

Estimation of Average Causal Effects

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Potential Outcomes Framework

Causality with Potential Outcomes

- Definition: **Treatment**

Z_i : Indicator of treatment assignment for *unit* i , where $i = 1, \dots, N$

$$Z_i = \begin{cases} 1 & \text{if unit } i \text{ receives treatment} \\ 0 & \text{otherwise} \end{cases}$$

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$$Z_i = \begin{cases} 1 & \text{if unit } i \text{ receives treatment} \\ 0 & \text{otherwise} \end{cases}$$

- Definition: **Potential Outcomes (assuming SUTVA)**

y_{Ti} or y_{Ci} : Fixed value of the outcome for unit i if it were to receive treatment or control

E.g., y_{Ti} : voter turnout of person i if person i were to receive mail encouraging turnout

E.g., y_{Ci} : voter turnout of person i if person i were *not* to receive mail encouraging turnout

Defining Causal Effects + Observed Outcomes

- Causal effect (treatment effect) for unit i

Additive causal effect of the treatment on the outcome for unit i :

$$\tau_i = y_{Ti} - y_{Ci}$$

- Other functions of individual potential outcomes possible, e.g., $\frac{y_{Ti}}{y_{Ci}}$

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- Other functions of individual potential outcomes possible, e.g., $\frac{y_{Ti}}{y_{Ci}}$
- **Fundamental Problem of Causal Inference** (Holland 1986):

We can never observe both y_{Ti} and y_{Ci} for the same i

- We can observe only one of the two potential outcomes:

$$Y_i = Z_i y_{Ti} + (1 - Z_i) y_{Ci}$$

- Therefore, τ_i is unobserved for every unit

The average treatment effect

Average treatment effect: An example

- Definition: Average Treatment Effect (ATE)

$$\tau = \frac{1}{N} \sum_{i=1}^N (y_{Ti} - y_{Ci})$$

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- Example: “Village heads” study (Gerber and Green 2012, Chapter 2):

Village	Budget share (%)		
	y_C	y_T	τ
1	10	15	5
2	15	15	0
3	20	30	10
4	20	15	-5
5	10	20	10
6	15	15	0
7	15	30	15
Average	15	20	5

Randomized experiments

Basic Setup for Randomized Experiment

- Units: $i = 1, \dots, N$
- Treatment: $Z_i = 0$ or $Z_i = 1$ is randomly assigned
- Potential outcomes: y_{Ci} and y_{Ti}
- Observed outcome: $Y_i = Z_i y_{Ti} + (1 - Z_i) y_{Ci}$

Basic Setup for Randomized Experiment

- Units: $i = 1, \dots, N$
- Treatment: $Z_i = 0$ or $Z_i = 1$ is randomly assigned
- Potential outcomes: y_{Ci} and y_{Ti}
- Observed outcome: $Y_i = Z_i y_{Ti} + (1 - Z_i) y_{Ci}$
- Treatment Assignment Mechanism
 - (1) **Bernoulli (simple) randomization**: Each unit is independently assigned to treatment with probability p
 - (2) **Complete randomization**: Exactly n_T units are treated and $N - n_T = n_C$ units are untreated
 - (3) In practice, (1) and (2) are equivalent when we fix n_T by conditioning on its observed value
- Under complete or simple (conditioning on observed n_T) randomization

$$E[Z_i] = \frac{n_T}{N}$$

Difference-in-Means estimator

Unbiasedness of Difference-in-Means: Proof

- Difference-in-Means estimator

$$\begin{aligned}\hat{\tau}(\mathbf{Z}, \mathbf{Y}) &= n_T^{-1} \mathbf{Z}^\top \mathbf{Y} - n_C^{-1} (\mathbf{1} - \mathbf{Z})^\top \mathbf{Y} \\ &= \frac{1}{n_T} \sum_{i=1}^N Z_i Y_i - \frac{1}{n_C} \sum_{i=1}^N (1 - Z_i) Y_i\end{aligned}$$

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- Unbiased for the ATE under complete randomization

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- **Unbiased** for the ATE under complete randomization

$$\begin{aligned}\mathbb{E}[\hat{\tau}(\mathbf{Z}, \mathbf{Y})] &= \mathbb{E}\left[\frac{1}{n_T} \sum_{i=1}^N Z_i Y_i - \frac{1}{n_C} \sum_{i=1}^N (1 - Z_i) Y_i\right] \\ &= \frac{1}{n_T} \sum_{i=1}^N \mathbb{E}[Z_i Y_i] - \frac{1}{n_C} \sum_{i=1}^N \mathbb{E}[(1 - Z_i) Y_i] \quad (\because \text{Linearity of } \mathbb{E}) \\ &= \frac{1}{n_T} \sum_{i=1}^N \mathbb{E}[Z_i y_{Ti}] - \frac{1}{n_C} \sum_{i=1}^N \mathbb{E}[(1 - Z_i) y_{Ci}] \quad (\because \text{Definition of POs}) \\ &= \frac{1}{n_T} \sum_{i=1}^N y_{Ti} \mathbb{E}[Z_i] - \frac{1}{n_C} \sum_{i=1}^N y_{Ci} \mathbb{E}[1 - Z_i] \quad (\because \text{POs are fixed}) \\ &= \frac{1}{n_T} \sum_{i=1}^N y_{Ti} \left(\frac{n_T}{N}\right) - \frac{1}{n_C} \sum_{i=1}^N y_{Ci} \left(\frac{n_C}{N}\right) \quad (\because \text{Complete randomization}) \\ &= \frac{1}{N} \sum_{i=1}^N y_{Ti} - \frac{1}{N} \sum_{i=1}^N y_{Ci} = \frac{1}{N} \sum_{i=1}^N (y_{Ti} - y_{Ci}) = \tau\end{aligned}$$

Unbiasedness of Difference-in-Means: Example

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1	10	15	5
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2 treated and 5 control villages

$\Rightarrow \binom{7}{2} = 21$ assignments

$$\Omega = \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \dots, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \right\}$$

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Therefore, there are $\binom{7}{2} = 21$ possible realizations of data:

z_1	y_C	y_T	y_1	z_2	y_C	y_T	y_2		z_{21}	y_C	y_T	y_{21}
1	?	15	15	1	?	15	15	...	0	10	?	10
1	?	15	15	0	15	?	15		0	15	?	15
0	20	?	20	1	?	30	30		0	20	?	20
0	20	?	20	0	20	?	20		0	20	?	20
0	10	?	10	0	10	?	10		0	10	?	10
0	15	?	15	0	15	?	15		1	?	15	15
0	15	?	15	0	15	?	15		1	?	30	30

Unbiasedness of Difference-in-Means: Example

z_1	y_C	y_T	y_1		z_2	y_C	y_T	y_2		z_{21}	y_C	y_T	y_{21}
1	?	15	15		1	?	15	15		0	10	?	10
1	?	15	15		0	15	?	15		0	15	?	15
0	20	?	20		1	?	30	30	...	0	20	?	20
0	20	?	20		0	20	?	20		0	20	?	20
0	10	?	10		0	10	?	10		0	10	?	10
0	15	?	15		0	15	?	15		1	?	15	15
0	15	?	15		0	15	?	15		1	?	30	30

- Random vectors Z and Y can take on any $(z_1, y_1), \dots, (z_{21}, y_{21})$

Unbiasedness of Difference-in-Means: Example

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1	?	15	15	1	?	15	15	...	0	10	?	10
1	?	15	15	0	15	?	15		0	15	?	15
0	20	?	20	1	?	30	30		0	20	?	20
0	20	?	20	0	20	?	20		0	20	?	20
0	10	?	10	0	10	?	10		0	10	?	10
0	15	?	15	0	15	?	15		1	?	15	15
0	15	?	15	0	15	?	15		1	?	30	30

- Random vectors \mathbf{Z} and \mathbf{Y} can take on any $(z_1, y_1), \dots, (z_{21}, y_{21})$
- Applying Diff-in-Means estimator to all 21 possible realizations of data
 \implies 21 possible outputs of estimator:

$$\hat{\tau}(z_1, y_1) = -1, \hat{\tau}(z_2, y_2) = 7.5, \dots, \hat{\tau}(z_{21}, y_{21}) = 7.5$$

Unbiasedness of Difference-in-Means: Example

z_1	y_C	y_T	y_1	z_2	y_C	y_T	y_2		z_{21}	y_C	y_T	y_{21}
1	?	15	15	1	?	15	15	...	0	10	?	10
1	?	15	15	0	15	?	15		0	15	?	15
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- Expected value of Diff-in-Means estimator:

$$E[\hat{\tau}(\mathbf{Z}, \mathbf{Y})] = \hat{\tau}(z_1, y_1) \Pr(\mathbf{Z} = z_1) + \dots + \hat{\tau}(z_{21}, y_{21}) \Pr(\mathbf{Z} = z_{21})$$

Unbiasedness of Difference-in-Means: Example

z_1	y_C	y_T	y_1	z_2	y_C	y_T	y_2		z_{21}	y_C	y_T	y_{21}
1	?	15	15	1	?	15	15	...	0	10	?	10
1	?	15	15	0	15	?	15		0	15	?	15
0	20	?	20	1	?	30	30		0	20	?	20
0	20	?	20	0	20	?	20		0	20	?	20
0	10	?	10	0	10	?	10		0	10	?	10
0	15	?	15	0	15	?	15		1	?	15	15
0	15	?	15	0	15	?	15		1	?	30	30

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- So, in “village heads” example

$$E[\hat{\tau}(\mathbf{Z}, \mathbf{Y})] = (-1)(1/21) + (7.5)(1/21) + \dots + (7.5)(1/21) = 5$$

Unbiasedness of Difference-in-Means: Example

- Diff-in-Means estimator under complete random assignment

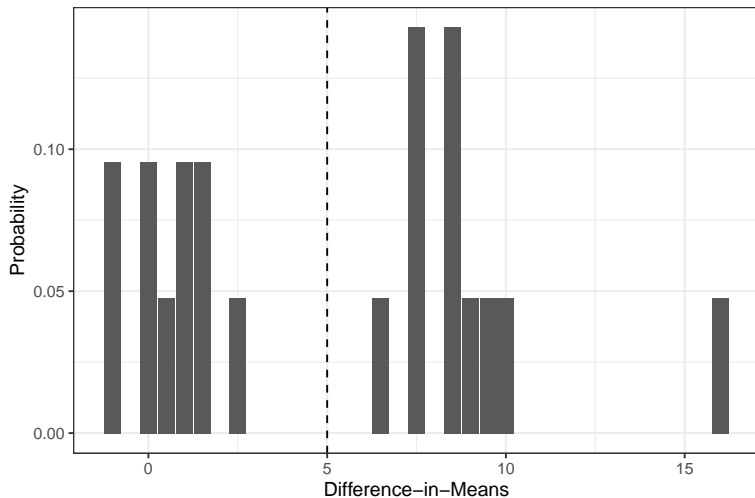


Figure 1: Difference-in-Means estimator in “Village heads” example

Next steps

- What happens when the size of our experiment grows large?
- Consistency of Difference-in-Means estimator for ATE
- Asymptotic validity of hypothesis tests about ATE