Session I
Survey Experiments in
Context

Thomas J. Leeper

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London School of Economics and Political Science

1. Introductions

2. Course Outline

3. History of Experiments

4. Logic of Experiments

Activity!

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1 Ask you to guess a number

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2. Number off 1 and 2 across the room

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3. Group 2, close your eyes

Activity!

Group 1
Think about whether the population of Chicago is more or less than 500,000 people. What do you think the population of Chicago is?

Activity!

1. Ask you to guess a number
2. Number off 1 and 2 across the room
3. Group 2, close your eyes
4. Group 1, close your eyes

Activity!

Group 2
Think about whether the population of Chicago is more or less than 10,000,000 people. What do you think the population of Chicago is?

Enter your data

- Go here: `http://bit.ly/297vEdd`

- Enter your guess and your group number

Results

- True population: 2.79 million

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- What did you guess? (See Responses)

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  - An experiment!
  - Demonstrates "anchoring" heuristic

Results

- True population: 2.79 million

- What did you guess? (See Responses)

- What's going on here?
  - An experiment!
  - Demonstrates "anchoring" heuristic

- Experiments are easy to analyze, but only if designed and implemented well

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2 Course Outline

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4 Logic of Experiments

Who am I?

- Thomas Leeper

- Assistant Professor in Political Behaviour at London School of Economics

    - 2013–15: Aarhus University (Denmark)
    - 2008–12: PhD from Northwestern University (Chicago, USA)
    - Birth–2008: Minnesota, USA

- Interested in public opinion and political psychology

- Email: t.leeper@lse.ac.uk

Who are you?

- Introduce yourself to a neighbour

- Where are you from?

- What do you hope to learn from the course?

Quick Survey

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3. How many of you have worked with experimental data before?

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3. How many of you have worked with experimental data before?

4. Of those, how many of you have *performed* an experiment before?

Course Materials

All material for the course is available at:

`http://www.thomasleeper.com/`
`surveyexpcourse/`

Learning Outcomes

By the end of the week, you should be able to. . .

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3. Evaluate the uses and limitations of several common survey experimental paradigms.

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1. Explain how to analyze experiments quantitatively.

2. Explain how to design experiments that speak to relevant research questions and theories.

3. Evaluate the uses and limitations of several common survey experimental paradigms.

4. Identify practical issues that arise in the implementation of experiments and evaluate how to anticipate and respond to them.

Schedule of Five Sessions

1. Survey Experiments in Context

2. Examples and Paradigms

3. External Validity

4. Sources of Heterogeneity

5. Lingering Issues

Questions?

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4 Logic of Experiments

Experiments

Oxford English Dictionary defines "experiment" as:

1. A scientific procedure undertaken to make a discovery, test a hypothesis, or demonstrate a known fact

2. A course of action tentatively adopted without being sure of the outcome

Experiments

- "Experiments" have a very long history

- Major advances in design and analysis of experiments based on agricultural and later biostatistical research in the 19th century
  - R.A. Fisher
  - Jerzy Neyman
  - Karl Pearson
  - Oscar Kempthorne

In Social Sciences

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  - Not randomized – more like "What if?" studies
  - Heavily laboratory-based or clinical

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- And have been a major part of the "credibility revolution" in economics
    - See, especially, LaLonde (1986)

In Political Science I

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- Gerber and Green (2000) first major *field* experiment

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- 1983: Merrill Shanks and the Berkeley Survey Research Center develop CATI

- Mid-1980s: Paul Sniderman & Tom Piazza performed the first survey experiment[1]

    - Then: the "first multi-investigator"
    - Later: Skip Lupia and Diana Mutz created TESS

---

[1] Sniderman, Paul M., and Thomas Piazza. 1993. *The Scar of Race*. Cambridge, MA: Harvard University Press.

TESS

- Time-Sharing Experiments for the Social Sciences

- Multi-disciplinary initiative that provides infrastructure for survey experiments on nationally representative samples of the United States population

- Funded by the U.S. National Science Foundation

- Anyone anywhere in the world can apply
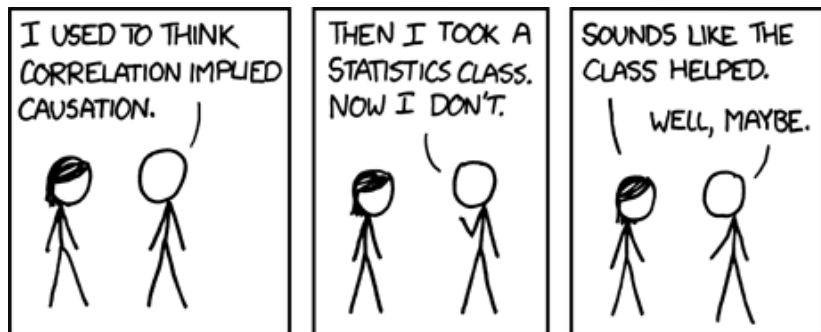
TESS-like Projects

There are some TESS-like initiatives outside the United States:

- Netherlands: LISS

- Norway: Bergen's Citizen Panel

- Sweden: Gothenburg's Citizen Panel

Questions?

Addressing Confounding

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3. "Condition" on all confounds
   - Calculate correlation between X and Y at each combination of levels of $\mathbf{Z}$
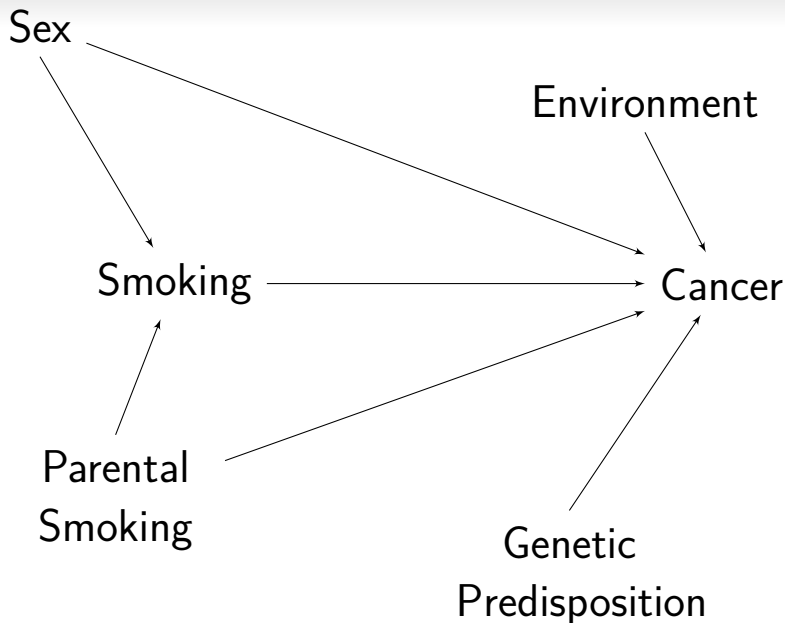
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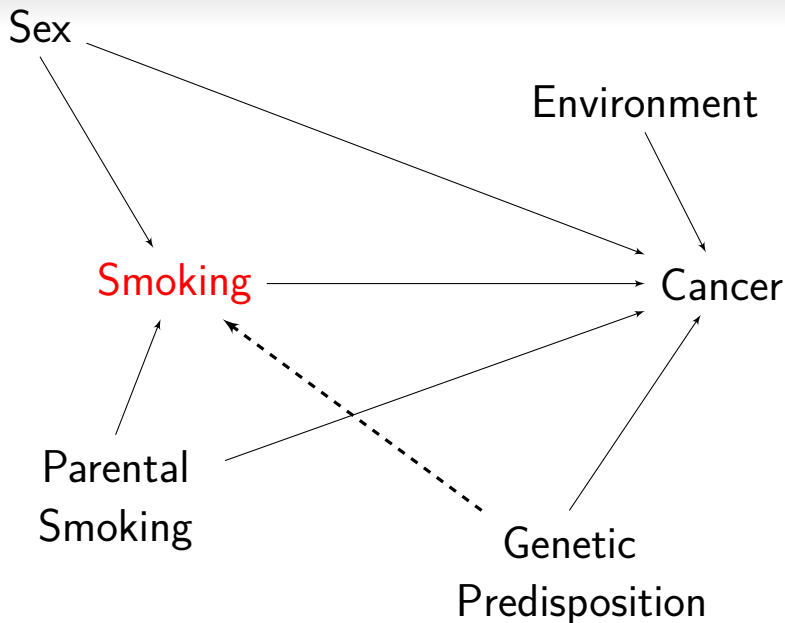   - Calculate correlation between X and Y at each combination of levels of $\mathbf{Z}$

4. Basically: $Y = \beta_0 + \beta_1 X + \beta Z + \epsilon$

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4. We see "causal effects" in the comparison of experimental groups

Mill's Method of Difference

If an instance in which the phenomenon under
investigation occurs, and an instance in which it
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common, that one occurring only in the former; the
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Mill's Method of Difference

If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, **have every circumstance save one in common**, that one occurring only in the former; **the circumstance in which alone the two instances differ, is the** effect, or **cause**, or an necessary part of the cause, **of the phenomenon**.

Definitions

Definitions

Unit: A physical object at a particular point in time

Definitions

Treatment: An intervention, whose effect(s) we wish to assess relative to some other (non-)intervention

Definitions

Potential outcomes: The outcome for each unit that we would observe if that unit received each treatment

- Multiple potential outcomes for each unit, but we only observe one of them

Definitions

Causal effect: The comparisons between the unit-level potential outcomes under each intervention

The Experimental Ideal

A randomized experiment, or randomized control trial is:

> *The observation of units after, and possibly before, a randomly assigned intervention in a controlled setting, which tests one or more precise causal expectations*

This is Holland's "statistical solution" to the fundamental problem of causal inference

The Experimental Ideal

- It solves both the temporal ordering and confounding problems of observational causal inference
  - Treatment (X) is applied by the researcher before outcome (Y)
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- Basically: $Y = \beta_0 + \beta_1 X + \epsilon$

Neyman-Rubin Potential Outcomes Framework

If we are interested in some outcome Y, then for every unit i, there are numerous "potential outcomes" $Y*$ only one of which is visible in a given reality. Comparisons of (partially unobservable) potential outcomes indicate causality.

Neyman-Rubin Potential Outcomes Framework

Concisely, we typically discuss two potential outcomes:

- Y_{0i}, the *potential* outcome *realized* if $X_i = 0$ (b/c $D_i = 0$, assigned to control)
- Y_{1i}, the *potential* outcome *realized* if $X_i = 1$ (b/c $D_i = 1$, assigned to treatment)

Historical Aside

- The history of the potential outcomes framework is contested

- Most people attribute it to Donald Rubin

- Paul Holland was the first to link to the philosophical discussions of causality

- Donald Rubin attributes this to Jerzy Neyman (1923)

- James Heckman denies all of this and attributes it Andrew Roy (1951)

Experimental Inference I

- Each unit has multiple *potential* outcomes, but we only observe one of them, randomly

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- In this sense, we are sampling potential outcomes from each unit's population of potential outcomes

unit	low	high
1	?	?
2	?	?
3	?	?
4	?	?

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unit	low	high	control	etc.
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2	?	?	?	. . .
3	?	?	?	. . .
4	?	?	?	. . .

Experimental Inference II

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    - Ex.: Average difference in cancer
      between those who do and do not smoke

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- But we still only see one potential outcome for each unit:

  $$ATE_{naive} = E[Y_{1i}|X = 1] - E[Y_{0i}|X = 0]$$

- Is this what we want to know?

Experimental Inference IV

- What we want and what we have:

$$ATE = E[Y_{1i}] - E[Y_{0i}] \tag{1}$$

$$ATE_{naive} = E[Y_{1i}|X = 1] - E[Y_{0i}|X = 0] \tag{2}$$

Experimental Inference IV

- What we want and what we have:

$$ATE = E[Y_{1i}] - E[Y_{0i}] \tag{1}$$

$$ATE_{naive} = E[Y_{1i}|X = 1] - E[Y_{0i}|X = 0] \tag{2}$$

- Are the following statements true?
  - $E[Y_{1i}] = E[Y_{1i}|X = 1]$
  - $E[Y_{0i}] = E[Y_{0i}|X = 0]$

Experimental Inference IV

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- Are the following statements true?
  - $E[Y_{1i}] = E[Y_{1i}|X = 1]$
  - $E[Y_{0i}] = E[Y_{0i}|X = 0]$

- Not in general!

Experimental Inference V

- Only true when both of the following hold:

$$E[Y_{1i}] = E[Y_{1i}|X = 1] = E[Y_{1i}|X = 0] \quad (3)$$
$$E[Y_{0i}] = E[Y_{0i}|X = 1] = E[Y_{0i}|X = 0] \quad (4)$$

- In that case, potential outcomes are *independent* of treatment assignment

- If true (e.g., due to randomization of X), then:

$$ATE_{naive} = E[Y_{1i}|X = 1] - E[Y_{0i}|X = 0] \quad (5)$$
$$= E[Y_{1i}] - E[Y_{0i}]$$
$$= ATE$$

Experimental Inference VI

- This holds in experiments because of a *physical process of randomization*[2]

---

[2]Random means "known probability of treatment" not "haphazard".

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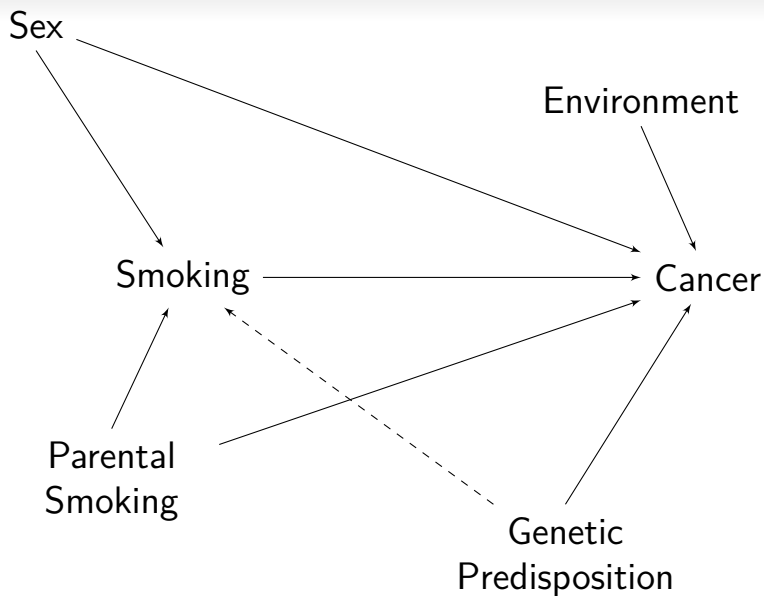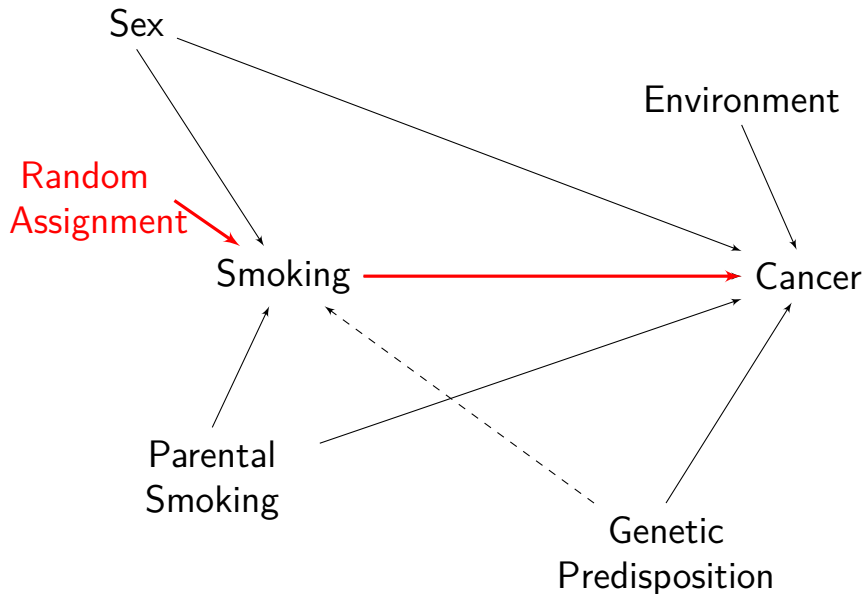 - $X_i = 1$ only because $D_i = 1$

- Implications:
  - Covariate balance
  - Potential outcomes balanced and independent of treatment assignment
  - No confounding (selection bias)

[2]Random means "known probability of treatment" not "haphazard".

Sex

Environment

Smoking ⟶ Cancer

Parental
Smoking

Genetic
Predisposition

Questions?

Experimental Analysis I

- The statistic of interest in an experiment is the *sample average treatment effect* (SATE)

- If our sample is *representative*, then this provides an estimate of the population average treatment (PATE)

- This boils down to being a mean-difference between two groups:

$$SATE = \frac{1}{n_1} \sum Y_{1i} - \frac{1}{n_0} \sum Y_{0i} \qquad (5)$$

Computation of Effects I

- In practice we often estimate SATE using t-tests, ANOVA, or OLS regression

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- Reasons to choose one procedure over another:
    - Disciplinary norms
    - Ease of interpretation
    - Flexibility for >2 treatment conditions

Computation of Effects II

An experimental data structure looks like:

unit	treatment	outcome
1	0	13
2	0	6
3	0	4
4	0	5
5	1	3
6	1	1
7	1	10
8	1	9

Computation of Effects III

Stata:

```
ttest outcome, by(treatment)
reg outcome i.treatment
```

R:

```
t.test(outcome ~ treatment, data = data)
lm(outcome ~ factor(treatment), data = data)
```

Questions?

Experimental Analysis II

- We don't just care about the size of the SATE. We also want to know whether it is significantly different from zero (i.e., different from no effect/difference)

- To know that, we need to estimate the *variance* of the SATE

- The variance is influenced by:
  - Total sample size
  - Variance of the outcome, Y
  - Relative size of each treatment group

Experimental Analysis III

- Formula for the variance of the SATE is:
$$\widehat{Var}(SATE) = \frac{\widehat{Var}(Y_0)}{n_0} + \frac{\widehat{Var}(Y_1)}{n_1}$$

  - $\widehat{Var}(Y_0)$ is control group variance
  - $\widehat{Var}(Y_1)$ is treatment group variance

- We often express this as the *standard error* of the estimate:
$$\widehat{SE}_{SATE} = \sqrt{\frac{\widehat{Var}(Y_0)}{n_0} + \frac{\widehat{Var}(Y_1)}{n_1}}$$

Intuition about Variance

- Bigger sample $\rightarrow$ smaller SEs

- Smaller variance $\rightarrow$ smaller SEs

- Efficient use of sample size:
  - When treatment group variances equal, equal sample sizes are most efficient
  - When variances differ, sample units are better allocated to the group with higher variance in Y

Statistical Power

- Power analysis to determine sample size
- Type I and Type II Errors
  - True positive rate is power
  - False negative rate is the significance threshold (α)

	H_0 True	H_0 False
Reject H_0	Type 1 Error	**True positive**
Accept H_0	False negative	Type II error

Doing a Power Analysis

- μ, Treatment group mean outcomes
- N, Sample size
- σ, Outcome variance
- α Statistical significance threshold
- ϕ, a sampling distribution

$$Power = \phi\left(\frac{|\mu_1 - \mu_0|\sqrt{N}}{2\sigma} - \phi^{-1}\left(1 - \frac{\alpha}{2}\right)\right)$$

Intuition about Power

Minimum detectable effect is the smallest effect we could detect given sample size, "true" effect size, variance of outcome, power, and α.

In essence: some non-zero effect sizes are not detectable by a study of a given sample size.[3]

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[3]Gelman, A. and Weakliem, D. 2009. "Of Beauty, Sex and Power." *American Scientist* 97(4): 310–16

Intuition about Power

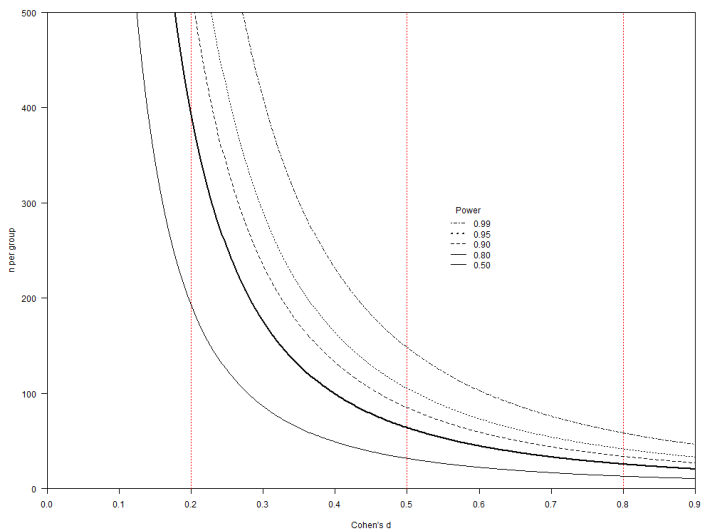- It can help to think in terms of "standardized effect sizes"

- Cohen's d:
  $d = \frac{\bar{x}_1 - \bar{x}_0}{s}$, where $s = \sqrt{\frac{(n_1-1)s_1^2 + (n_0-1)s_0^2}{n_1 + n_0 - 2}}$

- Intuition: How large is the effect in standard deviations of the outcome?
  - Know if effects are large or small
  - Compare effects across studies

- Small: 0.2; Medium: 0.5; Large: 0.8

Intuition about Power

Aside: Complex Designs

- An experiment can have any number of conditions
    - Up to the limits of sample size
    - More than 8–10 conditions is typically unwieldy

- Typically analyze complex designs using ANOVA or regression, but we are still ultimately interested in pairwise comparisons to estimates SATEs
    - Treatment–treatment, or treatment-control
    - Without control group, we don't know which treatment(s) affected the outcome

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- Lots of common paradigms for survey experiments (tomorrow)

Combining Survey Design and Experimental Design

- Sample is representative of population in every respect (in expectation)

- Sample Average Treatment Effect (SATE) is the average of the sample's individual-level treatment effects

  - Unbiased estimate of PATE

Combining Survey Design and Experimental Design

- Sample is representative of population in every respect (in expectation)

- Sample Average Treatment Effect (SATE) is the average of the sample's individual-level treatment effects

    - Unbiased estimate of PATE

- Says nothing about effect heterogeneity

    - Design is optimized for estimating SATE
    - Discuss this on Wednesday

Questions?

Homework!

- Get a sense of what can be studied experimentally
- Visit Time-Sharing Experiments for the Social Sciences
    - http://tessexperiments.org
- Pick two studies from TESS
- We will share them in class tomorrow

Randomization Distribution

```
# theoretical randomizations
onedraw <- function(eff=FALSE, dat = d) {
  r <- replicate(nrow(dat), sample(1:2,1))
  dat[cbind(1:nrow(dat),r)] <- NA
  if (eff) {
    return(mean(dat[,'y1'], na.rm=TRUE) -
           mean(dat[,'y0'], na.rm=TRUE) )
  } else {
    return(dat)
  }
}

onedraw() # one randomization
onedraw(TRUE) # one effect estimate

# simulate 2000 experiments from these data
x1 <- replicate(2000, onedraw(TRUE))
hist(x1, col=rgb(1,0,0,.5), border='white')
abline(v=-2, lwd=3, col='red') # true effect
```