Day 10: Noncompliance

Erin Rossiter

March, 2022

Announcements

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- Draft of final paper due tomorrow at 3pm
  - Github and/or email
  - Saving time today to talk about them
- Next week
  - Online markets & related issues (demand effects, manipulation checks, attention checks)
  - Attrition (moved!)
  - Let me know about any other topics
- Methods workshop on Friday
  - please tell other first years to come!
  - *especially* if interested in methods as second field :)

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- Difference-in-means is an **unbiased** estimator of the ATE assuming:
  1. Randomization of treatment
     - $E[Y_i(1)|D_i = 1] = E[Y_i(1)]$
     - $E[Y_i(0)|D_i = 0] = E[Y_i(0)]$
     - We can estimate left-hand terms using our observed data!
  2. Excludability
     - what does this mean?
  3. Noninterference
     - what does this mean?
- But, things don't always go as planned...

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     » **one-sided**, or failure-to-treat

       • some subject assigned to treatment aren't actually treated

     » **two-sided**

       • some subjects assigned to treatment aren't actually treated *and* some subjects assigned to control are treated

2. Attrition

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What's the difference between noncompliance and attrition?

Key difference:

- **noncompliance**
  - means you measured the outcomes for everyone, but people received treatments they weren't assigned to
- **attrition**
  - is more a missing data problem; everyone complied, you just didn't get Y measured for everyone

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Noncompliance examples

- Canvassing experiment
  - People assigned to treatment don't answer the door, or canvassers mess up and don't knock!
  - Should be treated (canvassed), but instead doesn't receive treatment
- Social interaction experiment
  - I ask people to talk about gun control, but they talk about meaning of life (control topic)
  - Should be treated (political convo), but instead doesn't receive treatment
- Drug trial
  - People assigned to take a pill don't do it
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- What about survey experiments?

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One-sided noncompliance

One-sided noncompliance example (GG pg 133)

- Treatment: face-to-face canvassing
- Outcome: voter turnout
- Suppose 1,000 assigned to treatment, 1,000 assigned to control
- BUT only 250 assigned to treatment are actually reached by canvassers
  - Gives us 3 groups of subjects:
    1. 250 assigned to treatment who actually were treated
    2. 750 assigned to treatment who remain untreated
    3. 1,000 (untreated) in the control group

What are simple approaches to analyzing these data? What's wrong with these approaches for estimating ITT? (Board 2)

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Formalizing noncompliance part 1

Sequence of an experiment $Z \rightarrow D \rightarrow Y$

- Z (treatment assignment)
- D (treatment actually received)
- Y (outcome)

In the voter mobilization experiment example, what is the difference when thinking about the:

- causal effect of Z on Y vs.
- causal effect of D on Y?

Today, the difference between "treatment assignment" and "treatment actually received" is crucial.

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- causal effect of D on Y?

Today, the difference between "treatment assignment" and "treatment actually received" is crucial.

Formalizing noncompliance part 2

z is the assigned treatment and $d_i(z)$ is a function of the actual treatment that results from an assignment

Compliers' "compliance" potential outcomes:

- $d_i(z = 1) = 1$
  - receive treatment if assigned to treatment
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Never-takers' "compliance" potential outcomes:

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Visual

D(0)	D(1)	Type
0	1	Complier
0	0	Never-taker

DeclareDesign for potential outcomes

Defining causal effects

Assumption 1: Noninterference

Notation note: $\mathbf{z}'$ is a vector of all treatment assignments, possibly altered except for i

- $\mathbf{z} = \mathbf{z}'$ i keeps same treatment assignment even if others' change

Part A:

$$d_i(\mathbf{z}) = d_i(\mathbf{z}') \text{ if } \mathbf{z} = \mathbf{z}'$$

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Part B:

$$Y_i(\mathbf{z}, \mathbf{d}) = Y_i(\mathbf{z}', \mathbf{d}') \;\; \mathbf{z_i} = \mathbf{z_i}' \text{ and } \mathbf{d_i} = \mathbf{d_i}'$$

- basically, my potential outcomes depend only on my assignment and what I do given that assignment
  - my potential outcomes don't depend on other peoples' z and d

Can you think of examples that violate this assumption?

- This assumption allow us to write potential outcomes just in terms of d (what is actually received)

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Excludability

$$Y_i(z, d) = Y_i(d)$$

- potential outcomes respond only to treatments, not treatment assignments (or anything else)
- often makes sense, right?
  - » $Y_i(z = 0, d = 0) = Y_i(z = 1, d = 0)$
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Potential outcomes notation

Table 5.1 pg 143 (Board 3)

- what a unit receives, depending on what they're assigned: $d_i(z)$
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Questions:

- What does $d_i(z = 0)$ mean?
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Intent-to-treat estimand

Intent-to-treat effect of z_i on d_i for each subject:

$$ITT_{i,D} = d_i(1) - d_i(0)$$

Average Intent-to-treat effect (assuming one-sided noncompliance):

$$ITT_D = E[ITT_D] = E[d_i(1)] - E[d_i(0)] = E[d_i(1)] - 0 = E[d_i(1)]$$

Measures proportion of subjects who are treated in the even that they are assigned to the treatment group

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If an experiment has 100% compliance, what quantity is the ITT_Y equivalent to?

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$$E[ITT_Y] = E[Y_i(z=1, d(1))] - E[Y_i(z=0, d(0))]$$

If an experiment has 100% compliance, what quantity is the ITT_Y equivalent to?

Measures average effect of experimental assignment on outcomes (i.e., *intent*, regardless of how many units are actually treated)

ATE and CACE estimands

We usually *want* to estimate ATE, but we don't have enough info to when there's noncompliance:

$$ATE = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = E[Y_i(d=1) - Y_i(d=0)]$$

Complier average causal effect (CACE) is more realistic to estimate

$$CACE = \frac{\sum_{i=1}^{N}(Y_i(1) - Y_i(0))d_i(1)}{\sum_{i=1}^{N} d_i(1)}$$
$$= E[Y_i(d=1) - Y_i(d=0) | d_i(1) = 1]$$

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Calculating estimands

(Board 3) let's calculate each estimand

DeclareDesign for estimands

Estimation

Estimation

- We are limited in what we can learn from experiments with non-compliance
- And of course, we don't have full potential outcomes!
- What estimators work?
  - no estimator for ATE :(
  - unbiased estimator for ITT – OLS or DIM
  - unbiased estimator for ITT_D – OLS or DIM
  - consistent estimator for $CACE = ITT/ITT_D$ (See Theorem 5.1) – 2SLS

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First estimates by hand, then uncertainty

Table 5.2, pg 150, New Haven voter mobilization experiment

- group means
- N size for group in parentheses

	Treatment Grp	Control Grp
Turnout rate among those contacted by canvassers	53.43 (395)	
Turnout rate among those not contacted by canvassers	36.48 (1050)	37.54 (5645)
Overall turnout rate	41.38 (1445)	37.52 (5645)

(Board 4)

- What is the cell we're not used to seeing?
- What is the $\widehat{ITT}$?
- What is the $\widehat{ITT}_D$?
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2SLS (or IV estimation)

2SLS is a consistent estimator for $CACE = ITT/ITT_D$ (See Theorem 5.1)

Model1: $TREATED_i = \alpha_0 + \alpha_1 ASSIGNED_i + \epsilon_i$

Model2: $VOTED_i = \beta_0 + \beta_1 TREATED_i + u_i$

- What parameter is the CACE?
- Exclusion restriction: *ASSIGNED* affects *VOTED* only through *TREATED*
- Instrument: *ASSIGNED*
  - predicts *TREATED*
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DeclareDesign for estimation + simulation

Two-sided noncompliance

Two-sided noncompliance

D(Z=0)	D(Z=1)	Type
0	1	Complier
0	0	Never-taker
1	1	Always-taker
1	0	Defier

- still able to estimate CACE, ITT, and ITT_D
- comes up when subjects have access to treatments and discretion for whether to take them
  - not a problem in survey experiments

Summing up noncompliance

Summing up noncompliance

You must be able to distinguish between assigned and actual treatment when estimating causal effects (i.e., these need to be columns in your data)

Be sure to estimate *ITT* or *CACE*

- these utilize random assignment and we can get unbiased/consistent estimates of our estimands
- yes, it changes interpretation of estimates
    - ITT – effect of assignment on outcomes
    - CACE – ATE among compliers
        - who are these people? who can I generalize to?
- avoid estimating *ATE* based on what units received – not random! prone to bias

Things get complicated with two-sided noncompliance and with more than 2 experimental conditions

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