Political Science 209 - Fall 2018

Causal Inference

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7th September 2018

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.

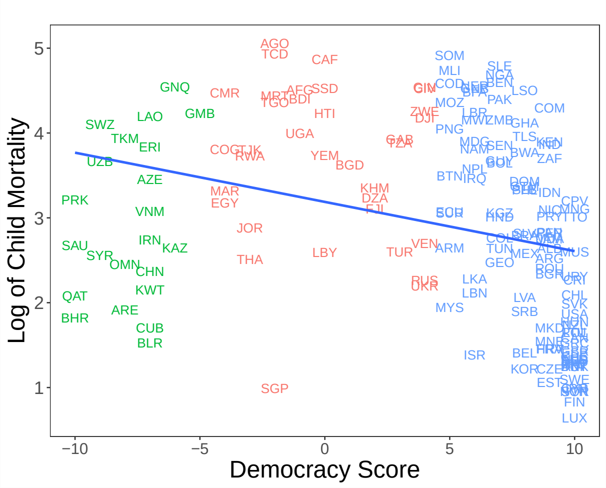
Causal Inference

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

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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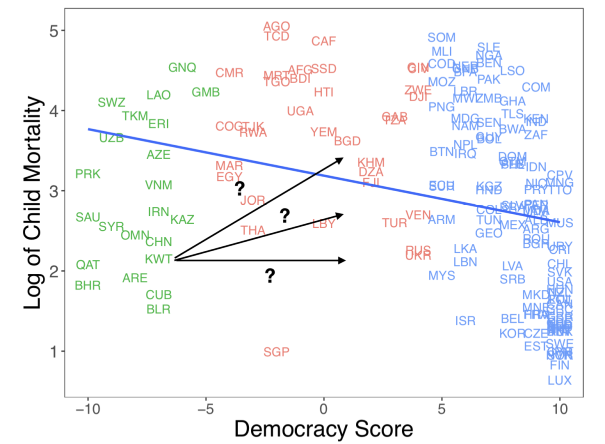

What if Kuwait was more democratic?

How would you know if two variables are causally related?

$X \rightarrow Y$?

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- if T, then change in Y

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If two things happen together a lot, we say they are correlated

Is correlation sufficient for causation?

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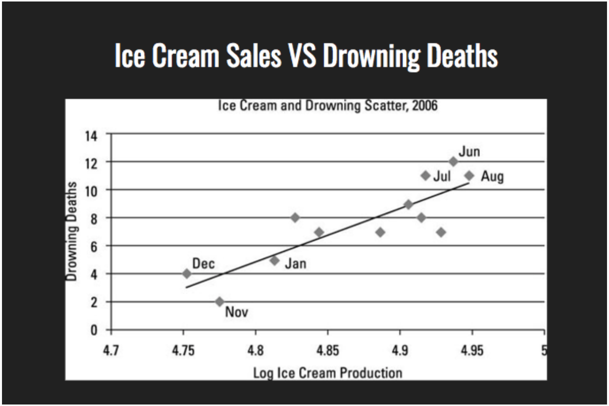
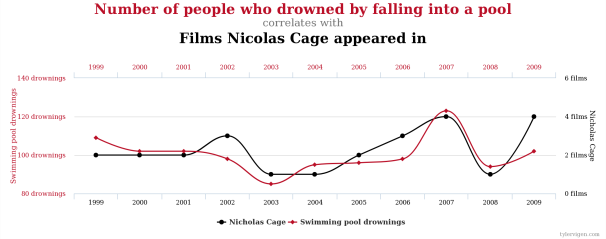


Is correlation sufficient for causation?

NO



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

Interlude

What is College about?

What is College about?

The effect of human capital on earnings: Evidence from a reform at Colombia's top university ☆

Carolina Arteaga

Abstract

In this paper I test whether the return to college education is the result of human capital accumulation or instead reflects the fact that attending college signals higher ability to employers. I exploit a reform at Universidad de Los Andes, which in 2006 reduced the amount of coursework required to earn degrees in economics and business by 20% and 14%, respectively, but did not change the quality of incoming or graduating students. The size of the entering class, their average high school exit exam scores, and graduation rates were not affected by the reform, indicating that selection of students into the degrees remained the same. Using administrative data on wages and college attendance, I estimate that wages fell by approximately 16% in economics and 13% in business. These results suggest that human capital plays an important role in the determination of wages and reject a pure signaling model. Surveying employers, I find that the reduction in wages may have resulted from a decline in performance during the recruitment process, which led students to be placed in lower-quality firms. Using data from the recruitment process for economists at the Central Bank of Colombia, I find that the reform reduced the probability of Los Andes graduates' being hired by 17 percentage points.

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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- In our sample, does the *Treatment* on average cause a change in *Y*?

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

- In *Randomized Control Trials* the researcher assigns *treatment* and *control* group status

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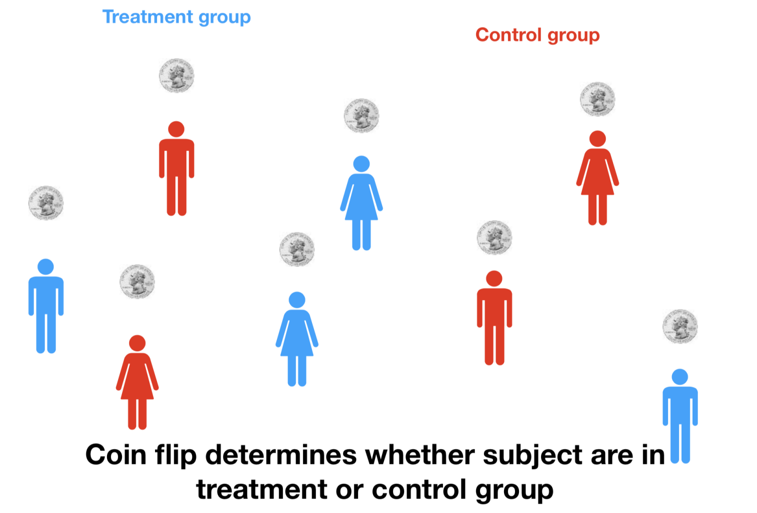
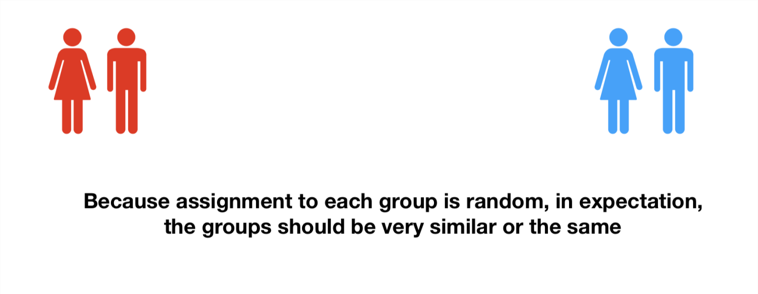
- In *Randomized Control Trials* the researcher assigns *treatment* and *control* group status
- By randomizing the assignment, we guarantee that the two groups are comparable (on average the same) in all other dimensions
- The random assignment *balances* out treatment and control group

Experiments/Randomized Control Trials



Experiments/Randomized Control Trials



Experiments/Randomized Control Trials

- On average the two groups are going to be the same on all (pre-treatment) dimensions
- The difference in the outcome is therefore *caused* by the treatment

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*)

Causal Effect of Intergroup Contact on Exclusionary Attitudes – by Ryan D. Enos

The effect of intergroup contact has long been a question central to social scientists. As political and technological changes bring increased international migration, understanding intergroup contact is increasingly important to scientific and policy debates. Unfortunately, limitations in causal inference using observational data and the practical inability to experimentally manipulate demographic diversity has limited scholars' ability to address the effects of intergroup contact. Here, I report the results of a randomized controlled trial testing the causal effects of repeated intergroup contact, in which Spanish-speaking confederates were randomly assigned to be inserted, for a period of days, into the daily routines of unknowing Anglo-whites living in homogeneous communities in the United States, thus simulating the conditions of demographic change. The result of this experiment is a significant shift toward exclusionary attitudes among treated subjects. This experiment demonstrates that even very minor demographic change causes strong exclusionary reactions. Developed nations and politically liberal subnational units are expected to experience a politically conservative shift as international migration brings increased intergroup contact.

Experiment on Exclusionary Attitudes

The experiment leveraged the tendency for commuters to ride the same train every day. I treated certain trains by assigning pairs of Spanish-speaking persons to visit the same train stations at the same time every day. Within each train station, these experimental confederates were the same persons every day. Other trains were randomly assigned to the control condition and had no intervention at the stations. Subjects were surveyed about their socio-political attitudes before and after the treatment. With this design, subjects were exposed to the same Spanish-speaking persons in a location near their homes for an extended period, as would be the situation if immigrants had moved into their neighborhood and used the public transportation. With this design, I experimentally manipulated the conditions of demographic change and, by comparing changes in survey responses before and after the treatments, I identified the effect of exposure to these Spanish-speaking persons.

Experiment on Exclusionary Attitudes

Treated subjects were far more likely to advocate a reduction in immigration from Mexico and were far less likely to indicate that illegal immigrants should be allowed to remain in this country. The ATEs and associated SEs allow me to reject the Null Hypothesis of no effect with a high degree of confidence. The ATE on favoring English as an official language, although in the same exclusionary direction, is smaller and does not allow me to reject the Null Hypothesis. However, baseline rates for this question are considerably higher (0.610, 0–1 scale) than for the other questions, indicating relatively high support for English as an official language, regardless of treatment.

Let's look at the data!