

FLS 6441 - Methods III: Explanation and Causation

Week 3 - Field Experiments

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Section 1

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 - ▶ **Design-Based Solutions** to the Fundamental Problem of Causal Inference: Which treatment assignment mechanisms **avoid these biases** and provide plausible counterfactuals

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 - ▶ **Design-Based Solutions** to the Fundamental Problem of Causal Inference: Which treatment assignment mechanisms **avoid these biases** and provide plausible counterfactuals
 - ▶ How much can we learn with better research design?
 - ▶ **Model-Based Solutions:** Not so much.

Rest of the Course

		Independence of Treatment Assignment	Researcher Controls Treatment Assignment?
Controlled Experiments	Field Experiments	✓	✓
	Survey and Lab Experiments	✓	✓
Natural Experiments	Randomized Natural Experiments	✓	
	Instrumental Variables	✓	
	Discontinuities	✓	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		

Section 2

Independence

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- ▶ So estimates of the ATE are **biased**
- ▶ The solution?
- ▶ **Treatment Assignment Mechanisms that *ARE* independent of potential outcomes**

Independent Treatment Assignment

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$$E(Y_1|D=1) - E(Y_0|D=0) = E(Y_1) - E(Y_0) \quad (4)$$

$$(5)$$

- ▶ Potential outcomes in the treatment and control groups are now **unbiased** and representative of *all* the units

Independent Treatment Assignment

- What is the treatment assignment mechanism under **randomization**?

Independent Treatment Assignment

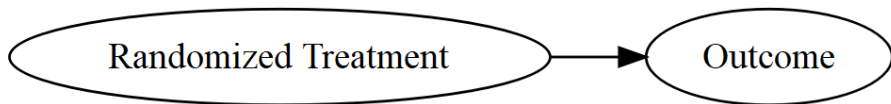
- ▶ What is the treatment assignment mechanism under **randomization**?
 - ▶ It has nothing to do with potential outcomes!
 - ▶ Every unit has **exactly the same** probability of treatment
 - ▶ No omitted variable bias is possible
 - ▶ No self-selection is possible
 - ▶ No reverse causation is possible

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 - ▶ We have no way of *verifying* if potential outcomes are biased

Section 3

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 - ▶ And a simple T-test for statistical significance
 - ▶ NO modelling assumptions (“non-parametric”)

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- ▶ Regression Results:

	term	estimate	std.error	statistic	p.value
1	(Intercept)	0.03459	0.07110	0.48647	0.62664
2	treatment	0.27065	0.10044	2.69472	0.00706

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 - ▶ Political pressure
 - ▶ We don't want to be guinea pigs!

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- ▶ So how do we confirm that randomization has succeeded?
 - ▶ We can't directly test potential outcomes
- 1. **Qualitative research:** to reconstruct the treatment process
- 2. **Balance tests:** We can directly test other variables between treatment and control
 - ▶ Randomization balances *all* variables, not just potential outcomes

Section 4

Implementing Field Experiments

Section 5

Designing Field Experiments