Vignette vs. Conjoint Experiments

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Outline for the Day

- What is a vignette experiment?
    - Why are they useful?
    - Design Considerations
    - Power calculations
    - Limitations
- What is a conjoint experiment?
    - Why are they useful?
    - Different types
    - Assumptions and Design Considerations
    - Causal Quantities of Interest
    - Power calculations
    - Limitations
- Pros/Cons of vignette and conjoint experiments
- Examples of conjoint analysis in the political science literature
- Quick tutorial on how to program vignettes and/or conjoint in Qualtrics

What is a vignette experiment?

- Participants are presented with hypothetical situations and are asked to indicate their opinions about desirable or anticipated behavior in the situation.
- The hypothetical situation is presented in the form of a **vignette**:
  - *"short description of a person or social situation which contains precise references to what are thought to be the most important factors in the decision-making or judgment-making process of respondents"* (Alexander & Becker 1978)
- Contrastive Vignette Techniques (CVT) randomly assign participants to subtle manipulations in the vignette structure or content to examine how responses vary based on the manipulations (Caro et al. 2012)

Example

Sally is a registered Democrat and has always voted for Democratic candidates. Based on conversations from previous elections, Sally knows that her coworkers are almost all registered **[Republicans / Democrats]**. Last Thursday morning at the office when she went to the common room to pour herself some coffee, several of her coworkers were standing around talking about the upcoming election. Sally started to listen, and realized that the group was talking about their support for the **[Republican / Democratic]** candidate.

- What is the likelihood that Sally expresses her true political opinions to the group?

Why are vignette experiments useful?

- Lack observational data for what we're interested in — or can't gain *causal* inferences from it
- Not **feasible** or **ethical** to manipulate the factors of interest in the real world
  - Randomly assigning parties, races, or genders to political candidates
  - Randomly assigning traits to immigrants
- Relatively inexpensive and efficient

Design Considerations

- Vignette Equivalence
  - *Although respondents have different life experiences, they use the same absolute scale to judge the levels of the variables presented in the vignettes*
  - Different respondents interpret and evaluate the vignettes similarly
- Response Consistency
  - *Respondents apply the same absolute scale to evaluating the vignette characters as they would to evaluating themselves*
  - i.e. If we're interested in job satisfaction, a respondent evaluates her own job in a similar way that she evaluates hypothetical jobs described in the vignettes.

Solutions

- Vignette Equivalence Bias: **Anchoring vignettes**
  - Prompt respondents to provide a self-rating of the variable of interest in addition to an evaluation of the ratings of the characters in the vignette whose descriptions keep the levels of the same variable fixed
  - Use the ratings of the vignette characters to adjust the self-rating

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- Response Consistency Bias: **Investigate the salience of the scope and magnitude of the manipulated variable levels**
  - Ask individuals similar to the future participants to describe relevant situations to the vignettes
  - Focus groups, qualitative methods

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- Length and Detail
  - Consider the medium (online, lab, face to face, etc.)
    - Online: shorter is better
    - Lab: can be longer because you have their captive attention
  - Consider the sample (Turk, college students, YouGov panel, etc.)
  - Consider the length of the rest of the survey
    - If part of a long survey, shorter is better; otherwise longer is fine

Power Calculations

- Value
  - Not all about N size
  - Distinguish signal from noise
- $\beta = \Phi\left(\frac{|\mu_t - \mu_c|\sqrt{N}}{2\sigma} - \Phi^{-1}\left(1 - \frac{\alpha}{2}\right)\right)$
- Only as helpful as your priors
  - Pilot study
- Power Calculator and Simulations
- Inclusion of covariates in your power calculations

Limitations

- Can identify causal effects of the manipulation(s) as a whole, but they typically do not allow us to determine which components of the manipulation produce the observed effects
  - Could design one-dimensional treatments (i.e. Hainmueller & Hiscox 2010—"low" vs. "high" skilled immigrants)
  - But, this forces us to pick just one factor and it likely lacks external validity

Conjoint Analysis

What is a conjoint experiment?

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- Technique asks respondents to choose from or rate hypothetical profiles that combine multiple attributes, enabling researchers to estimate the relative influence of each attribute value on the resulting choice or rating.
- Enables researchers to nonparametrically identify and estimate the causal effects of many treatment components simultaneously
- Resulting estimates represent effects on the same outcome, so they can be compared on the same scale to evaluate the relative influence of the components and to assess the plausibility of multiple theories

Conjoint Analysis Example

Jens Hainmueller et al.

Please read the descriptions of the potential immigrants carefully. Then, please indicate which of the two immigrants you would personally prefer to see admitted to the United States.

	Immigrant 1	**Immigrant 2**
Prior Trips to the U.S.	Entered the U.S. once before on a tourist visa	Entered the U.S. once before on a tourist visa
Reason for Application	Reunite with family members already in U.S.	Reunite with family members already in U.S.
Country of Origin	Mexico	Iraq
Language Skills	During admission interview, this applicant spoke fluent English	During admission interview, this applicant spoke fluent English
Profession	Child care provider	Teacher
Job Experience	One to two years of job training and experience	Three to five years of job training and experience
Employment Plans	Does not have a contract with a U.S. employer but has done job interviews	Will look for work after arriving in the U.S.
Education Level	Equivalent to completing two years of college in the U.S.	Equivalent to completing a college degree in the U.S.
Gender	Female	Male

- **Choice-based:** Respondents are presented with 2+ alternatives varying in multiple attributes and are asked to choose the one they most prefer.
    - Most common, most closely approximates real-world decision making
    - Ex.: Vote for a candidate, choose which immigrant to admit to the US, choose a policy

Types of Conjoint Analysis

- **Choice-based:** Respondents are presented with 2+ alternatives varying in multiple attributes and are asked to choose the one they most prefer.
  - Most common, most closely approximates real-world decision making
  - Ex.: Vote for a candidate, choose which immigrant to admit to the US, choose a policy
- **Rating-based:** Respondents give a numerical rating to each profile which represents their degree of preference for the profile
  - Provide more direct, finely grained information about respondents' preferences
  - Ex.: How likely are you to vote for Candidate A, how would you rate Immigrant 1, how strongly do you support Policy 1

Conjoint Analysis Example

Choice-Based

	Immigrant 1	Immigrant 2
If you had to choose between them, which of these two immigrants should be given priority to come to the United States to live?	○	○

Rating-Based

On a scale from 1 to 7, where 1 indicates that the United States should absolutely not admit the immigrant and 7 indicates that the United States should definitely admit the immigrant, how would you rate Immigrant 1?

Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
○	○	○	○	○	○	○

Using the same scale, how would you rate Immigrant 2?

Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
○	○	○	○	○	○	○

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1. **Stability and No Carryover Effects:** Potential outcomes always take on the same value as long as all the profiles in the same choice task have identical sets of attributes
   - *Respondents would choose the same immigrant as long as the two immigrants in the same choice task had identical attributes, regardless of the kinds of immigrants they had already seen or would see later in the study*
   - Not plausible if respondents use the information given in earlier choice tasks as a reference point in evaluating immigrants later in the experiment
   - If you suspect this assumption won't hold, you can assign a single choice task per respondent or use data only from each respondent's first task.

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3. **Randomization of Profiles:** Potential outcomes are statistically independent of the profiles
    - Potential problem: This implies that we must assign a non-zero probability to all possible attribute combinations, but some of these combinations might be theoretically implausible (i.e. having no formal schooling, but being a doctor)

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  - BUT, we're interested in multiple dimensions...

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  - Basically:
    1. Compute the probability that the educated immigrant is chosen over an opponent, compute the probability that an uneducated (but otherwise identical) immigrant is chosen over the same opponent, and take the difference
    2. Compute the same difference between an educated and uneducated immigrant, but with a different set of attributes (other than education)
    3. Take the weighted average of these differences over all possible combinations of the attributes according to the joint distribution

Power Calculations

- Not as straight forward as traditional calculations
    - Rule of Thumb
    - $N > 500 * C/(T * A)$
        - T= # of tasks
        - A= # of alternatives
        - C= # of levels for alternative (biggest)
    - Helpful? Maybe?
- Parametric
    - Louviere et al (2000)
        - Not suitable for determining the minimum N
    - Rose and Bliemer (2013)
        - Most critical parameter

Power Calculations Continued

- To calculate minimum sample size for coefficients
  - Significance level
  - Power
  - Model
  - Parameter Beliefs
  - Design
- Bejjer-Grob et al. (2015) provide a guide
- R code
- Benefit: This could be adapted to a pre-analysis plan relatively easily

Limitations

- Validity of conclusions based on stated preferences? Survey behavior $\neq$ Real world behavior
- Social desirability bias or demand effects
- Might be interested in attitudes that can't be expressed through the ranking or rating of alternatives
- Simultaneous provision of lots of information could induce cognitive processing different from those in the real world
- Can require significant computer programming to implement

Advantages over Traditional Survey Experiments

- Conjoint provides more information jointly and lets respondents employ the information they find most relevant
- In some cases (immigrant experiment, vote choice, etc.) conjoint analyses better mirror real world decision making
- Might get around some social desirability bias by allowing respondents to find multiple forms of justification for their decisions

Concluding Notes

- Both vignette and conjoint experiments are useful and prominent in the social sciences, largely because they allow us to gain *causal* identification on relationships we otherwise can't (shouldn't) observe or manipulate
- Both require important decisions on the design side—theory is important here!
- Vignettes and conjoints are not a cure-all and should only be used if they're the best research design for your question

Conjoint Analysis Examples in the Political Science Literature

Field	Author	Year	Title
American	Abrajano et al.	2014	Using Experiments to Estimate Geographic Variation in Racially Polarized Voting
	Crowder-Meyer et al.	2015	Complex Interactions: Candidate Race, Sex, Electoral Institutions, and Voter Choice
	Sen	2015	How Political Signals Affect Public Support for Judicial Nominations: Evidence from a Conjoint Experiment
Comparative	Carnes & Lupu	2015	Voters Biases and the Descriptive Underrepresentation of the Working Class
	Hansen et al.	2015	Cross-National Yardstick Comparisons: A Choice Experiment on a Forgotten Voter Heuristic
	Vivyan & Wagner	2016	House or Home? Constituent Preferences over Legislator Effort Allocation
IR	Bechtela &Scheve	2013	Mass Support for Global Climate Agreements Depends on Institutional Design
	Dafoe et al.	2015	Confounding in Survey Experiments
IR/American	Hainmueller & Hopkins	2015	The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants
Methods	Hainmueller et al.	2013	Causal Inference in Conjoint Analysis: Understanding Multidimensional Choices via Stated Preference Experiments
	Grimmer et al.	2013	Estimating Heterogeneous Treatment Effects and the Effects of Heterogeneous Treatments with Ensemble Methods
	Hainmueller et al.	2014	Do Survey Experiments Capture Real-World Behavior? External Validation of Conjoint and Vignette Analyses with a Natural Experiment
	Egami & Imai	2015	Causal Interaction in High-Dimension
	Ratkovic & Tingley	2015	Sparse Estimation and Uncertainty with Application to Subgroup Analysis
	Meyer & Rosenzweig	2016	Conjoint Analysis Tools for Developing Country Contexts

Quick Tutorial on Vignettes and/or Conjoint Analysis

- Tools
  - The Conjoint Survey Design Tool (Strezhnev et al. 2014)
  - Conjoint for Qualtrics Offline (Meyer & Rosenzweig 2016): "https://github.com/acmeyer/Conjoint-for-Qualtrics-Offline"
  - Conjoint with Images (Meyer & Rosenzweig 2016): "https://conjoint-pdf-app.herokuapp.com/"
- Example from Hainmueller et al. (2013) Using the Conjoint Survey Design Tool
  - Download and install the Conjoint Survey Design Tool from "http://scholar.harvard.edu/astrezhnev/conjoint-survey-design-tool"
    - Windows binary - Unpack and run conjointSDT.exe to launch the GUI.
    - Python Source (All Platforms) - Python 2.7+ required. Unpack and run conjointSDT.py through the Python interpreter to launch the GUI.
  - Export the conjoint design as a php file:
    - Randomized treatments from the Conjoint Survey Design Tool: "http://goo.gl/kLcyP9"

Quick Tutorial on Vignettes and/or Conjoint Analysis

- Embed your design into Qualtrics (Strezhnev et al. 2014).
  - Upload the .php file to a web server (make sure that the web server has PHP support).
  - In your Qualtrics control panel, navigate to the Survey Flow.
  - Add a new "Web Service" element to the top of your survey flow. Make sure that this element is above your question blocks in the survey flow.
  - In the URL field, enter the address of your .php file and press "Test URL."
  - Select all of the fields (click on "all" in the upper-left corner) and click "Add Embedded Data"
- Create a Qualtrics question/task.
  - Generate an .html file for every task in your design using the Create Qualtrics Question Templates command in the Edit menu of the Conjoint Survey Design Tool.
  - Create a new item in your Qualtrics survey, copy and paste the source from the html file, and edit the question in HTML view.
  - Sample survey on Qualtrics: "https://goo.gl/4egNb7"