Identifying Causal Effects in Experiments with Spillovers and Non-compliance

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Empirical Example with Potential for Indirect Treatment Effects

Crepon et al. (2013; QJE)

- Large-scale job-seeker assistance program in France.
- Randomized offers of intensive job placement services.

Displacement Effects of Labor Market Policies

"Job seekers who benefit from counseling may be more likely to get a job, but at the expense of other unemployed workers with whom they compete in the labor market. This may be particularly true in the short run, during which vacancies do not adjust: the unemployed who do not benefit from the program could be partially crowded out."

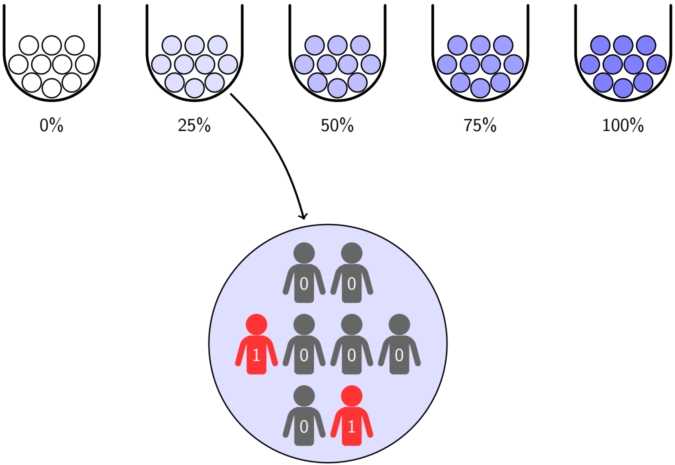
Studying Spillovers with Cluster Data

Partial Interference

Spillovers within but not between groups.

Randomized Saturation

Two-stage experimental design.



This Paper: Non-compliance in Randomized Saturation Experiments

Identification

Beyond Intent-to-Treat: Direct & indirect causal effects under 1-sided non-compliance.

Estimation

Simple, asymptotically normal estimator under large/many-group asymptotics.

Application

French labor market experiment: Crepon et al. (2013; QJE)

Overview of Assumptions

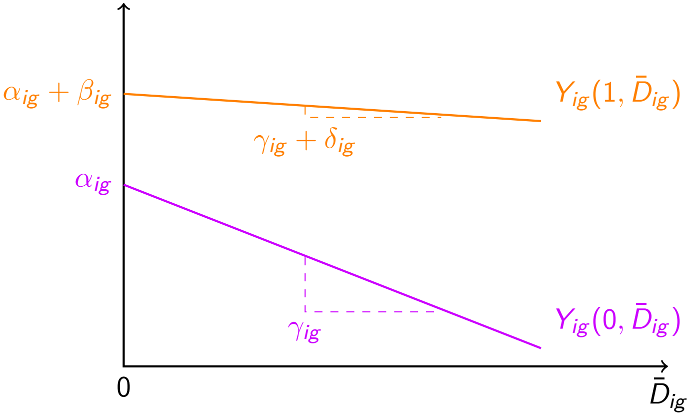
(i) Experimental Design: Randomized Saturation ✓

(ii) Standard IV Exclusion Restriction

(iii) Treatment Take-up: $\mathbf{1}(\text{Take Treatment}) = \mathbf{1}(\text{Offered}) \times \mathbf{1}(\text{Complier})$

(iv) Potential Outcomes: Correlated Random Coefficients Model

$$Y_{ig}(D_{ig}, \bar{D}_{ig}) = \alpha_{ig} + \beta_{ig} D_{ig} + \gamma_{ig} \bar{D}_{ig} + \delta_{ig} D_{ig} \bar{D}_{ig}$$



Indirect Effects

Treated: $\gamma_{ig} + \delta_{ig}$

Untreated: γ_{ig}

Direct Effects

$\beta_{ig} + \delta_{ig} \bar{D}_{ig}$

Näive IV Does Not Identify the Spillover Effect

Unoffered Individuals

$$
\begin{aligned}
Y_{ig} &= \alpha_{ig} + \cancel{\beta_{ig} D_{ig}} + \gamma_{ig} \bar{D}_{ig} + \cancel{\delta_{ig} D_{ig} \bar{D}_{ig}} \\
&= \underbrace{\mathbb{E}[\alpha_{ig}]}_{\alpha} + \underbrace{\mathbb{E}[\gamma_{ig}]}_{\gamma} \bar{D}_{ig} + \underbrace{(\alpha_{ig} - \mathbb{E}[\alpha_{ig}]) + (\gamma_{ig} - \mathbb{E}[\gamma_{ig}])\, \bar{D}_{ig}}_{\varepsilon_{ig}}
\end{aligned}
$$

IV Estimand

$$
\gamma_{IV} = \frac{\text{Cov}(Y_{ig}, S_g)}{\text{Cov}(\bar{D}_{ig}, S_g)} = \gamma + \frac{\text{Cov}(\varepsilon_{ig}, S_g)}{\text{Cov}(\bar{D}_{ig}, S_g)} = \ldots = \gamma + \frac{\text{Cov}(\gamma_{ig}, \bar{C}_{ig})}{\mathbb{E}(\bar{C}_{ig})}
$$

Identification – Average Spillover Effect when Untreated

One-sided Noncompliance

$$(1 - Z_{ig})Y_{ig} = (1 - Z_{ig})(\alpha_{ig} + \cancel{\beta_{ig} D_{ig}} + \gamma_{ig}\bar{D}_{ig} + \cancel{\delta_{ig} D_{ig}\bar{D}_{ig}}) = (1 - Z_{ig}) \begin{pmatrix} 1 \\ \bar{D}_{ig} \end{pmatrix}' \begin{pmatrix} \alpha_{ig} \\ \gamma_{ig} \end{pmatrix}$$

Theorem

$(Z_{ig}, \bar{D}_{ig}) \perp\!\!\!\perp (\alpha_{ig}, \gamma_{ig}) | (\bar{C}_{ig}, N_g)$.

$$\begin{aligned} \mathbb{E}\left[\begin{pmatrix} 1 \\ \bar{D}_{ig} \end{pmatrix} (1 - Z_{ig})Y_{ig} \middle| \bar{C}_{ig}, N_g \right] &= \mathbb{E}\left[(1 - Z_{ig}) \begin{pmatrix} 1 & \bar{D}_{ig} \\ \bar{D}_{ig} & \bar{D}_{ig}^2 \end{pmatrix} \begin{pmatrix} \alpha_{ig} \\ \gamma_{ig} \end{pmatrix} \middle| \bar{C}_{ig}, N_g \right] \\ &= \underbrace{\mathbb{E}\left[(1 - Z_{ig}) \begin{pmatrix} 1 & \bar{D}_{ig} \\ \bar{D}_{ig} & \bar{D}_{ig}^2 \end{pmatrix} \middle| \bar{C}_{ig}, N_g \right]}_{\equiv \mathbf{Q}_0(\bar{C}_{ig}, N_g)} \mathbb{E}\left[\begin{pmatrix} \alpha_{ig} \\ \gamma_{ig} \end{pmatrix} \middle| \bar{C}_{ig}, N_g \right] \end{aligned}$$

Identification – Average Spillover Effect

Iterated Expectations

$$\begin{bmatrix} \mathbb{E}(\alpha_{ig}) \\ \mathbb{E}(\gamma_{ig}) \end{bmatrix} = \mathbb{E}\left[\mathbf{Q}_0(\bar{C}_{ig}, N_g)^{-1}\begin{pmatrix} 1 \\ \bar{D}_{ig} \end{pmatrix}(1 - Z_{ig})Y_{ig}\right]$$

Feasible Consistent Estimation

- $\mathbf{Q}_0$ is a *known function*: determined by experimental design.
- IV with generated instruments: estimate share of compliers by $\widehat{C}_{ig} \equiv \bar{D}_{ig}/\bar{Z}_{ig}$
- $\log\left(\#\text{ of Groups}\right)/(\text{minimum group size}) \to 0$

We Identify the Following Effects

Popn. Average Indirect Effect

$\bar{D}_{ig} \rightarrow Y_{ig}$ for the population, holding $D_{ig} = 0$.

Direct Effect on the Treated

$D_{ig} \rightarrow Y_{ig}$ for compliers as a function of $\bar{d}$.

Indirect Effects on the Treated

$\bar{D}_{ig} \rightarrow Y_{ig}$ for compliers holding $D_{ig} = 0$ or $D_{ig} = 1$.

Indirect Effect on the Untreated

$\bar{D}_{ig} \rightarrow Y_{ig}$ for never-takers holding $D_{ig} = 0$.

Crepon Example: Labor Market Displacement Effects

(SEs clustered at labor market level)

$\mathbb{E}(\gamma_{ig}\|\text{Type})$	Popn.	Never	Complier
$\mathbb{P}(\text{Employed})$	-0.11	0.14	-0.56
	(0.06)	(0.09)	(0.24)

$$\mathbb{E}[Y_{ig}(0, \bar{d})|\text{Type}] = \mathbb{E}(\alpha_{ig}|\text{Type}) + \mathbb{E}(\gamma_{ig}|\text{Type}) \times \bar{d}$$

Conclusion

Identification

Go beyond ITTs to identify average direct and indirect effects in randomized saturation experiments with 1-sided non-compliance.

Estimation

Simple asymptotically normal estimator under large/many-group asymptotics.

Application

Negative spillovers for those willing to take up the program offset by positive direct treatment effects: selection on gains.

No Evidence Against IOR in Our Example

Data from Crepon et al. (2013; QJE)

(IOR) + (1-Sided)

Take-up only depends on *own* offer:

$D_{ig} = C_{ig} \times Z_{ig}$

Testable Implication

$\mathbb{E}[D_{ig}|Z_{ig} = 1, S_g] = \mathbb{E}[D_{ig}|Z_{ig} = 1]$

Figure at right

Take-up among offered doesn't vary with saturation (p = 0.62)