

# Introduction: Research design

17.871

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## The Biggest Problem in Research: Establishing Causality

- Class exercise: HIV and circumcision

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## Field Experiment example: HIV and male circumcision

- 3,274 uncircumcised men, aged 18–24, volunteered!
  - Randomly assigned to a control or an intervention group with
  - Follow-up visits at months 3, 12, and 21
- Did it work?
  - Control group: 2.1 per 100 person-years
  - Treatment group: 0.85 per 100 person-years

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## HIV and male circumcision

- When controlling for behavioral factors, including sexual behavior that increased slightly in the intervention group, condom use, and health-seeking behavior, the protection was
  - 61% (95% CI: 34%–77%).
- Male circumcision provides a degree of protection against acquiring HIV infection, equivalent to what a vaccine of high efficacy would have achieved.
- Male circumcision may provide an important way of reducing the spread of HIV infection in sub-Saharan Africa.

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## Field Experiment example: HIV and male circumcision

- Problems?
  - Internally valid!
    - Because of randomization intervention, no bias from nonrandom selection into the treatment group. That is,
      - No differences between the treatment and control group on confounding variables (only comparing apples with apples, no apples with oranges)
      - No possibility of reverse causation
    - Alternative interpretations of the treatment?
  - External validity?
    - Could the difference have occurred by chance?
      - Unlikely:  $p < 0.001$  on difference

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## Why is causality such a problem?

- In observational studies, selection into “treatment” and “control” cases rarely random
  - HIV example
  - Schooling examples (private vs. public)
  - Voting examples (pro-choice versus pro-life)
- Treatment and control cases may thus differ in other ways that affect the outcome of interest
  - Problem with internal validity
- The two primary drivers of selection are
  - Confounding variables
  - Reverse causation
- If you can address these problems, you have an internally valid study

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## Review of internal and external validity

## Internal validity: the two problems

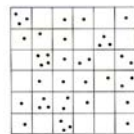
The two primary drivers of nonrandom selection into the treatment group (or on your key explanatory variable)

- 1. Confounding variables
  - Comparing
    - apples with apples
    - or apples with oranges?
  - Random assignment ensures apple to apple comparisons
  - Regression, matching, difference-in-differences also attempt to compare apples with apples
- 2. Reverse causation
  - The chicken and egg problem, which came first?
  - Is your dependent variable influencing your treatment (your explanatory variable)?
- If you can address these problems, you almost always have an internally valid study
- Randomly assigned experiments address both



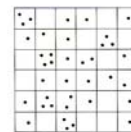
## External validity

- Is your sample representative of the population?
  - Address by randomly sampling
  - Avoiding case wise deletion because of missing data



Good research is about addressing

- Internal validity
- External validity



## Clarification

- Randomly sampling cases gets you?
  - External validity
- Randomly assigning to treatment group?
  - Internal validity
- Controlling for variables with regression addresses?
  - Internal validity
- What study design addresses both internal and external validity?
  - Field experiments

## How to Establish Causality

(i.e., how to rule out alternatives)

- How do we establish causality? By ruling out alternative explanations
  - Legal analogy: prosecutor versus defense
- Best approach to ruling out alternatives?
  - Run a field experiment!
    - E.g., HIV and circumcision

## Review

Classic Post-test only experiment

- Donald Campbell and Julian Stanley, *Experimental and Quasi-Experimental Designs for Research* (1963)
- Summary:

R	X	O
R		O

- No prior observation
- Classical scientific and agricultural experimentalism

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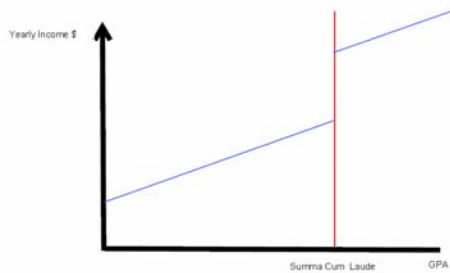
## How to Establish Causality

(i.e., how to rule out alternatives)

- But, running an experiment is often impossible
  - Try anyway: e.g., HIV and circumcision
- If you can't run an experiment: natural experiment
  - Exploit something that is exogenous
    - Accidental deaths
    - Timing of Senate elections
    - Imposition of new voting machines
    - 9/11 terrorist attacks
    - Geographical boundaries
  - Exploit a discontinuity
    - *Summa Cum Laude's* effect on income
    - Regression discontinuity (RD) design

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## Regression Discontinuity: The Picture



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## Regression discontinuity

Example from Brazil

Motivating Politicians:

The Impacts of Monetary Incentives on Quality and Performance\*

Claudio Ferraz<sup>1</sup>      Frederico Finan<sup>2</sup>  
 PUC-Rio                      UCLA

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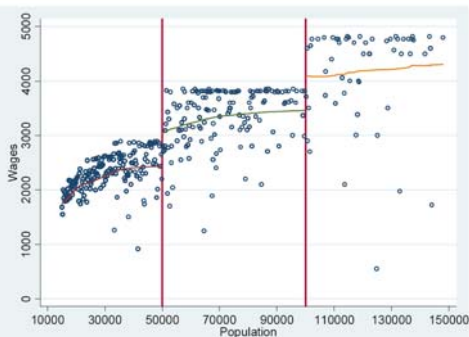


Table 10. The Effects of Wages on Public Good Provision

Dependent variable	Education			Health			Sanitation and Water				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: IV estimates											
Log Wages	1.27 [0.683]*	0.668 [0.029]**	0.175 [0.071]**	0.242 [0.129]*	0.639 [0.279]**	0.571 [0.241]**	0.073 [0.036]**	0.028 [0.052]	3.201 [2.353]	0.457 [1.741]	
F-test (one instrument)	26.21	26.21	26.21	27.31	28.59	30.23	21.54	26.49	22.65	26.68	
Panel B: OLS estimates											
Log Wages	-0.292 [0.093]***	-0.015 [0.060]***	-0.064 [0.011]***	0.104 [0.016]***	0.142 [0.033]***	-0.088 [0.035]***	-0.033 [0.005]	-0.063 [0.006]	-2.371 [0.326]	-2.025 [0.221]	
R-squared	0.48	0.07	0.54	0.04	0.31	0.16	0.27	0.27	0.31	0.50	
Municipal characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4736	4736	4736	4012	4837	4825	3479	3928	3463	3935	

## How to Establish Causality (i.e., how to rule out alternatives)

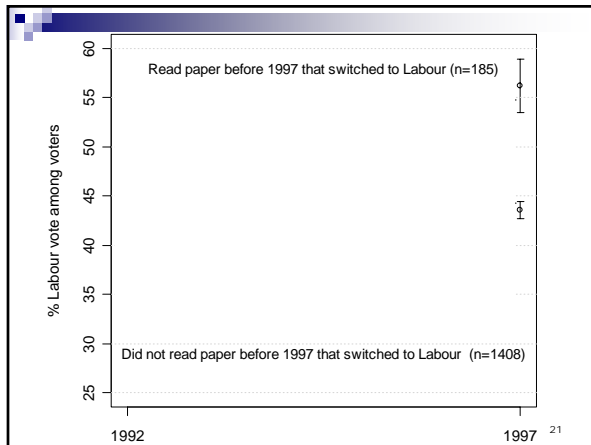
- If you can't run an experiment or find a natural experiment/discontinuity
  - Control for confounding variables
    - Difference-in-differences (DD)
    - Matching
    - Controlling for variables with parametric models, e.g., regression
  - Eliminate reverse causation
    - Exploit time with panel data, i.e., measure the outcome before and after some treatment

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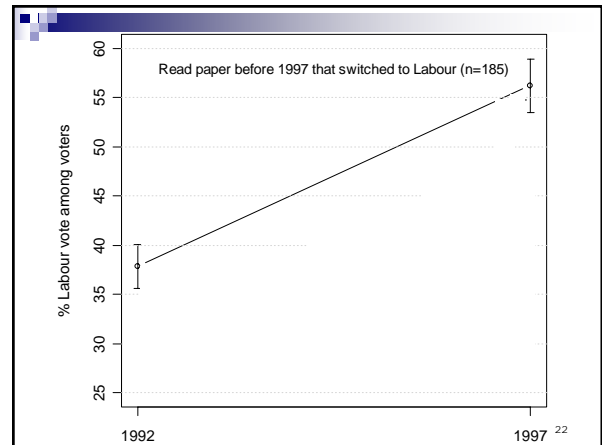
## Difference-in-differences

- Media effects example
  - Endorsement changes in the 1997 British election
  - Illustrates
    - Difference-in-differences, which reduces bias from confounding variables
    - Panel data, which can help rule out reverse causation

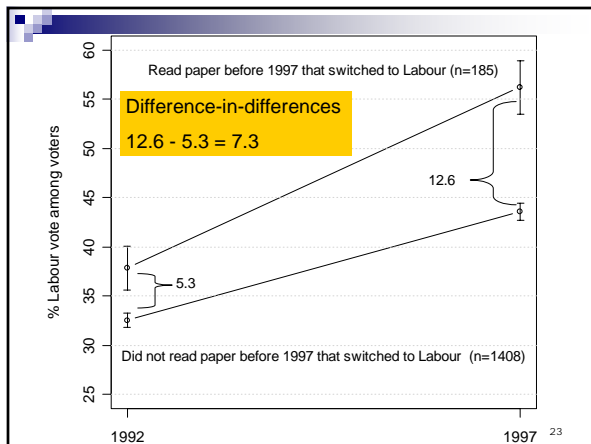
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## How to Establish Causality (i.e., how to rule out alternatives)

- If you can't run an experiment or find a natural experiment
  - Control for confounding variables
    - Difference-in-differences (DD)
    - Matching
    - **Controlling for variables with parametric models, e.g., regression**
  - Eliminate reverse causation
    - Exploit time with panel data, i.e., measure the outcome before and after some treatment

Much of 17.871 is about this

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## Summary

- Field experiment always preferred
  - Always keep a field experiment in mind when designing observational studies
- Strive for "natural" or quasi-experiments
  - Timing of Senate elections
  - Imposition of new voting machines
  - 9/11 terrorist attacks
  - Regression-discontinuity designs
- Use Difference-in-differences designs
- Gather as much cross-time data as possible (panel studies)
- If you only have cross-sectional data, be humble!

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## Supplemental examples

### Another regression discontinuity example

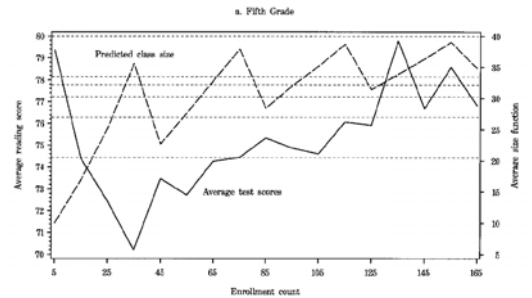
#### Example: Class size and achievement

**Hypothesis:** Maimonides's Rule: Class sizes large than 40 students are bad for kids.

**Context:** In Israel kindergarten class sizes are never greater than 40.

What is the pattern predicted? 0-40 grow as you expect, then at 41 average size 20.5, increase again to 80, at 81 avg. 27.

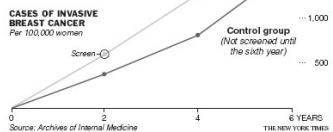
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(Angrist and Lavy, 1999)  
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#### Undetected, Some Cancers Might Regress

A six-year study of breast cancer in Norway found more invasive cancers in women screened every two years than in women who were not screened until the sixth year. The study suggests that a significant number of cancers in the control group regressed and went away without treatment, but would have been detected with more frequent screening.



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