Political Science 209 - Fall 2018

Introduction

Florian Hollenbach

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Causal Inference

What do you think is causal inference?

Causal Inference

- causal: relationship between things where one causes the other
- inference: to derive as a conclusion from facts or premises

Causal inference is the attempt to derive causal connection based on the conditions of the occurrence of an effect

Causal Inference

- Most questions that empirical (political) scientist are interested in are causal questions

Examples from Political Science

How to Elect More Women: Gender and Candidate Success in a Field Experiment

Christopher F. Karpowitz Brigham Young University
J. Quin Monson Brigham Young University
Jessica Robinson Preece Brigham Young University

Abstract: *Women are dramatically underrepresented in legislative bodies, and most scholars agree that the greatest limiting factor is the lack of female candidates (supply). However, voters' subconscious biases (demand) may also play a role, particularly among conservatives. We designed an original field experiment to test whether messages from party leaders can affect women's electoral success. The experimental treatments involved messages from a state Republican Party chair to the leaders of 1,842 precinct-level caucus meetings. We find that party leaders' efforts to stoke both supply and demand (and especially both together) increase the number of women elected as delegates to the statewide nominating convention. We replicate this finding in a survey experiment with a national sample of validated Republican primary election voters (N = 2,897). Our results suggest that simple interventions from party leaders can affect the behavior of candidates and voters and ultimately lead to a substantial increase in women's descriptive representation.*

Replication Materials: The data, code, and any additional materials required to replicate all analyses in this article are available on the *American Journal of Political Science* Dataverse within the Harvard Dataverse Network, at: http://dx.doi.org/10.7910/DVN/UQAIZI.

Examples from Political Science

Multiple Dimensions of Bureaucratic Discrimination: Evidence from German Welfare Offices

Johannes Hemker Columbia University
Anselm Rink Columbia University

Abstract: *A growing experimental literature uses response rates to fictional requests to measure discrimination against ethnic minorities. This article argues that restricting attention to response rates can lead to faulty inferences about substantive discrimination depending on how response dummies are correlated with other response characteristics. We illustrate the relevance of this problem by means of a conjoint experiment among all German welfare offices, in which we randomly varied five traits and designed requests to allow for a substantive coding of response quality. We find that response rates are statistically indistinguishable across treatment conditions. However, putative non-Germans receive responses of significantly lower quality, potentially deterring them from applying for benefits. We also find observational evidence suggesting that discrimination is more pronounced in welfare offices run by local governments than in those embedded in the national bureaucracy. We discuss implications for the study of equality in the public sphere.*

Examples from Political Science

Democracy Does Cause Growth*

Daron Acemoglu, MIT
Suresh Naidu, Columbia
Pascual Restrepo, BU
James A. Robinson, Chicago

April 2017

Abstract

We provide evidence that democracy has a significant and robust positive effect on GDP per capita. Our empirical strategy controls for country fixed effects and the rich dynamics of GDP, which otherwise confound the effect of democracy on economic growth. To reduce measurement error, we introduce a new dichotomous measure of democracy that consolidates the information from several sources. Our baseline results use a dynamic panel model for GDP, and show that democratizations increase GDP per capita by about 20% in the long run. We find similar effects of democratizations on annual GDP when we control for the estimated propensity of a country to democratize based on past GDP dynamics. We obtain comparable estimates when we instrument democracy using regional waves of democratizations and reversals. Our results suggest that democracy increases GDP by encouraging investment, increasing schooling, inducing economic reforms, improving the provision of public goods, and reducing social unrest. We find little support for the view that democracy is a constraint on economic growth for less developed economies.

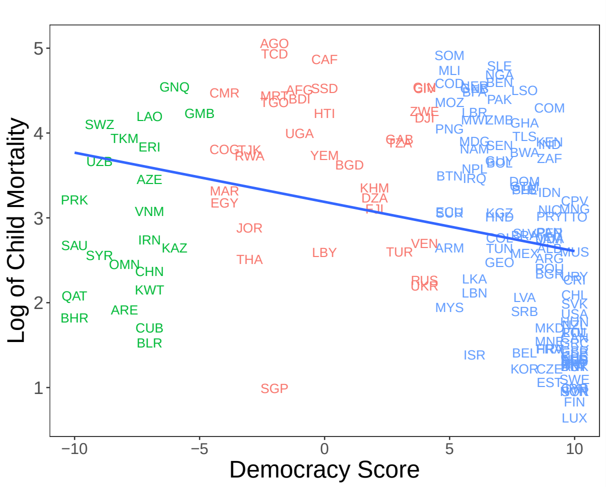
Do you think one of these questions is harder to answer than the others?

Causal Inference

Think of the causal effect as the difference between what happened and what could have happened with/without a "treatment" (or change in X)

How do we measure the causal effect?

Is there a causal effect of democracy on child mortality?



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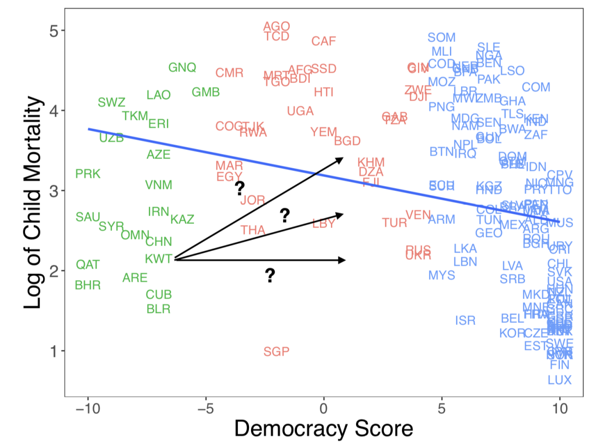

What if Kuwait was more democratic?

How would you know if two variables are causally related?

$X \rightarrow Y$?

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- if x goes up, y goes up
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If two things happen together a lot, we say they are correlated

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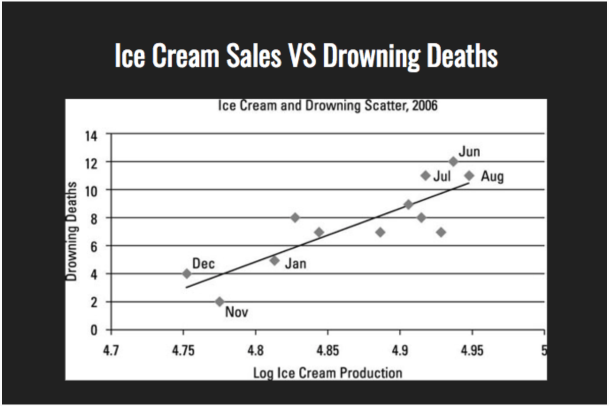

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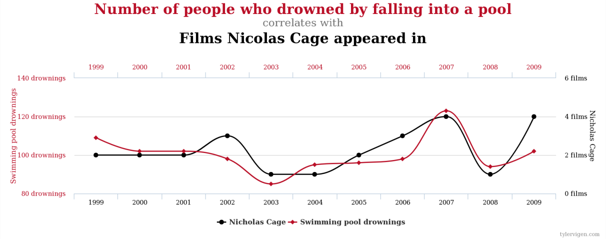

Causal Inference - Concepts

- Key causal variable: *Treatment (T)*
- Two *potential outcomes*: Y with T = 0 and Y with T = 1

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Example:

- *Treatment*: getting BS in political science instead of BA
- *potential outcomes*: Salary after getting BS (Y (T = 1)) or after BA (Y (T = 0))

Why is causal inference so hard?

- The causal effect of a *treatment* is the difference in the *outcome* with and without the treatment: Y(T = 1) - Y(T = 0) $\rightarrow$ Y(1) - Y(0)

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> For each observation i, we can define the **causal effect** of a binary treatment T_i as the difference between two potential outcomes, $Y_i(1) - Y_i(0)$, where $Y_i(1)$ represents the outcome that would be realized under the treatment condition ($T_i = 1$) and $Y_i(0)$ denotes the outcome that would be realized under the control condition ($T_i = 0$).

- Why might this be a problem?

Fundamental Problem of Causal Inference

We never observe the *counterfactual*, i.e. the outcome if the *treatment condition* was different

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Example:

- *Treatment*: getting BS in political science instead of BA
- *Potential outcomes*: Salary after getting BS ($Y(T = 1)$) or after BA ($Y(T = 0)$)
- For each of you we only observe one outcome

Fundamental Problem of Causal Inference

Examples:

- We don't observe Kuwait as a democracy
- You don't know how you would feel if you didn't drink that coffee
- We don't know how the world/US would look if Clinton had won the election

Fundamental Problem of Causal Inference

The **fundamental problem of causal inference** is that we only observe one of the two potential outcomes and which potential outcome is observed depends on the treatment status. Formally, the observed outcome Y_i is equal to $Y_i(T_i)$.

How can we estimate the causal effect?

- We try to estimate the *average causal effect* in our sample (SATE) by comparing groups
- In our sample, does the *Treatment* on average cause a change in Y?

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Formally, the **sample average treatment effect** (SATE) is defined as the sample average of individual-level causal effect, i.e., $Y_i(1) - Y_i(0)$,

$$\text{SATE} = \frac{1}{n}\sum_{i=1}^{n}\{Y_i(1) - Y_i(0)\} \tag{2.1}$$

where n is the sample size.

But again we only observe one outcome per person!

How can we find the causal effect?

Solution: We compare the average of those who received the treatment (*treated group*) to the average of those who did not (*control group*)

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Are the two groups comparable?

Experiments/Randomized Control Trials

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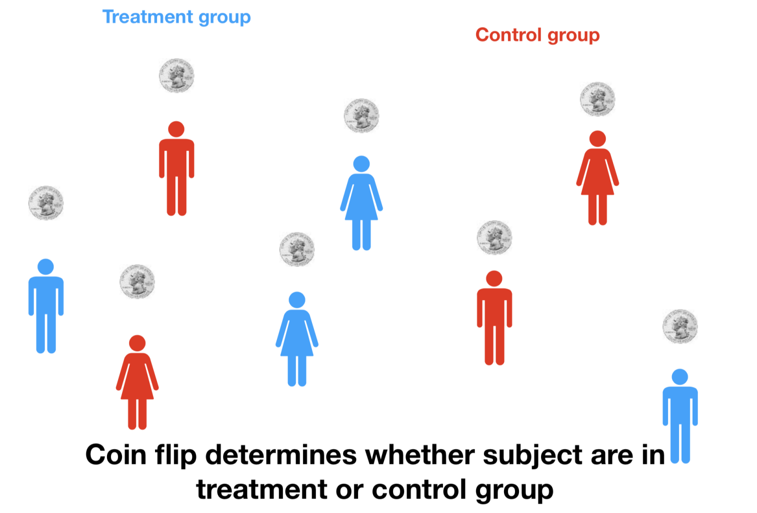
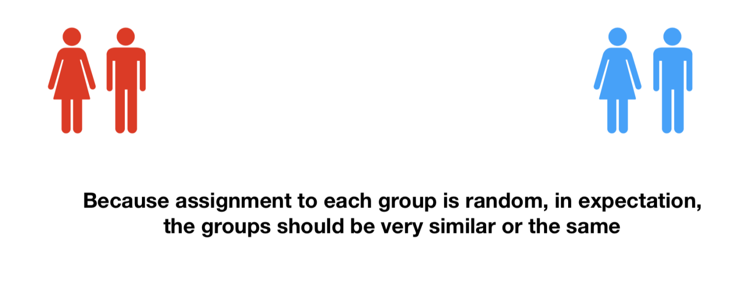
- By randomizing the assignment, we guarantee that the two groups are comparable in all other dimensions
- The random assignment *balances* out treatment and control group

Experiments/Randomized Control Trials



Experiments/Randomized Control Trials



Experiments/Randomized Control Trials

In a **randomized controlled trial (RCT)**, each unit is randomly assigned either to the treatment or control group. The randomization of treatment assignment guarantees that the average difference in outcome between the treatment and control groups can be attributed solely to the treatment because the two groups are on average identical to each other in all other pre-treatment characteristics.

Experiments/Randomized Control Trials

Internal validity vs external validity

Experiments/Randomized Control Trials

- People may behave differently because they are observed (*Hawthorne effect*)
- People may behave differently because they expect the *treatment* to work (*placebo effect*)