Low-Cost Randomized Controlled Trials in Education

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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.
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.

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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.
- \( \alpha_i \) student fixed effect.
- \( \lambda_l \) lesson fixed effect.

\( \hat{\beta} \) is a consistent impact estimate if \( T_{sl} \) 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:

\[ Y_{isl} = \beta T_{sl} + \sum_{j=1}^{J} \gamma_j T_{s(l-j)} + \alpha_i + \lambda_l + u_{isl} \]

- \( T_{s(l-j)} \) treatment \( j \) lessons prior.

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

- \( \sum_{j=1}^{l-1} T_{sj} \) 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.
- \( \rho \) intra-class correlation.
- \( \sigma^2 \) 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.