FLS 6441 - Methods III: Explanation and Causation

Week 3 - Field Experiments

Jonathan Phillips

April 2019

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  - **Design-Based Solutions** to the Fundamental Problem of Causal Inference:

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

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	Independence of Treatment Assignment?	**Researcher Controls Treatment Assignment?**
Controlled Experiments	✓	✓
Natural Experiments	✓	
Observational Studies		

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		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

Independent Treatment Assignment

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

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

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    - No reverse causation is possible

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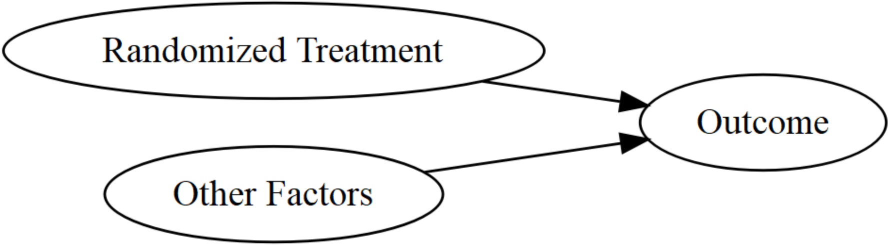

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- This works for observable *and* unobservable influences

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

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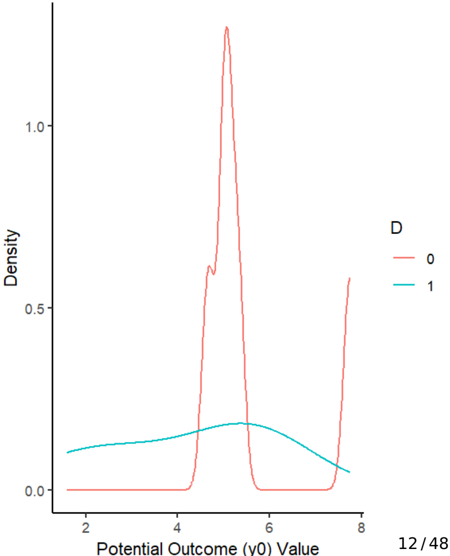
N=10



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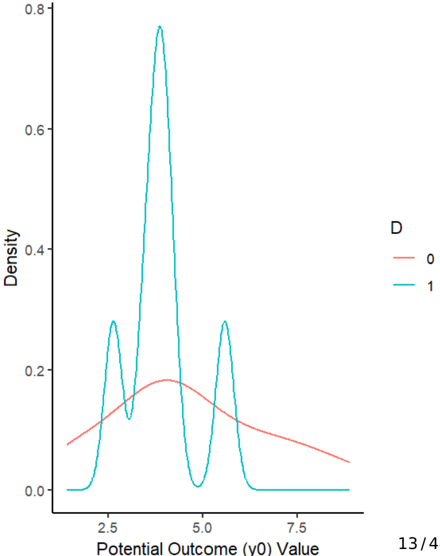

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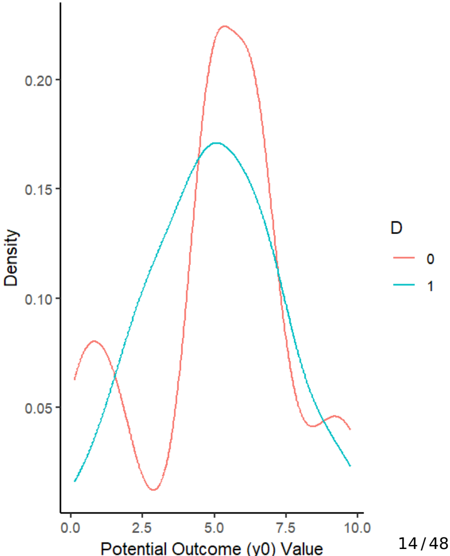

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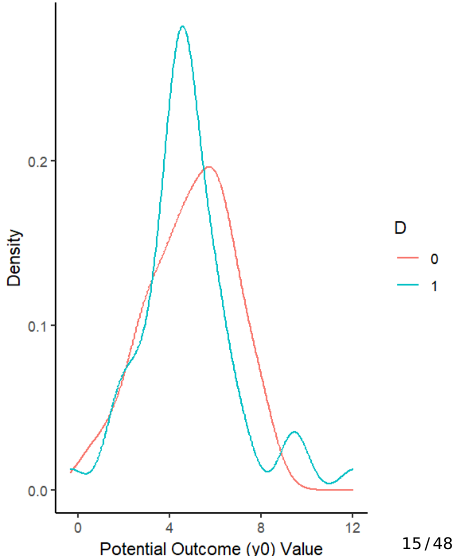

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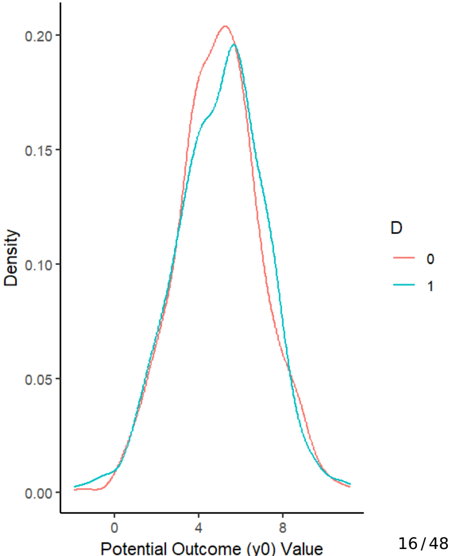

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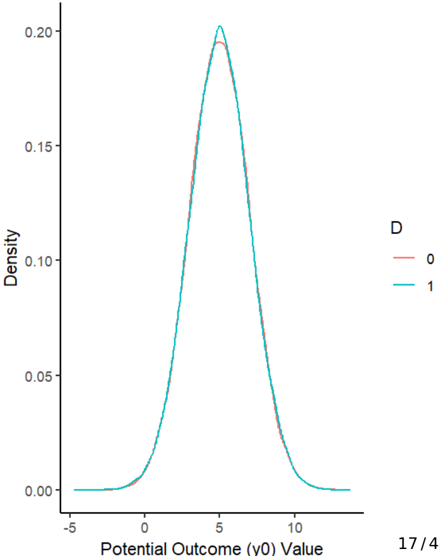

Section 2

Analysis

Analyzing Field Experiments

- If treatment is random we know that:

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  - **NO modelling assumptions** ("non-parametric")

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- So:

$$\hat{\beta} = E(Y_{1i} - Y_{0i})$$

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- T-test Results:

	estimate	statistic	p.value
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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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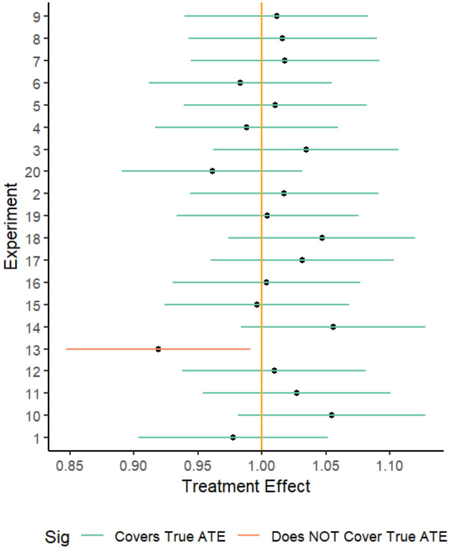

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  - But there is usually a cost trade-off

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  3. **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 effect of 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

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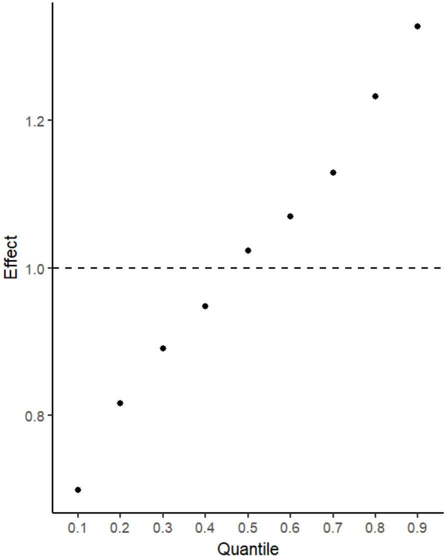

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  - We cannot interpret the ’moderator’ variable as having a causal effect, the different treatment effects could be due to omitted variables or selection

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- **Interpretation:** Does neighbourhood poverty cause health centres to have a negative impact?
  - We cannot interpret the 'moderator' variable as having a causal effect, the different treatment effects could be due to omitted variables or selection
  - Only the health centre was randomly assigned, not neighbourhood income!

Section 3

Assumptions

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- **Analysis:** More on how to respond to non-compliance next week

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

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- What should we do?
  - **Design:** Limit risk of spillovers, eg. leave 20 miles between each unit in sampling
  - **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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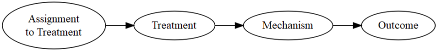
- **Design:** Careful specification of treatment and control

4. Excludability

Downstream Consequence of Treatment



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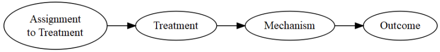

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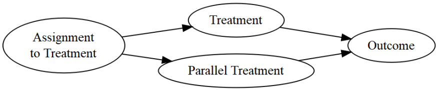

Section 4

Implementation

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  - We don't want to be guinea pigs!

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- To actually randomize, use the 'randomizr' package

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- We focus on within-block variation: $Y_i = \alpha + D_i + B_i + \epsilon_i$

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

Section 5

Critiquing

Critiquing Field Experiments

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

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- We want to test theories, not treatments

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     - Knowing you were randomly assigned to treatment rather than choosing treatment changes political ownership, perceptions and motivation.
  3. **General Equilibrium Effects:** Average test scores went from 70% to 90%, so the exam board readjusted the test and made it harder.

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  3. And politics was ignored (No implementation unless you give locals responsibility, but then you lose control)

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