Day 01: Introducing and Motivating Experiments in the Social Sciences

Erin Rossiter

January 11, 2022

Today’s plan

Outline

- Introductions
- Syllabus
  - Course goals
  - How we'll achieve those goals
- A little lecture
- A little lab

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Syllabus

Logistics

1 Course information

Location
DeBartolo Hall 336

Time
Tuesdays 3:30pm - 6:15pm

Office hours
Tuesdays 6:15pm-7:15pm
Fridays 10:30am-12:30pm
(or by appointment)
2077 Jenkins Nanovic Halls

Per University policy, students are required to wear masks in class and when attending office hours.

Course goals

2 Description

Political scientists across subfields are increasingly using experimental approaches. This course covers the design, implementation, and analysis of experiments. We will discuss both theoretical and practical aspects of experimentation. Core concepts will be applicable across types of experiments, including lab, survey, online, and lab-in-the-field.

3 Learning objectives

- The student will be able to identify key threats to causal inference and how to address them by experimental design
- The student will gain a command over key tools for designing and analyzing experiments
- The student will apply key concepts from the course and design an experiment that could be implemented to contribute to the student's research agenda
- The student will practice assessing experimental design choices via simulation of their own original experiment

Put differently

1. understand theory and concepts
2. work through the practical side of things
3. “speak the language"

The assignments and schedule were built to support these goals.

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Assignments

Problem sets 25%

We will have five short problem sets the first five weeks of class, each worth %5 of your grade. While the major goals of the course involve designing and planning the analysis for your own experiment, I strongly believe working through problems yourself (and to do so, carefully reading Gerber and Green textbook!) is a necessary step towards these goals.

Please note: the problem sets will be distributed via Canvas by 3pm on Wednesdays to best calibrate the question items to areas needing practice after we have gone through lecture on Tuesdays together. The problem sets will likewise be due by 3pm the following Wednesday. The Wednesday due date also allows us to devote time in class to work through problems together and for students to take advantage of office hours after class.

Assignments

Final paper 50%

The final paper will take the form of a pre-analysis plan and simulation using DeclareDesign. I'll simply refer to this as the "final paper." It can focus on any substantive area in political science and propose any kind of experiment. It is strongly recommended that the student proposes an experiment that tests a hypothesis to advance their research agenda.

I do not require a specific word or page count. For some rough guidance, the final paper might spend ∼5 pages motivating a research question and hypothesis(es). Then, the bulk of the paper, maybe ∼10-15 pages, will detail the design, implementation, and analysis of the experiment. We will talk about pre-registration early in the semester so the student knows the expectations for the written component of the final paper. This component should be a polished piece of writing.

The final paper also requires an assessment of the experimental design choices via simulation using DeclareDesign. The student will not only provide the code and numeric results of the simulation, but they will provide written annotations to explain how they are representing their design choices in code and an interpretation of the results.

Assignments

Final presentation 25%

I strongly believe that presenting your work verbally, as it requires a different type of communication than writing, requires you to clarify your own thinking and logic. It follows that both your project and paper will improve after crafting a presentation. This has been my experience.

Each student will have 10-15 minutes to present their final paper with slides and 10-15 minutes for Q&A from peers. The presentations will be held the final day of class. We will discuss more details of the final presentation at a later date.

Schedule part 1: problem sets to build foundation

19 Schedule

Day01: Tues, January 11

Introductions, course goals, syllabus, set up

- Reading: nothing
- Due: Qualtrics survey

Day02: Tues, January 18

Why experiment?

- Reading: GG chs. 1-2
- Due: HW1

Day03: Tues, January 25

Random assignment procedures

- Reading: GG ch. 3
- Due: HW2

Day04: Tues, February 1

Analyzing experimental data

- Reading: GG ch. 4
- Due: HW3

Schedule part 2: making good decisions in practice

Day05: Tues, February 8

Diagnosing experimental designs

- Reading: *Research Design: Declaration, Diagnosis, Redesign*, by Graeme Blair, Alexander Coppock, and Macartan Humphreys. chs. 1-4 (read carefully), chs. 5-10 (skim)
- Due: HW4, including one-pager on research topic, question, and hypothesis(es)

Day06: Tues, February 15

Pre-registration

- Reading:
  - Lula Chen & Chris Grady. 10 Things to Know About Pre-Analysis Plans
  - Daniel Lakens. Not All Flexibility P-Hacking Is, Young Padawan
  - Tim Ryan. What is pre-registration for?
  - Alexander Wuttke. JOP's new pre-registration policy
  - (skim) George Ofosu & Daniel Posner. 2021. Pre-analysis Plans: An Early Stocktaking. *Perspectives on Politics*.
  - Find and read two preregistrations on the EGAP Registry on research in your specific subfield by different scholars. Come ready to sha … istrations you read.
- Due: HW5

https://www.alexander-wuttke.de/jops-new-pre-registration-policy/

Schedule part 2 continued

Day07: Tues, February 22

Ethics in experimentation

- Reading:
  - Ethics guidelines from APSA here
  - Macartan Humphreys. 2015. "Reflections on the Ethics of Social Experimentation." Journal of Globalization and Development.
  - Tara Slough. 2020. "The Ethics of Electoral Experimentation: Design-Based Recommendations." Working paper.
  - Derek Willis. 2015. "Professors' Research Project Stirs Political Outrage in Montana." New York Times.
  - Adam Kramer, David Guillory, and Jeffrey Hancock. 2014. "Experimental evidence of massive-scale emotional contagion through social networks." Proceedings of the National Academy of Sciences.
- Due: complete CITI training and upload certificate to Canvas

Schedule part 3: advanced topics and focus on your own paper

Day08: Tues, March 1

Theory and experimentation (mediation)

- Reading: GG ch. 10

Tues, March 8 – Spring break, no class!

Day09: Tues, March 15

Sampling units and generalizability; internal and external validity

- Reading: Erin Hartman. Generalizing Experimental Results.

Day10: Tues, March 22

Heterogeneous treatment effects

- Reading: GG ch. 9
- Due: first draft of final paper, including simulations

Day11: Tues, March 29

Noncompliance

- Reading: GG chs. 5-6

Day12: Tues, April 5

Attrition

- Reading: GG ch. 7

Note: MPSA is April 7-10

Schedule part 3 continued

Day14: Tues, April 19

Open day in case we adjust the schedule, need extra time on a topic, etc.

Day15: Tues, April 26

Last class! In-class presentations. As noted above, we have enough time so that each student has approximately 30 minutes total, which should include presenting (10-15 min) and engaging with Q&A (10-15 min).

Thursday, May 5

No final exam. Final paper due at noon EST

Final syllabus notes:

- email policy
- mental health statement
- remember I'm a mandatory reporter

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A little lecture

Three goals of empirical research

1. Description
2. Prediction
3. Causal inference

How has your own work fallen into these categories?

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How has your own work fallen into these categories?

What exactly is an "experiment"?

- Formally, a study that randomly assigns units to treatment with *a known probability* between 0 and 1
  - In practice, how could we design a study to know the probability a unit is randomly assigned to treatment?
  - Given this definition, give me an example of something **not** an experiment?
  - (much more on this later!!)
- Might be called:
  - randomized experiment
  - randomized controlled trial (RCTs)
  - A/B testing
  - etc.
- Be on the lookout:
  - You might hear "experiment" used colloquially (e.g., my undergrads, computer science, etc.)
  - Don't confuse random *sampling* with random *assignment*

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Why experiment?

1. When you're after a causal explanation vs. description or prediction
2. You can ground statistical and causal inferences **in features of the design** rather than assumptions about the world
   - we already have an example of this
   - a coin toss to determine treatment assignment is a *design feature* helping us recover unbiased causal estimates
3. There's value in transparent & intuitive science that involves ex ante design and, therefore, limits researcher discretion
4. Experiments allow us to study the effects of phenomena that seldom occur naturally
5. Systematic experimental inquiry can lead to the discovery and development of new interventions (think psych papers)
6. Anything else?

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What kind of causal questions do social scientists ask?

A partial list:

- **Program evaluation** SAT prep classes, weight loss programs, fundraising, diversity training, deliberative polls, advertising campaigns
- **Public policy evaluation** speed traps, vouchers, alternative sentencing, job training, health insurance subsidies, public housing
- **Behavioral research (including elites)** persuasion, mobilization, education, income, interpersonal influence, discrimination
- **Research on institutions** rules for deliberation, representation, authorizing decisions, monitoring performance

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Experiments in political science

- In his 1909 address, the APSA president "advised the fledgling discipline against following the model of the natural sciences:" (from Cambridge Handbook of Experimental Political Science, pg 1)
  "We are limited by the impossibility of experiment. Politics is an observational, not an experimental science. . . "
- The first experimental paper in APSR appeared in 1956 (Eldersveld)
  - Control: no message
  - Three treatments: phone calls, personal visit, or a mailing
  - Found personal visits significantly increased voter turnout :)
- Experiments in political science didn't "start" until 1990s
- Now perhaps as common as observational studies in some subfields

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Stepping back: our goal in causal inference

Does an intervention (some X, e.g., an institution, policy, event, exposure) have a **causal effect** on an outcome (some Y)?

What are some causal questions in your work?

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Okay, but what exactly is a *causal effect*?

Causal effect – difference in outcome(s) *caused by* an intervention.

Determining a causal effect requires a valid counterfactual

- what would have happened if we were to change X aspect of the world?
- you must re-run history using your imagination
- Example from reading next week: how much budget would be allocated to drinking water if this village had a woman as council head vs. a man?

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The challenge of finding a valid counterfactual

Talk to me about examples of each of challenges:

1. Confounding factors (confounding bias)
   - both X and Y are influenced by some other factor, distorting their association
2. Selection bias
   - covariates pre-dispose you to intervention making treatment and control groups different

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Common approaches to finding “valid” counterfactuals

1. Diff-in-diff
2. Matching
3. Regression discontinuity
4. Instrumental variables
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- All techniques that relying on assumptions about creating a counterfactual after data is collected
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How do experiments help?

Remember, an experiment is a study in which outcomes are measured for a set of subjects to whom experimental conditions are assigned by chance with a known probability between 0 and 1

Intuition:

- We don't have to guess the selection process – we know it!
- For causal inference, we want two groups that are identical *but for the treatment* – experiments are a way of achieving this *by design*

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Example

Effect of campaign negativity on vote shares:

- a quick check of data might lead us to think negative candidates do worse than positive candidates
- selection bias: candidates that go negative are worse than those who stay positive
  - units select into treatment (going negative) for reasons related to the outcome (vote shares)
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Potential outcome framework

Much of the progress in causal inference in recent years made possible by the Neyman-Rubin Causal Model (aka the Potential Outcomes Model)

A formal way to discuss counterfactuals

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A formal way to discuss counterfactuals

Notation

- Finite population of units: $i \in 1, 2, ...N$
- Observed outcomes: Y_i
- Binary treatment:
  - $D_i = 1$ if treated
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  - (note this D_i a random variable; unit might be treated in a hypothetical study or not)
- Potential outcomes:
  - $Y_i(1)$ is the outcome if unit i is exposed to treatment
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  - Both versions of history
    - Potential outcomes describe what would happen if a treatment were or were not administered
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  - $\tau_i = T_i(1) - Y_i(0)$
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Treatment effects

- For each unit, we want to know the causal effect of treatment
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- **Fundamental problem of causal inference: we can only observe one potential outcome**
- What we *can* observe is:
  - $Y_i(d)$ is the value that Y would take under D_i set to d–observed treatment status
  - "switching equation"
  - one term will always be 0 – why?

$$Y_i = d_i Y_i(1) + (1 - d_i) Y_i(0)$$

- But, we are interested in ATE! -

$$ATE = \frac{1}{N} \sum_{i=1}^{N} \tau_i$$

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- Note: to be well-defined, D_i should be manipulable at least in principle
- Leads to common motto: "No causation without manipulation" (Holland 1986)
- Tricky causal problems:
  - effect of race, sex, etc.

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Lab

Setup part 1

Make sure these are installed

1. R
2. RStudio

Setup part 2

- We're going to try using GitHub in this course
  - In-class labs
  - Final paper design
  - Maybe problem sets...
- Allows easy, clean, and socially distanced(!) code sharing
- Good to be comfortable with it for access to cutting-edge methods, future collaboration, etc.

1. Create a github account here
2. Email me your username
3. Download GitHub Desktop (if you're okay with that) here

Setup part 3

- I'll invite you to the course repository
- Then you:
  - "fork" repository
  - "clone" to your desktop
  - open `lab.R`
- Then we can do our quick lab.