

Day 13: Professionalization and reflection

Erin Rossiter

March, 2022

Announcements

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- Last class next week!
- Presentations
 - » slides
 - motivation
 - hypotheses
 - estimands
 - design
 - etc. . .
 - » 15 minutes on paper
 - » 15 minute Q&A

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Today

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1. Mediation
2. Some of my experimental work
3. Professionalization
4. Reflection

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Mediation

What is mediation?

- Variables that “transmit the influence of an intervention”
- Ex: Limes reduced scurvy amongst 18th Century seafarers!
 - » treatment was limes, *but mediating ingredient was **vitamin C***
- Ex: Learning about outgroup is thought to be a mediator of intergroup contact's effects on prejudice
 - » treatment is contact, but mediating “ingredient” is increased knowledge
- Learning about mediators helps us understand the causal processes
 - » we're after the mechanisms underlying our interventions

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More specifically

We want to know:

- whether Z_i induced a change in mediating variable M_i , and
- whether a Z_i -induced change in M_i produced a change in Y_i
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Problems w/ mediation using standard experimental design

- Z_i randomly assigned
- M_i *not* pre-treatment nor randomly assigned

1. $M_i = \alpha_1 + aZ_i + e_{1i}$
2. $Y_i = \alpha_2 + cZ_i + e_{2i}$
3. $Y_i = \alpha_3 + dZ_i + bM_i + e_{3i}$

Questions:

- how do these equations align with our drawing?
- which are causal estimates? and why?

Notice:

- c is “total effect” of Z_i on Y_i
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Regression approaches

Must assume sequential ignorability

- Conditional on the observed pretreatment covariates, the treatment is independent of all potential values of the outcome and mediating variables
- The observed mediator is independent of all potential outcomes given the observed treatment and pretreatment covariates

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Experimental design to answer mediation questions

- Need to manipulate M_i !
- “Implicit mediation analysis”
 - » Design in which you add and subtract different “ingredients” from the treatment
 - » Allows us to:
 - get unbiased causal estimates
 - explore what ingredients cause a treatment to work
 - » Cons:
 - not really direct manipulation of mediator...

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Example

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

- control: no mailer
- civic duty: encouraged to vote
- hawthorne: encourage to vote + monitored
- self: encouraged to vote + monitored + shown past voting
- neighbors: encouraged to vote + monitored + shown past voting + shown others' past voting

“Implicit” mediation analysis because we aren’t positive we’ve manipulated social costs in neighborhood but some learning about norms of voting

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My ongoing work

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Experiments

- How does conversation affect affective polarization?
 - » dissertation & cross-partisan conversations
 - » electoral threat & heterogeneous effects by partisanship (with Taylor Carlson)
 - » amongst Mexican partisans (with Greene, Simpser, and Siera)
- How does self-selection into political conversation affect conversation's ideologically polarizing effects? (with Taylor Carlson)

Experimental design

1. How to *set up* a *good* cluster-randomized experiment when you create the clusters
2. Online chat experiments
3. Precision-retention tradeoff (with Gustavo Diaz)
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Slides

Professionalization

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We invite authors to submit concise articles (around 4000 words or fewer) that immediately address the subject of the research. We do not require lengthy explanations regarding and justifications of the experimental method. Nor do we expect extensive literature reviews of pros and cons of the methodological approaches involved in the experiment unless the goal of the article is to explore these methodological issues. We expect readers to be familiar with experimental methods and therefore to not need pages of literature reviews to be convinced that experimental methods are a legitimate methodological approach. We will consider longer articles in rare, but appropriate cases, as in the following examples: when a new experimental method or approach is being introduced and discussed or when novel theoretical results are being evaluated through experimentation. Finally, we strongly encourage authors to submit manuscripts that showcase informative null findings or inconsistent results from well-designed, executed, and analyzed experiments.

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JEPS submission formats

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The journal publishes four type of articles:

- 1) Research Articles (4000 words) that report novel empirical findings grounded in social science theory
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NYU CESS

- posters for grad students
- experimental methods and awesome, rigorous applied work
- network within the community

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- Online survey
- Can include randomization!
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Stuff on campus

Lab experiments in Behavioral Research Lab

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- The Trade Desk see [here](#) and [here](#)
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