PO479: Introduction to Causal Inference

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August 6, 2025

What is Causal Inference?

Different Kinds of Inference

- Descriptive Inference
- Predictive Inference
- **Causal Inference**

The Potential Outcomes Model

- This model determines the effect of treatment assuming that each unit has the potential to be treated or not treated (See work by Jerzy Neyman and Donald Rubin).
- The potential outcomes model provides a set of assumptions that can allow for valid causal inference when randomization is not possible (Morgan and Winship 2015).
    - a framework in which to ask carefully constructed what-if questions that lay bare the limitations of observational data and the need to clearly articulate assumptions that are believable because they are grounded in theory that is defendable (Morgan and Winship 2015, p. 13).

The Potential Outcomes Model

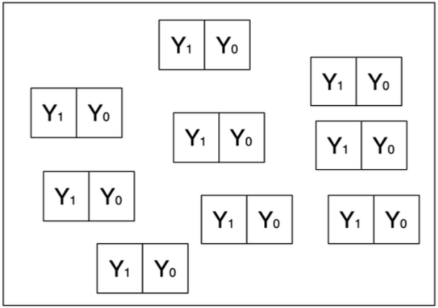

Figure: Potential Outcomes Urn (Source POLI666 Aaron Erlich)

The Potential Outcomes Model

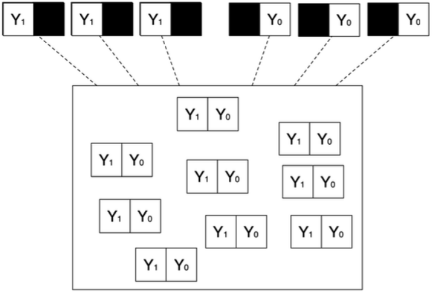

Figure: Draws from the Potential Outcomes Urn (Source POLI666 Aaron Erlich)

The Causal Effect

- Therefore, we can estimate the causal effect for a unit *i* as the difference between its two potential outcomes:

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

- However, we have a problem. We cannot obverse both Y_{1i} and Y_{0i} for the same *i*.

A missing data problem

- The fundamental problem in causal inference is that we cannot observe all the potential outcomes.
- Therefore, we cannot calculate τ_i

i	D_i	Y_{1i}	Y_{0i}	τ_i	Y_i
1	1	8	3	5	8
2	1	4	6	-2	4
3	0	6	6	0	6
4	0	10	8	2	10

Interested in Averages

- However, we are not usually interested in τ_i we are interested in τ_{ATE} or the Average Treatment Effect

i	D_i	Y_{1i}	Y_{0i}	τ_i	Y_i
1	1	6	6	0	6
2	1	10	8	2	8
3	0	8	3	5	8
4	0	4	6	-2	4

$$\tau_{ATE} = \mathbb{E}[\tau_i] = \mathbb{E}[Y_{1i} - Y_{0i}] = \frac{0+2+5+-2}{4} = 1.25$$

Interested in Averages

i	D_i	Y_{1i}	Y_{0i}	τ_i	Y_i
1	1		6	?	6
2	1		8	?	8
3	0	8		?	8
4	0	4		?	4

- Since we cannot observe any of the values in red, we need to estimate the ATE from the information we observe.

$$\tilde{\tau} = \mathbb{E}[Y_{i|D=1} - Y_{i|D=0}] = \frac{6+8}{2} - \frac{8+4}{2} = 1$$

- Notice how we can approximate the $\mathbb{E}[\tau_i]$ by taking the average of the observed values.
- But our $\tau_{ATE} \neq \tilde{\tau}$, this problem occurs when there is bias in selection to treatment. Therefore, we need a research design that reduces this bias.

Identification Strategies

- There are a number of assignment mechanisms that help researchers make claims that they are able to identity the causal effect.
- The goal is to ensure that potential outcomes are not correlated with assignment to treatment. In other words we want to ensure that the treatment and control groups are as similar as possible.

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    - Close elections
    - The weather
    - Administrative rules/boundaries
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3. Treatment is "*as-if*" randomly assigned after control
    - Matching
    - Regression
4. Treatment is self selected and there is no plausible control

ARTICLE

The ingroup love and outgroup hate of Christian Nationalism: experimental evidence about the implementation of the rule of law

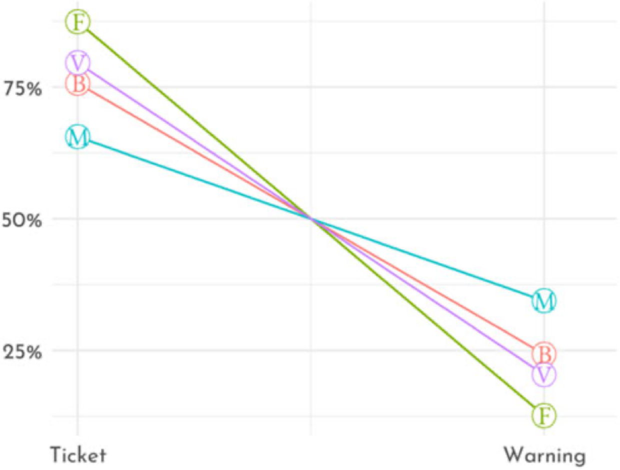
Zachary D. Broeren[1] and Paul A. Djupe[2]

Experiments

"A man in his car is pulled over for speeding. He explains to the officer that..." (Broeren and Djupe 2023, p. 46).

- he was speeding because he is late for worship at his Baptist church [Baptist].
- kickoff for a huge college football rivalry is soon and he needs to buy a 6 pack before it begins [Football].
- he was speeding because he is late for Jummah prayers at his Mosque [Muslim].
- he was speeding because he is running late for a lecture on veganism he has been looking forward to [Vegan].

Respondents were then asked, "Should he be given a warning or a ticket?"



Note: B=Baptist, F=Football, M=Muslim, V=Vegan

Experiments

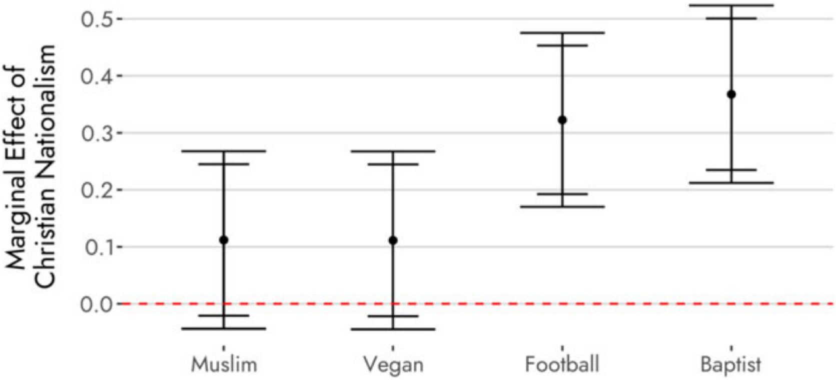


Figure 3. The marginal effect of Christian nationalism by treatment.

Natural Experiments

The Impact of Political Violence on Levels of Polarization: Evidence from a Natural Experiment in the United Kingdom

Rafael Campos-Gottardo[1,2]

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[2] *Centre for the Study of Democratic Citizenship*

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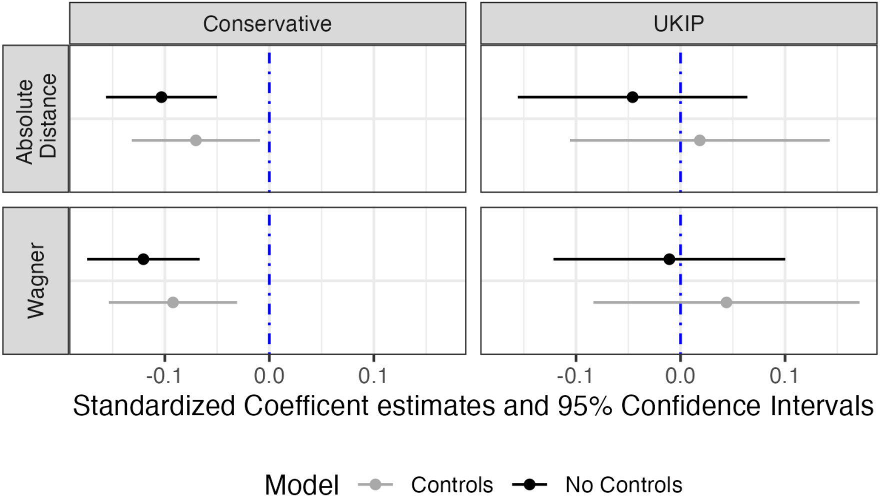
$$Y_i = \alpha + \tau D_i + \mathbf{Z}_i \gamma + \varepsilon_i \tag{2}$$

Natural Experiments

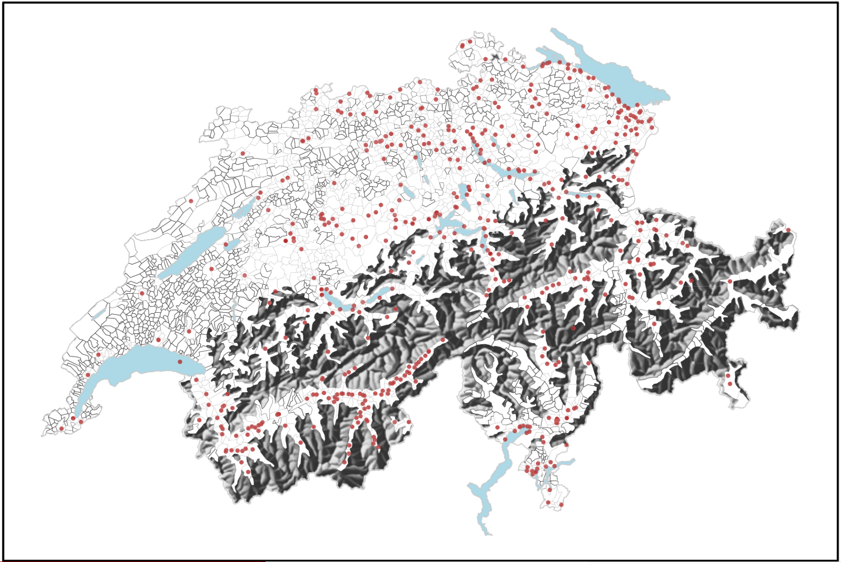


Do natural disasters help the environment? How voters respond and what that means[1]

Leonardo Baccini[1] and Lucas Leemann[2*]

[1]Department of Political Science, McGill University, Montreal, Canada and [2]Department of Political Science, University of Zurich, Zurich, Switzerland

Natural Experiments - Difference-in-Difference



Natural Experiments - Difference-in-Difference

Table 1. Voting and weather (OLS)

	Model I	Model II	Model III
EXPOSURE			
Flooded	0.86**	1.28***	1.19***
	(0.42)	(0.42)	(0.42)
VOTE SHARES			
	✓	✓	✓
PRECIPITATION			
	X	✓	✓
SURFACE			
	X	✓	✓
FIXED EFFECTS			
Votes	✓	✓	✓
Municipality	✓	✓	✓
R^2	0.82	0.84	0.85
Adj. R^2	0.80	0.82	0.82
Num. obs.	21024	18320	17934
RMSE	8.18	7.62	7.61

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, full table with all estimated coefficients is presented in the appendix (Table A.1).

Natural Experiments - Difference-in-Difference

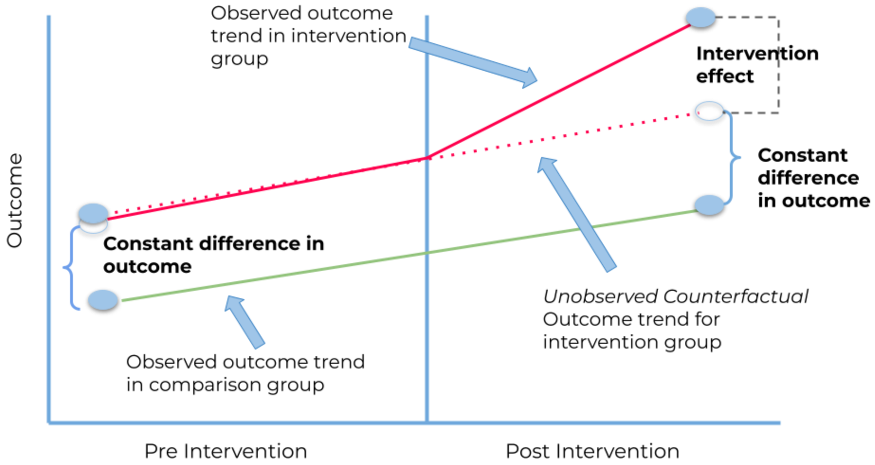


Figure: Source Medium

Questions?

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