Introduction to Causality

How do we know if X causes Y?

Umberto Mignozzetti
March 10

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Today's Agenda

- What is causal inference?
- Correlation vs causation
- Treatment effects and potential outcomes
- Randomized Controlled Trials

Brief Recap

- Past weeks you learned how to:
  - Load data into R
  - Data processing
  - Draw graphs
  - Work with R in general

Causal Inference

Causal Inference

- What is causal inference?
- Causal: relationship where one factor causes the other
- Inference: our ability to derive conclusion from facts and observations
- *Causal inference is an attempt to estimate a causal connection between two variables based on an observed effect*

Causal Inference

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.

Causal Inference

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.*

Causal Inference

Democracy Does Cause Growth*

Daron Acemoglu
MIT

Suresh Naidu
Columbia

Pascual Restrepo
BU

James A. Robinson
Chicago

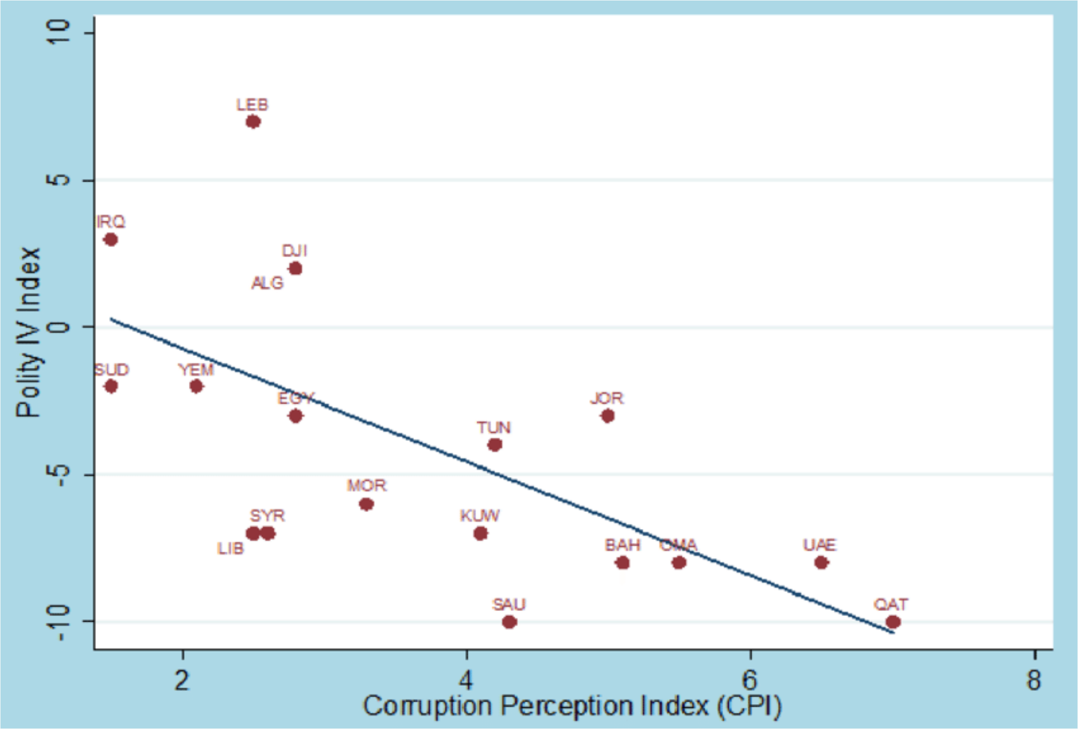
April 2017

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.

Which question is harder to answer?

Causal Inference

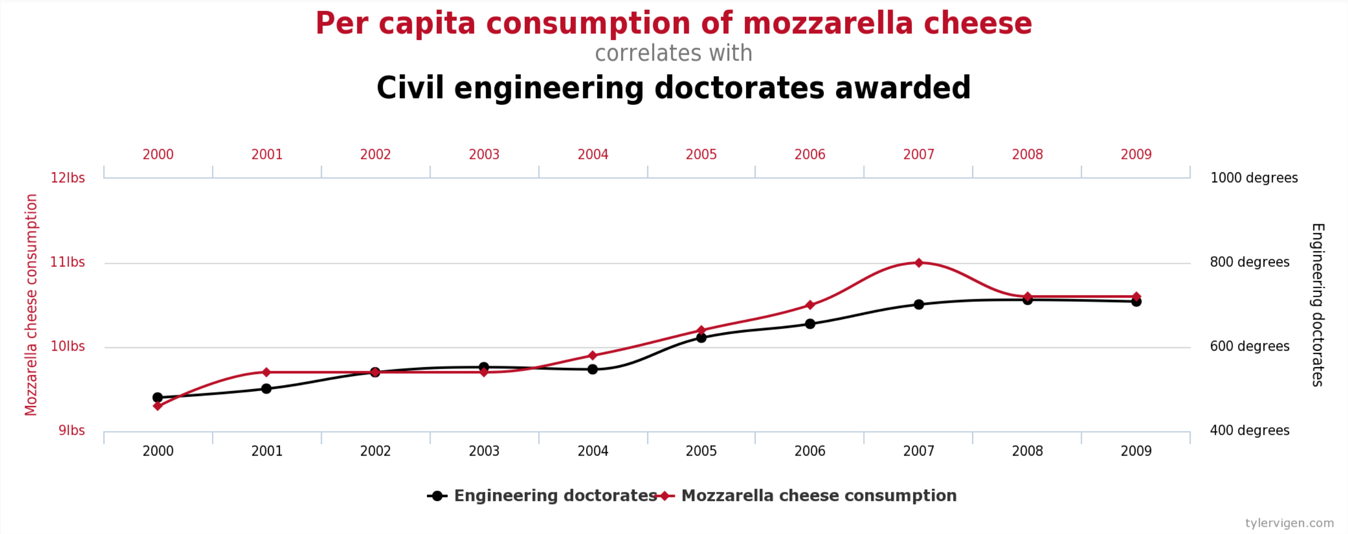


Does X cause Y?

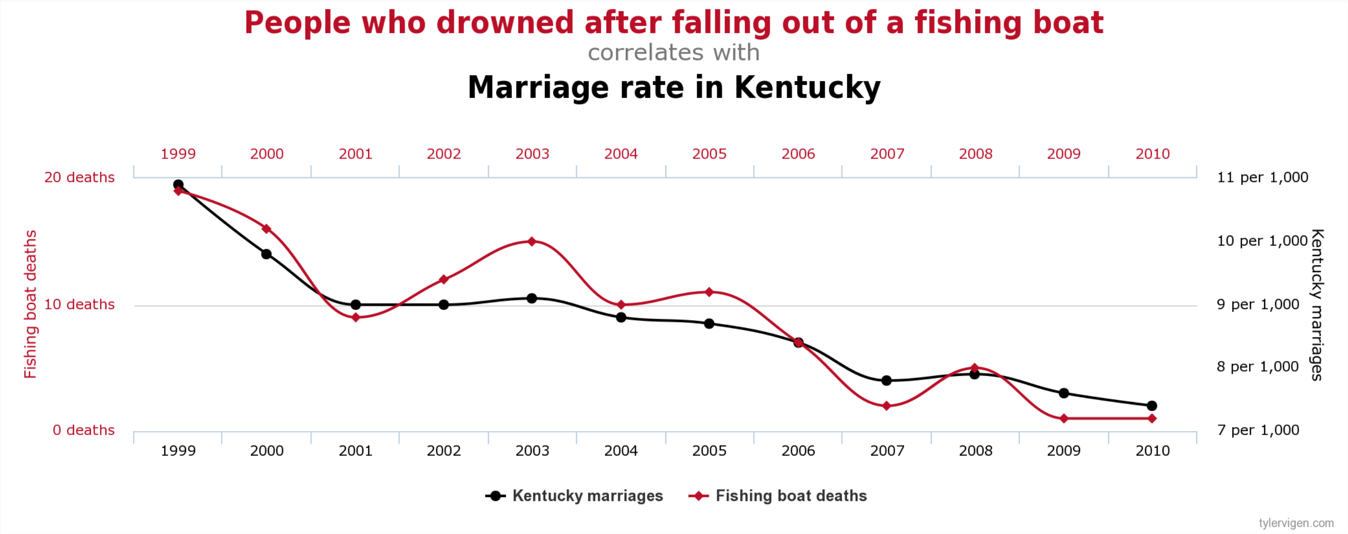
- Does *X* occur at the same time as *Y*?
- If *X* goes up or down, does *Y* also go up or down?
- If *X* is happens, does *Y* also happen?
- *Are X and Y causally related because of that?*

NO

Does X cause Y?



Does X cause Y?



Causal Inference -

- Treatment variable = *T*
- Two potential outcomes = *Y* when *T = 0* and *Y* when *T = 1*
- Example
    - Treatment: getting a university degree
    - Potential outcome: salary with a university degree (*Y when T = 1)* versus salary without a university degree (*Y when T = 0)*

Causal Inference -

- The causal effect of the treatment T is the difference in Y with and without T
- $Y(T=1) - Y(T=0)$ or $Y_1 - Y_0$

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 is that a problem?

Fundamental Problem

- *We can never observe Y where T = 1 and T = 0 at the same time*

- We only observe *one* outcome at a time, that's why it is called the *potential* outcomes framework

Fundamental Problem

$$Y_t(u) - Y_c(u). \quad (1)$$

I shall call the difference (1) the causal effect of t (relative to c) on u (as measured by Y). Expression (1) is the way that the model for causal inference expresses the most basic of all causal statements. It says that treatment t causes the effect $Y_t(u) - Y_c(u)$ on unit U (relative to treatment c) or more simply that

$$t \text{ causes the effect } Y_t(u) - Y_c(u). \quad (2)$$

Causal inference is ultimately concerned with the effects of causes on specific units, that is, with ascertaining the value of the causal effect in (1). It is frustrated by an inherent fact of observational life that I call the Fundamental Problem of Causal Inference.

Fundamental Problem of Causal Inference. It is impossible to *observe* the value of $Y_t(u)$ and $Y_c(u)$ on the same unit and, therefore, it is impossible to *observe* the effect of t on u.

Holland, Paul (1986), p. 947

Sample Average

- Solution: we estimate the *average causal effect* in the groups that received and did not receive the treatment
- We call it the *Sample Average Treatment Effect*, or SATE

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 is that enough?

Randomization

- The best solution to the problem of selection bias is *randomization*
- If the researcher randomized the treatment, she can be sure that it is unrelated to any observable characteristic
- We also assume randomized treatment is uncorrelated with any *unobservable* characteristic too
- Randomized Controlled Trials (RCTs): the researcher creates treatment and control groups
- If all other characteristics are equivalent on average between the two

Randomization

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 pretreatment characteristics.

Internal versus External

- RCTs have very strong internal validity, that is, there is very little chance the result is derived from causes other than the treatment
- However, they may not generalize well. Why?
- Samples may not reflect the whole population of interest

Class Exercise on

- Partial replication of: Jones, Benjamin F, and Benjamin A Olken. 2009. Hit or Miss? The Effect of Assassinations on Institutions and War. *American Economic Journal: Macroeconomics* 1(2): 55–87.

- **Abstract**: Assassinations are a persistent feature of the political landscape. Using a new dataset of assassination attempts on all world leaders from 1875 to 2004, we exploit inherent randomness in the success or failure of assassination attempts to identify the effects of assassination. We find that, on average,

Class Exercise on

- One longstanding debate in polisci is whether individual political leaders can make a difference.
- Some emphasise that leaders with different ideologies and personalities can significantly affect the course of a nation.
- Others argue that political leaders are severely constrained by historical and institutional forces.
- Did individuals like Hitler, Mao, Roosevelt, and Churchill make a big difference?

Class Exercise on

- In this exercise, we consider a *natural experiment* in which the success or failure of assassination attempts is assumed to be essentially random.
- Each observation of the CSV data set `leaders.csv` contains information about an assassination attempt.
- The variables are:

Class Exercise on

Name	Description
`country`	The name of the country
`year`	Year of assassination
`leadername`	Name of leader who was targeted
`age`	Age of the targeted leader
`politybefore`	Average polity score during the 3 year period prior to the attempt
`polityafter`	Average polity score during the 3 year period after the attempt

Class Exercise on

Name	Description
`civilwarbefore`	1 if country is in civil war during the 3 year period prior to the attempt, or 0
`civilwarafter`	1 if country is in civil war during the 3 year period after the attempt, or 0
`interwarbefore`	1 if country is in international war during the 3 year period prior to the attempt, or 0
`interwarafter`	1 if country is in international war during the 3 year period after the attempt, or 0

Class Exercise on

The `polity` variable represents the so-called *polity score* from the Polity Project. The Polity Project systematically documents and quantifies the regime types of all countries in the world from 1800. The polity score is a 21-point scale ranging from -10 (hereditary monarchy) to 10 (consolidated democracy).

The `result` variable is a 10 category factor variable describing the result of each assassination attempt.

Class Exercise on

- **Question 1**
- How many assassination attempts are recorded in the data? How many countries experience at least one leader assassination attempt? (The `unique` function, which returns a set of unique values from the input vector, may be useful here). What is the average number of such attempts (per year) among these countries?

Class Exercise on

- **Question 2**
- Create a new binary variable named `success` that is equal to 1 if a leader dies from the attack and to 0 if the leader survives. Store this new variable as part of the original data frame. What is the overall success rate of leader assassination? Does the result speak to the validity of the assumption that the success of assassination attempts is

Class Exercise on

- **Question 3**
- Investigate whether the average polity score over 3 years prior to an assassination attempt differs on average between successful and failed attempts. Also, examine whether there is any difference in the age of targeted leaders between successful and failed attempts. Briefly interpret the results in light of the validity of the aforementioned assumption.

Class Exercise on

- **Question 4**
- Repeat the same analysis as in the previous question, but this time using the country's experience of civil and international war. Create a new binary variable in the data frame called `warbefore`. Code the variable such that it is equal to 1 if a country is in either civil or international war during the 3 years prior to an assassination attempt. Provide a brief

Class Exercise on

- **Question 5**
- Does successful leader assassination cause democratization? Does successful leader assassination lead countries to war? Answer these questions by analyzing the data. Be sure to state your assumptions and provide a brief interpretation of the results.

Questions?

See you next Thursday!