FLS 6441 - Methods III: Explanation and Causation

Week 3 - Field Experiments

Jonathan Phillips

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  - **Design-Based Solutions** to the Fundamental Problem of Causal Inference: Which treatment assignment mechanisms **avoid 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 1

Independence

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- The solution?
- **Treatment Assignment Mechanisms that *ARE* independent of potential outcomes**

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$$\tag{5}$$

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

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    - No omitted variable bias is possible
    - No self-selection is possible
    - No reverse causation is possible

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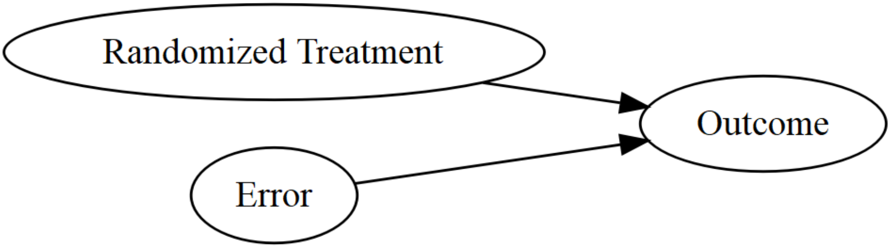

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$$\hat{ATE} = \underbrace{\alpha}_{\text{Real ATE}} + \underbrace{E(Y_0|D=1) - E(Y_0|D=0)}_{\text{Bias}}$$

- Now, use the Independence of Treatment Assignment:

$$E(Y_0|D=1) = E(Y_0|D=0)$$

$$\hat{ATE} = \underbrace{\alpha}_{\text{Real ATE}}$$

- This works for observable *and* unobservable variables

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

Balance in Repeateed Experiments

-

Section 2

Analysis

Analyzing Field Experiments

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  - NO modelling assumptions (“non-parametric”)

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- Regression Results ($Y_i = \alpha + \beta D_i = \epsilon_i$):

	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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- In repeated experiments, 95% of confidence intervals will cross the true treatment effect

```
## Error in eval(predvars, data, env):  object 'Y'
not found
```

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    - But there is usually a cost trade-off

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  - To improve precision, i.e. reduce the standard errors on β
    - The more variation in Y we can explain with covariates, the more certain we can be on the effectof D

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- Average treatment effects are easiest (difference-in-means equals mean-difference)
- But we can also estimate Quantile treatment effects, eg. the effect of treatment on the bottom 10% of the distribution

Section 3

Assumptions

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1. Compliance with Randomization procedure
2. Randomization produced balance on potential outcomes
3. SUTVA
4. Excludability

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- **Design:** Double-blind assignment
- **Checks:** Qualitative fieldwork

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- **Check:** Or a Kolmogorov-Smirnov Test of identical distributions

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- Why are spillovers a problem?
  - **Design:** Limit risk of spillovers, eg. leave 20 miles between each unit
  - **Check:** Qualitative fieldwork
  - **Analysis:** Try to *measure* spillovers

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- Or do we want to measure these additional effects?

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- Others we don't want to capture
  - Eg. Measurement bias: Researchers treat treated units differently and record higher outcomes for them
  - Or Hawthorne Effects arising from being studied, not treatment (more next week)
- *Design:* Careful specification of treatment and control

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- Experimental treatment effects capture *all* net downstream effects

Section 4

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  - Pressure to help the most needy
  - Political pressure
  - We don't want to be guinea pigs!

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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

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Implementing Field Experiments

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- What's the difference between these three options?
- What % treated? 50:50 is usually most efficient

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  - Eg. We have 10 states and a sample size of 5000 - so we fix 250 treated and 250 control in each state
- "Block what you can; randomize what you cannot"

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- Both work in the same way - randomization avoids selection (into the data/treatment)

Section 5

Critiquing Field Experiments

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- Field experiments are easy to evaluate. What can go wrong??

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- We know that giving people money causes them to vote more often. So what?
- We want to learn about generalizable political processes.
- What theory is this testing? Does it reject any theory?

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  - Selection bias has come back!

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  3. **General Equilibrium Effects:** Average test scores went from 75% to 95%, so the exam board readjusted the test and made it harder.

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- Treatment could not be scaled (Every village cannot get visits from Columbia professors twice a year)
- And politics was ignored (No implementation unless you give them responsibility, but lose control)

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