# Making Causal Critiques

## Day 3 - Assessing Causal Evidence

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January 23, 2019

# Solving the Problem of Causal Inference

- We cannot!
- But we can try and minimize the risks
- Selecting units that provide appropriate counterfactuals, avoiding:
  - Omitted variable bias
  - Selection Bias
  - Reverse Causation

# Field Experiments

- Field experiments provide confidence because treatment assignment is **controlled by the researcher**
- But still take place in real-world environments, so they identify (hopefully) meaningful treatment effects

## Field Experiments

- Why does randomization help us achieve causal inference?

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- Why does randomization help us achieve causal inference?
  - A treatment assignment mechanism that balances potential outcomes
    - Every unit has **exactly the same** probability of treatment
    - No omitted variable bias
    - No self-selection
    - No reverse causation

## Field Experiments

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  - With randomization, $Y_1, Y_0 \perp D$:

$$\begin{aligned}
E(Y_1|D=1) &= E(Y_1) && (3)\\
E(Y_0|D=0) &= E(Y_0) && (4)\\
E(Y_1|D=1) - E(Y_0|D=0) &= E(Y_1) - E(Y_0) && (5)\\
&= E(Y_1 - Y_0) && (6)
\end{aligned}$$

# Field Experiments

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- But these are just **expectations** (averages)
    - On average, potential outcomes will be balanced
    - More likely in larger samples
    - We cannot verify potential outcomes
    - But we can assess balance in *observable* covariates
    - What if some covariates are imbalanced?

# Field Experiments

- Analysing field experiments
  - Comparison of means: t-test to test significance
  - Regression achieves the same thing
    - $Y_i \sim \alpha + \beta D_i + \epsilon_i$
    - $Y_i = Y_{0i} + (Y_{1i} - Y_{0i}) D_i + \epsilon_i$
    - Just the conditional expectation function: $E(Y|D = d)$
  - Include covariates if:
    - There is residual imbalance
    - To increase precision of standard errors

# Field Experiments

- Assumptions
  - **Compliance with randomization** - Treatment was truly random and accepted
  - **SUTVA** - Treatment of one unit doesn't affect potential outcomes of other units
  - **Excludability** - Effects of treatment assignment operate **only** through treatment
    - Depends if these effects are part of the causal chain

# Field Experiments

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- Limitations of Field Experiments: **Answerable Questions**
  - Small sample sizes still prevent inference
  - Ethics
  - Logistics/Finance
  - Some treatments can't be manipulated (history)
  - Lack of control over treatment content and context - is it informative?
  - Long-term effects/adaptation?

## Field Experiments

- Limitations of Field Experiments: **Internal Validity**

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- Limitations of Field Experiments: **Internal Validity**
  - No guarantee of actual balance (and Inefficient if we already know confounders)
  - Hawthorne effect: participants adapt behaviour in experiments
  - Biased measurement if not double-blind (non-excludability)
  - Average Treatment Effect can be skewed by Outliers
  - Always complications of non-compliance, SUTVA, attrition
  - Publication/Selection bias
  - Unbiased but imprecise; variation still high if lots of other variables also affect Y
  - Treatment assignment mechanism itself affects outcomes

# Field Experiments

- All these complications mean we need lots of assumptions and background knowledge
- Just as with other methodologies

# Lab Experiments

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- Causal Inference
- Why lab experiments?
    - Treatments we cannot administer in reality
    - Outcome measurements that are hard to take in reality
    - Random treatment assignment not permitted in reality

## Lab Experiments

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- **Treatment Assignment**: Same as a Field Experiment
- **Treatment**: Not a manipulation of real world political or economic processes, but establishing controlled 'lab' conditions
  - The advantage: Control over context helps isolate mechanisms
  - The disadvantage: Can we generalize to the real world from this artificial context?

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- What is a natural experiment?
  - Treatment assignment is independent of potential outcomes
    - So randomized or 'as-if' random ('exogenous')
  - BUT The researcher doesn't control the treatment assignment process or treatment itself
    - So not a field experiment
  - Can make possible analysis of questions that researchers might find unethical or impractical

# Natural Experiments

## Analysis Types and Assumptions

| Week | Assumption: | Researcher Controls Treatment Assignment? | Treatment Assignment Independent of Potential Outcomes | SUTVA | Additional Assumptions |
|---|---|---|---|---|---|
| | **Controlled Experiments** | | | | |
| 1 | Field Experiments | ✓ | ✓ | ✓ | |
| 2 | Survey and Lab Experiments | ✓ | ✓ | ✓ | Controlled Environment for treatment exposure |
| | **Natural Experiments** | | | | |
| 3 | Randomized Natural Experiments | X | ✓ | ✓ | |
| 4 | Instrumental Variables | X | ✓ | ✓ | First stage and Exclusion Restriction (Instrument explains treatment but not outcome) |
| 5 | Regression Discontinuity | X | ✓ | ✓ | Continuity of covariates; No manipulation; No compounding discontinuities |
| | **Observational Studies** | | | | |
| 6 | Difference-in-Differences | X | X | ✓ | No Time-varying confounders; Parallel Trends |
| 7 | Controlling for Confounding | X | X | ✓ | Blocking all Back-door paths |
| 8 | Matching | X | X | ✓ | Overlap in sample characteristics |

# Natural Experiments

- Three types of natural experiments
  - 'Pure' natural experiments, where policy is as-if random
  - Instrumental Variables
  - Regression Discontinuities

# Natural Experiments

- Because we don't control assignment, we need to verify the assumptions behind natural experiments
  - How do we know assignment was truly random?
  - How was the treatment applied? Consistently?
- We need 'Causal-process observations'

## Natural Experiments

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# Natural Experiments

- Challenges due to lack of control over treatment:
  - We must be lucky to ’find’ natural experiments; what if the treatments/experiments that exist don’t answer useful political economy questions?
  - The treatment and control groups produced by ’nature’ may not produce treatment and control groups which differ in ways that represent a causal effect of interest (Sekhon and Titiunik 2012)
  - We also must be lucky to find a sample that is relevant and interesting - unlike a controlled trial we don’t control the recipients either (eg. if we care about states, not municipalities, the audits are no use)

# Natural Experiments

- Challenges due to lack of control over treatment:
  - Spillovers can be an issue - treatment units affect control units' potential outcomes (eg. women's quotas discourage women in non-reserved seats)
  - Generalizability a very open question; what causal process does the experiment really capture?
  - The treatment assignment of a natural experiment might have unique effects (excludability)

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## Instrumental Variables

- What can we do when the treatment assignment mechanism is not 'as-if' random?
- Natural experiments focus on a specific **part** of treatment assignment that is 'as-if' random
- An 'instrument' is a variable which assigns treatment in an 'as-if' random way
  - Or at least in a way which is 'exogenous' - not related to confounders
  - Even if other confounding variables **also** affect treatment

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- NOT the effect of the instrument on the outcome

## Instrumental Variables

- Example Instruments:
  - Rainfall for conflict
  - Sex-composition for effect of third child
  - Distance from the coast for exposure to slave trade

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  - **Strong First Stage:** The Instrument must **affect** the treatment
  - We can test this with a simple regression: $Treatment \sim Instrument$
  - The instrument should be a significant predictor of treatment
  - Rule-of-thumb: $F - statistic > 10$

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  - Formally, $cov(Instrument,$ errors in main regression $Y \sim D) = 0$
  - **We cannot test or prove this assumption!**
  - Theory and qualitative evidence needed to argue that the instrument is not correlated with any other factors affecting the outcome
  - Sometimes, the exclusion restriction may be more credible if we include controls

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     - Estimate how the predicted values affect the outcome: $Y \sim \hat{D}$
     - Interpret the coefficient on $\hat{D}$

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  - ’Local’ to the units whose treatment status actually changed
- Remember, those ’Local’ units are not representative so we can’t generalize