Day 12: Advanced experimental design topics

Erin Rossiter

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Announcements

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- Touch base with me about final papers if I haven't given comments yet
- Today: advanced topics
- April 12: wrap up, reflection, and opportunities moving forward
- April 19: final class & presentations!
  - I'll bring snacks; any food allergies?

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Conjoints

Motivation

- Useful to test treatments that are themselves **collections of attributes**
- Ex: candidate A vs B
  - experience
  - descriptive representation
  - position on immigration policy
  - position on . . .
- Choice entails:
  - preference on each dimension
  - trade-offs across dimensions

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Why conjoints?

- Compare to "traditional" design w/only one attribute
  - assume a treatment as one-dimensional as possible (low vs. high skilled immigrant)
    1. we only learn about one thing from costly experiment
    2. external validity concerns (one thing, but a complex decision-making process!)

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Conjoint analysis

"survey-experimental methods that estimates respondents' preferences given their overall evaluations of alternative profiles that vary across multiple attributes, typically presented in tabular form" (Bansak et al. pg 20)

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Background

- Conjoint analysis became very popular in *marketing*
- Makes sense right?
- Image from here

Q1. Which of the following would you choose?

	Option 1	Option 2	Option 3	Option 4
Cuisine	Italian	Hamburgers	Thai	Chinese
Ordering method	Phone and online	Phone and app	Phone, online and app	Phone only
Nutrition information	Unavailable	Unavailable	On menu	On menu
Average review rating (out of 5 stars)	3	4.7	4.2	4

In the news

CBS News in 2019

- “latent appetite”

What are we doing here?

- Hainmueller et al. 2014 discuss conjoint data using *potential outcomes framework*
  - (not the only one, but first and most widely cited)
- Causally identifying the **average marginal component effect (ACME)**
  - What attributes causally increase or decrease the appeal of a Democratic primary candidate, on average, when varied independently of the other candidate attributes included in the design?
- We can also get **conditional ACMEs**
  - not talking about that today

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Example

	CANDIDATE A	CANDIDATE B
Military Service Experience	Served in the Navy	Did not serve
Supports Creating Pathway to Citizenship for	Unauthorized immigrants with no criminal record who entered the U.S. as minors	All unauthorized immigrants with no criminal record
Previous Occupation	Lawyer	Lawyer
Age	53	45
Gender	Female	Female
Race/Ethnicity	White	Hispanic/Latino
Sexual Orientation	Gay	Straight
Position on Climate Change	Ban the use of fossil fuels after 2040, substantially reducing economic growth	Impose a tax on using fossil fuels, moderately reducing economic growth
Supports Government Healthcare for	Only Americans who are older, poor, or disabled	Only Americans who are older, poor, or disabled
Prior Political Experience	U.S. Senator	No prior political experience

Typical design

- Randomly assign attributes in the tables, order of attributes within the tables per respondent, and tables to respondents
- Outcomes:
  - **rating** of each candidate
  - **choice** between candidates

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Notation and definitions

Notation

- respondents $i \in 1, ..., N$
- K choice or rating/choice tasks, where she rates/chooses between J profiles, with L discretely valued attributes
  - D_l is total number of levels for attribute l

Example

- $N = 311$ respondents
- $K = 6$ tasks per respondent
- $J = 2$ profiles in each task
- $L = 8$ candidate attributes
- $D_1 = 6$ levels for candidate age

Treatment

- vector T_{ijk} is the jth profile in task k given to respondent i
  - T_{ijkl} refers to the lth attribute of the profile
- board!

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Potential outcomes

$Y_{ik}(\bar{\mathbf{t}})$

- J-dimensional vector (i.e., how many profiles)
- outcome given $\bar{\mathbf{t}}$ (i.e., the vector of attributes)

Choice outcome

- $Y_{i=1,j=1,k=1}(\bar{\mathbf{t}}) \in [0, 1]$

Rating outcome

- $Y_{i=1,j=1,k=1}(\bar{\mathbf{t}}) \in [1, 2, ..., 5]$

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Assumptions

To define causal quantities, we have to make assumptions about these potential outcomes

Assumption 1

Assumption 1. Stability and no carry over effects

- potential outcomes remain stable across the choice tasks (i.e., early vs. late in the survey)
- treatment in one task doesn't affect response in later task
- overall, important to remember, **no task order effects**

$$Y_{ik}(\bar{\mathbf{T}}_i) = Y_{ik}(\bar{\mathbf{T}}_i{}') \text{ if } \mathbf{T}_{ik} = \mathbf{T}'_{ik'}$$

if it's a different task (k'), but attribute profile remains the same ($\bar{\mathbf{T}}_i$), then potential outcomes should be the same

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Assumption 1 implications

- Assumption 1 allows us to simply say $Y_{ij}(\mathbf{t})$ because now which task the attribute profile showed up on (k) doesn't matter!
- Practically, we can now **pool data** across all tasks and disregard order.
- Can always test this assumption.
  - If problems, use each respondents' **first task only** as robustness check.

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Assumption 2

Assumption 2. No profile-order effects

- potential outcomes remain stable even if we shuffle the order of the profiles within a task

$$Y_{ij}(\mathbf{T}_{ik}) = Y_{ij'}(\mathbf{T}'_{ik}) \text{ if } \mathbf{T}_{ijk} = \mathbf{T}'_{ij'k}$$

if it's a different order of profiles (j'), but attribute profile remains the same in the same task ($\bar{\mathbf{T}}_{ik}$), then potential outcomes should be the same

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Assumption 2 implications

- Assumption 2 allows us to drop j subscript, too.
  - $Y_i(\mathbf{t})$
- Practically, we can now **ignore order profile was presented within the task** and pool data across profiles
- Can test this assumption
  - Did first profile get chosen more?

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- looks at effect of **an individual attribute** (vs. comparing entire profiles)
- Ex: does $l = highexperience$ vs. $l = lowexperience$ change probability that profile j is chosen?
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ACME estimand

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\bar{\pi}_l(t_1, t_0, p(\boldsymbol{t})) &\equiv \mathbb{E}\Big[Y_i(t_1, T_{ijk[-l]}, \boldsymbol{T}_{i[-j]k}) - Y_i(t_0, T_{ijk[-l]}, \boldsymbol{T}_{i[-j]k}) \big| \big(T_{ijk[-l]}, \boldsymbol{T}_{i[-j]k}\big) \in \widetilde{\mathcal{T}} \Big] \\
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Intuition:

- prob candidate chosen when $I = rich$ - prob identical candidate chosen but $I = poor$, and chosen over the same other candidate
- repeat calculating the rich vs poor effect, but with different candidate and opponent attributes
- ACME estimand = weighted average of these differences according to joint distribution of attribute combinations

ACME summarizes the average difference in [candidate] preference between two levels of one attribute, averaging over all of the levels of the other attributes

- In election context, interpretable as the attribute's **causal effect on a candidate's expected vote share**

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DeclareDesign team says, the data strategy for conjoints, requires making these four [new] choices:

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- increased realism of treatment; external validity
- test lots of causal hypotheses in one study
- easily compare relative effects of attributes
- assuage social desirability bias concerns

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- Their argument
  - randomization does not mean our **inquiry** is a causal one
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Resources

DeclareDesign

- book chapter draft
- need code here to run it yourself, thanks Alejandra!

Two R packages:

1. cregg
2. cjoint

Example

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 pause
- and, whether a Z_i-induced change in M_i produced a change in Y_i
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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
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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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