Interpreting and Critiquing Causal Evidence

Day 3 - Assessing Causal Evidence

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Section 1

Introduction

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

Solving the Problem of Causal Inference

- Experiments
  - Field Experiments
  - Lab Experiments
  - Survey Experiments

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- Natural Experiments
  - Instrumental Variables
  - Regression Discontinuity

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- Not-quite natural experiments
  - Difference-in-DIfferences

Causal Inference

Types of Research Design:

	Researcher controls the treatment assignment	Treatment assignment mechanism likely to create comparable potential outcomes ('Conditional Independence')
Controlled Experiments	Yes	Yes
Natural Experiments	No	Yes
Observable Studies	No	No

Section 2

Experiments

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
  - If treatment is randomly distributed, **so are potential outcomes**
- Potential outcomes are - on average - the same for treated and control units
  - No omitted variable bias
  - No self-selection
  - No reverse causation

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  - We cannot measure 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
  - $Y_i = \alpha + \beta D_i + \epsilon_i$

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    - If I receive a vaccine, that reduces the risks to everyone
    - If you are given information about a policy, you might pass it on to your family

Field Experiments

- Limitations of Field Experiments:

Field Experiments

- Limitations of Field Experiments:
  - Small sample sizes still prevent inference
  - Ethical/financial constraints
  - Some treatments can't be manipulated (history)
  - Scale effects - is the effect the same when implemented by a government?
  - Hawthorne effects - people react to being part of an experiment
  - Generalizability/external validity often poor
  - No information about the mechanism

Lab/Survey Experiments

- Why lab and survey experiments?

Lab/Survey Experiments

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  - Treatments we cannot administer in reality
  - Outcome measurements that are hard to take in reality
  - Random treatment assignment not permitted in reality

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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?

Section 3

Instrumental Variables

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- An 'instrument' is a variable which assigns *part of* treatment in an 'as-if' random way
  - Even if other variables **also** affect treatment

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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  - 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

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     - Interpret the coefficient on $\hat{D}$

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  - They don't tell us about the causal effect for other units that never responded to the instrument
  - We call our causal effect estimate a 'Local Average Treatment Effect' (LATE)
  - 'Local' to the units whose treatment status actually changed

Instrumental Variables

- Limitations:
  - Most treatments do not have a valid instrument
  - The exclusion restriction is not testable
  - The conclusion has narrow scope/generalizability - LATE
  - Low precision
  - No information about the mechanism

Section 4

Regression Discontinuities

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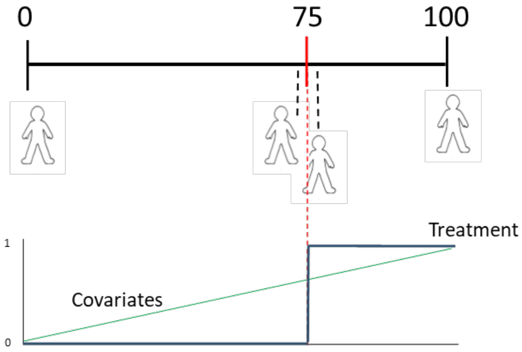
- Regression discontinuities take advantage of social rules that **treat similar people differently**
- Specifically, similar people with slightly different ’scores’ are assigned to treatment/control

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
  - Administrative boundaries

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

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    5. No compound treatments

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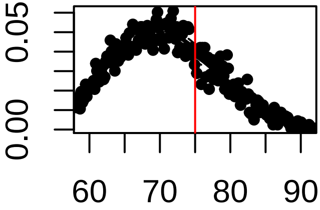
- We need qualitative evidence to support these assumptions

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



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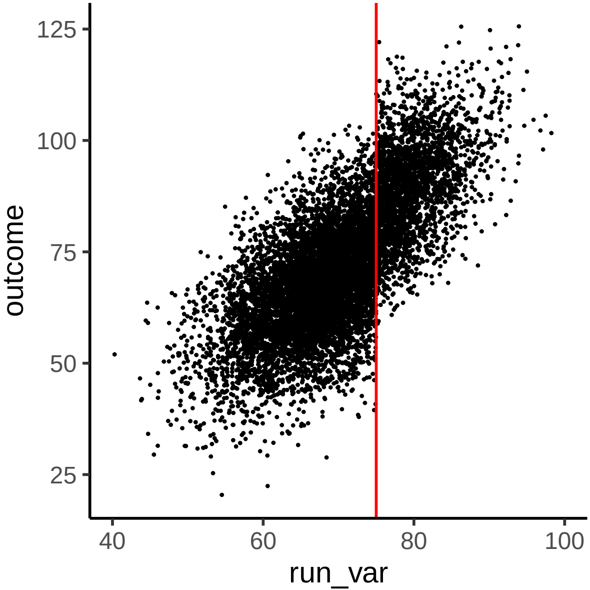
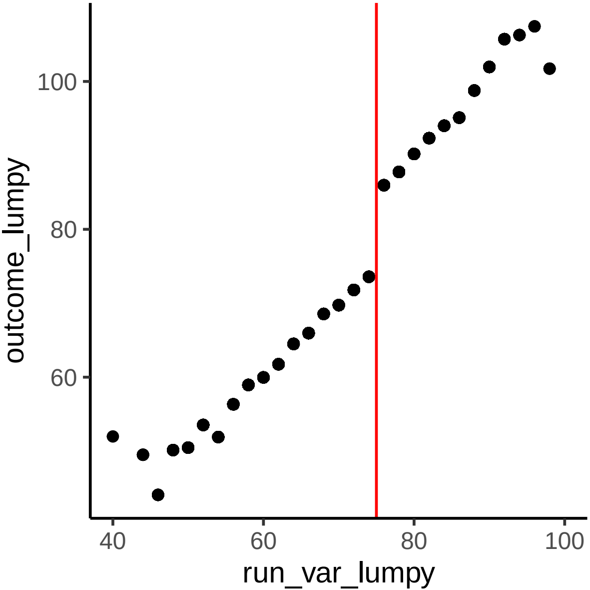
  - We may need to make the running variable non-linear

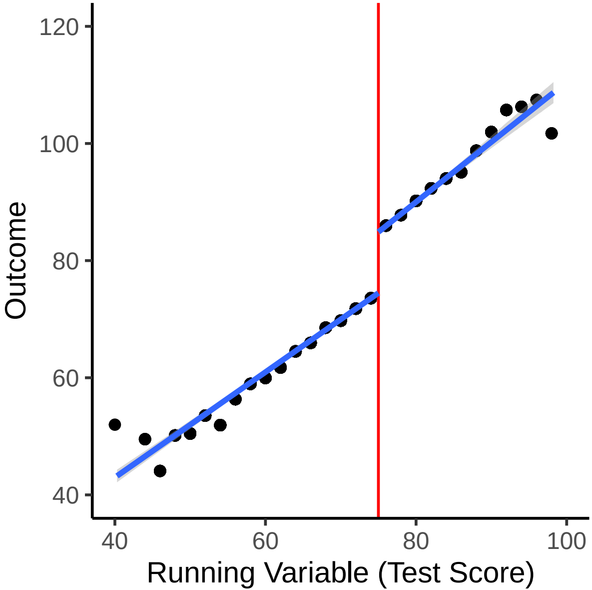
Raw Data



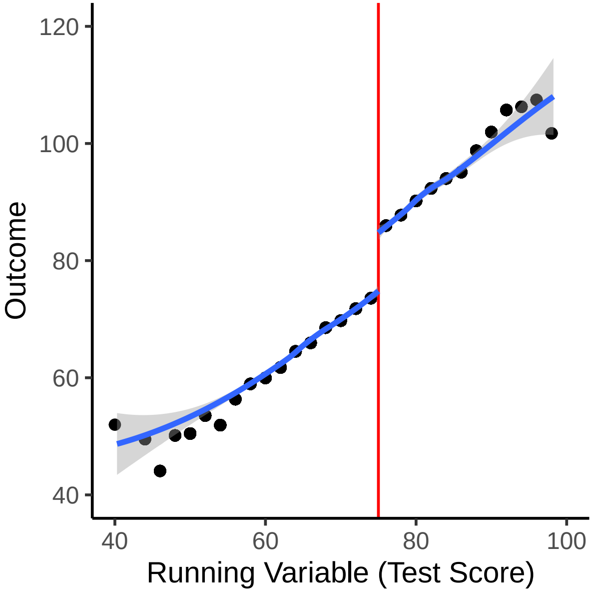
'Binned' Data



Parametric Regression - Linear



Parametric Regression - Non-linear



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  - Our estimates are only applicable/generalizable to units close to the threshold: a **Local Average Treatment Effect**
  - Units far from the threshold are very different for a reason, and causal effects are likely to be different

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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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  - They have extremely detailed information to predict vote results
  - So potential outcomes are not balanced
  - But no other case (9 countries) has this problem

Section 5

Difference-in-Differences

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- Some treatments happen at a specific point in time
  - Can't we compare the same unit before and after treatment?
  - Surely this limits the number of omitted variables - Chile today is very similar to Chile tomorrow
- But No!
  - Other factors influencing the outcome might also have changed between our measurements (eg. any news event!)
  - Eg. a worldwide recession

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- 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
- There is nothing 'as-if random' here, but we are more easily able to limit the risk of omitted variables

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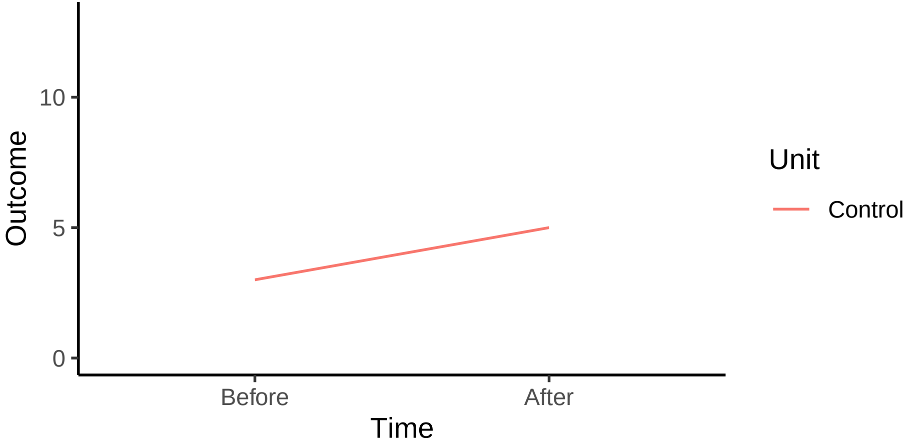

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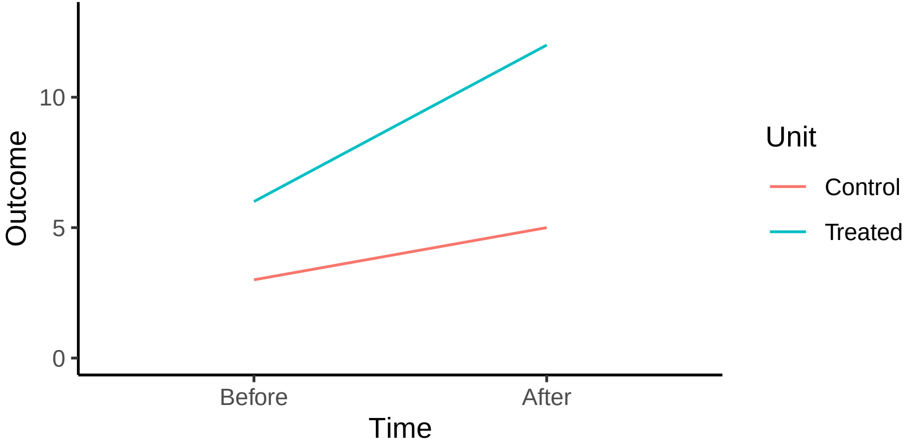

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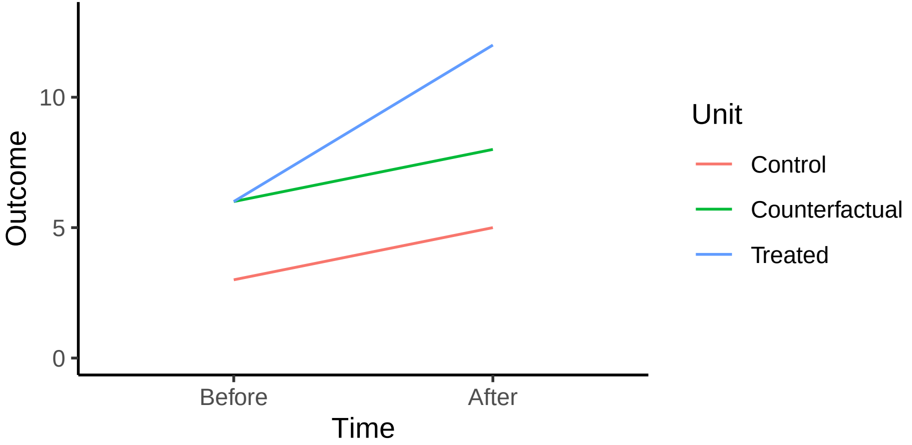

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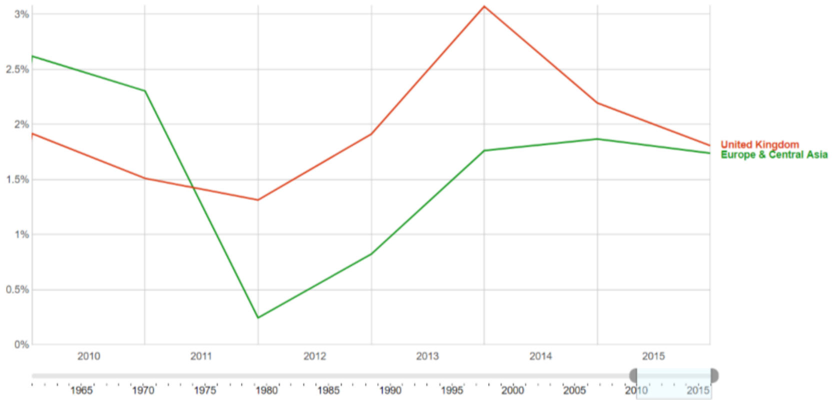

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- Difference-in-differences removes **time-invariant ('levels') confounders**
  - Even if they are unobserved/unmeasured
  - Most omitted variables affect 'levels', so this makes our counterfactuals more plausible
  - Eg. different laws affect growth rates, not the change in growth over time
- We still need to *make the assumption or argument* that there are **no time-varying confounders**

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  - Even if they are unobserved/unmeasured
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- We still need to *make the assumption or argument* that there are **no time-varying confounders**
- Factors that affect the **trend** in the outcome *differentially* in treated and control units
- Eg. Even before Brexit, the UK had falling growth while growth in the eurozone was improving due to differences in investment/productivity

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- 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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  4. **Groups are stable** (eg. no migration due to treatment)

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- Eg. Participants who join a training program usually experience income falls in the previous few months

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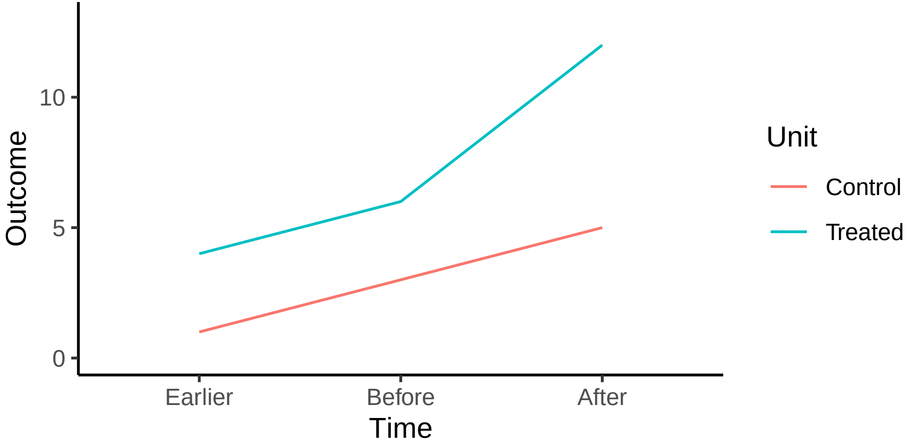
- One test of this is to check if **pre-treatment trends are parallel**
- Then our counterfactual makes sense

Difference-in-Differences



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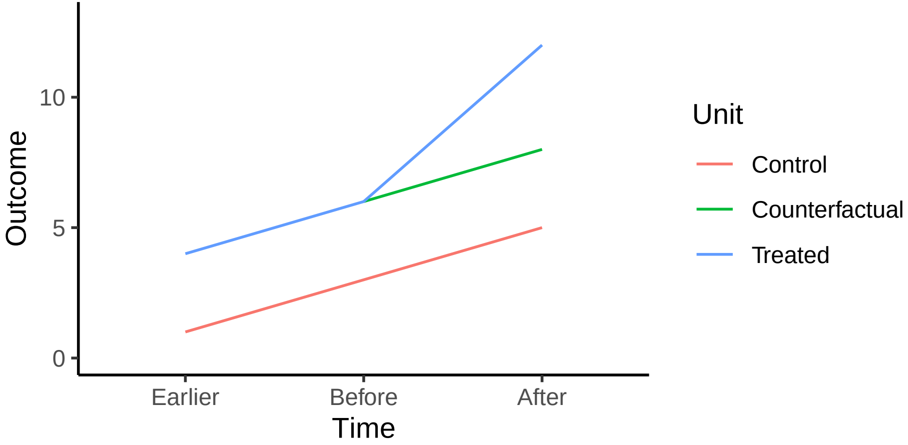

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  - Reliant on no time-varying confounders/parallel trends assumption
  - Often we have no control units - everyone gets treated at the same time
  - No information about the mechanism

Assumptions

Causal Methodology Assumptions

Research Design	**Assumptions required for valid causal inference**
Field/Lab/Survey Experiments	No spillovers, Randomization implemented correctly, Randomization complied with, No Hawthorne Effects
Instrumental Variables	No Spillovers, First stage predicts treatment, Exclusion restriction
Regression Discontinuities	No Spillovers, Continuity (balance) of covariates, No precise manipulation, No strategic threshold, No compounding discontinuities
Difference-in-Differences	No Spillovers, No time-varying confounders (parallel trends), Well-defined treatment, Stable groups