IV/Wald estimator)	$\widehat{\tau} = -0.41$	95% CI $(-0.29, -0.53)$
Bound on total effect among COs	reduced infection from 12% to 79%	95% CI* $(0\%, 100\%)$
Bound on spillover effect among NTs	reduced infection from 0% to 100%	95% CI* $(0\%, 100\%)$

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- Q1: Does the standard IV analysis of CRTs with noncompliance **actually** estimate the complier average treatment effect (CATE) when spillover effects are present?
  A: No. It estimates a **mixture** of effects from different subgroups.

- Q2: Can **any** analysis of CRTs estimate other (network) causal effects (spillover effects, total effects, etc.)
  A: No. You can't **unbiasedly estimate** network effects from CRT data with noncompliance.

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- Q3: What can we **learn** from CRT data, specifically to understand network causal effects?
  A1: Bounds on total and spillover effects under treatment monotonicity with standard IV analysis
  A2: Informative bounds $\propto$ **IV strength** $+$ **standard IV analysis**.

Bibliography

E. Miguel and M. Kremer. Worms: identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, 72(1):159–217, 2004.