Lecture VI: Problems with Experiments: Spillovers

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1. Introduction

- Experiments are subject to implementation issues that have profound consequences in the way they are analyzed and interpreted
- We focus on this lecture on spillovers:
  - Programs often have a specific population of beneficiaries but they may also affect the non-target population
  - Failing to account for these spillovers may severely bias the estimation of the impact of the intervention
- Some examples?

Types of spillovers (Glennerster et al 2013)

- Physical
  - Example: Immunization programs
- Behavioral
  - Example: Adoption of fertilizers
- Informational
  - Example: Bed nets distribution against malaria
- Market-wide or general equilibrium effects
  - Example: Incentives for hiring young workers may displace older workers

2. Potential Outcomes Framework with Spillovers

- Notation:
  - i is an index for individuals in a population of size N
  - D_i is the treatment level
    - $D_i = 1$ if individual has been exposed to treatment
    - $D_i = 0$ if individual has not been exposed to treatment
  - Y_i is the outcome of interest
  - E_i is the individual-eligibility to treatment:
    - $E_i = 1$ if eligible to treatment
    - $E_i = 0$ if not eligible to treatment
- We can define two treatment effects:

$$ATE_E = \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 1) \qquad (1)$$

$$ITE = \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 0) \qquad (2)$$

- Estimating ATE for the eligible population requires knowing the following counterfactual:

$$\mathbb{E}(Y_i(0)/D_g = 1, E_i = 1) \tag{3}$$

- Under which conditions this counterfactual is observable?
  - Treatment status is independent of potential outcomes
  - SUTVA
- If SUTVA is true and eligibility is randomized, then:

$$\begin{aligned}\mathbb{E}(Y_i(0)/D_g = 1, E_i = 1) &= \mathbb{E}(Y_i(0)/D_g = 1, E_i = 0)\\ &= \mathbb{E}(Y_i/D_g = 1, E_i = 0)\end{aligned}$$

- When SUTVA is violated, this condition is not longer true:

$$\mathbb{E}(Y_i(0)/D_g = 1, E_i = 1) \neq \mathbb{E}(Y_i(0)/D_g = 1, E_i = 0)$$

Partial Population Experiments (Moffitt 2001)

- An approach to identify treatment effects under spillovers is double randomization:
  - Randomly assign units (villages, schools, etc.)
  - Randomly assign eligibility in all units
- There are three distinct groups: E in treatment units and IN in treatment units. All subjects in control units
- If the two randomizations work, then:

$$
\begin{aligned}
ATE_E &= \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 1) \\
&= \mathbb{E}(Y_i(1)/D_g = 1, E_i = 1) - \mathbb{E}(Y_i(0)/D_g = 1, E_i = 1) \\
&= \mathbb{E}(Y_i/D_g = 1, E_i = 1) - \mathbb{E}(Y_i/D_g = 0)
\end{aligned}
$$

- Besides ATE on eligible subjects, this design can also recover ITE:

$$
\begin{aligned}
ITE &= \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 0) \\
&= \mathbb{E}(Y_i(1)/D_g = 1, E_i = 0) - \mathbb{E}(Y_i(0)/D_g = 1, E_i = 0) \\
&= \mathbb{E}(Y_i/D_g = 1, E_i = 0) - \mathbb{E}(Y_i/D_g = 0)
\end{aligned}
$$

- Notice that SUTVA is still violated in treatment units

Partial Population Experiments with Nonrandomized Within-unit Treatment

- In many interventions, eligibility is non-randomized within units
  - Example: PROGRESA selected villages in a random way but households within each village were selected based on a poverty score
- Measuring spillover effects is still possible for ineligible subjects in treatment units if we are able to observe outcomes for eligible and ineligible subjects in treated and control units:

$$\begin{aligned} ATE_E &= \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 1) \\ &= \mathbb{E}(Y_i/D_g = 1, E_i = 1) - \mathbb{E}(Y_i/D_g = 0, E_i = 1) \end{aligned}$$

$$
\begin{aligned}
ITE &= \mathbb{E}(Y_i(1) - Y_i(0)/D_g = 1, E_i = 0) \\
&= \mathbb{E}(Y_i/D_g = 1, E_i = 0) - \mathbb{E}(Y_i/D_g = 0, E_i = 0)
\end{aligned}
$$

- These comparisons are valid as long as treatment is randomized and spillover effects are local (only within the treated unit)

3. Estimation

- Consider the following regression model:

$$Y_{ig} = \alpha_0 + \alpha_1 D_g + \alpha_2 E_i + \alpha_3 D_g E_i + \alpha_4 D_{ig} + \epsilon_{ig} \qquad (4)$$

- Under the above assumptions:

$$ATE_E = \alpha_1 + \alpha_3$$

$$ITE = \alpha_1$$

- When data is experimental, an OLS regression recovers ATE for eligible subjects and ITE

4. Practical issues

- Develop or adopt a theory about what may cause the spillovers
- Measuring spillovers required to incorporate a strategy to deal with them in the design
- Critical to keep a pure control group to identify ATE on eligible subjects
- Understand the mechanisms that cause spillover effects