Low-Cost Randomized Controlled Trials in Education

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Low-Cost RCTs

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RCTs in education

Studies of online learning:

- Alpert, Couch, and Harmon (2016).
- Bowen et al. (2013).
- U.S. Department of Education studies:
 - Agodini et al. (2010) (elementary math curricula).

Simulated impact analysis

Hypothetical data from four classrooms (p < 0.01).



Simulated impact analysis

Data separated by classroom.



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Simulated impact analysis

With classroom means (p > 0.10 with clustering adjustment).



Randomization by lesson

- Proposal: randomize treatment by section (classroom) and lesson.
- Similar potential for consistent impact estimates as traditional RCT.
- Smaller sample required for same precision.



Unconditional random assignment

$$Y_{isl} = \beta T_{sl} + \alpha_i + \lambda_l + u_{isl}$$

- Y_{isl} assessment score for student *i*, section *s*, lesson *l*.
- T_{sl} binary treatment indicator.
- α_i student fixed effect.
- λ_l lesson fixed effect.

 $\hat{\beta}$ is a consistent impact estimate if $\mathcal{T}_{s\prime}$ is unconditionally randomly assigned.

Conditional random assignment

Unconditional random assignment may be impractical:

- Fairness considerations.
- Logistical constraints (e.g., resources, grading).

Alternative: Randomly assign T_{sl} conditional on equal number of treatment lessons across sections.

- Treatment lesson more likely to be followed by control lesson.
- Treatment may affect subsequent lessons (spillover effects).
- Impact estimates biased towards zero.

Spillover effects

Solution 1: randomize blocks of related lessons to minimize spillover effects.

Solution 2: model spillover effects in analysis: $Y_{isl} = \beta T_{sl} + \sum_{j=1}^{J} \gamma_j T_{s(l-j)} + \alpha_i + \lambda_l + u_{isl}$ $T_{s(l-i)} \text{ treatment } j \text{ lessons prior.}$

$$Y_{isl} = \beta T_{sl} + \delta \sum_{j=1}^{l-1} T_{sj} + \alpha_i + \lambda_l + u_{isl}$$

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$$\sum_{j=1}^{l-1} T_{sj}$$
 number of prior treatment lessons.

Other threats to identification

- Differential attrition
 - Attrition equal in treatment/control by design.
- Hawthorne effect
 - Treatment/control exam questions difficult to distinguish.
- Instructor bias
 - Scoring bias easily avoided by blind, parallel grading.
 - Bias in class preparation must be carefully avoided.

Clustered RCTs

Variance of impact estimator: (Schochet 2008) $\frac{2(1-\rho)\sigma^2}{N} + \frac{2\rho\sigma^2}{s}$

- N number of students.
- **s** number of sections.
- ρ intra-class correlation.
- σ^2 variance of outcome residual.

Example: 54 sections of 25 students required to detect 0.2 standard deviation impact.

Treatment assignment by lesson

Variance of impact estimator (no spillover): $\frac{2(1-\rho)\sigma^2}{NL} + \frac{2\rho\sigma^2}{sL}$

L number of lessons.

Example: 5 sections of 25 students with 11 experimental lessons required to detect 0.2 standard deviation impact.

Cluster at section and/or student level.

Implementation challenges

- Intervention must be appropriate for single lessons or blocks of lessons.
- Instructor(s) must be well-versed in both methods.
- Assessments must measure achievement specific to a lesson.
- Treatment noncompliance must be minimized.

Conclusions

- RCTs likely uncommon in education due to high cost.
- Diversity of teaching methods, heterogeneous effects by setting require wide body of literature.
- Small-scale RCTs have the potential to expand body of knowledge at lower cost.