Section 11: Research Design for Causal Inference [1]

April 17, 2013

[1] Credit to Gary King, Patrick Lam, Maya Sen, and Brandon Stewart

Outline

Announcements

A few pieces of business:

- Last assignment due today

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- Gary's party on Friday

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- Replications Due May 1st

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- Gary's party on Friday
- Replications Due May 1st
- Last section next week

What is a Causal Effect?

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$$Y_i(1) - Y_i(0)$$

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- represent the outcomes for individual i
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- *if* they received treatment or control

The **fundamental problem of causal inference:**

- only one of $Y_i(1)$ and $Y_i(0)$ is observed

Average Treatment Effects

Average treatment effect (ATE):

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$$E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]$$

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$$E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]$$

Average treatment effect on the treated (ATT):

$$E[Y(1|T = 1) - Y(0|T = 1)] = E[Y_t(1) - Y_t(0)]$$

Average Treatment Effects

Average treatment effect (ATE):

$$E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]$$

Average treatment effect on the treated (ATT):

$$E[Y(1|T = 1) - Y(0|T = 1)] = E[Y_t(1) - Y_t(0)]$$

ATT & ATE: can't estimate because of unobserved potential outcomes.

Fundamental Problem of Causal Inference

In an ideal world, we would see this:

$Unit_i$	X_i^1	X_i^2	X_i^3	T_i	$Y_i(0)$	$Y_i(1)$	$Y_i(1) - Y_i(0)$
1	2	1	50	0	69	75	6
2	3	1	98	0	111	108	-3
3	2	2	80	1	92	102	10
4	3	1	98	1	112	111	-1

Fundamental Problem of Causal Inference

But in the real world, we see this:

$Unit_i$	X_i^1	X_i^2	X_i^3	T_i	$Y_i(0)$	$Y_i(1)$	$Y_i(1) - Y_i(0)$
1	2	1	50	0	69	?	?
2	3	1	98	0	111	?	?
3	2	2	80	1	?	102	?
4	3	1	98	1	?	111	?

Fundamental Problem of Causal Inference

- For control units, $Y_i(1)$ is the **counterfactual**.

Fundamental Problem of Causal Inference

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- For treatment units, $Y_i(0)$ is the **counterfactual**.

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Alternative Quantities of Interest

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- Sample average treatment effect:

$$\text{SATE} \equiv \frac{1}{n/2} \sum_{i \in \{I_i = 1\}} \text{TE}_i$$

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- Sample average treatment effect on the treated:

$$\text{SATT} \equiv \frac{1}{n/2} \sum_{i \in \{I_i = 1, T_i = 1\}} \text{TE}_i$$

Alternative Quantities of Interest

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- Population average treatment effect:

$$\text{PATE} \equiv \frac{1}{N}\sum_i \text{TE}_i$$

Alternative Quantities of Interest

- Population average treatment effect:

$$\text{PATE} \equiv \frac{1}{N} \sum_{i} \text{TE}_i$$

- Population average treatment effect on the treated:

$$\text{PATT} \equiv \frac{1}{N^*} \sum_{i \in \{T_i = 1\}} \text{TE}_i$$

where $N^* = \sum_{i=1}^{N} T_i$ is the number of treated units in the population.

Outline

Decomposition of Causal Effect Estimation Error

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- Difference in means estimator: D

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- Difference in means estimator: D
- Estimation Error:

$$\Delta \equiv \text{PATE} - D$$

- Pretreatment confounders: X are observed and U are unobserved
- Decomposition:

$$\begin{aligned} \Delta &= \Delta_S + \Delta_T \\ &= (\Delta_{S_X} + \Delta_{S_U}) + (\Delta_{T_X} + \Delta_{T_U}) \end{aligned}$$

Error due to Δ_S (sample selection), Δ_T (treatment imbalance), and each due to observed (X_i) and unobserved (U_i) covariates

Selection Error

Selection Error

- Definition:

$$\begin{aligned} \Delta_S &\equiv \text{PATE} - \text{SATE} \\ &= \frac{N-n}{N}(\text{NATE} - \text{SATE}), \end{aligned}$$

where NATE is the nonsample average treatment effect.

Selection Error

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- Δ_S vanishes if:

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  1. The sample is a census ($I_i = 1$ for all observations and $n = N$);

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  where NATE is the nonsample average treatment effect.

- Δ_S vanishes if:
  1. The sample is a census ($I_i = 1$ for all observations and $n = N$);
  2. SATE = NATE; or

Selection Error

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$$
\begin{aligned}
\Delta_S &\equiv \text{PATE} - \text{SATE} \\
&= \frac{N-n}{N}(\text{NATE} - \text{SATE}),
\end{aligned}
$$

  where NATE is the nonsample average treatment effect.

- Δ_S vanishes if:
  1. The sample is a census ($I_i = 1$ for all observations and $n = N$);
  2. SATE = NATE; or
  3. Switch quantity of interest from PATE to SATE.

Decomposing Selection Error

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- Decomposition:

$$\Delta_S = \Delta_{S_X} + \Delta_{S_U}$$

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- $\Delta_{S_U} = 0$ when empirical distribution of (unobserved) U is identical in population and sample: $\widetilde{F}(U \mid I = 0) = \widetilde{F}(U \mid I = 1)$.

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- $\Delta_{S_U} = 0$ when empirical distribution of (unobserved) U is identical in population and sample: $\widetilde{F}(U \mid I = 0) = \widetilde{F}(U \mid I = 1)$.
- conditions are unverifiable: X is observed only in sample and U is not observed at all.

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- $\Delta_{S_U} = 0$ when empirical distribution of (unobserved) U is identical in population and sample: $\widetilde{F}(U \mid I = 0) = \widetilde{F}(U \mid I = 1)$.
- conditions are unverifiable: X is observed only in sample and U is not observed at all.
- Δ_{S_X} vanishes if weighting on X

Decomposing Selection Error

- Decomposition:

$$\Delta_S = \Delta_{S_X} + \Delta_{S_U}$$

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- $\Delta_{S_U} = 0$ when empirical distribution of (unobserved) U is identical in population and sample: $\widetilde{F}(U \mid I = 0) = \widetilde{F}(U \mid I = 1)$.
- conditions are unverifiable: X is observed only in sample and U is not observed at all.
- Δ_{S_X} vanishes if weighting on X
- Δ_{S_U} cannot be corrected after the fact

Balance in Observed and Unobserved Covariates

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- Decomposition:

$$\Delta_T = \Delta_{T_X} + \Delta_{T_U}$$

Balance in Observed and Unobserved Covariates

- Decomposition:

$$\Delta_T = \Delta_{T_X} + \Delta_{T_U}$$

- $\Delta_{T_X} = 0$ when X is balanced between treateds and controls:

$$\widetilde{F}(X \mid T = 1, I = 1) \;\; = \;\; \widetilde{F}(X \mid T = 0, I = 1).$$

  Verifiable from data; can be generated ex ante by blocking or enforced ex post via matching or parametric adjustment

Balance in Observed and Unobserved Covariates

- Decomposition:

$$\Delta_T = \Delta_{T_X} + \Delta_{T_U}$$

- $\Delta_{T_X} = 0$ when X is balanced between treateds and controls:

$$\widetilde{F}(X \mid T=1, I=1) \quad = \quad \widetilde{F}(X \mid T=0, I=1).$$

  Verifiable from data; can be generated ex ante by blocking or enforced ex post via matching or parametric adjustment

- $\Delta_{T_U} = 0$ when U is balanced between treateds and controls:

$$\widetilde{F}(U \mid T=1, I=1) \quad = \quad \widetilde{F}(U \mid T=0, I=1).$$

  Unverifiable. Achieved only by assumption or, on average, by random treatment assignment

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}

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Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Complete blocking				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\rightarrow ?$	$\rightarrow ?$	$\rightarrow ?$	$\rightarrow ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\rightarrow ?$	$\rightarrow ?$	$\rightarrow ?$	$\rightarrow ?$
Random treatment assignment			$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Ignorability				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Ignorability				$\stackrel{\text{avg}}{=} 0$

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\stackrel{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to?$	$\to?$	$\to?$	$\to?$
Random treatment assignment			$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$		
Ignorability				$\stackrel{\text{avg}}{=} 0$
No omitted variables				

Effects of Design Components on Estimation Error

Design Choice	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Random sampling	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Stratified Random Sampling	$= 0$	$\overset{\text{avg}}{=} 0$		
Focus on SATE rather than PATE	$= 0$	$= 0$		
Weighting for nonrandom sampling	$= 0$	$=?$		
Large sample size	$\to ?$	$\to ?$	$\to ?$	$\to ?$
Random treatment assignment			$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Complete blocking			$= 0$	$=?$
Exact matching			$= 0$	$=?$
Assumption				
No selection bias	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$		
Ignorability				$\overset{\text{avg}}{=} 0$
No omitted variables				$= 0$

The Benefits of Major Research Designs: Overview

	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Ideal experiment	$= 0$	$\rightarrow 0$	$= 0$	$\rightarrow 0$

The Benefits of Major Research Designs: Overview

	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Ideal experiment	$= 0$	$\to 0$	$= 0$	$\to 0$

The Benefits of Major Research Designs: Overview

	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Ideal experiment	$= 0$	$\to 0$	$= 0$	$\to 0$
Randomized clinicial trials (Limited or no blocking)	$\neq 0$	$\neq 0$	$\stackrel{\text{avg}}{=} 0$	$\stackrel{\text{avg}}{=} 0$

The Benefits of Major Research Designs: Overview

	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Ideal experiment	$= 0$	$\to 0$	$= 0$	$\to 0$
Randomized clinicial trials (Limited or no blocking)	$\neq 0$	$\neq 0$	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Randomized clinicial trials (Full blocking)	$\neq 0$	$\neq 0$	$= 0$	$\overset{\text{avg}}{=} 0$

The Benefits of Major Research Designs: Overview

	Δ_{S_X}	Δ_{S_U}	Δ_{T_X}	Δ_{T_U}
Ideal experiment	$= 0$	$\rightarrow 0$	$= 0$	$\rightarrow 0$
Randomized clinicial trials (Limited or no blocking)	$\neq 0$	$\neq 0$	$\overset{\text{avg}}{=} 0$	$\overset{\text{avg}}{=} 0$
Randomized clinicial trials (Full blocking)	$\neq 0$	$\neq 0$	$= 0$	$\overset{\text{avg}}{=} 0$

The Benefits of Major Research Designs: Overview

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Outline

Research Designs and Estimation Strategies

So here are some possible solutions

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- Principles of Experimentation: Replication, Randomization, Blocking

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Other issues as well like missing data (measurement error and structural).

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Treatment assignment is independent of the outcomes (Y) given covariates X.

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  - We try to alleviate the curse of dimensionality and problem of continuous covariates by specifying a model.
  - Estimates of ATE or ATT may differ depending on the model you specify.

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We are estimating the conditional mean, not the causal effect.

Matching: A way to Ameliorate Model Dependence

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- But remember: Don't match on post-treatment variables!

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Example: The veteran status and civilian mortality of any man was not affected by the draft status of others.

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   Example: There is no one who would have served if given a high lottery number, but not if given a low lottery number.

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- We basically take care of ignorability. (Note: you still have to worry about SUTVA.)

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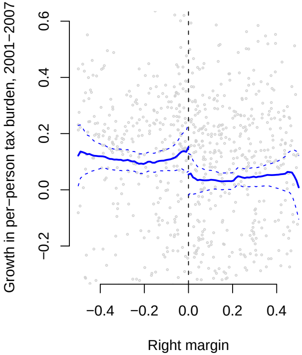
It's sometimes easier to see this visually.

Regression Discontinuity (Eggers)

Example: In some French cities, the rightist party wins with 50.5 of the vote%; in other cities, they lose with 49.5% of the vote. What is the effect of rightist governments on tax policies?



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- If you are working on elections: "Are Close Elections Random?" Grimmer, Hersh, Feinstein, Carpenter (2011)
- Remember who you are generalizing to!

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- Take First Differences and Compare

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The Idea: We can use two units observed at two time points.

- Imagine two sets of units (treated and control, $T = 1, 0$) each observed at two time points ($D = 1, 2$)
- There is some intervention on the treated units between the two time points but not the controls
- Take First Differences and Compare

$$(E[Y(D=2)|T=1] - E[Y(D=2)|T=0]) - (E[Y(D=1)|T=1] - E[Y(D=1)|T=0])$$

Similarity is critical! E.g. Card and Krueger on the minimum wage (1994)

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