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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- **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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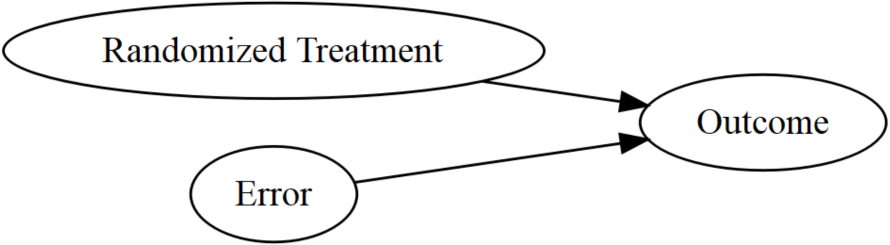

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- This works for observable *and* unobservable variables

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

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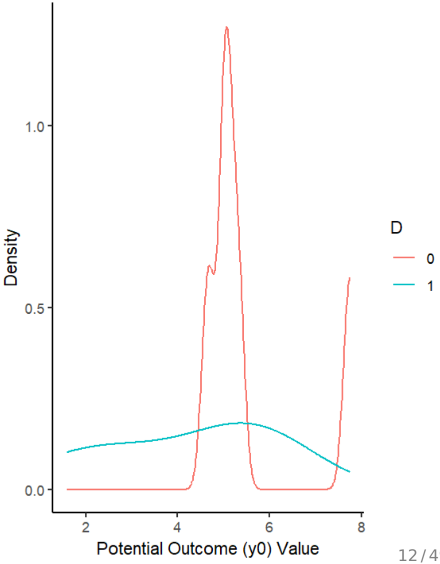
N=10



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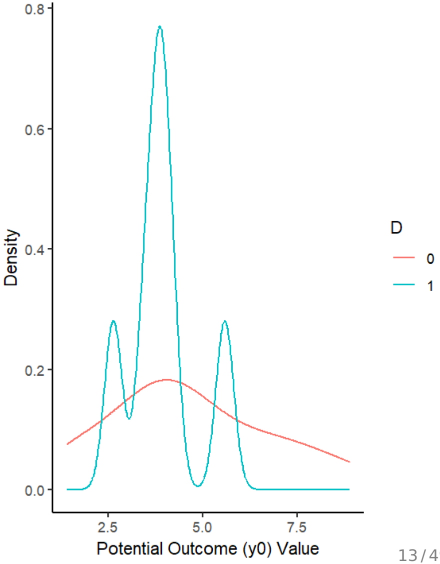

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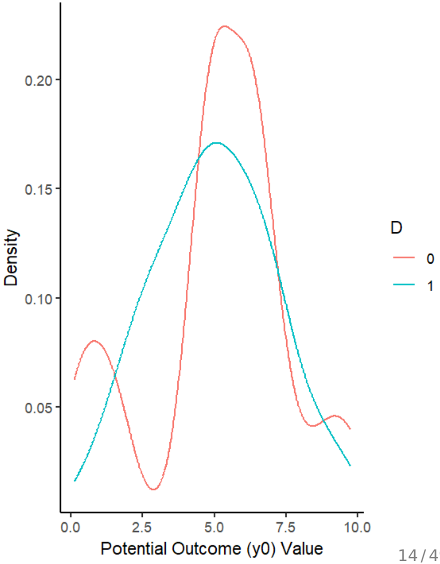

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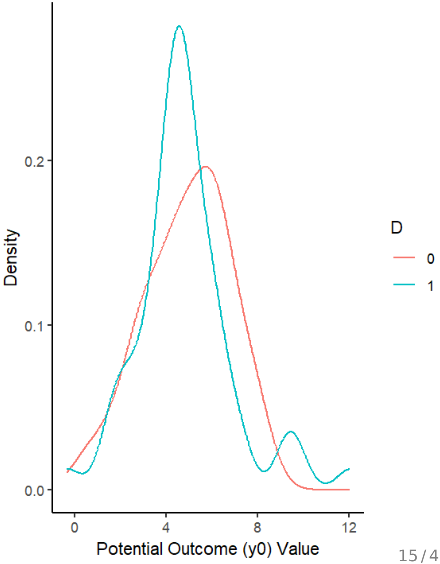

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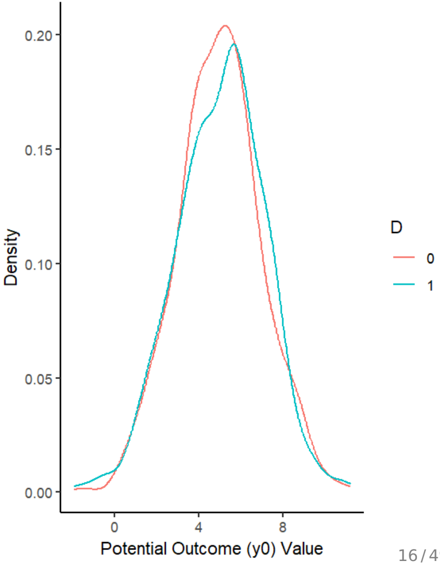

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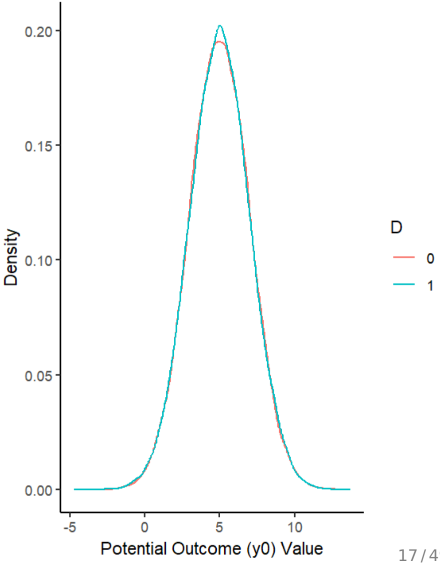

Section 2

Analysis

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

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	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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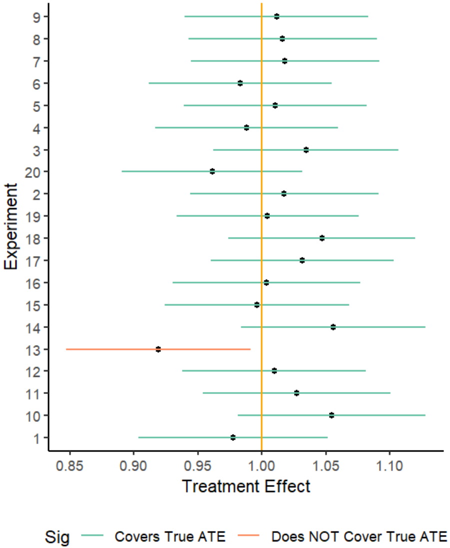

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  - But there is usually a cost trade-off

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  - 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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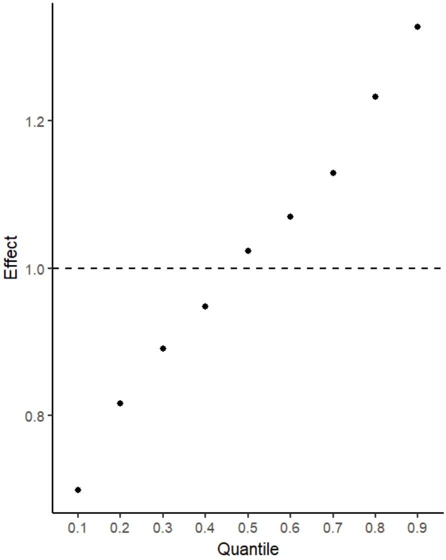

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- **Analysis:** More on how to respond to non-compliance next week

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

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- What if a balance test comes back with a p-value < 0.05?
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    1. We are testing many variables, so some differences arise by chance

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- Why are spillovers a problem?
  - **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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  - 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

Implementing Field Experiments

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

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  - Blocking means randomizing *within* fixed groups
  - 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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- What theory is this testing?

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- 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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