Making Causal Critiques

Day 3 - Assessing Causal Evidence

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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?

Field Experiments

- 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

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

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

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

- Limitations of Field Experiments: **Answerable Questions**

Field Experiments

- 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**

Field Experiments

- 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

- Causal Inference

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- Why lab experiments?

Lab Experiments

- 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**: Not a manipulation of real world political or economic processes, but establishing controlled ’lab’ conditions

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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?

Natural Experiments

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Natural Experiments

- 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

- Challenges due to lack of control over treatment:

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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- We can use the instrument to isolate ’as-if’ random variation in treatment, and use that to estimate the effect of treatment on the outcome
- 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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  - 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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  - **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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     - Save the predicted values from this regression: $\hat{D} = D \sim Instrument$
     - 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

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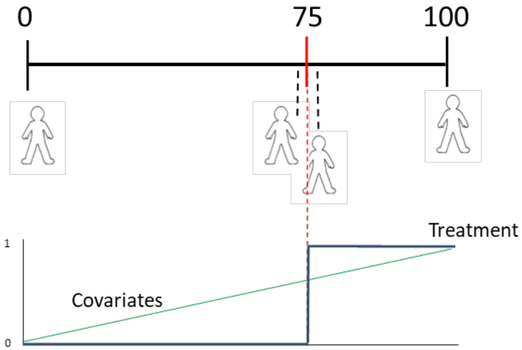
  - As always, we need some ’as-if’ random variation in assignment to treatment to get plausible counterfactuals
  - Regression discontinuities take advantage of social rules that **treat similar people differently**
  - Specifically, similar people with slightly different ’scores’ are assigned to treatment/control

Regression Discontinuities



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  - For units just above and below the threshold:
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  - So we can compare them directly

- Example thresholds:
    - Exam cutoffs
    - Age cutoffs
    - Policy eligibility rules
    - Close elections
    - Adminsitrative boundaries

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  - **Outcome,** Y_i**:** Any subsequent outcome you have measured

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  - No compound treatments

- Thresholds more likely to be exogenous if:

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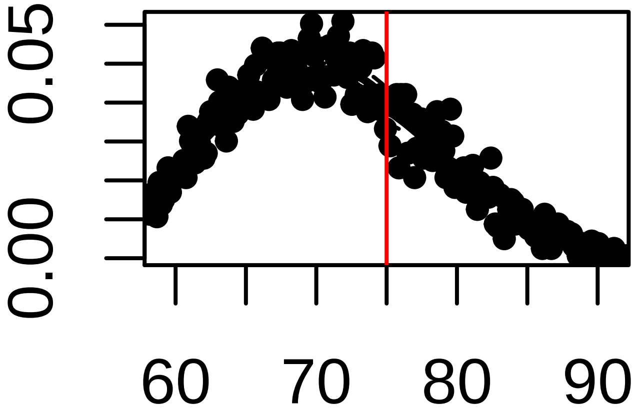
  - Units are not aware of the threshold
  - The threshold is decided after units make choices
  - The running variable is hard to manipulate precisely
- We need qualitative evidence to support these assumptions

- We can check for sorting with a density test
- If units are bunched just above the threshold, this suggests manipulation



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$$Y_i = \alpha + \beta_1 Running\_Variable_i + \beta_2 Treatment_i + \epsilon_i$$

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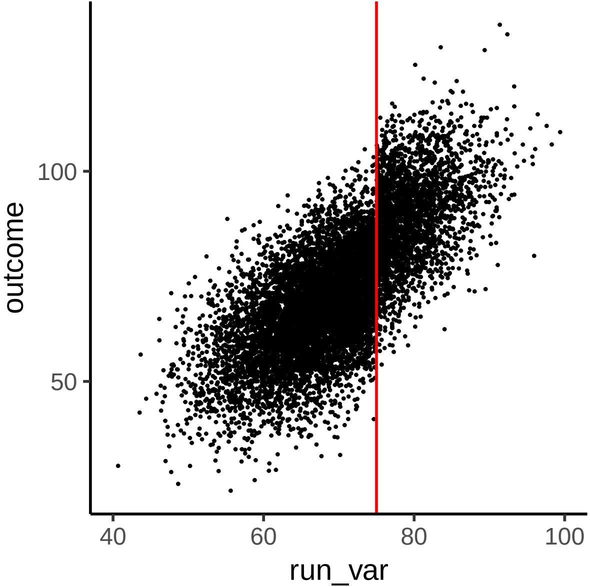
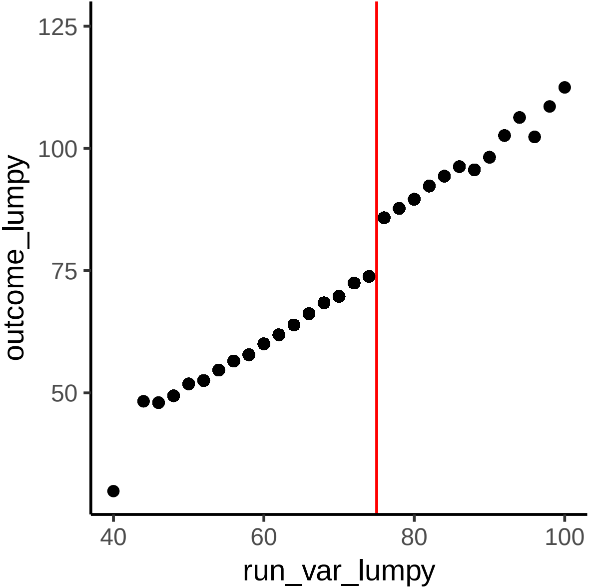
  3. **Combined approach:** Focus on values close to the threshold, but use a (local) regression
     - What bandwidth around the threshold do we use?

Raw Data



'Binned' Data



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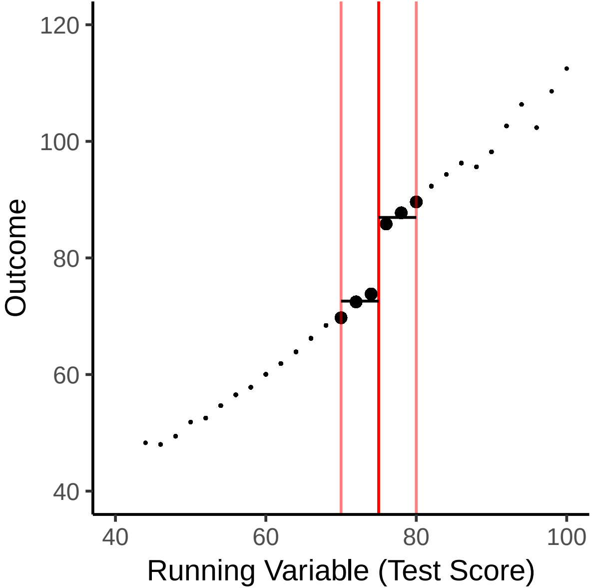
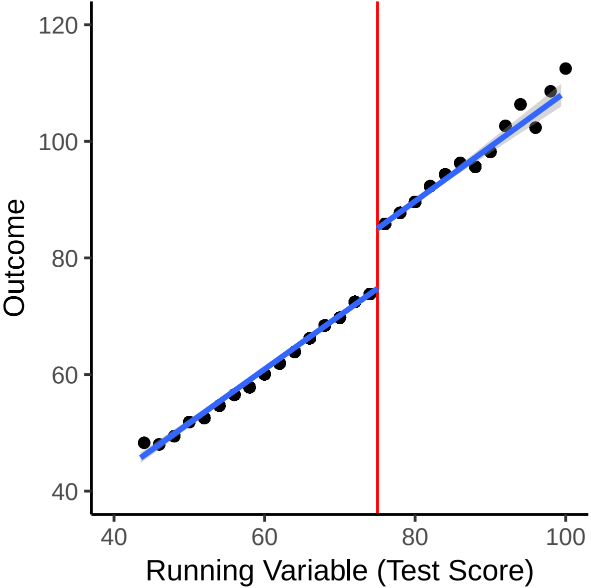
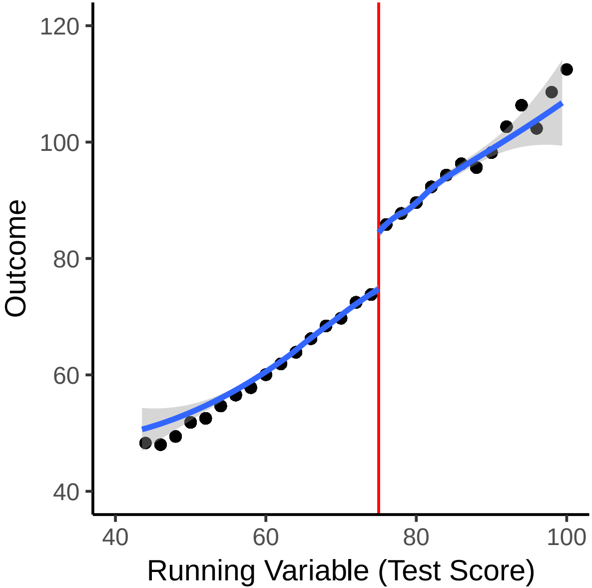


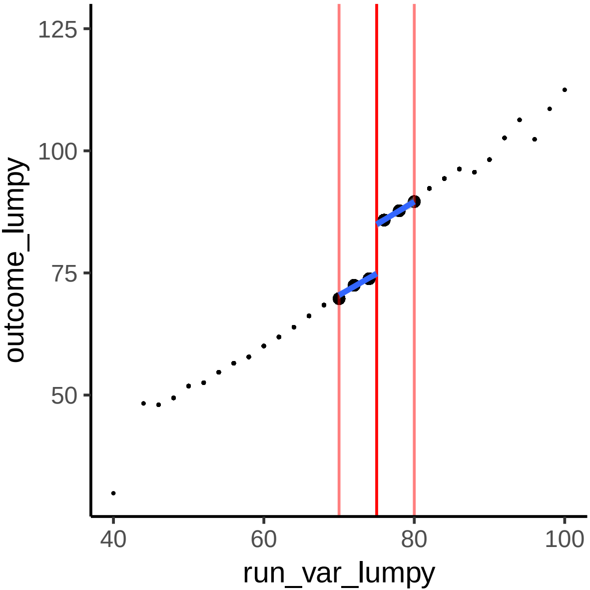
2a. Parametric Regression - Linear



2b. Parametric Regression - Non-linear



3. Combined Approach - Local Linear



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- In practice, apply all three as robustness checks

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  - Units far from the threshold are very different for a reason, and causal effects are likely to be different

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  - Risk of sorting/manipulation

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- Particularly useful for understanding the effects of political power
  - **Running Variable:** Margin of victory
  - **Treatment:** Winning a close election
  - **Control:** Losing a close election
  - **Outcome:** Anything that happens later...

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  - So potential outcomes are not balanced
  - But no other case (9 countries) has this problem

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- If we compare separate treatment and control units when treatment assignment is not random:
    - The control units have different levels of the outcome for many reasons, not just treatment
- If we compare the same unit before and after treatment:
    - Other factors influencing the outcome might also have changed between our measurements (eg. any news event!)

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- But what if we combine these approaches?
- We can keep lots of variables fixed if we compare the same unit before and after treatment
- We can measure how much other factors changed over time if we have units that were not exposed to treatment

Difference-in-Differences

- Example: How has Brexit affected the UK's growth rate?

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  - Comparing with European growth rates is biased - UK growth is influenced by oil, different labour laws etc.

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- We're now comparing *changes* (differences), not *levels* of the outcome
  - Most confounders affect levels, so this makes our counterfactuals more plausible
    - Eg. different laws affect growth rates, not the change in growth over time
  - And crucially, we can remove confounding even for *unobserved* confounders
  - So Diff-in-Diff is 'better' than controlling or matching, which only eliminate observed (measured) confounding

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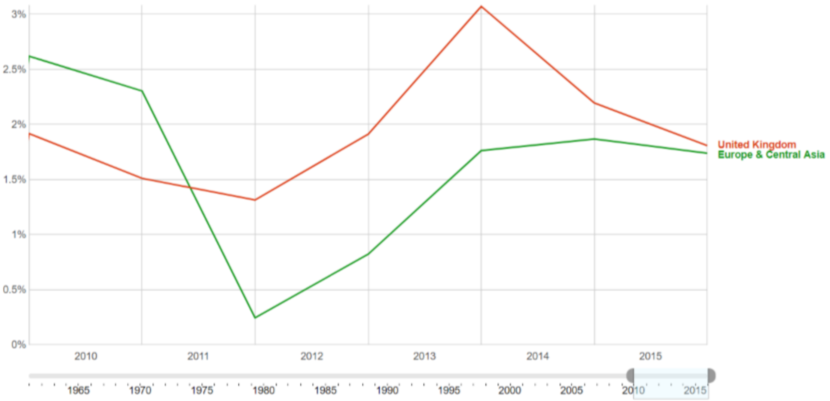
Difference-in-Differences



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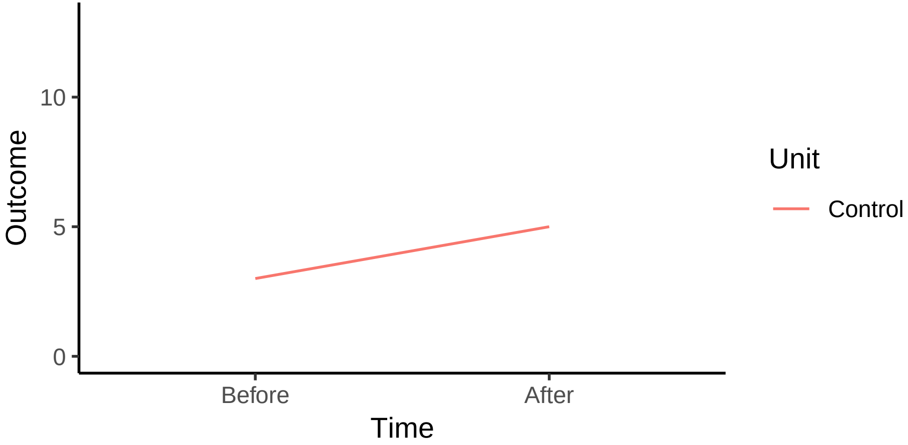

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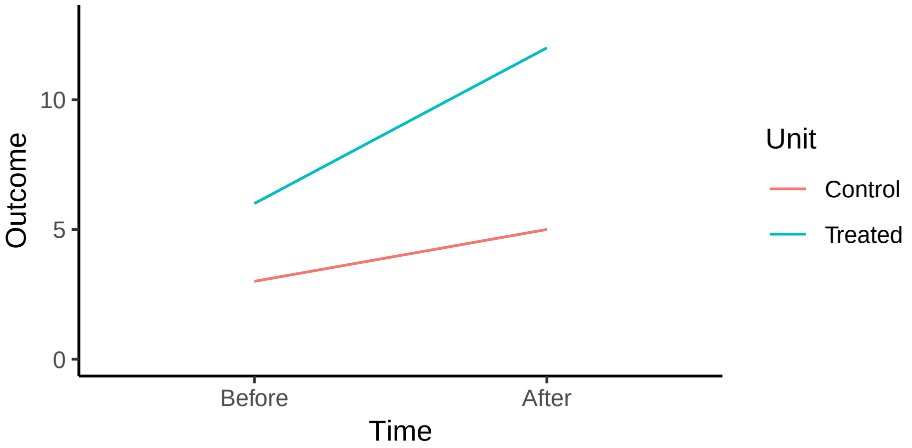

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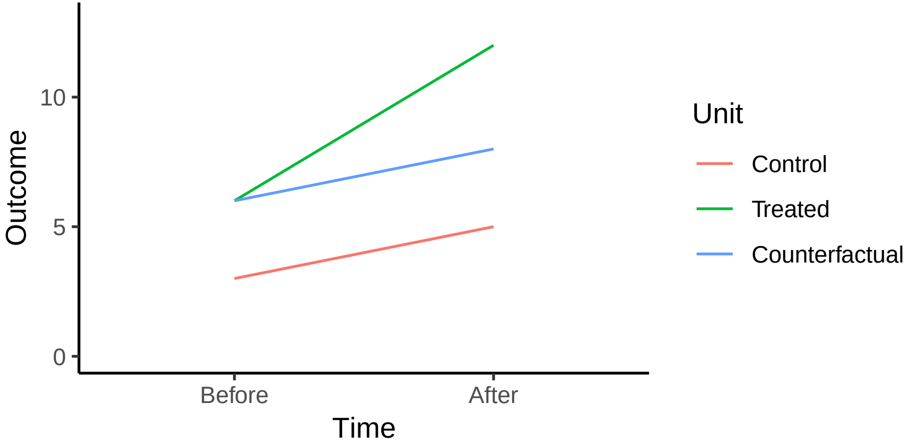

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$$Y_{it} = \alpha + \gamma D_i$$

- The difference-in-differences estimate is just the *interaction* of time and treatment status

$$Y_{it} = \alpha + \gamma D_i + \delta T_t + \beta D_i * T_t$$

- β is our causal effect estimate

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- Difference-in-Differences means:

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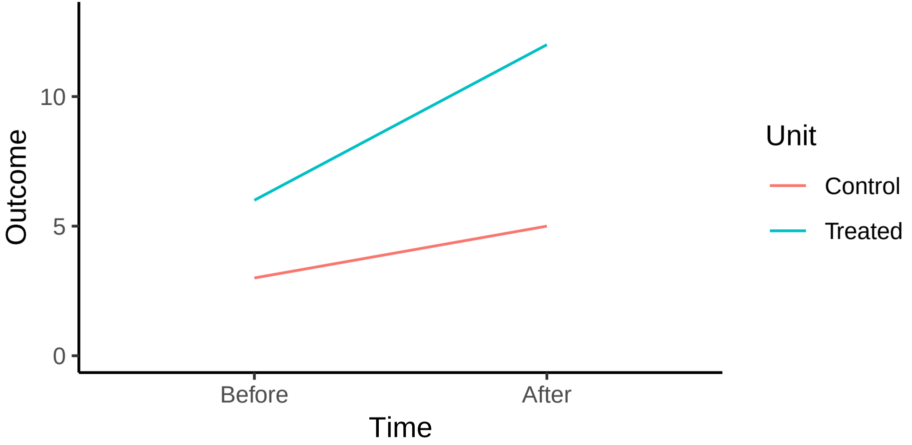
- That’s our causal effect

Difference-in-Differences

Raw Data:



Difference-in-Differences

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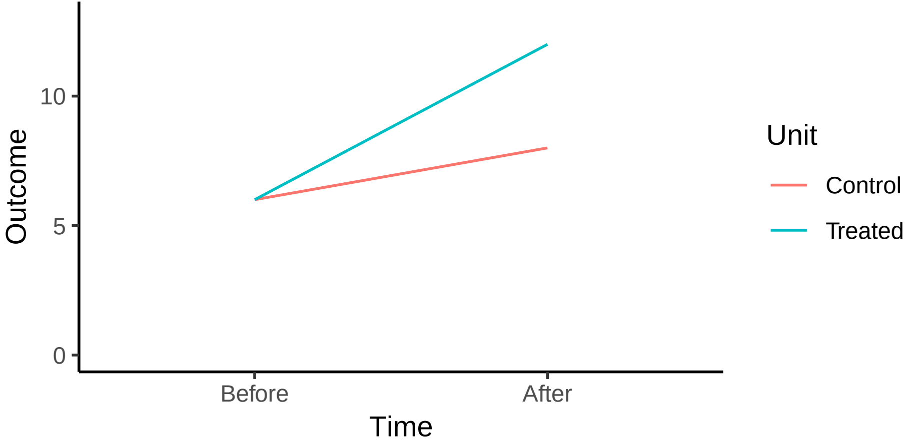

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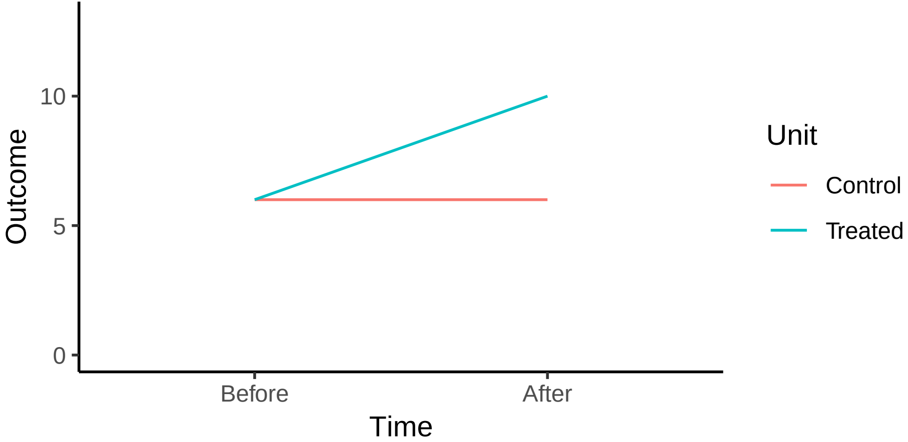

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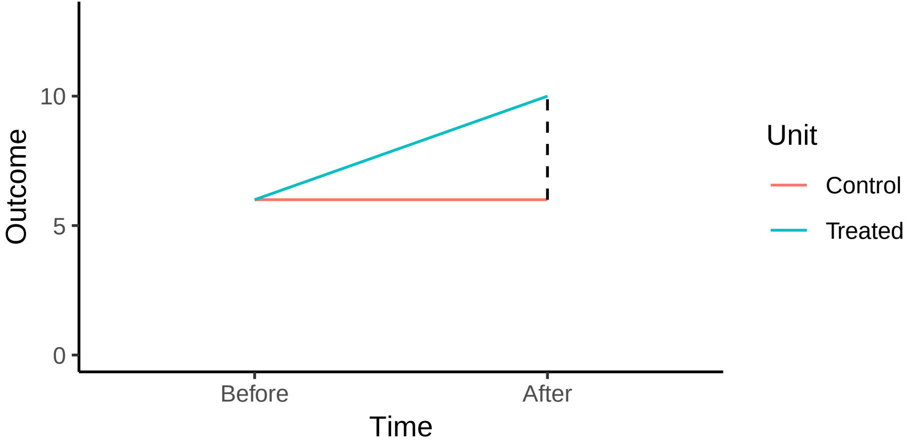

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- Then our counterfactual makes sense

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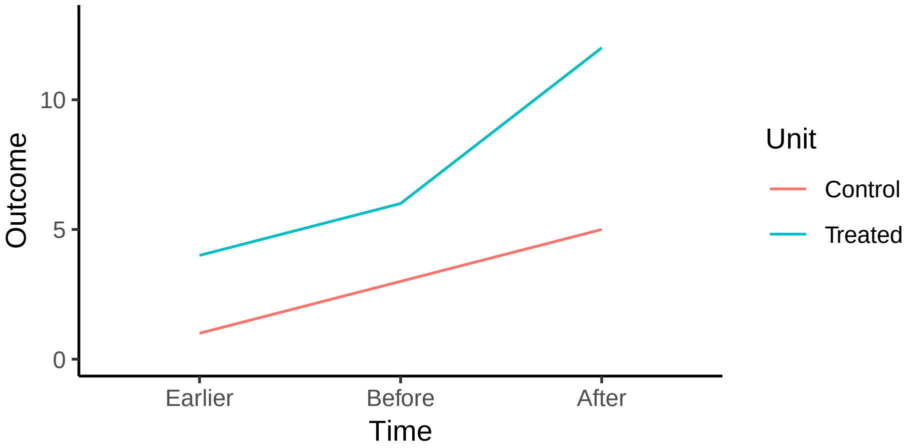

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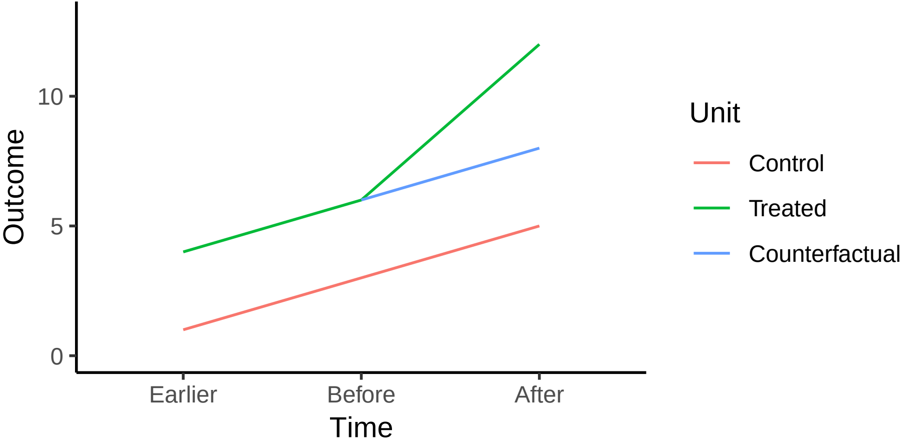

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- Parallel trends (no time-varying confounders) is a difficult assumption
- Selection into treatment is usually not just due to mostly ’fixed’ variables (eg. gender) but due to ’time-varying’ variables (eg. income, employment etc.)
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- Eg. training program participants' income has usually fallen a lot in the past few months
- A good test is to see if there is an effect from 'placebos' - testing for treatment effects at times before treatment happened

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- Eg. The UK also announced new rules to regulate the banking sector on the same day as Brexit

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- Bertrand et al (2003):
  - Careful with standard errors
  - Especially if more than two time periods (auto-correlation)
  - So cluster standard errors by each cross-sectional unit (eg. each country)