Week 9: Regression in the Social Sciences and Frameworks for Causal Inference

Brandon Stewart[1]

Princeton

October 26–31, 2020

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

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

- Last Week
  - diagnostics
- This Week
  - making an argument in social sciences
  - causal inference
  - two frameworks: potential outcomes and directed acyclic graphs
  - the experimental ideal
  - causation for non-manipulable variables
- Next Week
  - selection on observables
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

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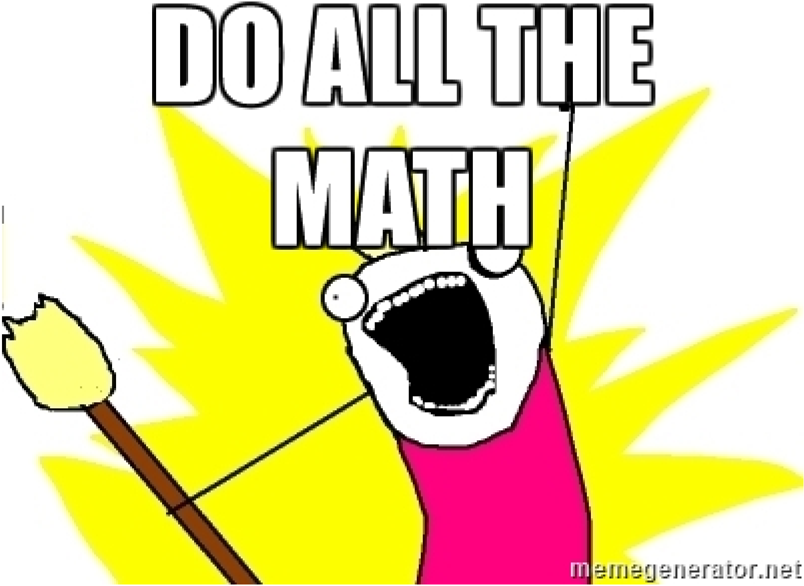
- Knowing how methods work also makes you a better reader of work.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memegenerator.net

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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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- This is because they are about different groups of units not about the same unit under intervention.

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What is the variance of the marginal effect?

$$\begin{aligned} Var\left(\frac{\partial Y}{\partial X}\right) &= Var(\hat{\beta}_1 + Z\hat{\beta}_3) \\ &= Var(\hat{\beta}_1) + Z^2 Var(\hat{\beta}_3) + 2ZCov(\hat{\beta}_1, \hat{\beta}_3) \end{aligned}$$

If this model is fit using the `lm()` function, we can use `vcov(fit)` to extract the variance covariance matrix that has these variance and covariance elements.

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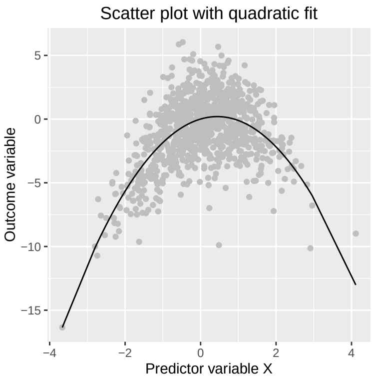
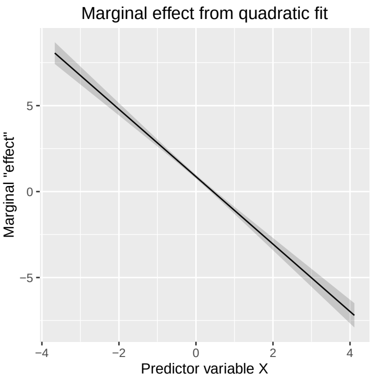
$$\begin{aligned} Var\left(\frac{\partial Y}{\partial X}\right) &= Var(\hat{\beta}_1 + 2X\hat{\beta}_2) \\ &= Var(\hat{\beta}_1) + (2X)^2 Var(\hat{\beta}_2) + 2 * 2X * Cov(\hat{\beta}_1, \hat{\beta}_2) \end{aligned}$$

Plotting Marginal Effects

Given estimated coefficients, we could plot the marginal effect of X on Y as a function of X





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- You can see how this lends itself to improper causal thinking!

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- This will be the subject of the rest of the week but for now let's change gears. . .

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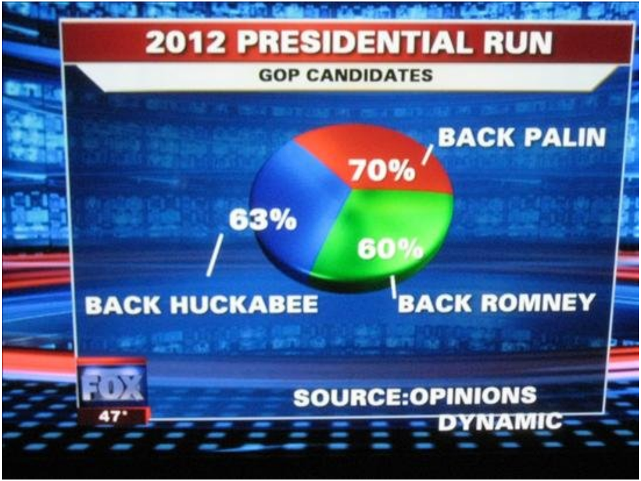

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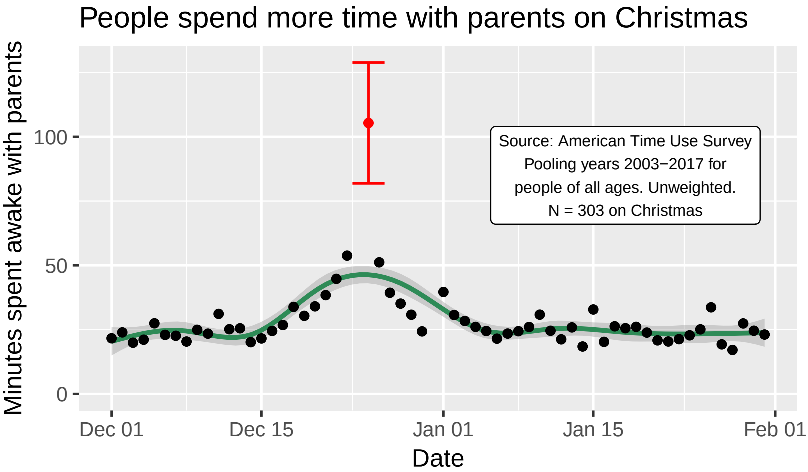
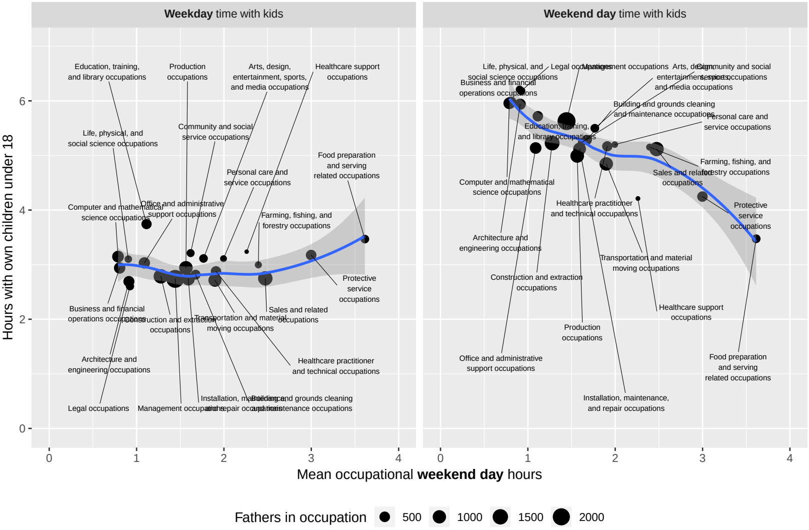
- I strongly recommend Kieran Healy's visualization book — great summary of the fundamentals plus R code.

Examples



Source: Ian Lundberg

Examples



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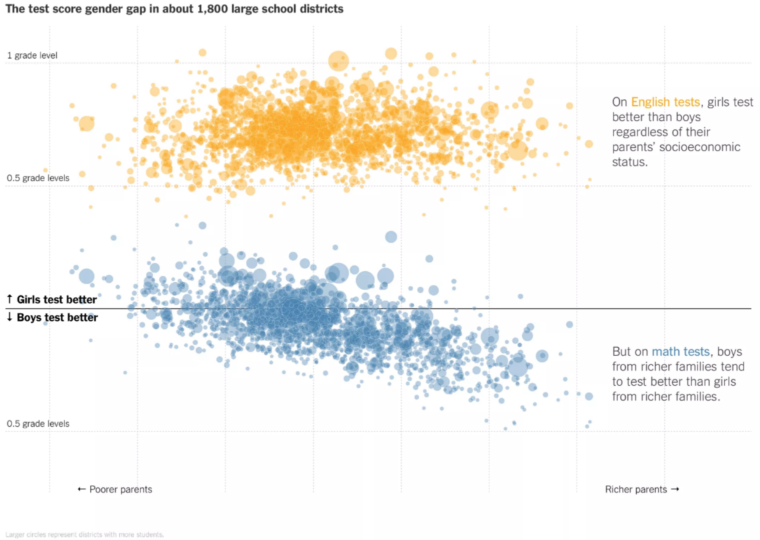
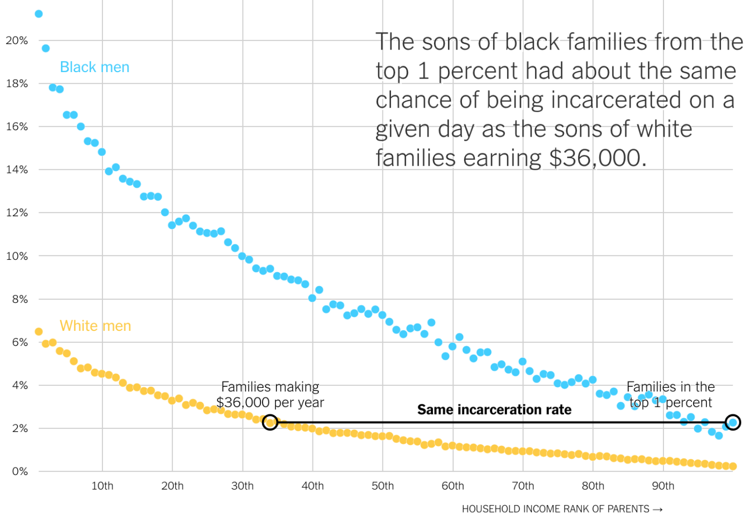


Source: New York Times

Examples



Includes men who were ages 27 to 32 in 2010.

Source: New York Times

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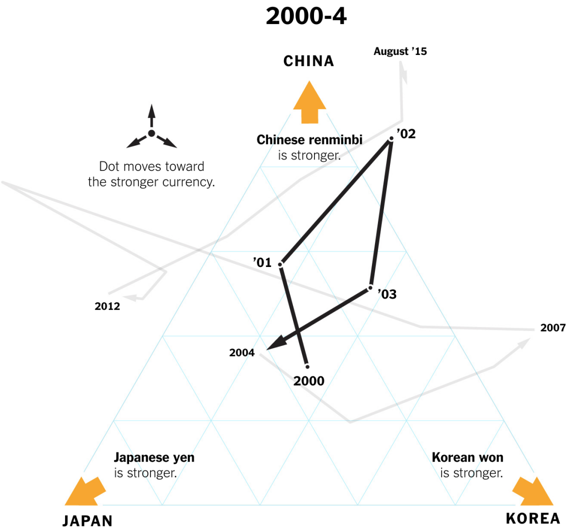

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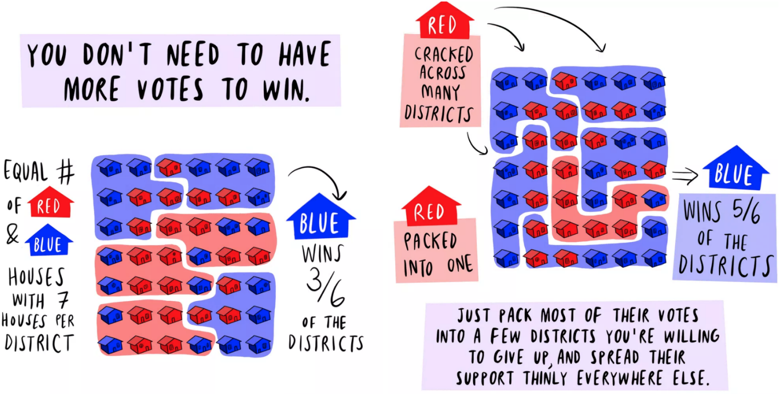
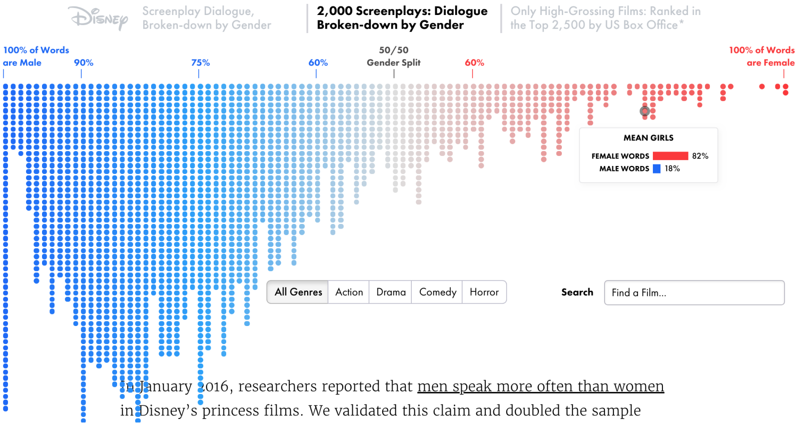


Source: Olivia Walch

Examples



Source: The Pudding

Examples

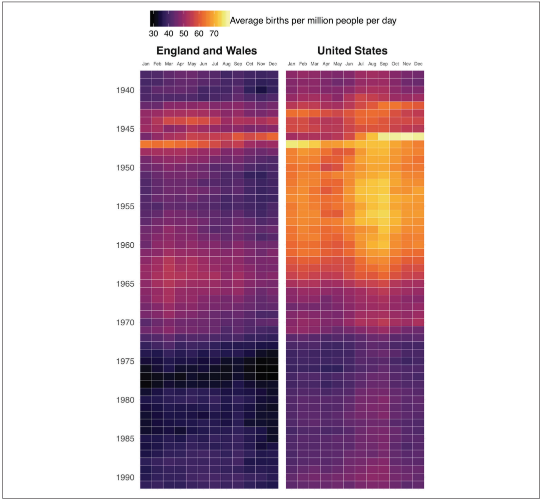
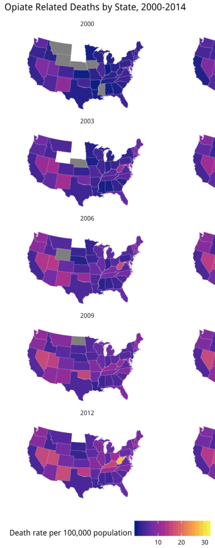


Figure 1. Average births per million people per day, 1938–1991. Each tile represents one month. The underlying count is number of births per month, standardized first by the total population for the period and then by the number of days in that month. Data for the United States are from the U.S. Census Bureau. Data for England and Wales are from the U.K. Office of National Statistics.

Source: Kieran Healy

Examples



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Case Study 1: Visualization in the New York Times

AMERICAS

How Stable Are Democracies? 'Warning Signs Are Flashing

The Interpreter
By AMANDA TAUB NOV. 29, 2016

WASHINGTON — Yascha Mounk is used to being the most pessimistic person in the room. Mr. Mounk, a lecturer in government at Harvard, has spent the past few years challenging one of the bedrock assumptions of Western politics: that once a country becomes a liberal democracy, it will stay that way.

His research suggests something quite different: that liberal democracies around the world may be at serious risk of decline.

Mr. Mounk's interest in the topic began rather unusually. In 2014, he published a book, "Stranger in My Own Country." It started as a memoir of his experiences growing up as a Jew in Germany, but became a broader investigation of how contemporary European nations were struggling to construct new, multicultural national identities.

Case Study 1: Visualization in the New York Times

The Danger of Deconsolidation

THE DEMOCRATIC DISCONNECT

Roberto Stefan Foa and Yascha Mounk

Roberto Stefan Foa *is a principal investigator of the World Values Survey and fellow of the Laboratory for Comparative Social Research. His writing has appeared in a wide range of journals, books, and publications by the UN, OECD, and World Bank.* ***Yascha Mounk*** *is a lecturer on political theory in Harvard University's Government Department and a Carnegie Fellow at New America, a Washington, D.C.–based think tank. His dissertation on the role of personal responsibility in contemporary politics and philosophy will be published by Harvard University Press, and his essays have appeared in* Foreign Affairs, *the* New York Times, *and the* Wall Street Journal.

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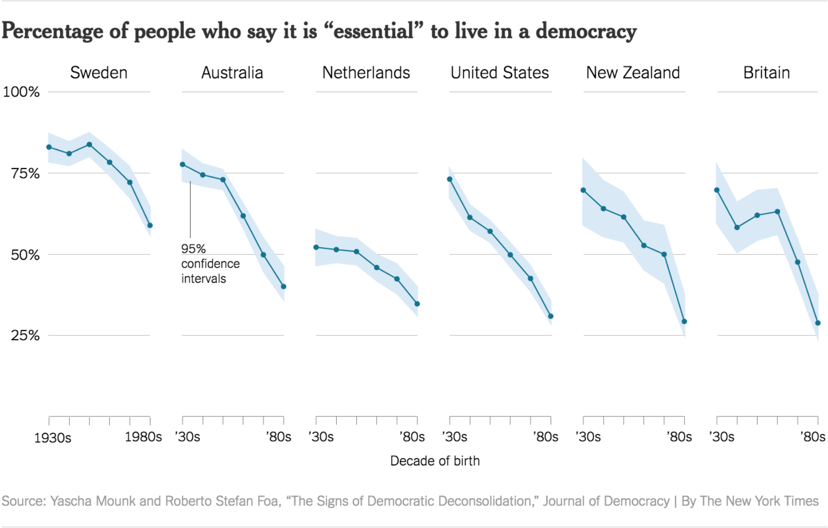
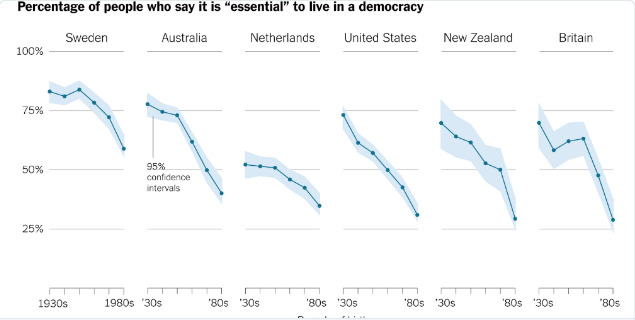


Case Study 1: Visualization in the New York Times

Ryan D. Enos @RyanDEnos · 19h

Lots of worried chatter a/b @amandataub article on work of @Yascha_Mounk. Important, but want to raise cautions 1/

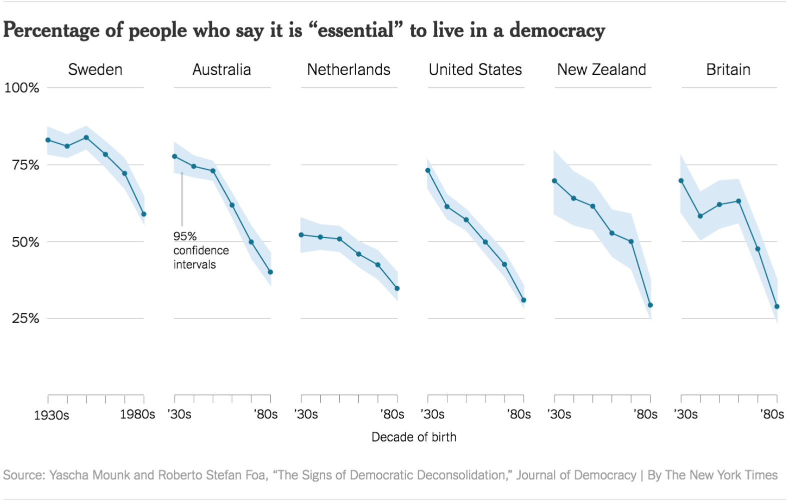


How Stable Are Democracies? 'Warning Signs Are Flashing Red'

New research tries to spot the collapse of liberal democracies before they happen, and it suggests that Western democracy may be seriously ill.

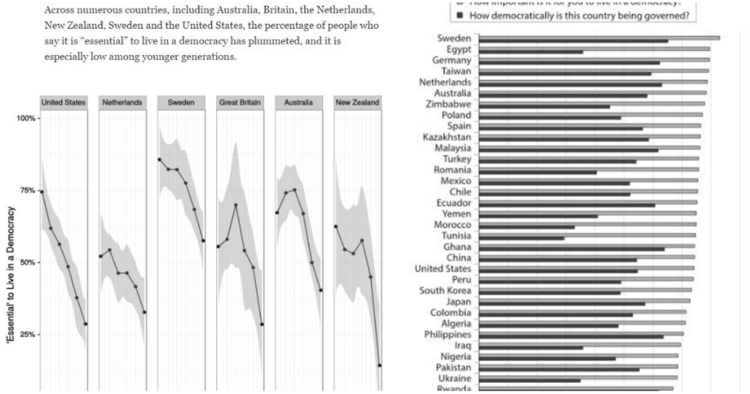
nytimes.com

Alternate Graphs



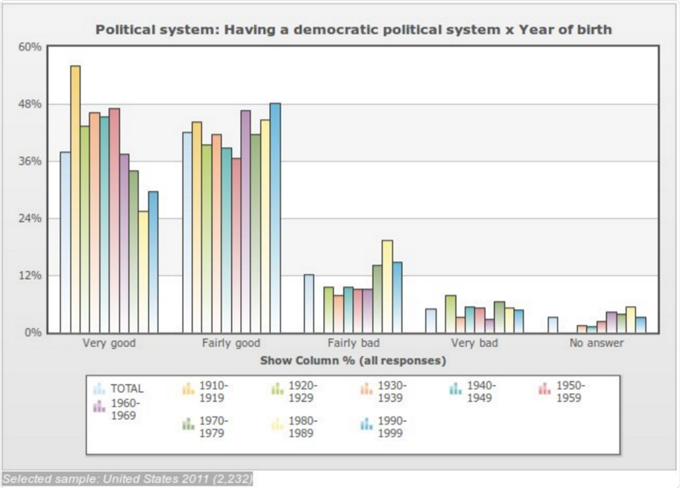
Alternate Graphs

.@RyanDEnos Compare NYT/JoD (left) to the very same data analysed differently by Bartels and Achen (2016) (right). Extreme score vs means.



Alternate Graphs

@RyanDEnos They also stop at the 80s cohort. The data has the 90's as well. I wonder why they would stop there...



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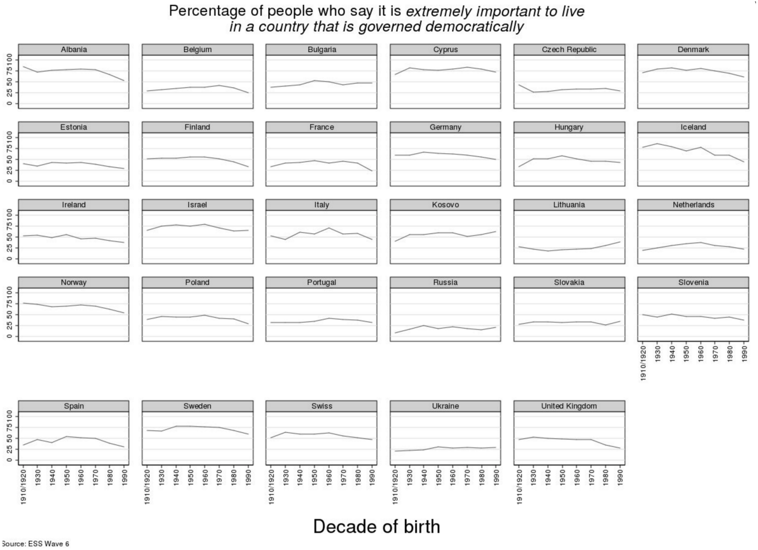
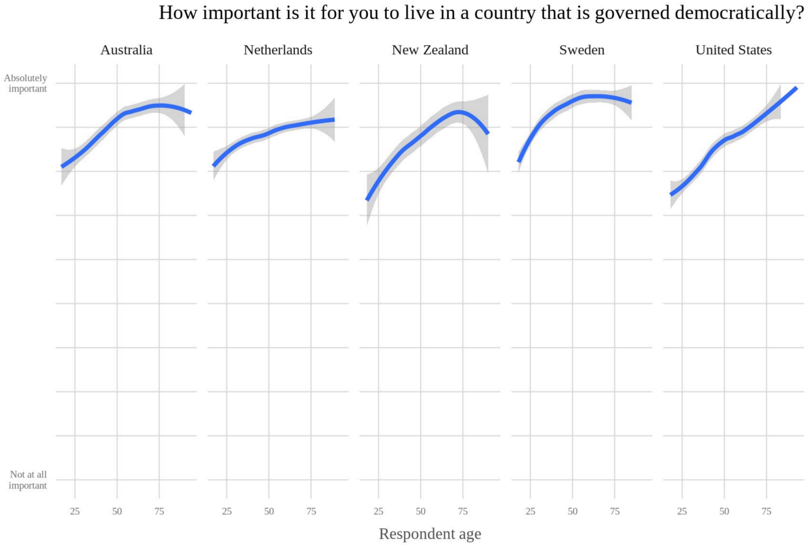


In reply to Ryan D. Enos

Benjamin Sack @bcsack · 15h

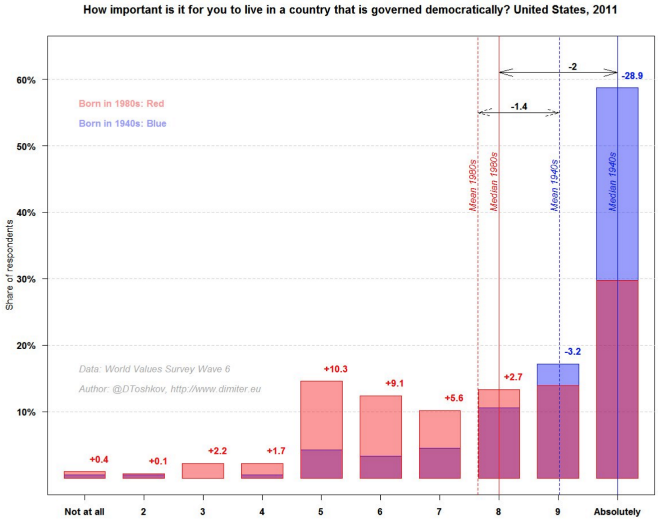
@RyanDEnos Same analysis strategy with comparable data from @ESS_Survey (similar item, 0-10 scale) shows slightly different pattern, too.

Alternate Graphs



614 Bantam @jpbach · 15h
@RyanDEnos @bshor @nataliemjb @TomWGvdMeer this is a "quick and dirty" plot I did with WVS wave 6. Not quite so terrifying.

Alternate Graphs



Dimiter Toshkov @DToshkov · 31m
my take on the democratic deconsolidation graph that scared everyone yesterday. Blue is 1940s cohort, red is 1980s. First, United States

Thoughts

Two stories here:

Thoughts

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1. Visualization and data coding choices are important

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1. Visualization and data coding choices are important
2. The internet is amazing (especially with replication data being available!)

Case Study 2: Sean Taylor's Night Off

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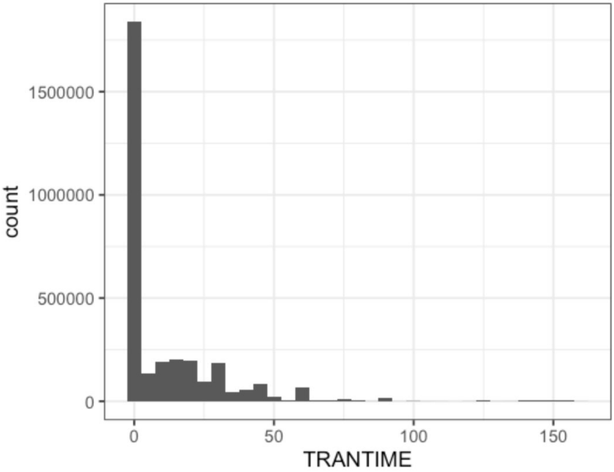
https://twitter.com/seanjtaylor/status/1185415182761254912

Case Study 2: Sean Taylor's Night Off

```r
df %>%
  ggplot(aes(x = TRANTIME)) + geom_histogram(binwidth=5)
```

```
Don't know how to automatically pick scale for object of type haven_la
```



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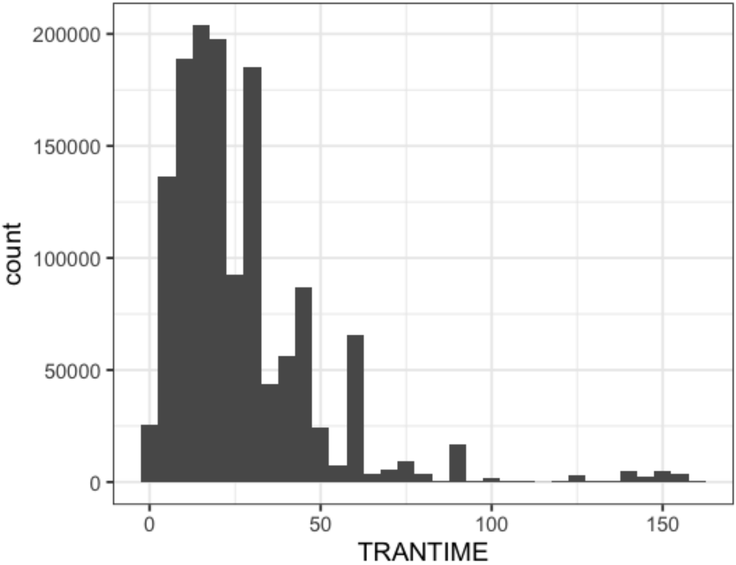

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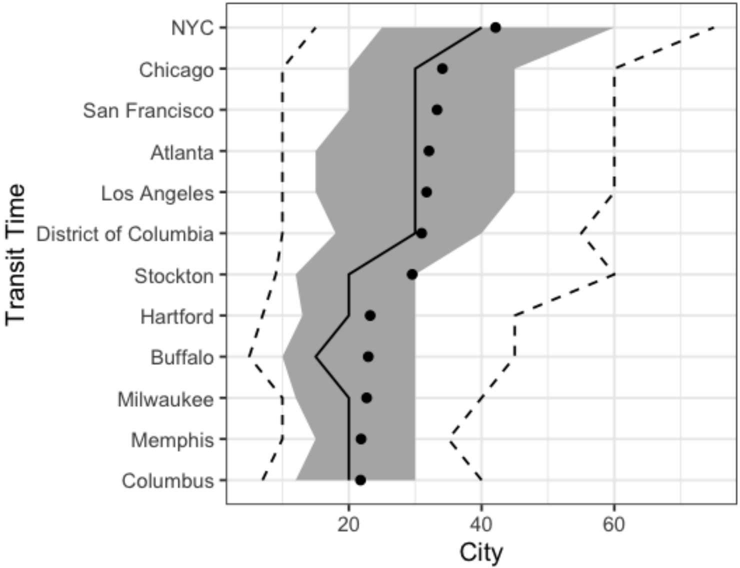

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We Covered

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Next Time: Core Ideas in Causal Inference

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

- Last Week
  - diagnostics
- This Week
  - making an argument in social sciences
  - causal inference
  - two frameworks: potential outcomes and directed acyclic graphs
  - the experimental ideal
  - causation for non-manipulable variables
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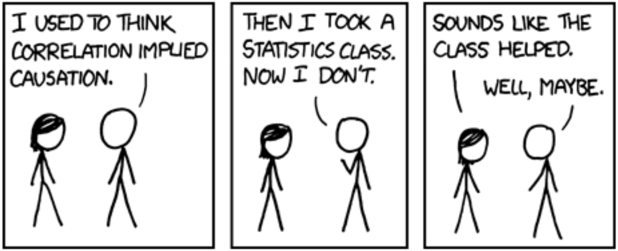
  - selection on observables
- Long Run
  - probability → inference → regression → causal inference

1. Making Arguments
    - Regression
    - Causal Inference
    - Visualization
2. Core Ideas in Causal Inference
3. Potential Outcomes
    - Framework
    - Estimands
    - Three Big Assumptions
    - Average Treatment Effects
    - What Gets to Be a Cause
4. Causal Directed Acyclic Graphs
5. Causation for Non-Manipulable Variables

Causation


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

Fundamental Problem of Causal Inference

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- When it works though it can be a powerful view into the things that we care the most about.
- By convention we often care the counterfactual levels we care about treated and control and we often consider only binary treatment variables because continuous variables are often even more complicated!

Causal Workflow

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- Identification depends on assumptions not statistical models.
- As we will see this is not a conversation about estimation: in other words, if someone answers "regression" they have made a category error

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- Law of Decreasing Credibility (Manski): The credibility of inference decreases with the strength of the assumptions maintained

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- No unmeasured confounding assumes that we've measured all sources of confounding.

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- estimation of causal effects does not require identical treatment and control groups
- you need a clear counterfactual to have a well-defined causal effect. For example of 'the recession was caused by Wall Street' may make intuitive sense but is it well-defined?

http://egap.org/methods-guides/10-things-you-need-know-about-causal-inference

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Next Time: Potential Outcomes

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- It is a way of thinking about counterfactuals and the assumptions required to make statements about them.
- We will first step through the framework, then discuss estimands, three big assumptions and finally what counts as a cause.

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T_i: Dichotomous Treatment assignment for unit i (multi-valued treatments are possible too–just more potential outcomes for each unit)

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τ_i: The treatment effect

$$\tau_i = Y_i(1) - Y_i(0)$$

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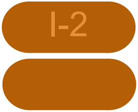

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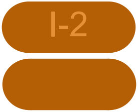

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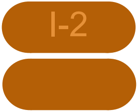

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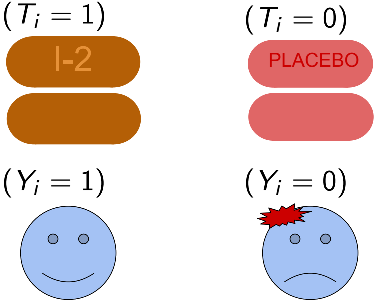

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Pre-treatment covariates X_i

Illustrated potential outcomes here and later courtesy of Erin Hartman

What is random in the potential outcomes framework?

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Treatment assignment is the source of randomness

Causal Inference is a Missing Data Problem

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$$Y_i = T_i * Y_i(1) + (1 - T_i) * Y_i(0)$$

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No methodology allows us to simultaneously observe both potential outcomes, $Y_i(1)$ and $Y_i(0)$, making τ_i unobservable–and unidentifiable without additional assumptions (Fundamental Problem of Causal Inference Holland (1986))

Causal Inference is a Missing Data Problem

Example: Asprin's Impact on Headaches

Patient i		Pill T_i	Headache Status Y_i(PLACEBO)	Y_i(I-2)	Y_i	Age X_{1i}	Academic X_{2i}
1						25	Y
2						55	N
3						62	Y
4						80	N
5						32	Y
6						45	B
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
n						71	N

Causal Inference is a Missing Data Problem

Example: Asprin's Impact on Headaches

Patient i		Pill T_i	Headache Status Y_i(PLACEBO)	Y_i(I-2)	Y_i	Age X_{1i}	Academic X_{2i}
1						25	Y
2						55	N
3						62	Y
4						80	N
5						32	Y
6						45	B
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
n						71	N

Step 1: (Randomly) sample units

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Step 2: Randomly assign treatment

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Step 3: Measure revealed potential outcome

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Patient i		Pill T_i	Headache Status $Y_i(0)$	$Y_i(1)$	Y_i	Age X_{1i}	Academic X_{2i}
1		1	0	0	0	25	Y
2			0	1		55	N
3			1	1		62	Y
4		0	1	1	1	80	N
5		1	0	1	1	32	Y
6			1	0		45	N
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
n		0	0	0	0	71	N

Some Estimands of Interest

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- Treatment effect heterogeneity: Zero ATE doesn't mean zero effect for everyone

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  - Ex: in an experiment with 3 units, if the potential outcomes for unit i depend on the treatment assignment of units j and k, the potential outcomes for unit i are defined by $Y(i, j, k)$:

$$\begin{array}{ll} Y(1,0,0) & Y(0,0,0) \\ Y(1,1,0) & Y(0,1,0) \\ Y(1,0,1) & Y(0,0,1) \\ Y(1,1,1) & Y(0,1,1) \end{array}$$

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- Same version of the treatment

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We also need to assume Positivity $0 < P(T_i = 1) < 1 \; \forall \; i$ with probability 1.

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- Another way of thinking of it: The distributions of the potential outcomes $(Y_i(1), Y_i(0))$ are the same for the treatment and control group.
- Yet another way of thinking of it: The treatment and control group are exchangeable, or balanced (on observables and unobservables) on average

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- This is conditional ignorability.

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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."
(Imbens and Rubin, 2015, p. 31)

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- Probabilistic assignment: Requires the assignment mechanism to imply a non-zero probability for each treatment value, for every unit
- Unconfounded assignment: Disallows dependence of the assignment mechanism on the potential outcomes

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

Three Big Assumptions

To review, we've talked about three big assumptions

1. SUTVA
2. Positivity
3. (Conditional) Ignorability

1. Making Arguments
    - Regression
    - Causal Inference
    - Visualization
2. Core Ideas in Causal Inference
3. Potential Outcomes
    - Framework
    - Estimands
    - Three Big Assumptions
    - Average Treatment Effects
    - What Gets to Be a Cause
4. Causal Directed Acyclic Graphs
5. Causation for Non-Manipulable Variables

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- Population parameter
- It is fixed and unchanging

Estimating ATE under Random Assignment

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

Average Treatment Effect

Imagine a study population with 4 units:

i	T_i	$Y_i(1)$	$Y_i(0)$	τ_i
1	1	10	4	6
2	1	1	2	-1
3	0	3	3	0
4	0	5	2	3

What is the ATE?

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$$E[Y_i(1) - Y_i(0)] = 1/4 \times (6 + -1 + 0 + 3) = 2$$

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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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$$E[Y_i(1) - Y_i(0)|T_i = 0] = 1/2 \times (0 + 3) = 1.5$$

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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 $(Y(1), Y(0)) \perp T$

What Gets to Be a Cause?

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  - If that experiment does not exist, be concerned about interpretation

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

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- 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.

Neyman-Rubin Potential Outcomes Model

Figure: Neyman

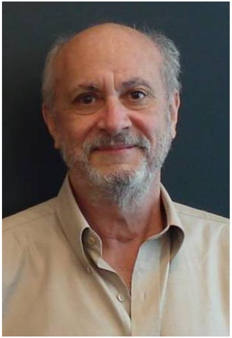

Figure: Rubin

Brief History of Potential Outcomes and Causal Inference

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For more detailed see Morgan and Winship.

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- Pearl (1995) develops graphical models for causal inference

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Next Time: Causal Directed Acyclic Graphs (Causal DAGs)

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

- Last Week
  - diagnostics
- This Week
  - making an argument in social sciences
  - causal inference
  - two frameworks: potential outcomes and directed acyclic graphs
  - the experimental ideal
  - causation for non-manipulable variables
- Next Week
  - selection on observables
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

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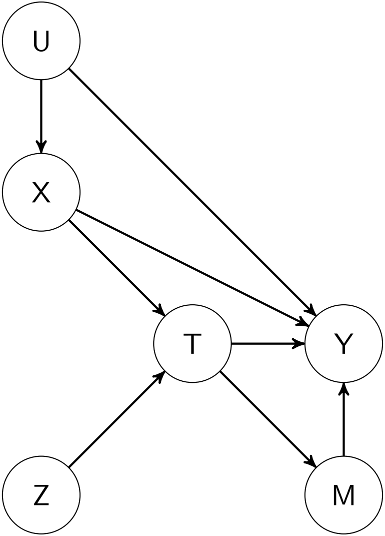
- Provides a graphical representation of the models and a set of rules (do-calculus) for identifying the causal effect.
- Nice software that takes the graph and returns an identification strategy: DAGitty at `http://dagitty.net`

Components of a DAG



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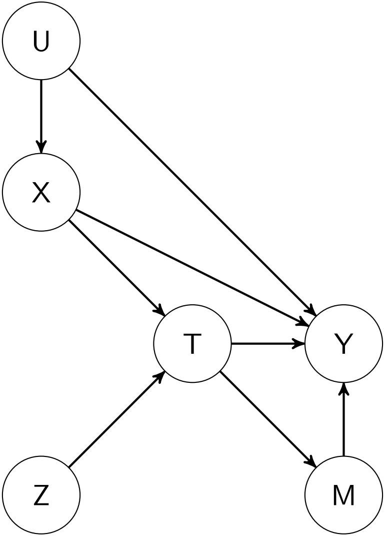

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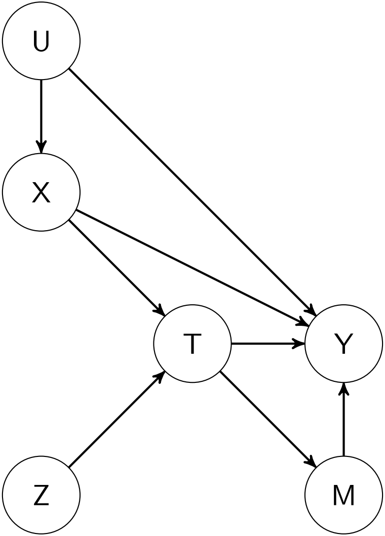

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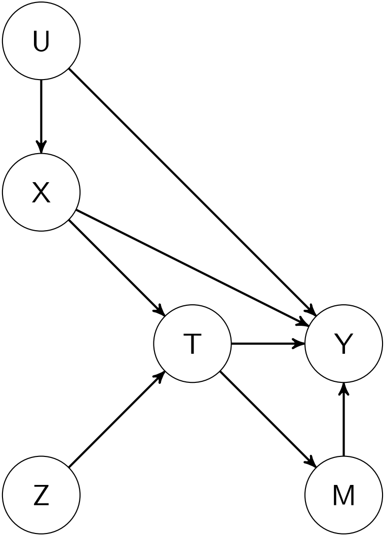

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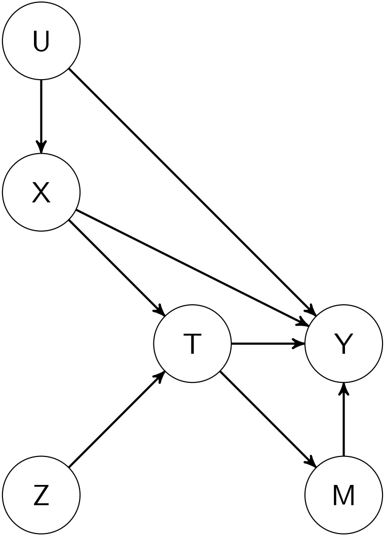

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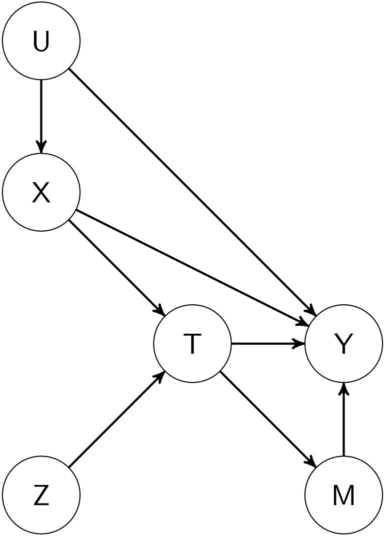

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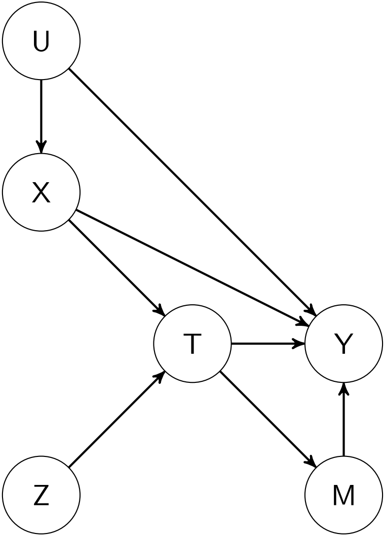

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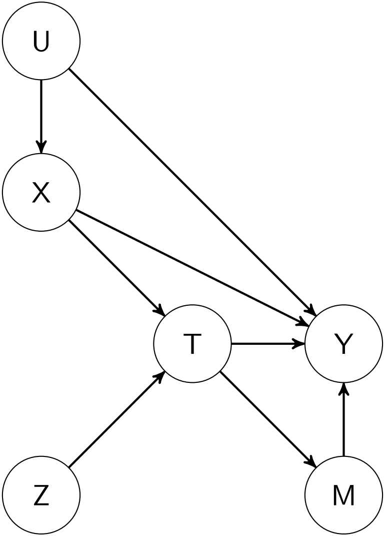

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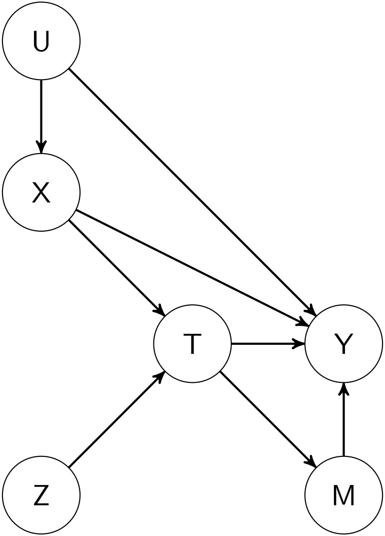

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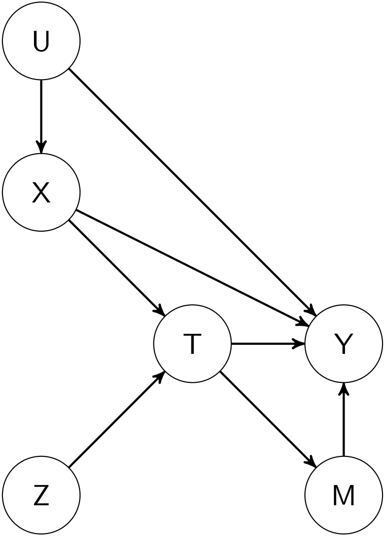

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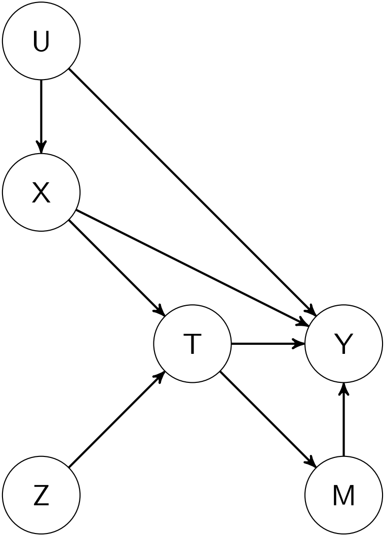

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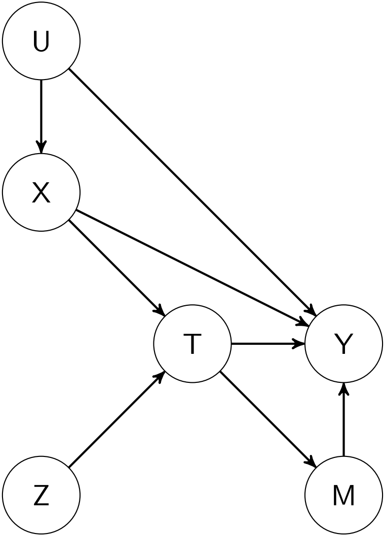

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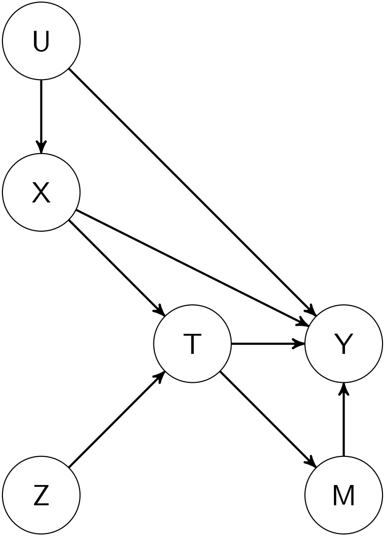

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- We will talk in depth about two types of relationships: confounders and colliders

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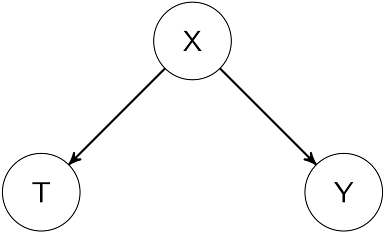

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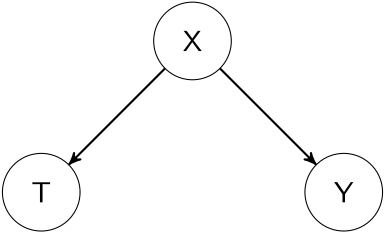

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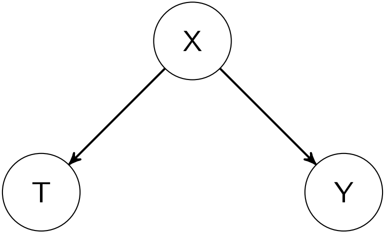

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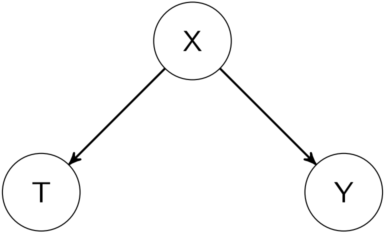

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- We can think of conditioning on a confounder as blocking the flow of association.

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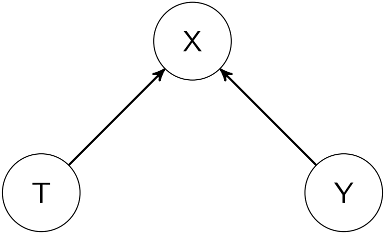

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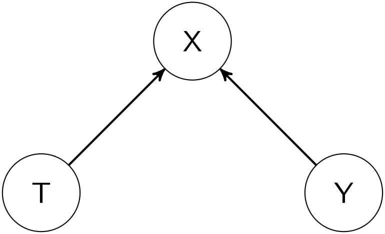

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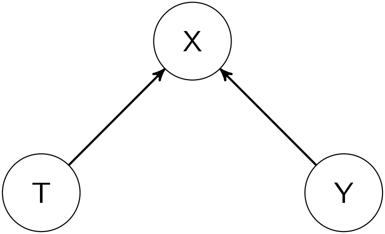

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- If we control for X they become associated and create a connection between T and Y

Colliders are scary because you can induce dependence

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

Felix Elwert[1] and Christopher Winship[2]

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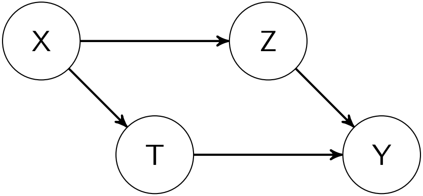
Keywords

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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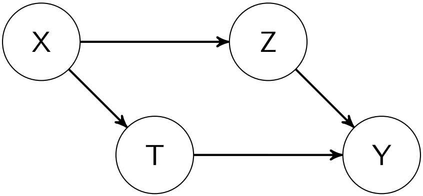

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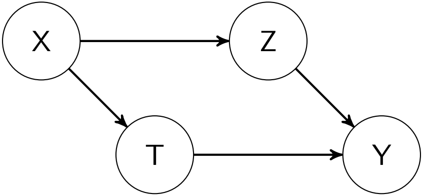

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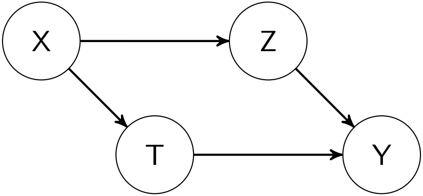

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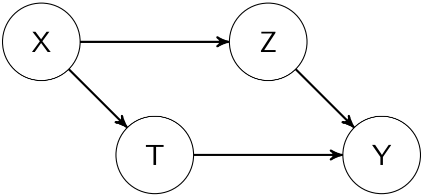

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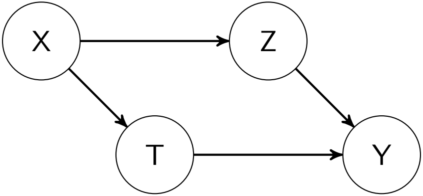
From Confounders to Back-Door Paths



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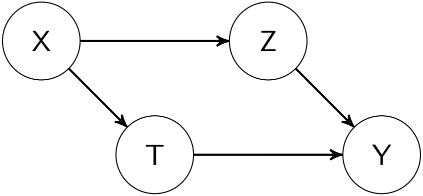

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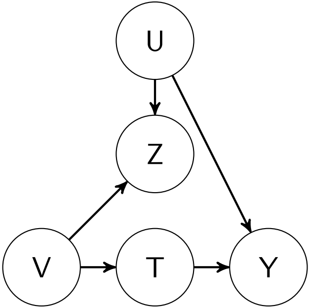
Colliders and Back-Door Paths



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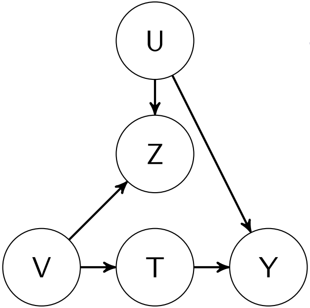

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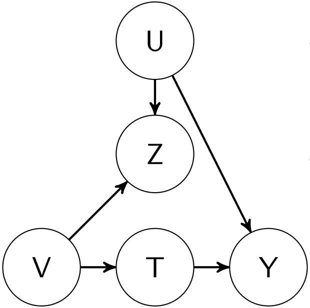

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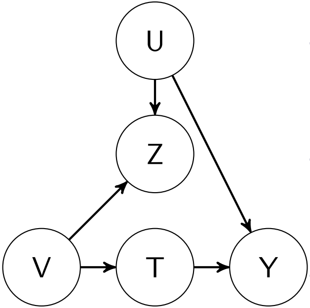

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- So how do we know which back-door paths to block?

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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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- We will see some other approaches late in the semester.

Blocking backdoor paths: College and earnings

What do we need to include to block all backdoor paths between college and earnings?

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Ability, parents' income, parents' education, extended family who pay for college and help you find a job, neighborhood characteristics that affect high school quality and also the availability of local jobs, ... lots of things!

Non-causal paths: Part 2

Now consider this graph. Is there an unblocked backdoor path from T to Y?

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No need to condition! X_2 already blocks this path. it is a collider.

Colliders: Be careful!

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Should we worry about this design? It depends on our theory about how these variables are related. We can argue about identification with a DAG.

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Suppose working in Hollywood is a function of two factors: acting ability and beauty. In the general population, these two are uncorrelated. However, among those who work in Hollywood, those who are bad at acting must be beautiful.

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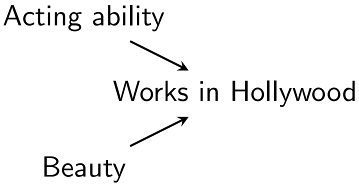

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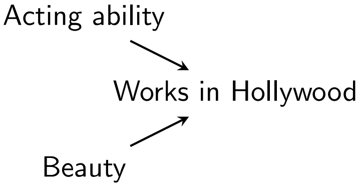

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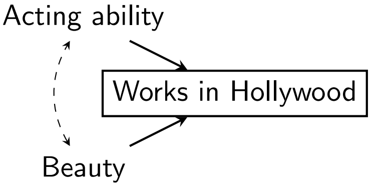

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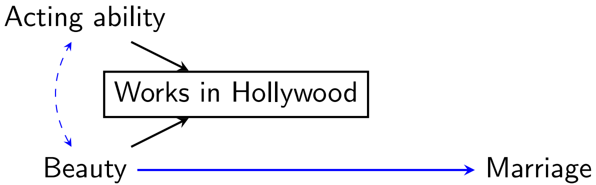
Example extended from Elwert & Winship 2014

This is an example of conditioning on a collider! We induce a negative association between acting ability and beauty.



Under the assumptions above, our results are driven by collider conditioning!

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- This can often be helpful for distinguishing data as it exists in the world and data as it might exist in the counterfactual world.
- The do-calculus is actually a much broader set of rules that operate on the DAG structure to help us calculate causal effects (or learn when we can't!).

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Next Time: Causation for Non-Manipulable Variables

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

- Last Week
  - diagnostics
- This Week
  - making an argument in social sciences
  - causal inference
  - two frameworks: potential outcomes and directed acyclic graphs
  - the experimental ideal
  - causation for non-manipulable variables
- Next Week
  - selection on observables
- Long Run
  - probability → inference → regression → causal inference

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- Lundberg offers a perspective where the non-manipulable variable defines social categories but is not the treatment itself.
- More broadly there is a need to define what the proposed intervention is because even cases that can be manipulated can be very opaque (e.g. obesity).

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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   - there is substantial variance across treatments which is a SUTVA violation

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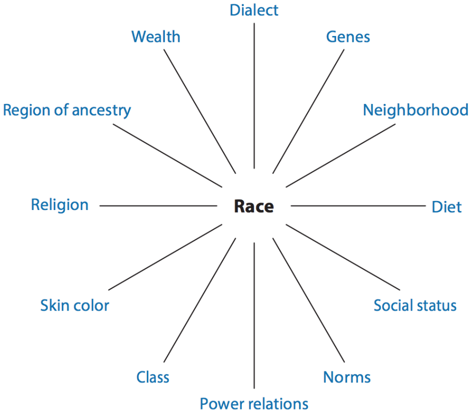

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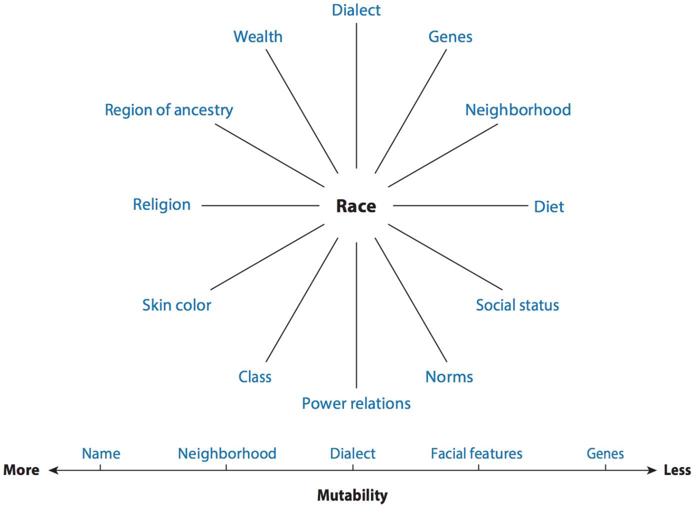

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  - Audit/Correspondence Studies (Pager 2003, Bertrand and Mullainathan 2004)

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  b) "subjects are treated by exposure to the racial cue"
  c) "unit of analysis is the individual or institution being exposed"
- Examples
  - Psychology (Steele 1997 on stereotype threat)
  - Audit/Correspondence Studies (Pager 2003, Bertrand and Mullainathan 2004)
  - Survey Experiments with Racial Cues (Mendelberg 2001)

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

Design 2: Within-Group Studies

- Approach: identify variation within the racial group along constitutive element.

Design 2: Within-Group Studies

- Approach: identify variation within the racial group along constitutive element.
- 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.

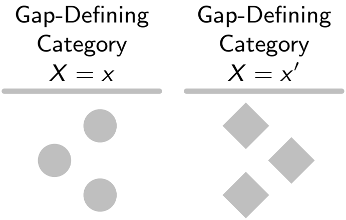
Table 2 Overview of exposure and within-group research designs

	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

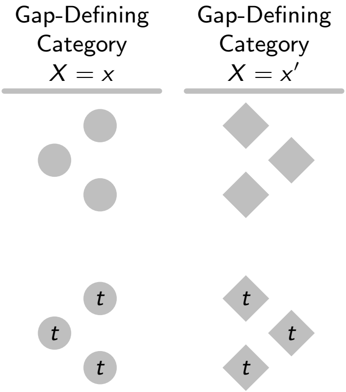
Gap Closing Estimands

Lundberg (2020) "The gap-closing estimand: A causal approach to study interventions that close disparities across social categories" Working Paper.

Thanks to Ian Lundberg for the slides that follow!

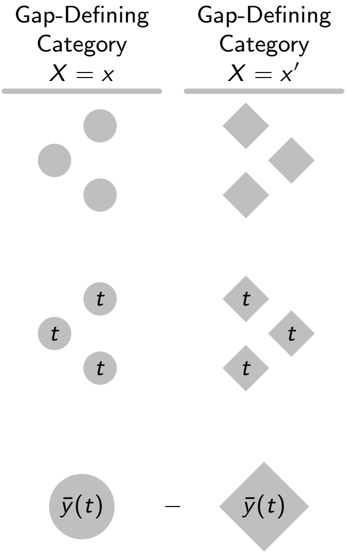


Collections of units



Collections of units

Exposed to the gap-closing treatment $T = t$



Collections of units

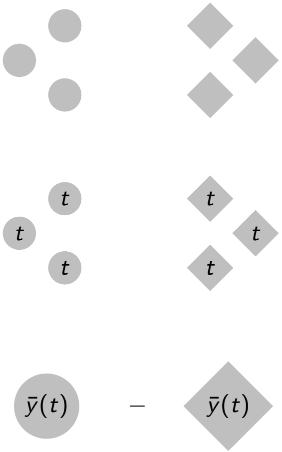
Exposed to the gap-closing treatment $T = t$

To yield a counterfactual disparity

Gap-Closing Estimand

	Gap-Defining Category $X = x$	Gap-Defining Category $X = x'$

Race
Class Origin
Gender

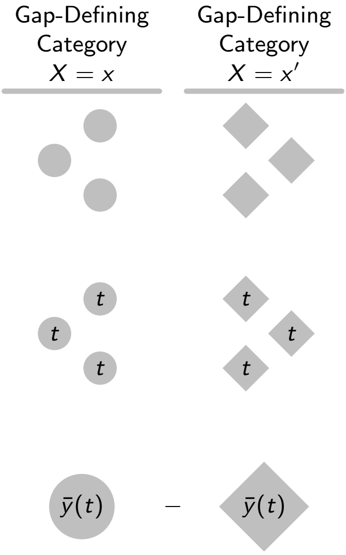


Collections of units

Exposed to the gap-closing treatment $T = t$

To yield a counterfactual disparity

Gap-Closing Estimand



Race
Class Origin
Gender

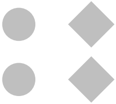
Collections of units

Incarceration
College
Occupation

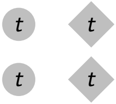
Exposed to the gap-closing treatment $T = t$

To yield a counterfactual disparity

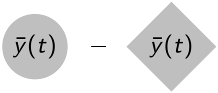
Gap-Closing Estimand



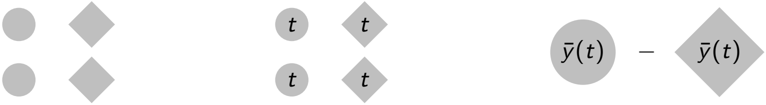
Categories



Treatment



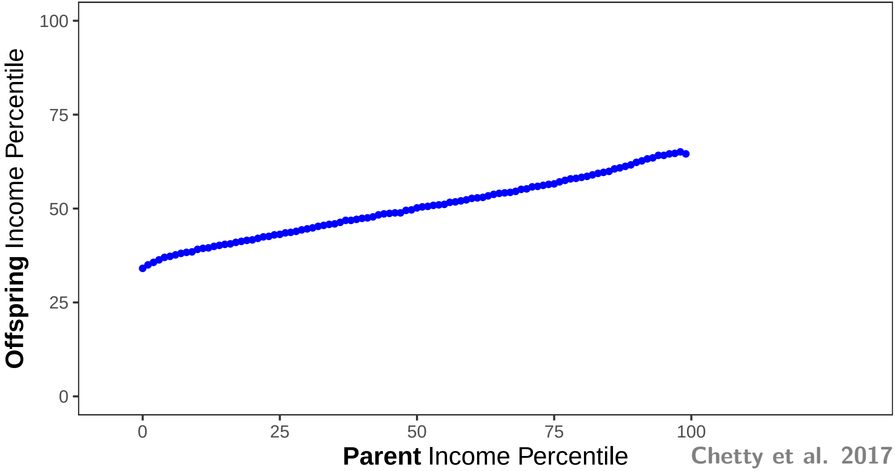
Counterfactual Disparity



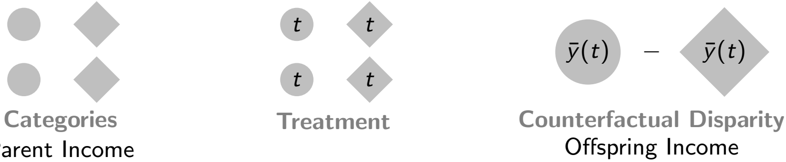
Categories Parent Income

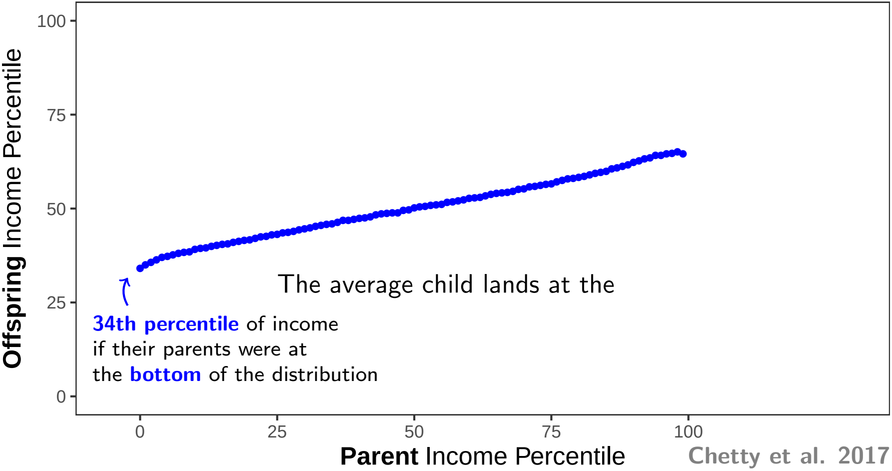
Treatment

Counterfactual Disparity Offspring Income



Chetty et al. 2017





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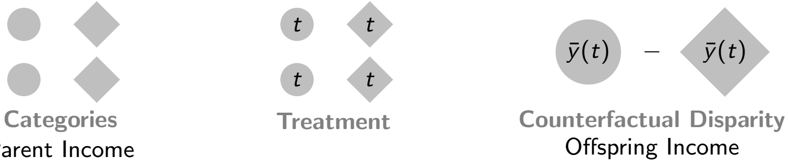

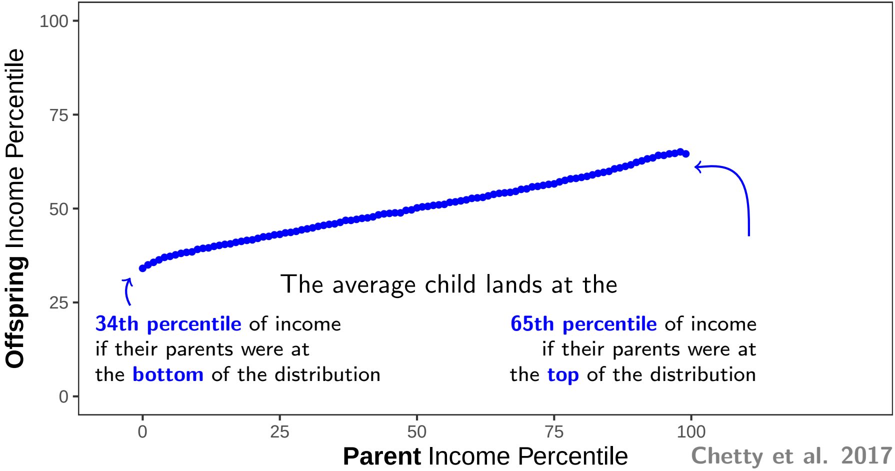

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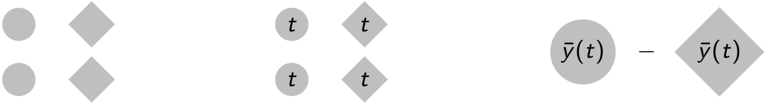
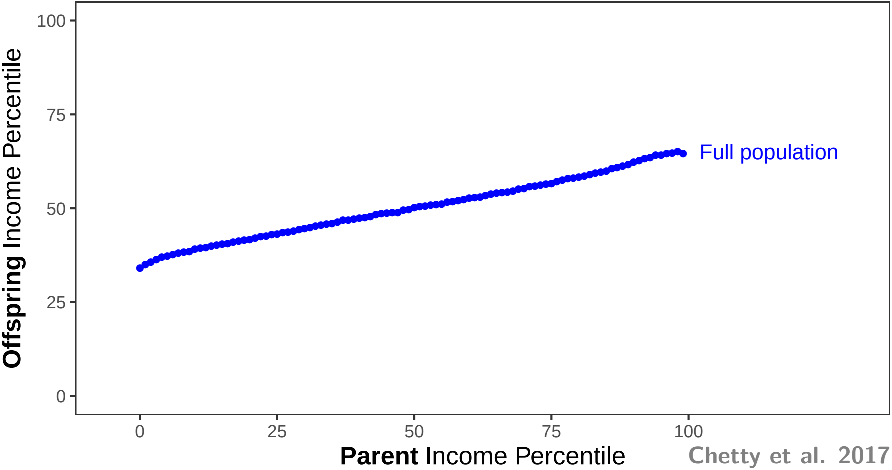


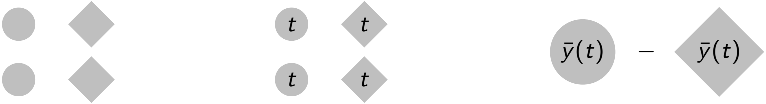
Categories
Parent Income

Treatment

Counterfactual Disparity
Offspring Income



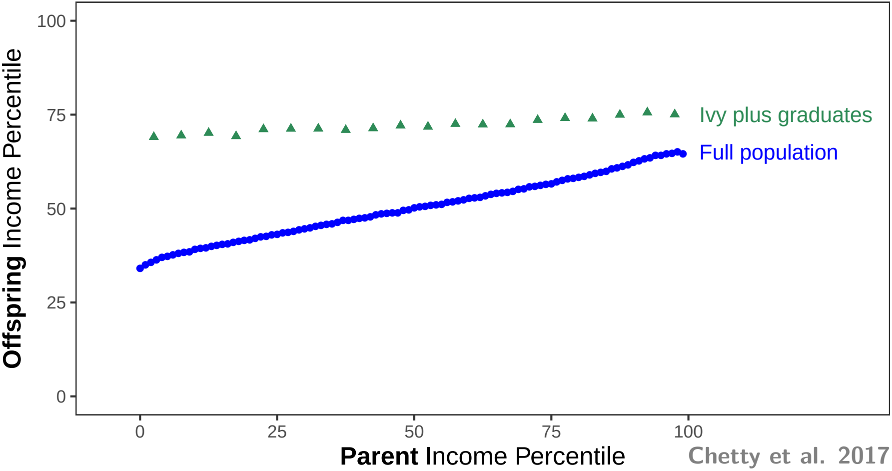
Chetty et al. 2017



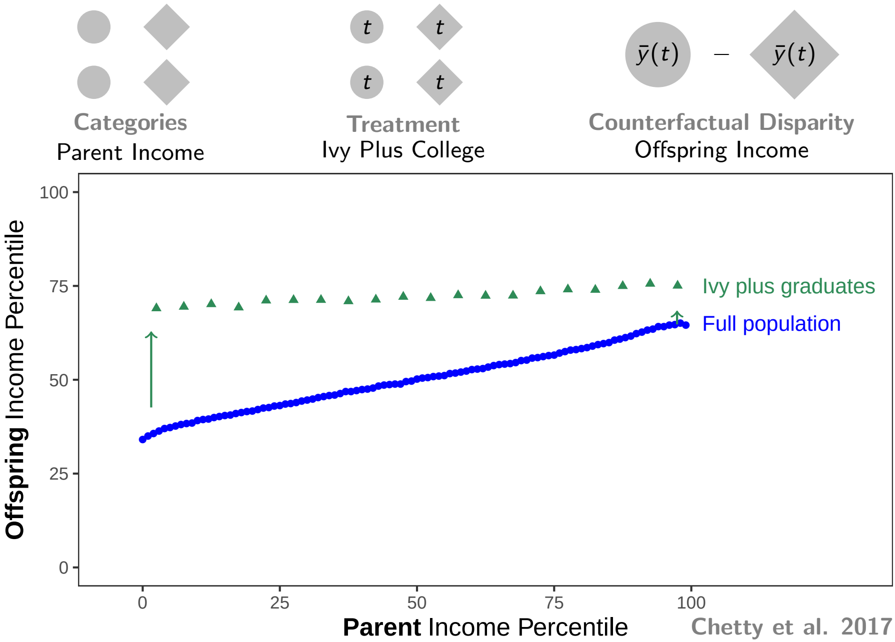
Categories Parent Income

Treatment Ivy Plus College

Counterfactual Disparity Offspring Income



Chetty et al. 2017



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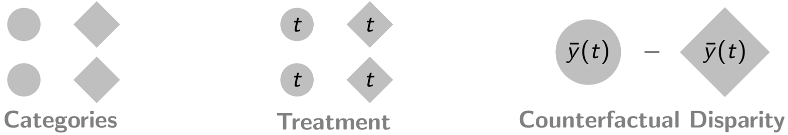
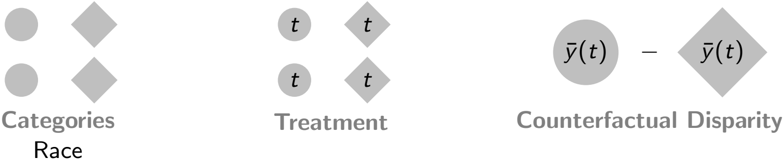


The difference in earnings between blacks and whites would be reduced only by about 3 percent if the incarceration rate were zero.

— Western 2006:12



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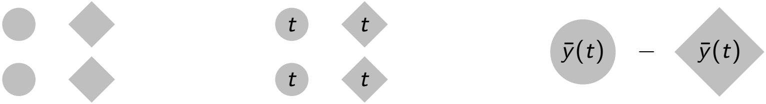

Categories
Race

Treatment
Incarceration

Counterfactual Disparity

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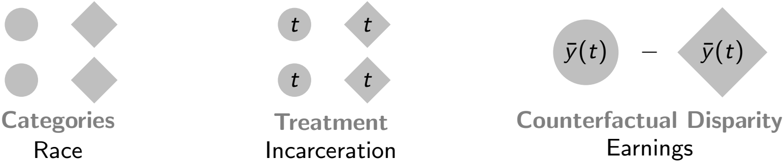

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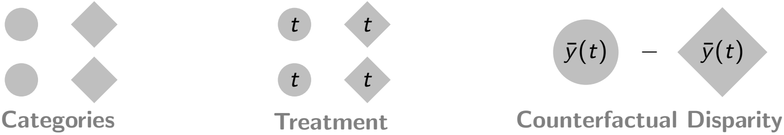
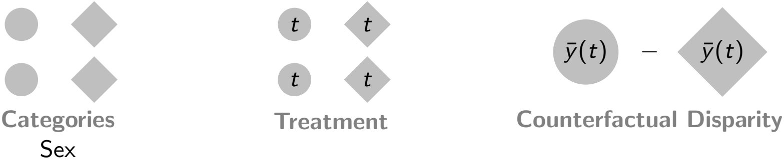


Suppose sex segregation—by occupation, establishment, or occupation-establishment—were abolished; what then would the remaining gender relative wages be?

— Petersen and Morgan 1995:338



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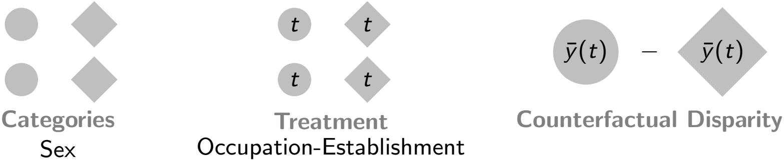

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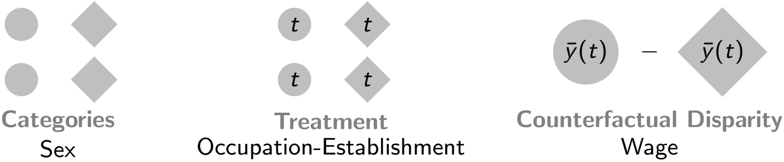

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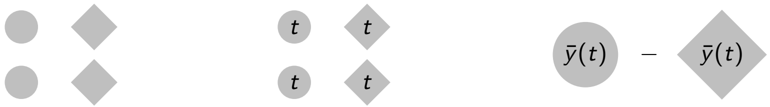
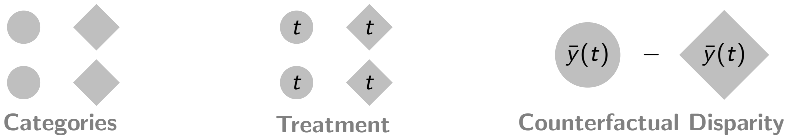
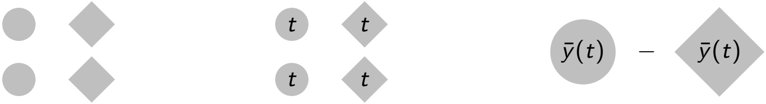


Categories Treatment Counterfactual Disparity



Perennial Question Can individual attainment liberate one from the constraints of class origin?

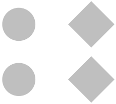
Hout 1988; Torche 2011; Zhou 2019



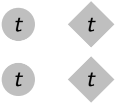
Categories **Treatment** **Counterfactual Disparity**

Annual Income

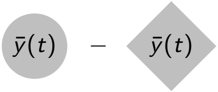
Perennial Question: Can individual attainment liberate one from the constraints of class origin?



Categories
Professional
Class Origin

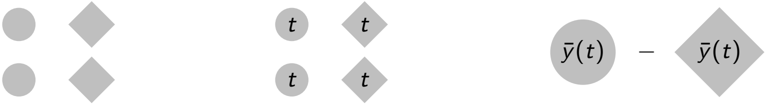


Treatment



Counterfactual Disparity
Annual Income

Perennial Question	Can individual attainment liberate one from the constraints of class origin?

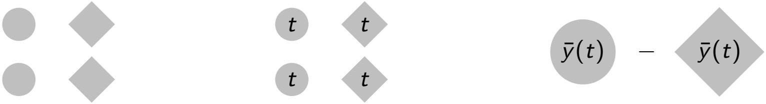


Categories Professional Class Origin

Treatment Professional Class Destination

Counterfactual Disparity Annual Income

Perennial Question Can individual attainment liberate one from the constraints of class origin?



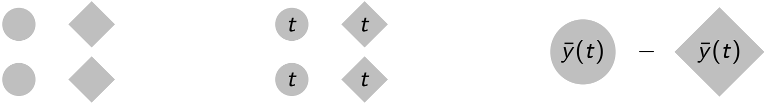
Categories
Professional
Class Origin

Treatment
Professional
Class Destination

Counterfactual Disparity
Annual Income

Perennial Question	Can individual attainment liberate one from the constraints of class origin?
Descriptive Version	Does class origin predict income net of class destination and other covariates?

Laurison and Friedman 2016



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Professional
Class Origin

Treatment
Professional
Class Destination

Counterfactual Disparity
Annual Income

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Descriptive Version Does class origin predict income net of class destination and other covariates?

Gap-Closing Version What counterfactual income disparity by class origin would persist if class destinations were reallocated?

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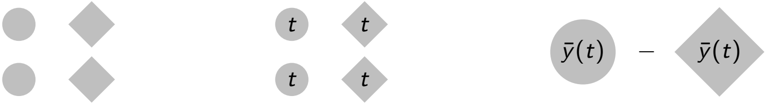


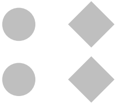
Categories	Treatment	Counterfactual Disparity
Professional Class Origin	Professional Class Destination	Annual Income

Category — Father held a professional occupation (binary)

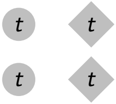
Gap-Closing Version — What counterfactual income disparity by class origin would persist if class destinations were reallocated?

Category	Father held a professional occupation (binary)
Treatment	Respondent held a professional occupation (binary)

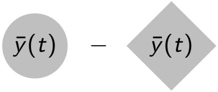
Gap-Closing Version What counterfactual income disparity by class origin would persist if class destinations were reallocated?



Categories
Professional
Class Origin



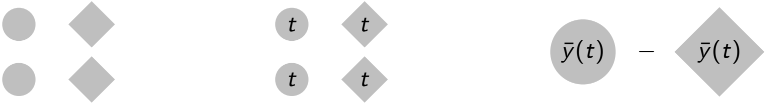
Treatment
Professional
Class Destination



Counterfactual Disparity
Annual Income

Category	Father held a professional occupation (binary)
Treatment	Respondent held a professional occupation (binary)
Outcome	Log(Annual Income)

Gap-Closing Version What counterfactual income disparity by class origin would persist if class destinations were reallocated?



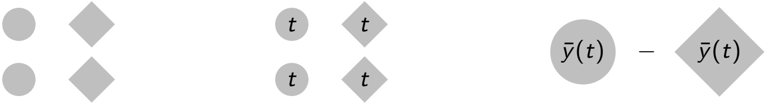
Categories
Professional
Class Origin

Treatment
Professional
Class Destination

Counterfactual Disparity
Annual Income

Category	Father held a professional occupation (binary)
Treatment	Respondent held a professional occupation (binary)
Outcome	Log(Annual Income)
Covariates	Race, Sex, Age, Education

Gap-Closing Version What counterfactual income disparity by class origin would persist if class destinations were reallocated?



Categories
Professional
Class Origin

Treatment
Professional
Class Destination

Counterfactual Disparity
Annual Income

Category	Father held a professional occupation (binary)
Treatment	Respondent held a professional occupation (binary)
Outcome	Log(Annual Income)
Covariates	Race, Sex, Age, Education
Target Population	U.S. population ages 30–45 in 1975–2018, with years equally weighted (General Social Survey)

Gap-Closing Version What counterfactual income disparity by class origin would persist if class destinations were reallocated?

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Next Time: Causality with Measured Confounding