Week 8: Regression in the Social Sciences

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Princeton

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[1]These slides are heavily influenced by Matt Blackwell, Justin Grimmer, Jens Hainmueller, Erin Hartman, Kosuke Imai and Gary King.

Where We've Been and Where We're Going...

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  - matrix form of linear regression
  - inference and F-tests

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- Long Run
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Questions?

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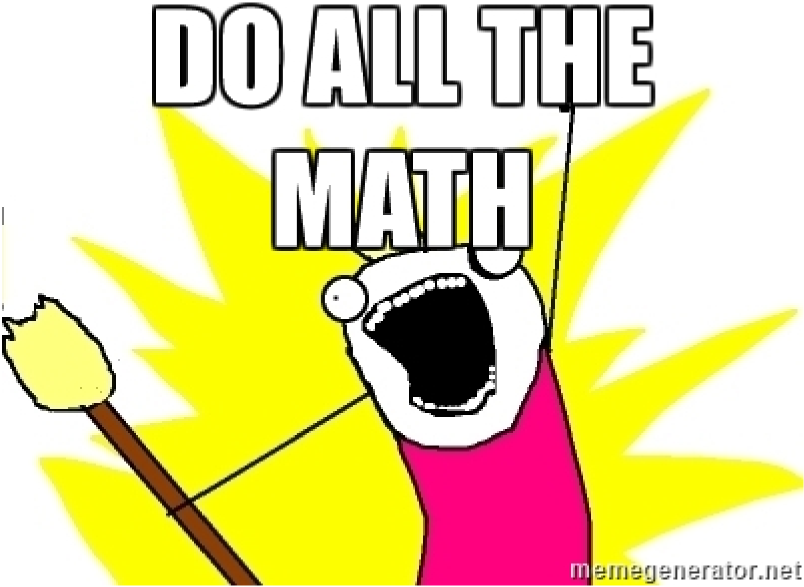
- Knowing how methods work also makes you a better reader of work.


DO ALL THE
MATH
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We will mostly talk about statistical methods here (it is a statistics class!) but the best work is a combination of substantive and statistical theory.

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- Ioannidis (2005) "Why most published research findings are false" *PLOS Medicine*
- Begley and Ellis (2012) "Drug development: raise standard for preclinical cancer research" *Nature*
- Johnson (2013) "Revised standards for statistical evidence" *PNAS*
- Franco, Malhotra, Simonovits (2014) "Publication Bias in the Social Sciences: Unlocking the File Drawer" *Science*
- Nosek et al (2015) "Estimating the reproducibility of psychological science" *Science*
- Leek and Jager (2017) "Is Most Published Research Really False?" *Annual Review of Statistics and Its Applications*

An Example Gerber, Green and Larimer (2008)

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
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- We choose the sample size that can ensure that we can detect what we think is the true treatment effect (i.e. reject the null of no effect).
- Small effects will require more observations than large effects. But how many more?

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4) Number of observations

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Key question: given true value of $\mu^*_{\text{diff}} \neq 0$ what is the probability t falls in "fail to reject" region?

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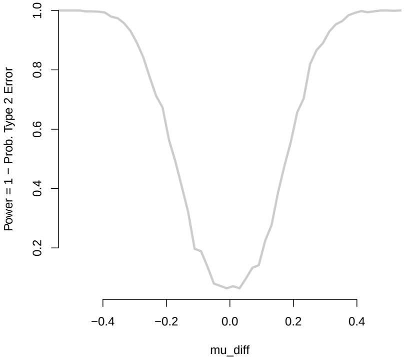

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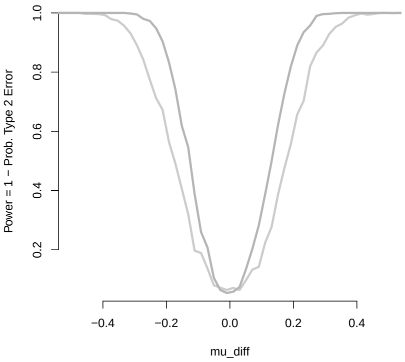

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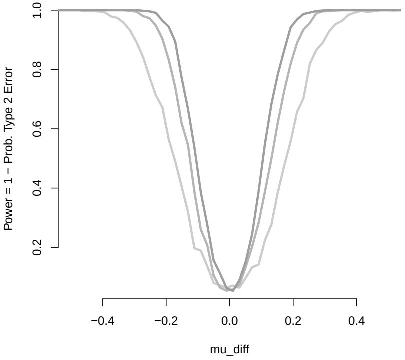

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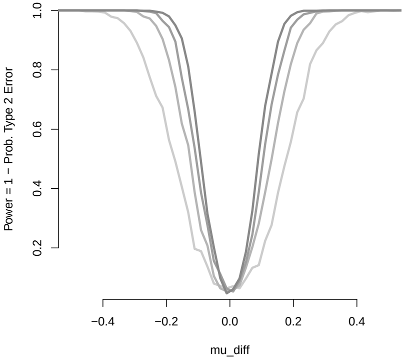

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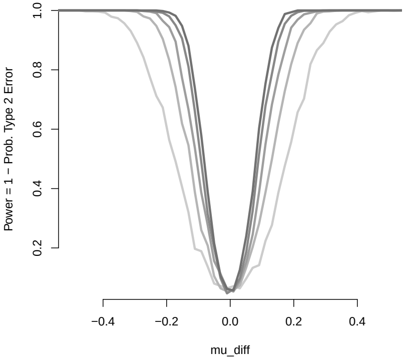

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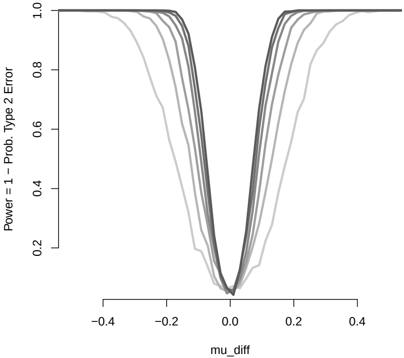

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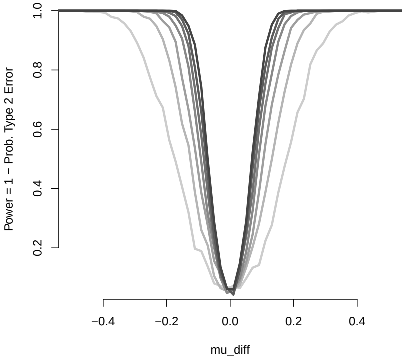

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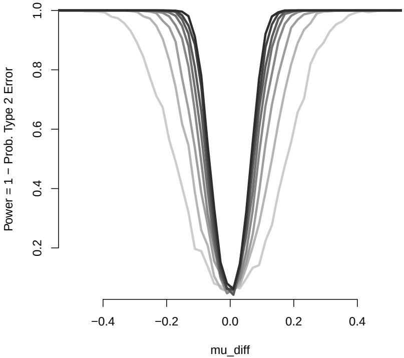

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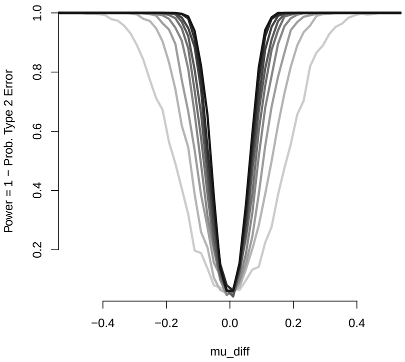

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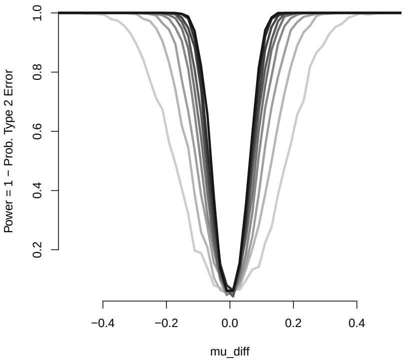

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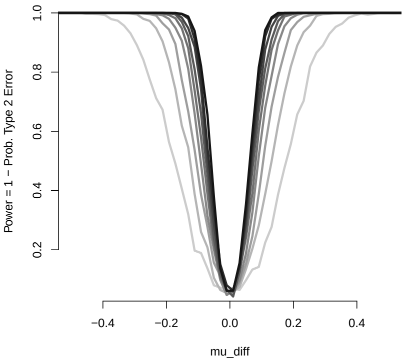

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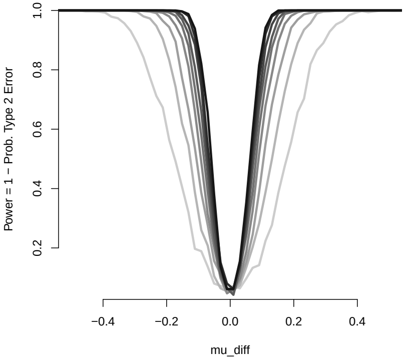

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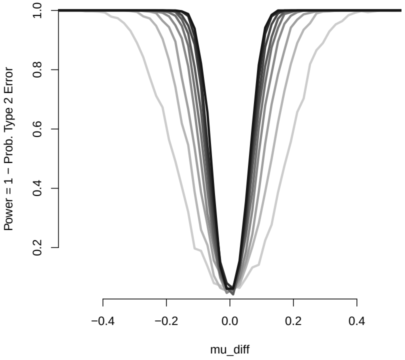

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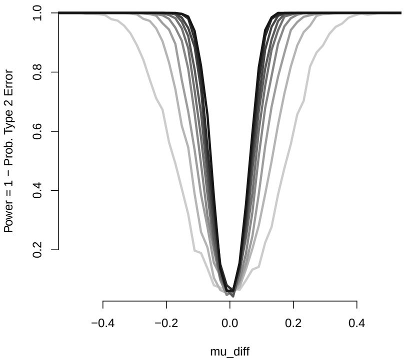

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- Let's say we want to run another experiment where we believe the true effect is $\mu_y - \mu_x = 0.05$ and the variances are $\sigma_y^2 = \sigma_x^2 = .2$

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- Let's say we want to run another experiment where we believe the true effect is $\mu_y - \mu_x = 0.05$ and the variances are $\sigma_y^2 = \sigma_x^2 = .2$
- We can only afford to send out 500 mailers. Should we run the experiment?

Back to Gerber, Green and Larimer

- Before starting they did a power analysis
- Steps to a power analysis
  1. Pick some hypothetical effect size $\mu_y - \mu_x = .05$
  2. Calculate the distribution of test statistic T under that effect size
  3. Calculate the probability of rejecting the null under that distribution
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- To the board!

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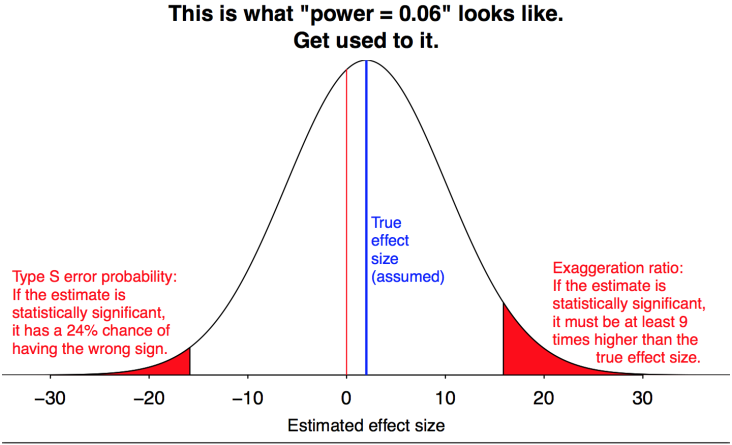
  - perform a power analysis under given effect size, observed standard error of measurement.
  - power comes out to 0.06

A Troubling Figure (via Gelman)



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- p-values are not:
  - an indication of a large substantive effect
  - the probability that the null hypothesis is true
  - the probability that the alternative hypothesis is false
- a large p-value could mean either that we are in the null world OR that we had insufficient power

So what is the basic idea?

The idea was to run an experiment, then see if the results were consistent with what random chance might produce. Researchers would first set up a 'null hypothesis' that they wanted to disprove, such as there being no correlation or no difference between groups. Next, they would play the devil's advocate and, assuming that this null hypothesis was in fact true, calculate the chances of getting results at least as extreme as what was actually observed. This probability was the P value. The smaller it was, suggested Fisher, the greater the likelihood that the straw-man null hypothesis was false.
(Nunzo 2014, emphasis mine)

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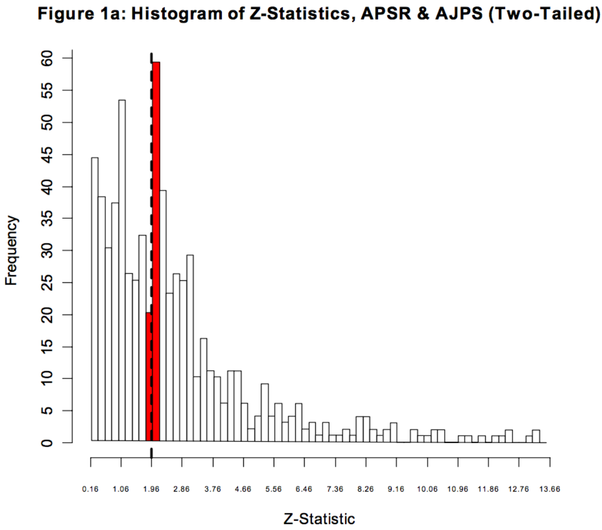
- they lead to publication filtering on arbitrary cutoffs.

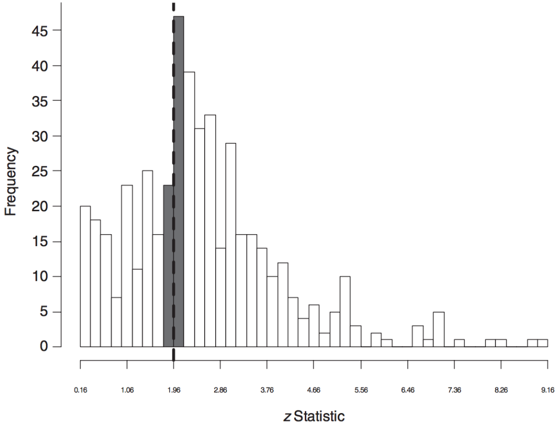
Arbitrary Cutoffs



Gerber and Malhotra (2006) Top Political Science Journals

Arbitrary Cutoffs

Figure 1
Histogram of *z* Statistics From the *American Sociological Review*, the *American Journal of Sociology*, and *The Sociological Quarterly* (Two-Tailed)



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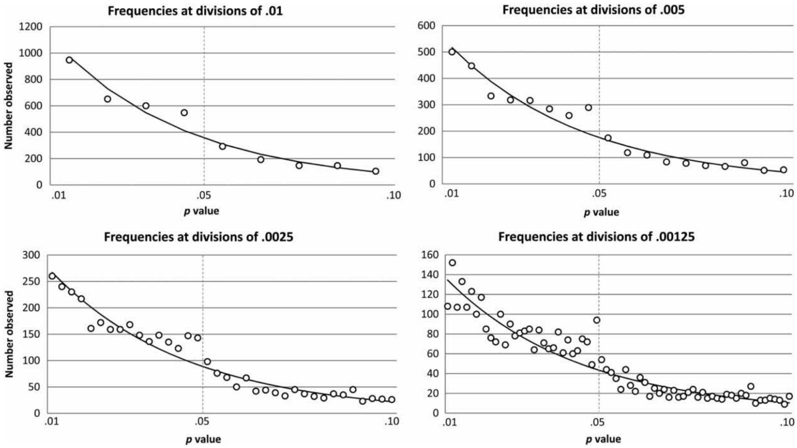

Figure 1.. *The graphs show the distribution of 3,627* p *values from three major psychology journals.*

Masicampo and Lalande (2012) Top Psychology Journals

Still Not Convinced?
The Real Harm of Misinterpreted p-values

ELSEVIER

Accident Analysis and Prevention 36 (2004) 495–500

ACCIDENT ANALYSIS & PREVENTION

www.elsevier.com/locate/aap

Viewpoint

The harm done by tests of significance

Ezra Hauer*

35 Merton Street, Apt. 1706, Toronto, Ont., Canada M4S 3G4

Abstract

Three historical episodes in which the application of null hypothesis significance testing (NHST) led to the mis-interpretation of data are described. It is argued that the pervasive use of this statistical ritual impedes the accumulation of knowledge and is unfit for use.

Keywords: Significance; Statistical hypothesis; Scientific method

Example from Hauer: Right-Turn-On-Red

Table 1
The Virginia RTOR study

	Before RTOR signing	After RTOR signing
Fatal crashes	0	0
Personal injury crashes	43	60
Persons injured	69	72
Property damage crashes	265	277
Property damage (US$)	161243	170807
Total crashes	308	337

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- Core issue is that lack of significance is not an indication of a zero effect, it could also be a lack of power (i.e. a small sample size relative to the difficulty of detecting the effect)

The Point in Hauer

- Two other interesting examples in Hauer (2004)
- Core issue is that lack of significance is not an indication of a zero effect, it could also be a lack of power (i.e. a small sample size relative to the difficulty of detecting the effect)
- On the opposite end, large tech companies essentially never use significance testing because they have huge samples which essentially always find some non-zero effect. But that doesn't make the effect significant in a colloquial sense of important.

P-values and Confidence Intervals

P-values one of most used tests in the social sciences–and you're telling me not to rely on them?

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- Basically, yes.

P-values and Confidence Intervals

What's the matter with you?

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- Two reasons not to worship p-values [of many]
  1) Statistical: they represent a very specific quantity under a null distribution. If you don't really care about rejecting just that null, then you should focus on providing more information
  2) Substantive: p-values are divorced from your quantity of interest–which almost always should relate to how much an intervention changes a quantity of social scientific interest (Grandparent rule)

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P-values and Confidence Intervals

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1) Me too, good luck.
2) That's not what p-values measure
3) No one study is going to eliminate an entire hypothesis; even if that study generates a really small p-value, you'd probably want an entirely different infrastructure

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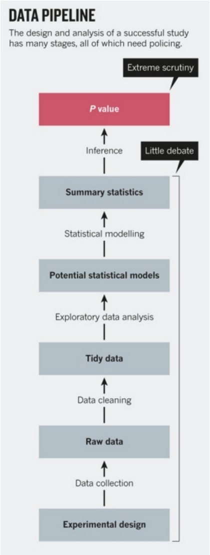
Why?

1) Substantive significance and statistical significance simultaneously
2) Make comparisons across factors approximately and accurately (though exercise caution)
3) Harder to hide weird looking effects

But Let's Not Obsess Too Much About p-values



From Leek and Peng (2015) "*P* values are just the tip of the iceberg" *Nature*.

An Intro Motivation

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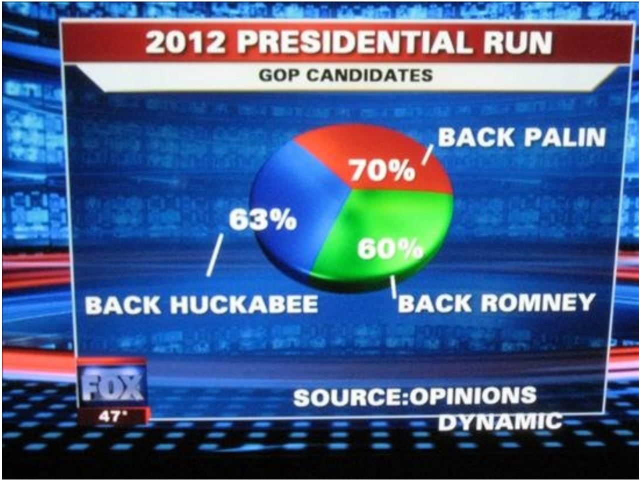

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  2. estimate quantities of interest

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- Good design involves thinking carefully about the audience

Examples via Gelman

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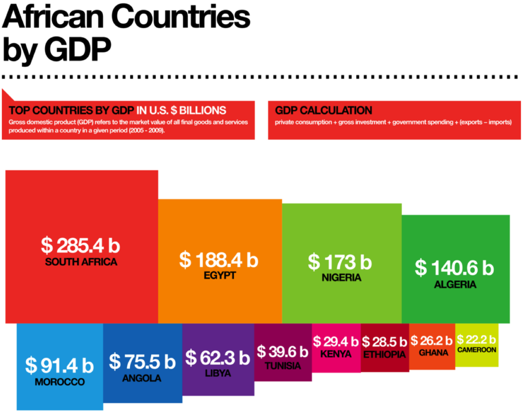

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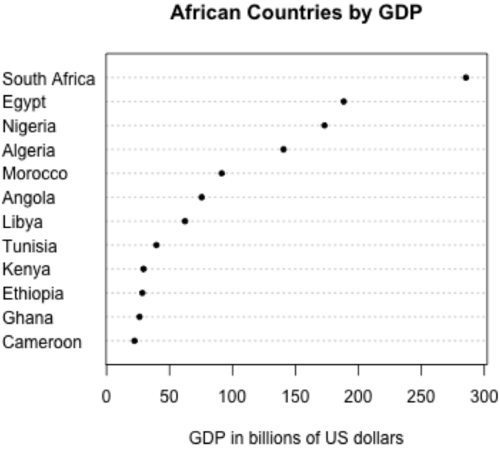
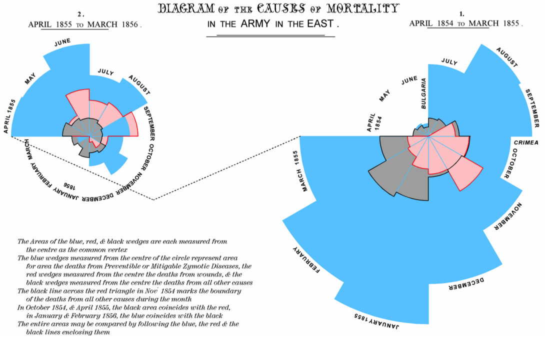


One may be better for drawing people in, the other for evidence.

Examples via Gelman



A classic infographic by Nightingale. Dramatizes the problem.

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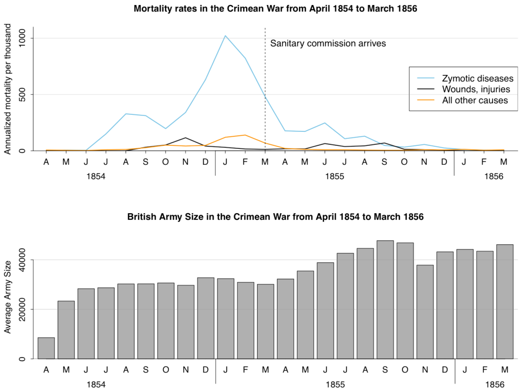

A simpler version where it is easier to see the patterns.

How Not to Present Statistical Results

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TABLE 1
Predicting Which Ethnic Group Conquered Most of Bosnia

Attention to Bosnia crisis	.609**
Age	.007**
Education	.289**
Family income	.151**
Race (non-White/White)	.695**
Gender (female/male)	.789**
Region (South/non-South)	.076
Network coverage	.000
Education × Time	–.003*
Time in months	.078**
Constant	–9.257**
Number	7,021
–2 log-likelihood	7,215.231
Goodness of fit	6,789.45
Cox & Snell R^2	.212
Nagelkerke R^2	.295
Overall correct classification (%)	73.96

SOURCE: *Times Mirror* polls from September 1992, January 1993, September 1993, January 1994, and June 1995.
NOTE: Unstandardized coefficients for logistic regression. Dependent variable is knowledge of which group conquered most of Bosnia.
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- What does the star-gazing add?

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*$p \leq .05$, two-tailed. **$p \leq .01$, two-tailed.

- What does the star-gazing add?
- Can any be interpreted as causal estimates?

How Not to Present Statistical Results: Continued

TABLE 1
Predicting Which Ethnic Group Conquered Most of Bosnia

Attention to Bosnia crisis	.609**
Age	.007**
Education	.289**
Family income	.151**
Race (non-White/White)	.695**
Gender (female/male)	.789**
Region (South/non-South)	.076
Network coverage	.000
Education × Time	–.003*
Time in months	.078**
Constant	–9.257**
Number	7,021
–2 log-likelihood	7,215.231
Goodness of fit	6,789.45
Cox & Snell R^2	.212
Nagelkerke R^2	.295
Overall correct classification (%)	73.96

SOURCE: *Times Mirror* polls from September 1992, January 1993, September 1993, January 1994, and June 1995.
NOTE: Unstandardized coefficients for logistic regression. Dependent variable is knowledge of which group conquered most of Bosnia.
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- What does the star-gazing add?
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- Can you compute a quantity of interest from these numbers?

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4. King, Tomz, Wittenberg, "Making the Most of Statistical Analyses: Improving Interpretation and Presentation" *American Journal of Political Science*, Vol. 44, No. 2 (March, 2000): 341-355.

How to Calculate Quantities of Interest

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- Parametric simulation uses the estimated coefficients and variance-covariance matrix to simulate outcomes (we will cover this in Soc504)
- Non-parametric simulation uses the bootstrap. Calculate the quantity of interest within each bootstrap sample and then aggregate to get an estimate of the variance.

Visualization

Looking at data

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Looking at data

- Most basic method of inference

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- Most basic method of inference
- Hardest method of inference

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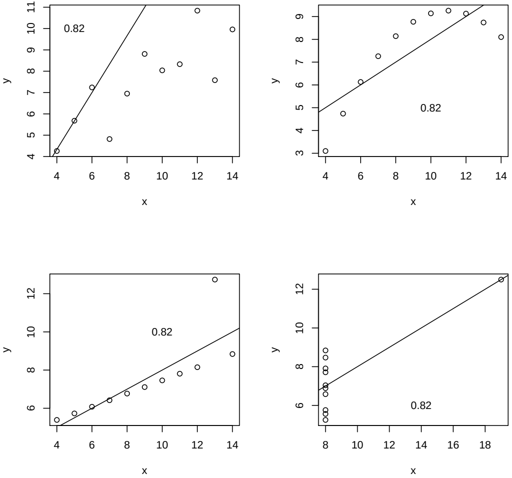
Four (related) reasons

Reason 1: Models Lie

Remember anscombe's quartet?



Reason 2: Delivery of Information

	x	y
1	-10.00000	-95.89003
2	-9.00000	-82.65720
3	-8.00000	-62.42655
4	-7.00000	-40.87958
5	-6.00000	-26.67474
6	-5.00000	-22.43607
7	-4.00000	-24.55663
8	-3.00000	-16.21567
9	-2.00000	-5.69815
10	-1.00000	5.80266
11	0.00000	-6.36366
12	1.00000	0.83601
13	2.00000	4.10150
14	3.00000	0.79349
15	4.00000	-19.63152
16	5.00000	-17.76795
17	6.00000	-41.61587
18	7.00000	-43.49159
19	8.00000	-68.36981
20	9.00000	-88.86339
21	10.00000	-101.64692

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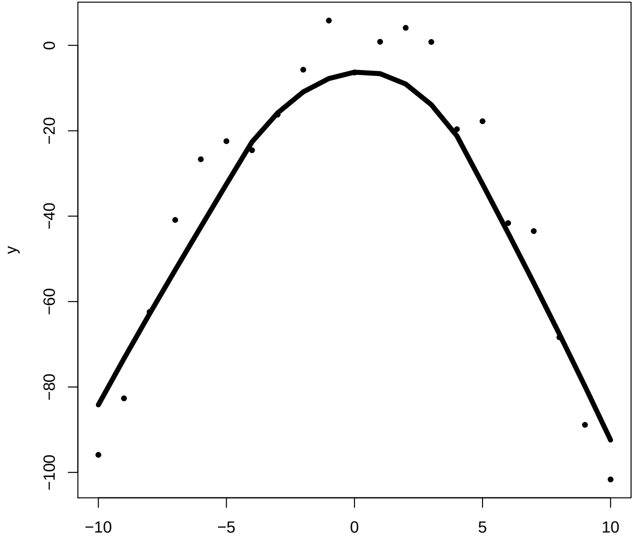

Reason 3: Model Skepticism

Reason 3: Model Skepticism and Checking

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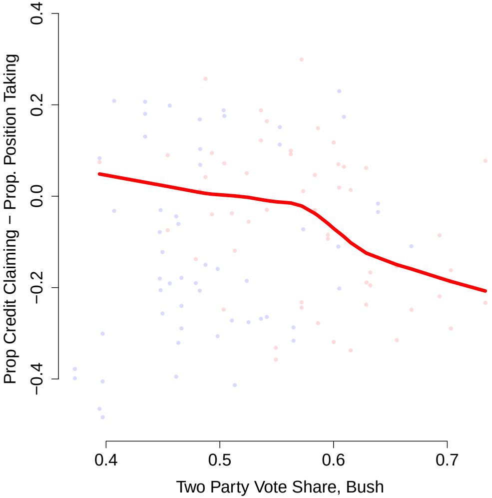
Reason 3: Model Skepticism and Checking

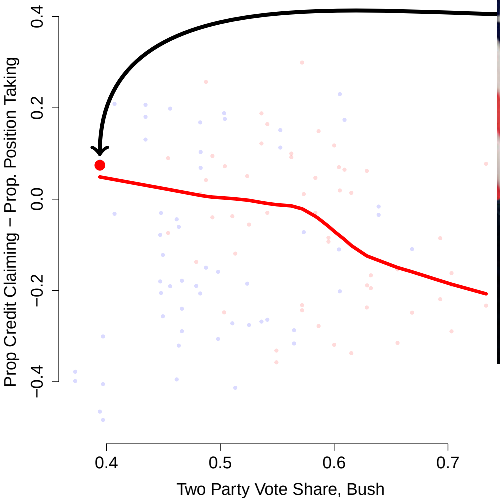
All inferences rest on assumption–visualization is a particularly reliable method for identifying obvious violations

Reason 4: Presentation and Persuasion



Example from Justin Grimmer's work.

Reason 4: Presentation and Persuasion



Lincoln Chafee, (R-RI)

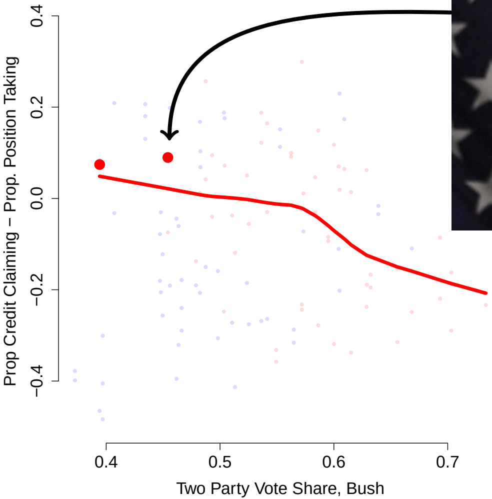
33% Credit Claiming

26% Position Taking

Airport Grants

Example from Justin Grimmer's work.

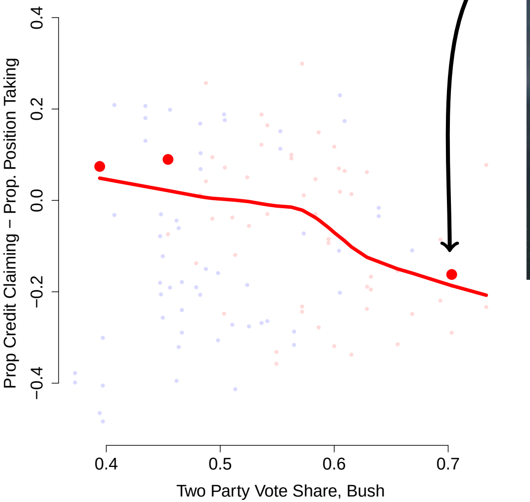
Reason 4: Presentation and Persuasion



Susan Collins, (R-RI)
29% Credit Claiming
20% Position Taking
Airport Grants

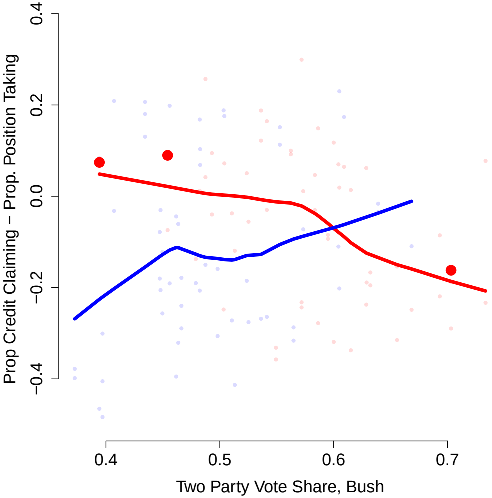
Example from Justin Grimmer's work.

Reason 4: Presentation and Persuasion



Mike Enzi, (R-WY)
18% Credit Claiming
35% Position Taking
Tax Reform

Reason 4: Presentation and Persuasion



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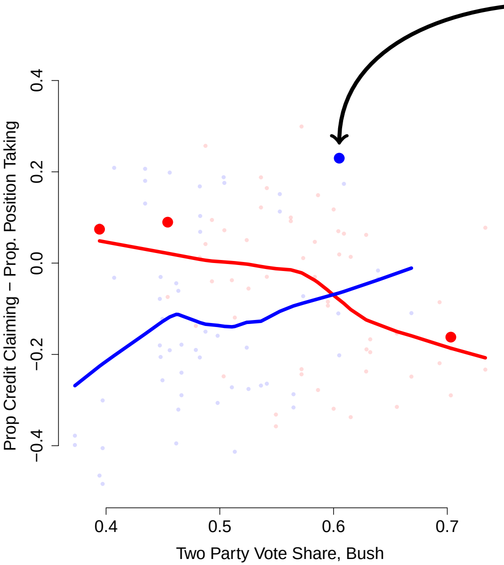
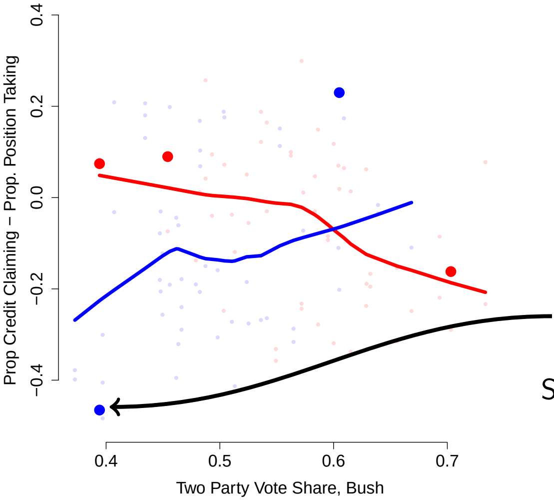


John Tester, (D-MT)
43% Credit Claiming
20% Position Taking
Water Grants

Example from Justin Grimmer's work.

Reason 4: Presentation and Persuasion



Sheldon Whitehouse, (D-RI)
8% Credit Claiming
54% Position Taking
Iraq War

Example from Justin Grimmer's work.

Power, *p*-values and quantities of interest

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- Many of these concerns have motivated a turn towards causal inference

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- The difference between prediction and causal inference is the intervention on the system under study
- Like it or not, social science theories are almost always expressed as causal claims: e.g. "an increase in X causes an increase in Y"
- The study of causal inference helps us understand the assumptions we need to make this kind of claim.

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- This means the relevant question is "what's your identification strategy?" or what are the set of assumptions that let you claim you've estimated a causal effect?
- As we will see this is not a conversation about estimation (in other words the answer cannot be "regression")

Identification vs. Estimation

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- Even when identification is possible, estimation may impose additional assumptions (i.e. regression)
- Law of Decreasing Credibility (Manski): The credibility of inference decreases with the strength of the assumptions maintained

Next Time

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- Causal inference is tricky and I highly recommend you take a look at Morgan and Winship Chapter 1 before class.

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- They use very simple (statistical) methods to great effect.
- This line of work is one of my favorites.

Sequence of slides that follow courtesy of King, Pan and Roberts

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Either or both could be right or wrong.

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(They also censor 2 other smaller categories)

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  - (Carefully) revisit each later to determine if it was censored
  - Use computer-assisted methods of text analysis (some existing, some new, all adapted to Chinese)

Censorship is not Ambiguous: BBS Error Page

For 2 Unusual Topics: Constant Censorship Effort

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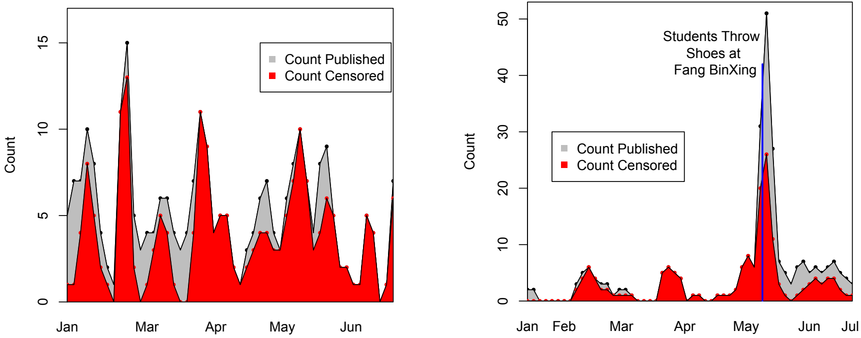

Pornography

Criticism of the Censors

All other topics: Censorship & Post Volume are "Bursty"

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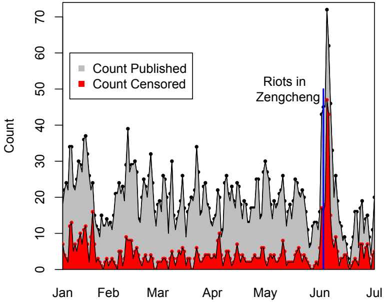

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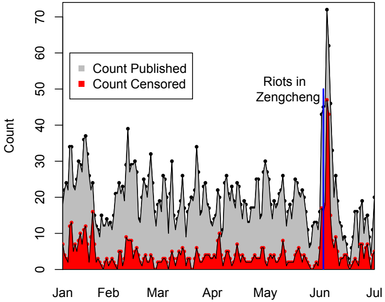

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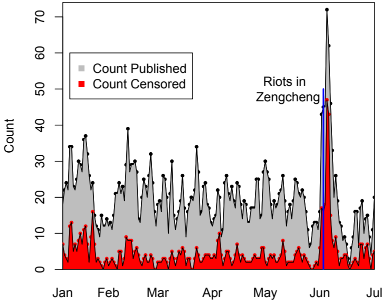

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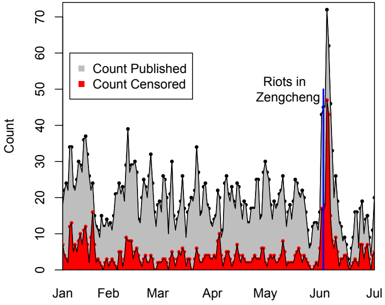

- Unit of analysis:
  - volume burst
  - (≈ 3 SDs greater than baseline volume)

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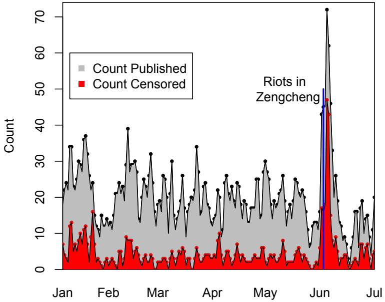

- Unit of analysis:
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  - ($\approx$ 3 SDs greater than baseline volume)
- They monitored 85 topic areas (Jan–July 2011)

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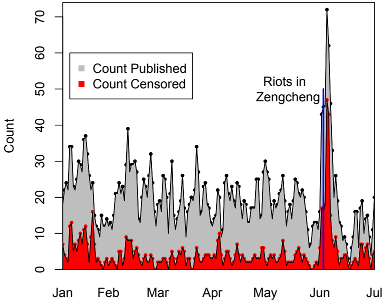

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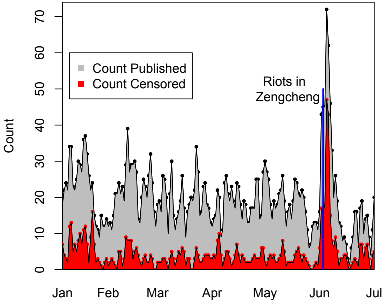

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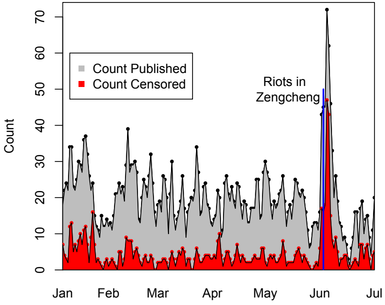

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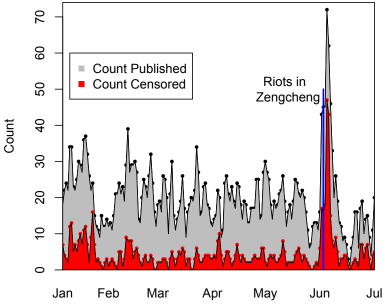

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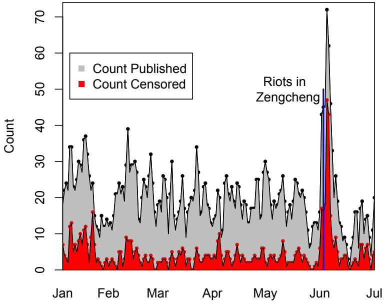

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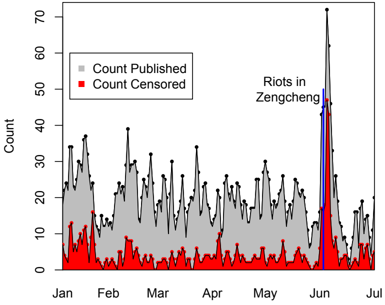

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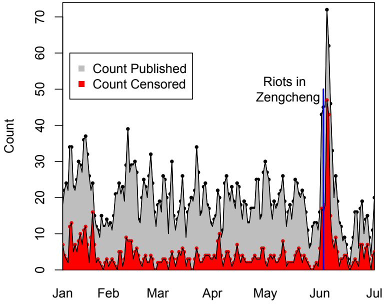

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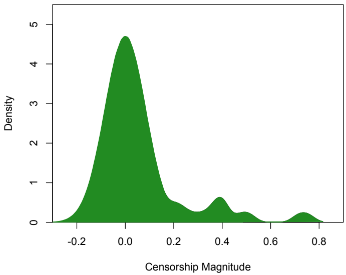

Observational Test 2: The Event Generating Volume Bursts

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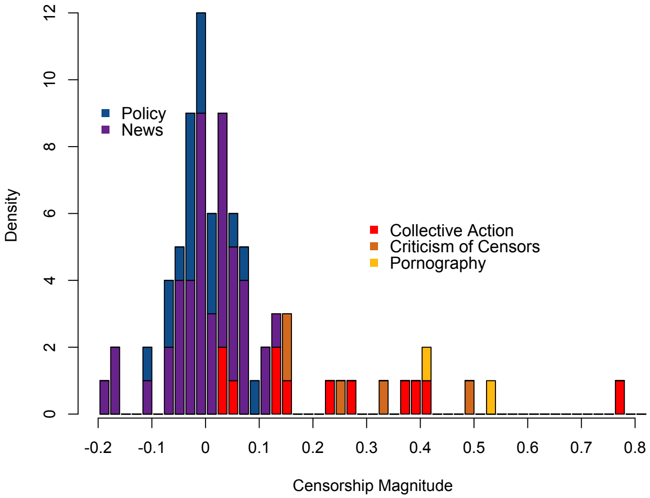
What Types of Events Are Censored?



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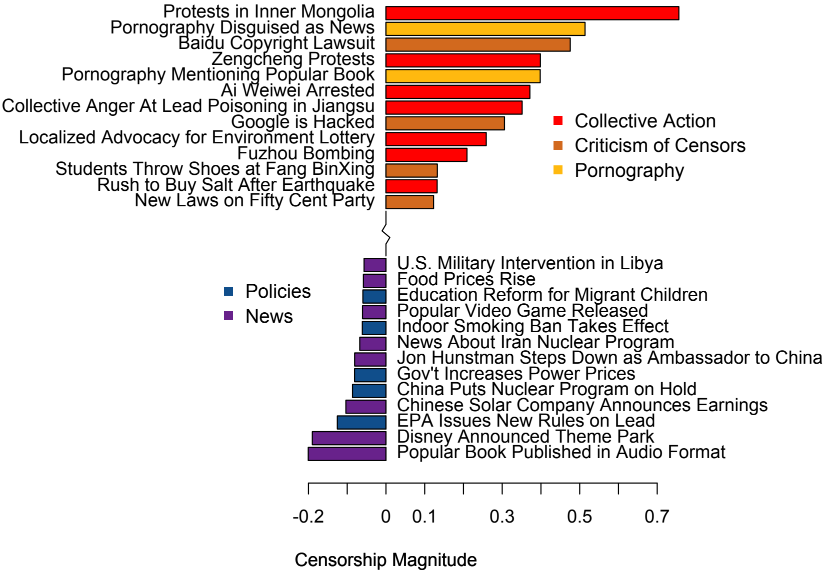
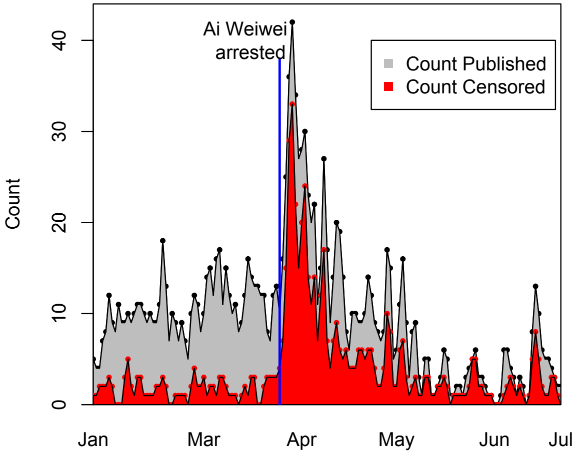
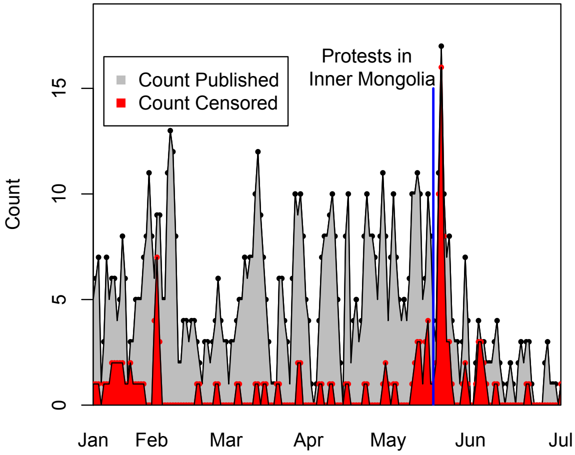


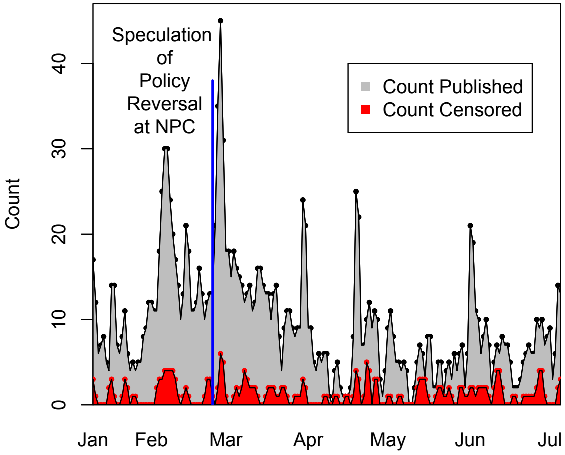
Censoring Collective Action: Ai Weiwei's Arrest



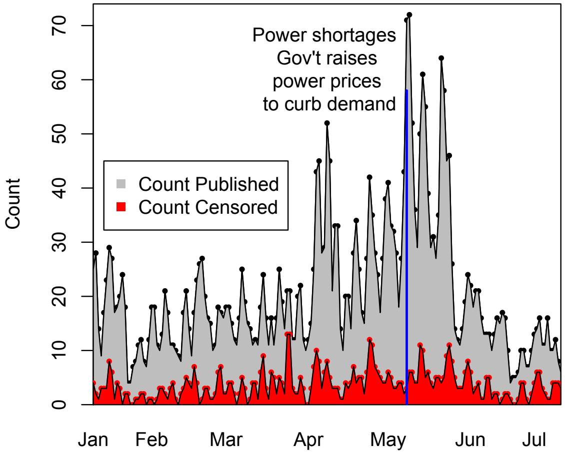
Censoring Collective Action: Protests in Inner Mongolia



Low Censorship on One Child Policy



Low Censorship on News: Power Prices



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Where We've Been and Where We're Going...

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- Last Week
  - matrix form of linear regression
  - inference and F-tests

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  - regression $\rightarrow$ diagnostics $\rightarrow$ causal inference

Questions?

Causation

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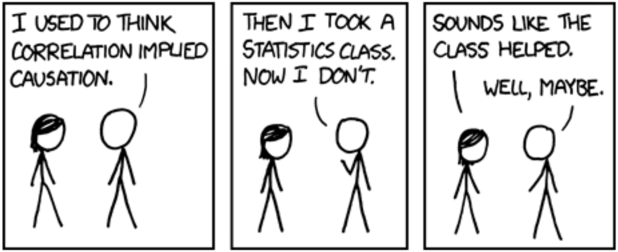
I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.

Neyman-Rubin Potential Outcomes Model

Figure: Neyman

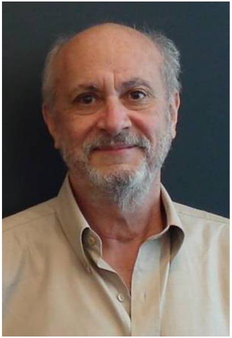

Figure: Rubin

Neyman-Rubin Model

Two possible conditions:

Neyman-Rubin Model

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Two possible conditions:

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Definition: no differences between treatment and control worlds

A Concrete Example

A Concrete Example

Job Training Programs:

A Concrete Example

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- Treatment: Receive job training ($T = 1$)

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Response: Income (Dollars per year)

A Concrete Example

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- Treatment: Receive job training ($T = 1$)
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Response: Income (Dollars per year)

	Treatment ($Y_i(1)$)	Control ($Y_i(0)$)
Person 1	45,000	32,000
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Compare responses in hypothetical worlds

Fundamental Problem of Causal Inference

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Causal Effect:

Fundamental Problem of Causal Inference

Causal Effect:

Response Under Treatment - Response Under Control

Fundamental Problem of Causal Inference

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Job Training Program:

Fundamental Problem of Causal Inference

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Fundamental Problem of Causal Inference

Causal Effect:

Response Under Treatment - Response Under Control

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Fundamental Problem of Causal Inference

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Fundamental Problem of Causal Inference (Holland (1986)):

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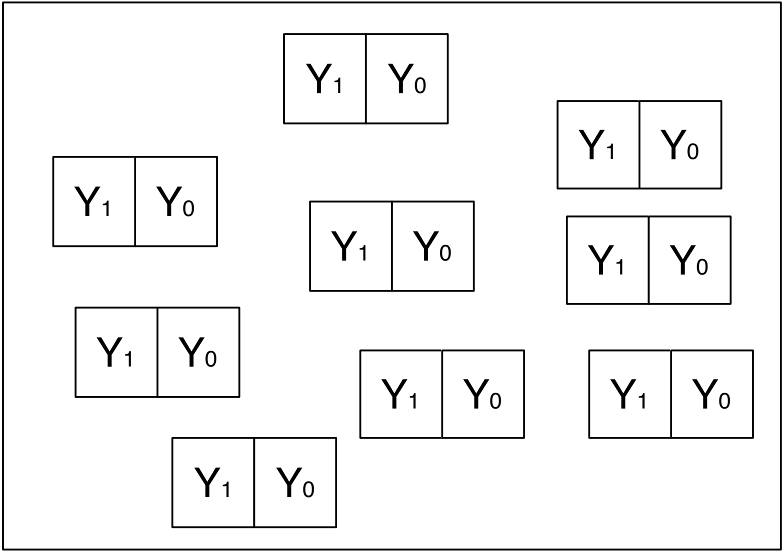
Fundamental Problem of Causal Inference (Holland (1986)):

It is impossible to observe both $Y_i(1)$ and $Y_i(0)$

Neyman Urn Model



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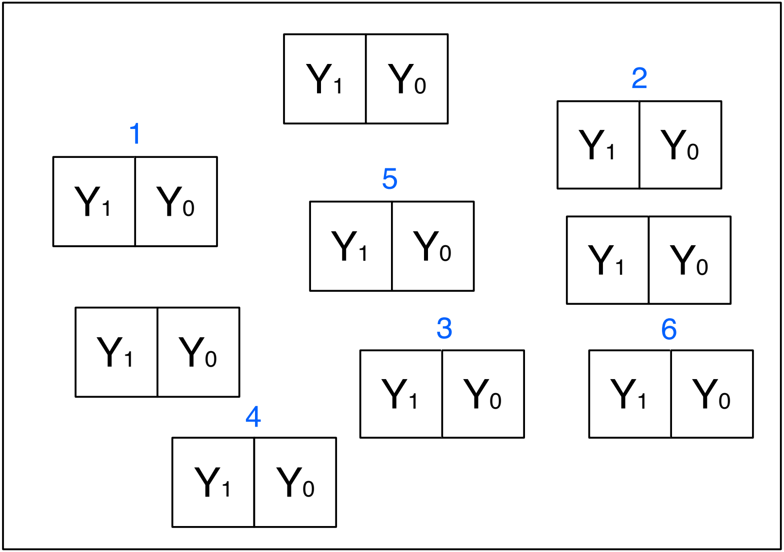

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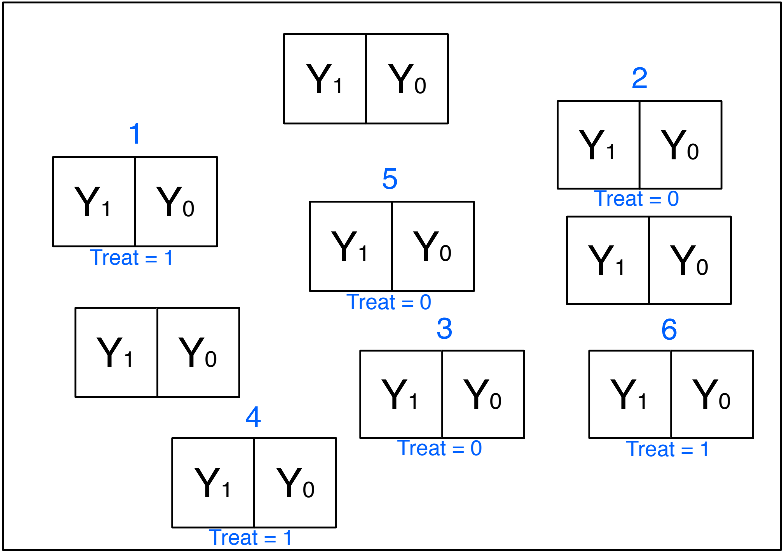

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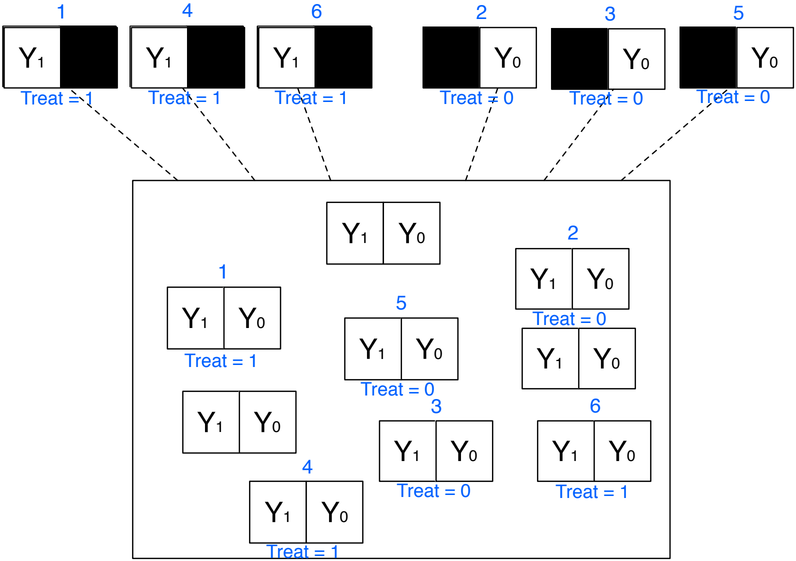

Some Useful Terms

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Definition (Treatment)

D_i: Indicator of treatment intake for unit i

$$D_i = \begin{cases} 1 & \text{if unit } i \text{ received the treatment} \\ 0 & \text{otherwise.} \end{cases}$$

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Definition (Potential Outcome)

Y_{0i} and Y_{1i}: Potential outcomes for unit i

$$Y_{di} = \begin{cases} Y_{1i} & \text{Potential outcome for unit } i \text{ with treatment} \\ Y_{0i} & \text{Potential outcome for unit } i \text{ without treatment} \end{cases}$$

Some Useful Terms

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Definition (Causal Effect)

Causal effect of the treatment on the outcome for unit i is the difference between its two potential outcomes:

$$\tau_i = Y_{1i} - Y_{0i}$$

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Definition (Causal Effect)

Causal effect of the treatment on the outcome for unit i is the difference between its two potential outcomes:

$$\tau_i = Y_{1i} - Y_{0i}$$

Assumption

Observed outcomes are realized as

$$Y_i = D_i \cdot Y_{1i} + (1 - D_i) \cdot Y_{0i} \textit{ so } Y_i = \begin{cases} Y_{1i} & \textit{if } D_i = 1 \\ Y_{0i} & \textit{if } D_i = 0 \end{cases}$$

Causal Inference as a Missing Data Problem

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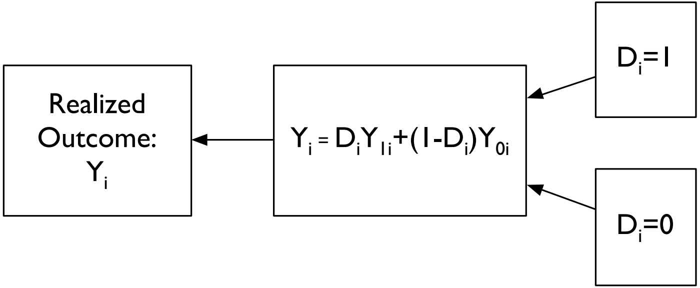

Fundamental Problem of Causal Inference

Cannot observe both potential outcomes, so we how can we calculate $\tau_i = Y_{1i} - Y_{0i}$?

Causal Inference as a Missing Data Problem

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In social phenomenon, unfortunately, homogeneity is very rare.

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- Naive estimator = Average Treatment Effect on Treated + Selection Bias
- Selection bias: how different the treated and control groups are in terms of their potential outcome under control.

Selection Makes Us Care About Assignment Mechanisms

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Assignment Mechanism

"The process that determines which units receive which treatments, hence which potential outcomes are realized and thus can be observed, and, conversely, which potential outcomes are missing."
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Together: (1) and (2) constitute:
SUTVA: Stable Unit Treatment Value Assumption
Also sometimes referred to as the "No Interference" assumption.

The Trouble with Interference

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Let $\mathbf{D} = \{D_i, D_j\}$ be a vector of treatment assignments for two units i (me) and j (you).

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How many potential outcome are observed for unit i?

Since we only observe one of the four potential outcomes, the missing data problem for causal inference is even more severe.

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The No Interference assumption states that unit i's potential outcomes depends on D_i, not $\mathbf{D}$:

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No interference is an example of an **exclusion restriction**. We rely on outside information to rule out the possibility of certain causal effects (eg. you taking the treatment has no effect on my potential outcomes).

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- Displacement
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Causal inference in the presence of interference between subjects is an area of active research. Specially tailored experimental designs have been developed to study these interactions, e.g. Miguel and Kremer (2004) and Sinclair, McConnell, and Green (2012).

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No Causation Without Manipulation

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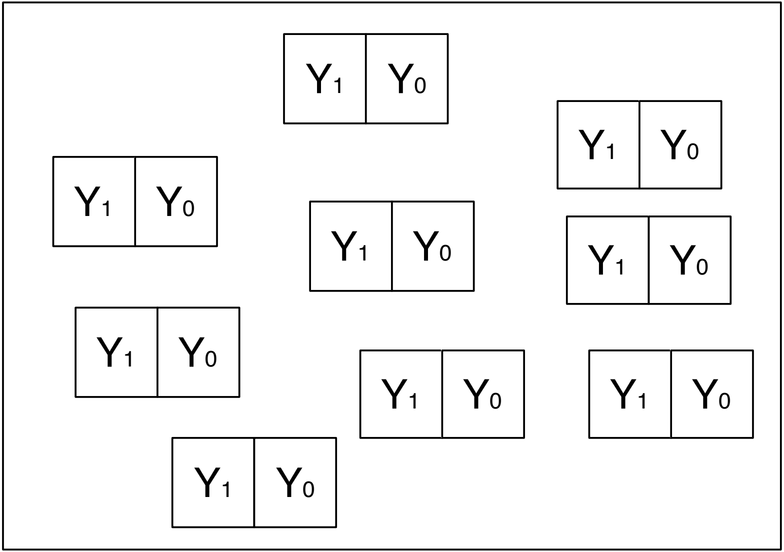
Back to the Neyman Urn Model



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- It is fixed and unchanging

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&= \frac{\sum_{i=1}^{N} Y_i(1) T_i}{\sum_{i=1}^{N} T_i} - \frac{\sum_{i=1}^{N} Y_i(0)(1-T_i)}{\sum_{i=1}^{N}(1-T_i)} \\
&= \sum_{i=1}^{N} [\frac{Y_i(1) T_i}{n_t} - \frac{Y_i(0)(1-T_i)}{n_c}]
\end{aligned}
$$

Estimating ATE under Random Assignment

Estimator for ATE:

$$
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&= \sum_{i=1}^{N} [\frac{Y_i(1) T_i}{n_t} - \frac{Y_i(0)(1 - T_i)}{n_c}] \\
&= E[Y(1)|T = 1] - E[Y(0)|T = 0]
\end{aligned}
$$

Estimands

Because τ_i are unobservable, we shift what we are interested to:

Definition (Average Treatment Effect (ATE))

$$\tau_{ATE} = \text{Average of all treatment potential outcomes} - \text{Average of all control potential outcomes}$$

or

$$\tau_{ATE} = \frac{\sum_i^N Y_{1i}}{N} - \frac{\sum_i^N Y_{0i}}{N}$$

or

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

or

$$\tau_{ATE} = E[\tau_i]$$

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Definition (Average treatment effects for subgroups)

$$\tau_{ATE(X)} = E[Y_{1i} - Y_{0i} | X_i = x]$$

or

$$\tau_{ATT(X)} = E[Y_{1i} - Y_{0i} | D_i = 1, X_i = x]$$

Average Treatment Effect

Imagine a study population with 4 units:

i	D_i	Y_{1i}	Y_{0i}	τ_i
1	1	10	4	6
2	1	1	2	-1
3	0	3	3	0
4	0	5	2	3

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Note: Average effect is positive, but τ_i are negative for some units!

Average Treatment Effect on the Treated

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- units which select treatment may not be like units which select control.
- i.e. selection into treatment is often associated with the potential outcomes
- this means we have violated the assumption of unconfoundness $(Y(1), Y(0)) \perp D$

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- Countries with gender quotas are likely countries where women are politically mobilized.
- Given this difference, policies targeted towards women would be more common in quota countries even if these countries had not adopted quotas.

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Most statistical models of causal inference attain identification of treatment effects by restricting the assignment mechanism in some way.

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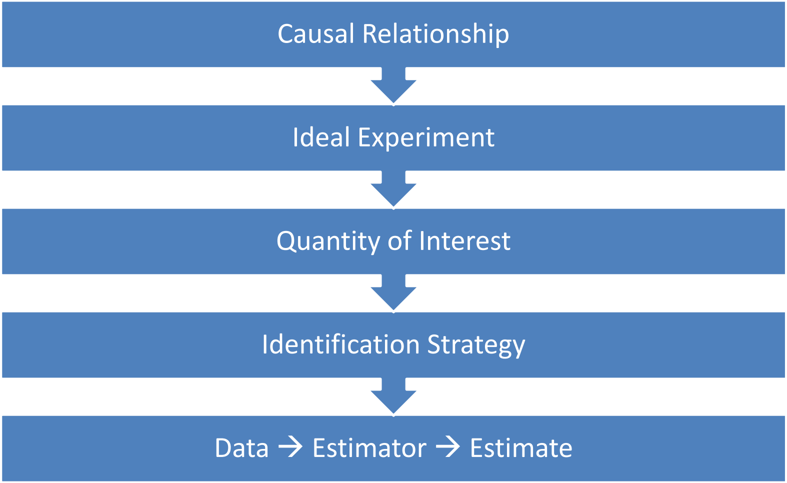
Always ask:
what is the experiment I would run if I had infinite resources and power?

Causal Inference Workflow



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- No assumption of homogeneity, allows for causal effects to vary unit by unit
  - No single "causal effect", thus the need to be precise about the target estimand.
- Distinguishes between <u>observed</u> outcomes and <u>potential</u> outcomes.
- Causal inference is a missing data problem: we typically make assumptions about the assignment mechanism to go from descriptive inference to causal inference.

Summary: Observational Studies and Causal Inference

Experimental studies:

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- Many, many, potential strategies for limiting bias

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- For now while doing diagnostics, it is safest to treat β as a purely descriptive/predictive quantity

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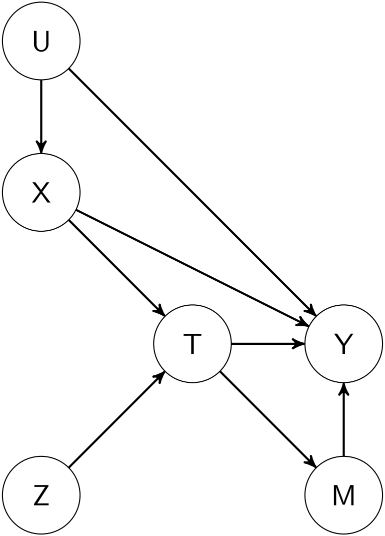
- Nice software that takes the graph and returns an identification strategy: DAGitty at `http://dagitty.net`

Components of a DAG



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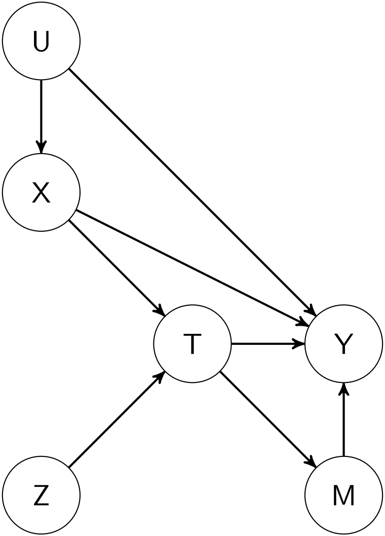

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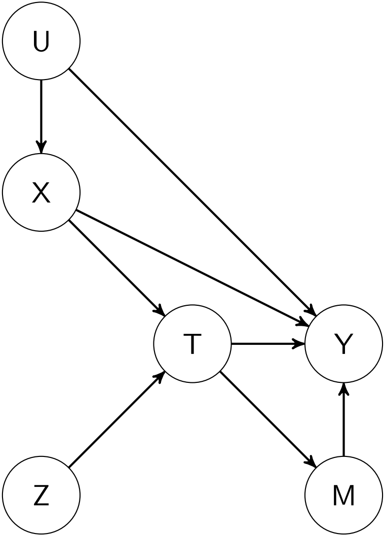

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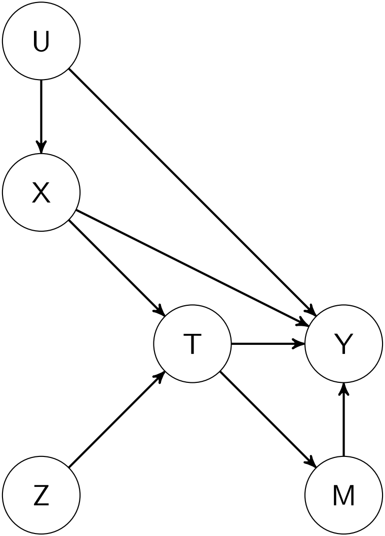

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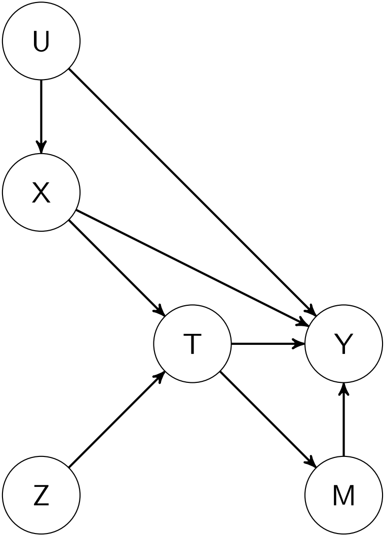

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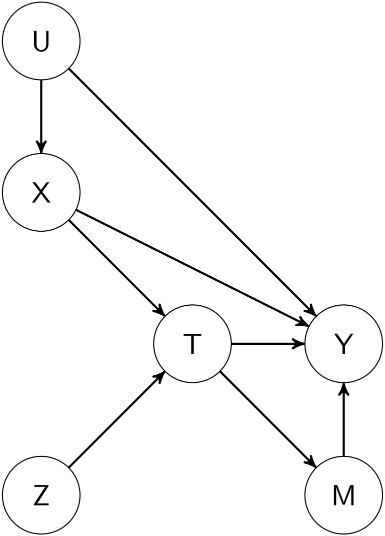

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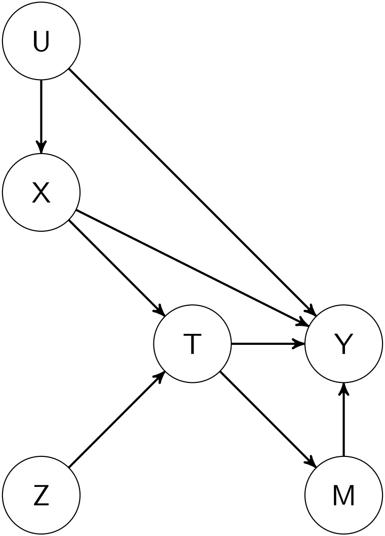

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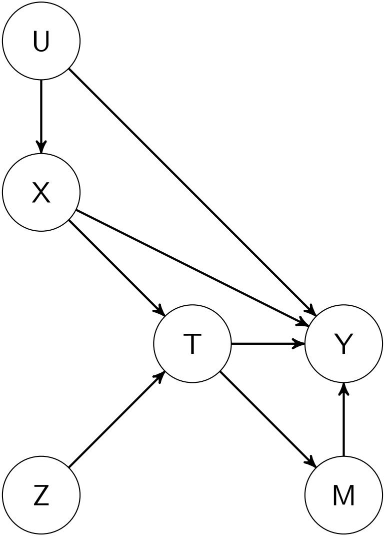

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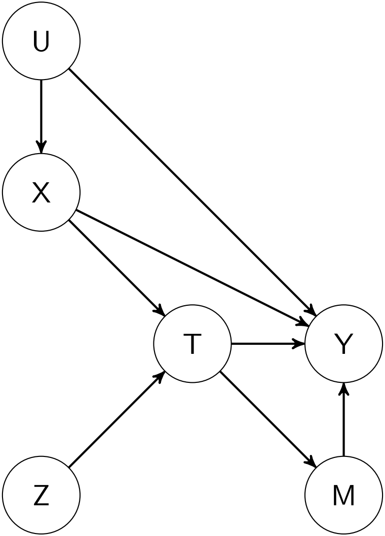

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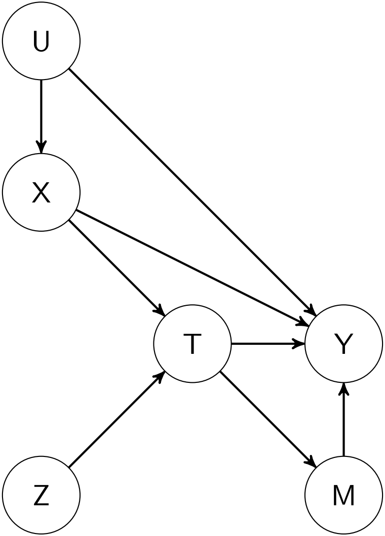
Relationships in a DAG



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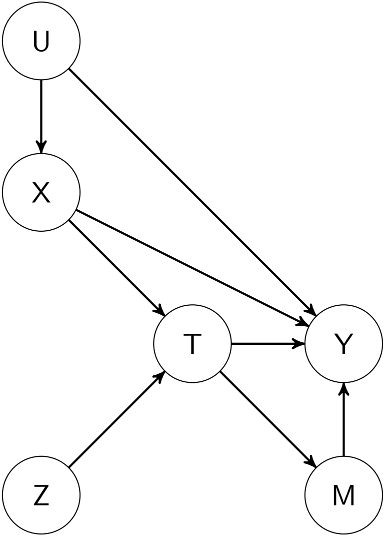

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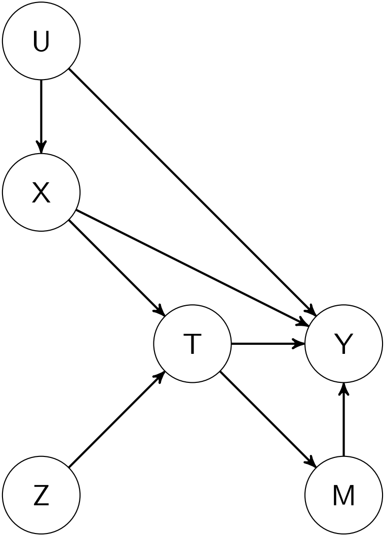

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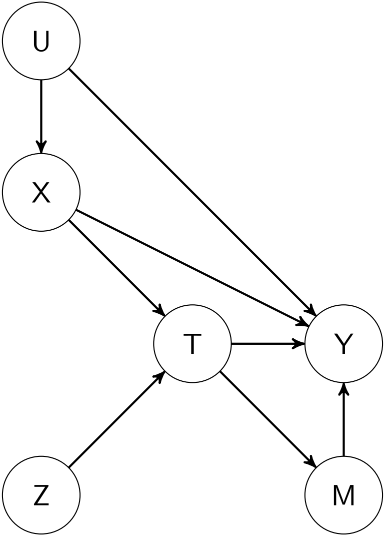

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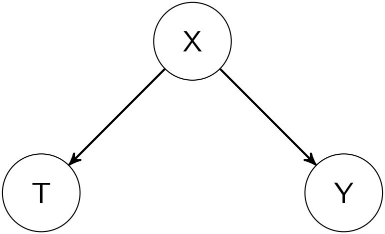
- We will talk in depth about two types of relationships: confounders and colliders

Confounders



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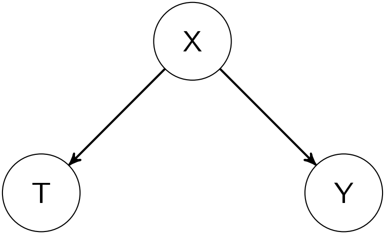

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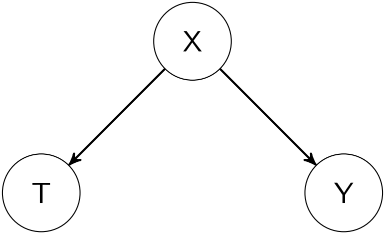

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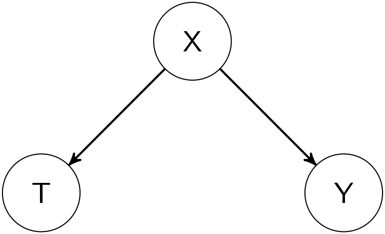

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- We can think of conditioning on a confounder as blocking the flow of association.

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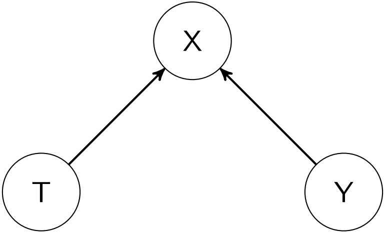

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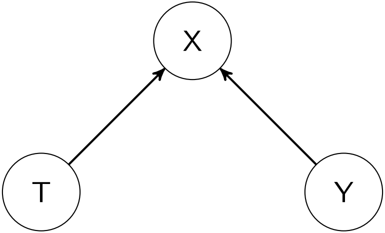

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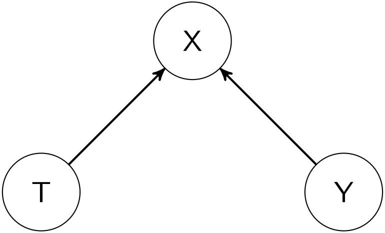

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Colliders are scary because you can induce dependence

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Endogenous Selection Bias: The Problem of Conditioning on a Collider Variable

Felix Elwert[1] and Christopher Winship[2]

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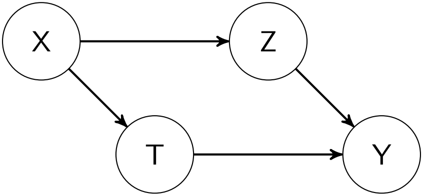
Keywords

causality, directed acyclic graphs, identification, confounding, selection

Abstract

Endogenous selection bias is a central problem for causal inference. Recognizing the problem, however, can be difficult in practice. This article introduces a purely graphical way of characterizing endogenous selection bias and of understanding its consequences (Hernán et al. 2004). We use causal graphs (direct acyclic graphs, or DAGs) to highlight that endogenous selection bias stems from conditioning (e.g., controlling, stratifying, or selecting) on a so-called collider variable, i.e., a variable that is itself caused by two other variables, one that is (or is associated with) the treatment and another that is (or is associated with) the outcome. Endogenous selection bias can result from direct conditioning on the outcome variable, a post-outcome variable, a post-treatment variable, and even a pre-treatment variable. We highlight the difference between endogenous selection bias, common-cause confounding, and overcontrol bias and discuss numerous examples from social stratification, cultural sociology, social network analysis, political sociology, social demography, and the sociology of education.

From Confounders to Back-Door Paths



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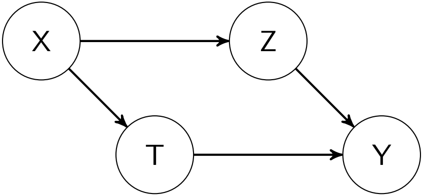

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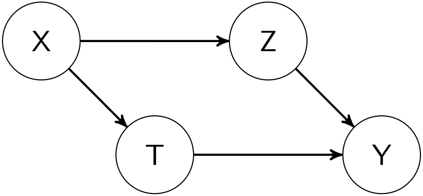

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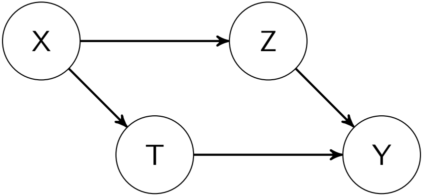

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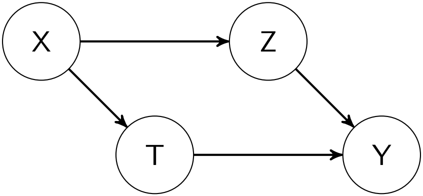

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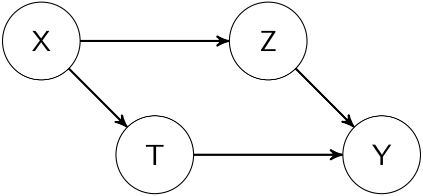

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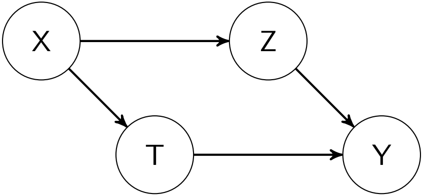

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- We want to block the back-door path to leave only the causal effect

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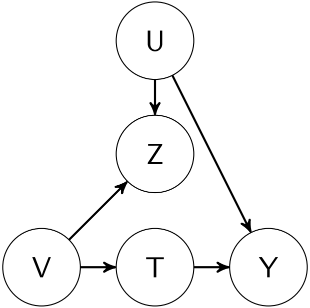

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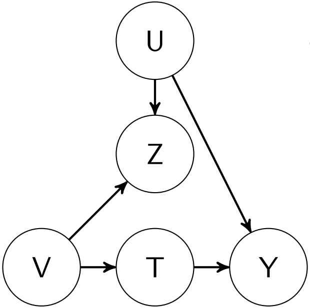

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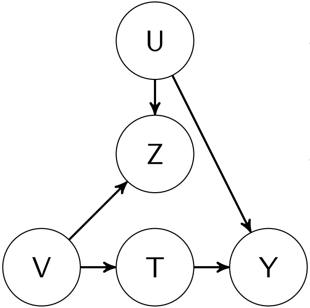

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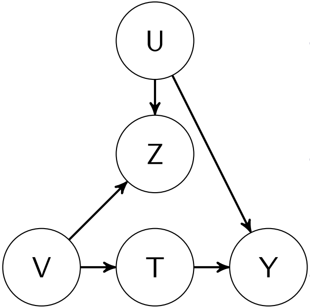

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- So how do we know which back-door paths to block?

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- If A is not D-separated from B by C we say that A is *D*-connected to B by C

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- See also Frontdoor Criterion in the social sciences in work by Glynn and Kashin

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  - Bad: identification results for identification only holds when variable is completely controlled for (which may be difficult!)

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- Reading:
  - Fox Chapters 11-13
  - Optional: Fox Chapter 19 Robust Regression
  - Optional: King and Roberts "How Robust Standard Errors Expose Methodological Problems They Do Not Fix, and What to Do About It." *Political Analysis*, 2, 23: 159179.
  - Optional: Aronow and Miller Chapters 4.2-4.4 (Inference, Clustering, Nonlinearity)
  - Optional: Angrist and Pishke Chapter 8 (Nonstandard Standard Error Issues)

Fun with a Bundle of Sticks

Sen and Wasow (2016) "Race as a Bundle of Sticks: Designs that Estimate Effects of Seemingly Immutable Characteristics" *Annual Review of Political Science*.

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- Sen and Wasow argue that we can improve our empirical work on this by seeing race/ethnicity as a composite variable or ‘a bundle of sticks’ which can be manipulated separately

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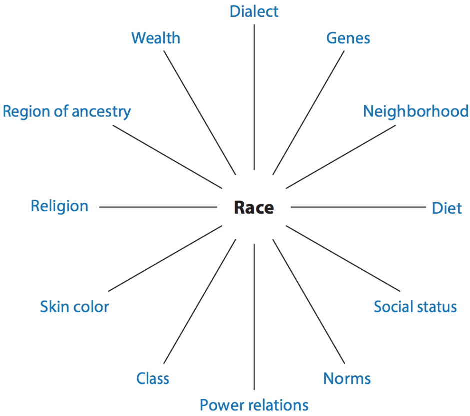
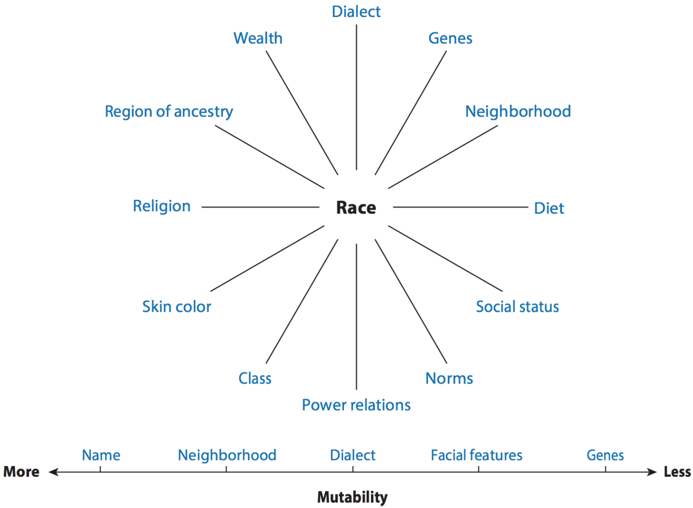


The Bundle of Sticks



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  - Observational Studies (Greiner and Rubin 2010, Wasow 2012)

Design 2: Within-Group Studies

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- Example: Sharkey (2010) exploiting temporal variation in local homicides in Chicago to identify a significant neighborhood effect of proximity to violence on cognitive performance of African-American children

Concluding Thoughts

We can study race with causal inference, it just takes very careful design.

Table 2 Overview of exposure and within-group research designs

	Exposure	Within-Group
Unit	Individuals or institutions, potentially from any group	Members of a particular group
Typical treatment	Racial cue or signal (e.g., include distinctively ethnic names on a resume)	Constitutive element of the composite of race (e.g., address anxiety about social belonging in college)
Role of element of race	One "stick" is a proxy for the bundle (e.g., in a phone call with a landlord, dialect signals many traits associated with race)	One "stick" explains part of the bundle (e.g., Middle Passage might partly explain high rates of hypertension among African-Americans)
Examples	Correspondence and audit studies Implicit Association Tests	Experimental manipulation of a constitutive psychological dimension of race Within-race matching