Intro to Conjoint Experiments
ECPR Winter School

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2020-02-14

Section 1

The Workshop

About us: Alberto

- PhD Candidate at KU Leuven, Belgium
- Previously...
  - MA at Central European University
- My research:
  - Radial Beliefs: Measurement, Causes, Consequences
  - Polarization: Measurement, Causes, Consequences
  - Liberal Values: Measurement, Causes
  - Methods: Causality, experimental and semi-experimental design, SEM etc.
- Contact: alberto.stefanelli@kuleuven.be
- Website: www.albertostefanelli.com
- Twitter: @sergsagara

About us: Martin

- Previously
  - MSc in Statistics, KU Leuven
  - MA in Social Policy Analysis, KU Leuven and Luxembourg Institute for Socio-Economic Research
  - MA in Governance and Global Affairs, Moscow State Institute of International Relations (MGIMO)
- My research and interests:
  - Substantial: Labour market segmentation, online labour markets, social policy attitudes
  - Methodological: latent variable models (LCA & extensions), network science, agent-based modelling, and causal inference -Computational: R, Python, web-scraping
- Contact: m.b.lukac@gmail.com
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- Twitter: `@mblukac`

Your turn

- Name?
- Affiliation? Country?
- Research interests?
- Previous experience with experimental designs?
- Previous experience with R?
- Why are you taking this workshop?

Structure (1/2) I

Day 1 - Afternoon (tentative)

1. 13.00 - 13.30 Get to know each other and WS Presentation
   - Who are we ?
   - Your turn
   - Workshop presentation and rational
2. 13.30 - 14.00 "The problem of Causality"
   - Terminology
   - Equifinality and Manipulation
3. 14.00 - 15.00 Conjoint Experiments
   - A brief history
   - Why CJs are relevant
   - Different types of CJs
   - Basic Terminology for choice-based CJ
4. **15.00 - 15.30 Coffee Break**
5. 15.30 - 16.30 The Challenge of design
   - Attributes
   - Levels

Structure (1/2) II

6. 15.30 - 16.30 Profile Construction
   - Full Factorial
   - Fully randomized design (types and assumptions)
7. 16.30 - 17.00 Implementation (Conjointsdt)
   - Using Conjointsdt
   - Exporting PHP randomiser
   - Exporting HTML tables
8. 17.00 - 17.30 **Exercise**
   - Exercise: Design your own CJ
9. 17.30 - 18.00 **Exercise**
   - Exercise: Upload PHP randomiser

Structure (1/2) I

Day 2 - Morning (tentative)

1. 9.00 - 9.15 Recap
2. 9.15 - 9.45 Qualtrics Implementation
   - Why Qualtrics
   - Web Implementation
3. 9.45 - 10.30 **Exercise**
   - Have fun with Qualtrics
4. **10.30 - 11.00 Coffee Break**
5. 11.00 - 11.45 Analysing CJ
   - Strategies and modelling approaches
   - AMCEs
   - Clustering
6. 12.00 - 12.30 A practical Example in R
   - Loading Dataset in R
   - Preparing the Dataset for Analysis
   - Running a basic Analysis
7. 12.30 - 14.00 Lunch Break

Structure (1/2) II

Day 2 - Afternoon (tentative)

1. 14.00 - 14.30 Manipulation and AMCE LAB (**LAB session 1**)
   - Load
   - Manipulate
   - Run Analysis
2. 14.30 - 15.00 Interaction
   - Interaction Attributes
   - Interaction Attributes X Respondent's characteristics
   - Restricted randomization
3. 15.00 - 15.30 A practical Example in R
   - Interactions
   - Restricted randomization
4. **15.30 - 16.00 Coffee Break**
5. 16.00 - 16.30 Interaction LAB (**LAB session 2**)
   - Conditional AMCEs
6. 16.45 - 17.00 Diagnostics
   - Carryover
   - Fatigue

Structure (1/2) III

7. 17.00 - 17.15 A practical Example in R
   - ggplot
   - Diagnostics
8. 17.15 - 17.30 Visualization and Diagnostics LAB (**LAB session 2**)
   - ggplot
   - Diagnostics
9. If we have time
   - Advances in CJ Experiments

Section 2

Where to find the material

Where to find the material

1. Slides: On my website
    - Class Slides:
    - Lab Session 1:
    - Lab Session 2:
    - Lab Session 3:
2. Slides: On Moodle
3. Solutions Labs
    - Will be uploaded
4. Data
    - CEU Experimental Political Science https://drive.google.com/uc?export=download&id=1MUkRNTnF4C2MeAloj6qmfKfp3QuhJJnh
    - Belgian data https://drive.google.com/uc?export=download&id=11C278fvGII9784P_dUY7rXJXUXJyDEeA
    - (Teele, Kalla, and Rosenbluth 2018) Data https://drive.google.com/uc?export=download&id=1h0uE1Sbaksg8MBJS0g6Yg-sydXkv7IIf

Rationale of the Workshop

1. Theoretical foundations
    - Understanding Causal Analysis
    - Understanding CJ Experiments
2. Technical skills
    - Designing CJ
    - Deploying in Qualtrics
    - Gain visual understanding of data
    - Learning by doing in R
3. Have fun!

Reading list I

Recommended – Day 1:

- Morton, R.B. & Williams, K. (2010). Experimental Political Science and the Study of Causality. From Nature to the Lab. Cambridge University Press. (Chapter 2 and 7)
- Gustafsson, A., Herrmann, A., Huber, F. (Eds.) (2010), Conjoint Measurement, Methods and Applications. Springer. (Chapter 2)
- Auspurg, K. & Hinz, T. (2015). Factorial Survey Experiments. Series: Quantitative Applications in social Sciencs, Sage Publications (Chapter 3)
- Knudsen, E., & Johannesson, M. P. (2018). Beyond the Limits of Survey Experiments: How Conjoint Designs Advance Causal Inference in Political Communication Research. Political Communication, 0(0), 1–13. https://doi.org/10.1080/10584609.2018.1493009
- Hainmueller, J., & Hopkins, D. J. (2015). The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants. American Journal of Political Science, 59(3), 529–548. https://doi.org/10.1111/ajps.12138

Reading list II

Recommended – Day 2:

- Hainmueller, J., Hangartner, D., & Yamamoto, T. (2015). Validating vignette and conjoint survey experiments against real-world behavior. Proceedings of the National Academy of Sciences, 112(8), 2395–2400. https://doi.org/10.1073/pnas.1416587112
- Horiuchi, Yusaku, Daniel M Smith and Teppei Yamamoto. 2015. "Identifying Multidimensional Policy Preferences of Voters in Representative Democracies: A Conjoint Field Experiment in Japan." Available at SSRN 2627907 .
- Strezhnev, A., Hainmueller, J., Hopkins, D. J., & Yamamoto, T. (2013). Conjoint Survey Design Tool: Software Manual.
- Leeper, T. J., Hobolt, S. B., & Tilley, J. (2018). Measuring Subgroup Preferences in Conjoint Experiments. 55.
- Kaczmirek, L. (2015) Conducting web surveys: Overview and introduction in Engel, Uwe, et al., eds. Improving survey methods: Lessons from recent research. Routledge. (Chapter 13)
- Toepoel, V. (2016). Doing Surveys Online. SAGE. (Chapters 6 and 15)

Reading list III

- Callegaro, M., Manfreda, K. L., and Vehovar, V. (2015). Web survey methodology. Sage. (Chapters 5, 6 and 7)

Before Starting

- Make sure the conjoint design program works
- Make sure to register on 000webhost.com
- Make sure R works (for tomorrow)
- Make sure to have access to the Qualtrics account (for tomorrow)
- **Make sure to ask questions**

Section 3

Experimental logic

An experiment

A process in which we are able to identify a causal mechanism trough the manipulation of certain elements.

1. Process
2. Identification
3. Manipulation

Example

1. Does this workshop (treatment X) affect your knowledge on CJ (outcome Y)?
2. Discussion
   - Q: Is it a process?
   - Q: If yes, what is the causal mechanism that we are trying to isolate?
   - Q: Does involve any manipulation?

Causal analysis: The basic terminology

1. In broader terms, causality is a connection of phenomena that connects one element (the cause) with another elements (effect/outcome/response)
   - It is a **process**. The 1st element of this process is responsible for 2nd and the 2nd dependent on the 1st.
   - Causality is temporally bound. The cause(s) must precede the effect and **all lie in its past.**
2. Terminology (many terms that refers to same phenomena)
   - "Causality" = "Causation" = "Cause and Effect" = "causal Mechanism"
   - Treatment (yes, it is a variable) = Cause = treatment and control groups = pre-treatment post-treatment
   - Outcomes/response (yes, it is a variable) = Effect

Causal analysis: Equifinality

3. Social reality is complex. An outcome can be a cause of many other effects.
   - This is called equifinality.
   - It is what Hume (1772) summaries in the **billiard ball example.**

Figure 1: Pool Break

Causal analysis: Identification

2. The longer the time gap between treatment and outcome
   - the more fuzzy the theory (causal chain).
   - the more likely something else, unrelated happened in between.
3. Intervening mediating variables can make the process difficult to identify (K. Imai et al. 2011)
   - Want to think more about it?
   - Read "Republic should pray for rain" (Gomez, Hansford, and Krause 2007)
   - Weather -> Outcome of 1960 and 2000 presidential elections
   - Weather -> voter turnout -> republican vote
   - Q: Are there intervening phenomena ?

Causal Analysis: Manipulation (1/2)

1. Example of the causes in the social sciences
   - Income
   - Social class
   - Exposure to political news/information
   - Education
   - Genes
   - Personality traits
   - Gender
   - Ethnic background
   - Exposure to particular policy intervention
2. Q: The outcome is the exam result: What is the difference between the "causes" in the following examples?
   - She did well on the exam because she is a woman.
   - She did well on the exam because she studied for it.
   - She did well on the exam because she was properly coached by her teacher.

Causal Analysis: Manipulation (2/2)

1. **No Causation WITHOUT Manipulation"**
    1. "[C]auses are only those things that could, in principle, be treatments in experiment" (**???**)
    2. "[C]auses are experiences that units undergo and not attributes that they possess" (**???**)

Section 4

Conjoint Analysis: an intro

A Short History

1. Conjoint Analysis stems from what researchers calls multi-attribute utility models from the 50s
2. Developed by Luce and Tukey (1964) in an article on the Journal of Mathematical Psychology
3. Quickly become popular in marketing research Green, Krieger, and Wind (2001)
4. Initially implemented using rank-ordered response variable and modelled using Monanova
5. First trade-off and choice-based conjoint task implemented by Westwood, Beazley, and Lunn (1997) and Daniel McFadden Manski (2001).
6. Implementation of orthogonal main-effects plans, based on Addelman's [1962] fractional factorial designs.
7. Behavioural scientists catch up only during the 90s
8. Gained popularity in Political Science thanks to the paper by Hainmueller, Hopkins, and Yamamoto (2014)

Recent Growth of Conjoint Analysis (2014 - 2018)

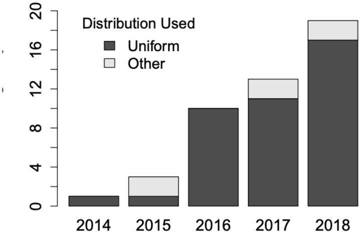


Figure 1: Recent Growth of Conjoint Analysis and Use of the Uniform Distribution for Randomization in Political Science Journal Articles. Darker (lighter) fill represents the proportion of articles in which all the factors are randomized with the uniform distribution. 88% of all reviewed articles use the uniform distribution. The plot is based on a review of articles published in political science journals from 2014 to 2018. See Appendix A for the information about how the review was conducted.

Figure 2: Conjoint Growth (2014 – 2018) (Cuesta et al., Working Paper)

Applicability: Voting Behaviour I

1. Measuring Voters' Multidimensional Policy Preferences with Conjoint Analysis: Application to Japan's 2014 Election Horiuchi, Smith, and Yamamoto (2018)
2. Voting in a Multi-dimensional Space: A Conjoint Analysis Employing Valence and Ideology Attributes of Candidates Franchino and Zucchini (2015)
3. What Goes with Red and Blue? Mapping Partisan and Ideological Associations in the Minds of Voters Goggin, Henderson, and Theodoridis (2019)
4. The Ties That Double Bind: Social Roles and Women's Underrepresentation in Politics Teele, Kalla, and Rosenbluth (2018)
5. Choice sets, gender, and candidate choice in Brazil Aguilar, Cunow, and Desposato (2015)
6. A Different Kind of Disadvantage: Candidate Race, Cognitive Complexity, and Voter Choice Crowder-Meyer et al. (2018)
7. Using Experiments to Estimate Racially Polarized Voting Abrajano, Elmendorf, and Quinn (2015)
8. Do Voters Dislike Working-Class Candidates? Voter Biases and the Descriptive Underrepresentation of the Working Class Carnes and Lupu (2016)
9. Candidate Choice Without Party Labels: Kirkland and Coppock (2018)

Applicability: Voting Behaviour II

10. Race, class, or both? Responses to candidate characteristics in Canada, the UK, and the US Kevins (2019)
11. Do Local Party Chairs Think Women and Minority Candidates Can Win? Evidence from a Conjoint Experiment Doherty, Dowling, and Miller (2019)

Applicability: Immigration Attitudes

1. The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants Hainmueller and Hopkins (2015)
2. From "Different" to "Similar": An Experimental Approach to Understanding Assimilation Schachter (2016)
3. Public Attitudes Toward Immigration Policy Across the Legal/Illegal Divide: The Role of Categorical and Attribute-Based Decision-Making Wright, Levy, and Citrin (2016)
4. Exposure to Immigration and Admission Preferences: Evidence from France Clayton, Ferwerda, and Horiuchi (2019)
5. The Matching Hierarchies Model: Evidence from a Survey Experiment on Employers' Hiring Intent Regarding Immigrant Applicants Auer et al. (2019)

Applicability: Policy Preferences

1. The Structure of American Income Tax Policy Preferences Ballard-Rosa, Martin, and Scheve (2017)
2. Why Austerity? The Mass Politics of a Contested Policy Bansak, Bechtel, and Margalit (2019)

Section 5

Conjoint experiments: getting into it

What is a conjoint experiment

1. **Substantively:** An instrument to predict and understand people's choices
2. **Technically :** A (factorial) survey experiment designed to measure preferences
    1. Whether showing one profiles as opposed to another would change the respondent's choice
    2. In political science, why do voters choose one party, candidate, policy over another?
3. It deals with options that simultaneously vary across two or more attributes (**multi-dimensionality**)
4. As such, involves trade-offs (e.g., Male Republican VS Female Republican)
    1. The possibility that option X (Candidate A) is better than option Y (Candidate B) on attribute Gender (Female) while Y is better than X on attribute PID (Republican).

How a CJ looks like?

Suppose there is a primary in your party for an open seat for the U.S. House of Representatives and the two individuals below are considering running. We'd like you to consider the following two potential candidates for this office.

Please review the following two resumes:

	Candidate 1	Candidate 2
Number of Children	3	3
Gender	Female	Male
Number of Years in Politics	3 years	8 years
Current Occupation	Mayor	Corporate Lawyer
Age	65	65
Spouse's Occupation	Farmer	Farmer

Based on the limited information above, which of the two candidates would you be more likely to support in the congressional primary?

Candidate 1Candidate 2

1. Q: What the causal process involves?
2. Q: What are we manipulating in this example? (**No Causation without manipulation.**)

Limitation of survey questions

1. Respondent's preferences and priority ranking without putting them in the context of a vote choice.
    1. Answers to survey questions can fluctuate considerably depending on how the questions are asked Kahneman, Slovic, and Tversky (1982).
2. Separation of priority ranking and preference intensity. In actual voting decisions, these two steps are inseparably connected in voters' minds.
    1. Voting is both preference towards a party/candidate and intensity of such preference
    2. e.g. a voter may evaluate a particular policy position differently depending on the other policies with which it is bundled in the proposed party platform.
3. causal identification and causal ordering is difficult (or almost impossible) in traditional observation studies
    1. Q: Does issue proximity cause vote choice or is the other way around?

Why CJ are relevant for causal analysis?

1. Evaluate the relative explanatory power of different theories, moving beyond unidimensional tests of a single hypothesis.
    1. Permit analysis of more complex causal questions
    2. Relatively cheap and fast to implement
2. Display high(er) levels of validity
    1. External validity: Conjoint design can effectively approximate real-world outcomes Hainmueller, Hangartner, and Yamamoto (2015) Auerbach and Thachil (2018)
    2. Internal Validity: enhance realism relative to the direct elicitation of preferences on a single dimension for a variety of research questions
    3. Measurement quality: Respondents are found to be consistent even for quite complex tasks @
3. Reduce social desirability biases such as vote for female political candidates Teele, Kalla, and Rosenbluth (2018) and opposition to construct a low-income housing project in one's neighborhood Hankinson (2018).
4. Good prediction device that can provide insights into practical problems such as policy design.

Section 6

Different type of CJs

Rating (scales) Conjoint

1. It usually involves only one profile at the time
2. As such, no trade-off between attributes
3. Similar to vignette studies
4. PRO: Easy to execute, implement, and model
5. CONS: No trade offs as it often occurs in real choice settings
6. CONS: Often no clear differentiation between profiles
7. CONS: causal interpretation might be difficult in certain situation
    1. What liking a candidate actually means?
    2. Does liking a candidate would imply that people actually vote for that candidate?

Ranking Based Conjoint

1. It involves more than one profile at the time
2. As such, trade-offs are easier to see
3. Clear differentiation between most-preferred and least-preferred profiles
4. PRO: Easy to execute, implement, and model
5. CONS: causal interpretation might be difficult due to mid ranks
    1. What the difference between the 6th and the 5th candidate in a 15 candidates rank conjoint
    2. Does the ranking a candidate first would imply that people actually vote for that candidate?
6. CONS: Often increase measurement error (Boyle et al. 2001)

Choice Based Conjoint (1/2)

2. "The most widely used flavour of conjoint analysis" Software (2008)
3. Revealed Preference (RP): Real life choices
   - Studying people's observed actions has clear validity advantages Diamond and Hausman (1994)
   - Which type of insurance plan peoples have chosen after having compared several different offers
4. **Stated Preference (SP):** Experimental setting where we ask respondents **what would they do** instead of observing what they have done.
   - What type of insurance plan people would choose after having compared several different offers
   - Can be used to assess the choice decision in an hypothetical or future scenario
   - However, what people say in surveys can diverge from what they would do in actual decisions

Choice Based Conjoint (2/2)

1. PRO: Higher external validity
    1. Trade-off between 2 or 3 profiles is more natural and close to real-life choice scenarios
2. PRO: Quite easy modelling approaches
3. PRO: Context manipulations are easy to implement
    1. E.g., priming respondents with certain informations
4. CONS: VERY VERY careful experimental design
5. CONS: Can be difficult to set up

Other type of Conjoint

1. Point allocation
2. Combination of the previous methods such as Likert Rating with Choice Based
3. Adaptive Conjoint
    1. Adaptive choice-sets based on respondent's characteristics, preferences or attitudes
    2. E.g., in the choice of transport mode, the choice set of an individual without driving license and/or car should not include the alternative "car as a driver".

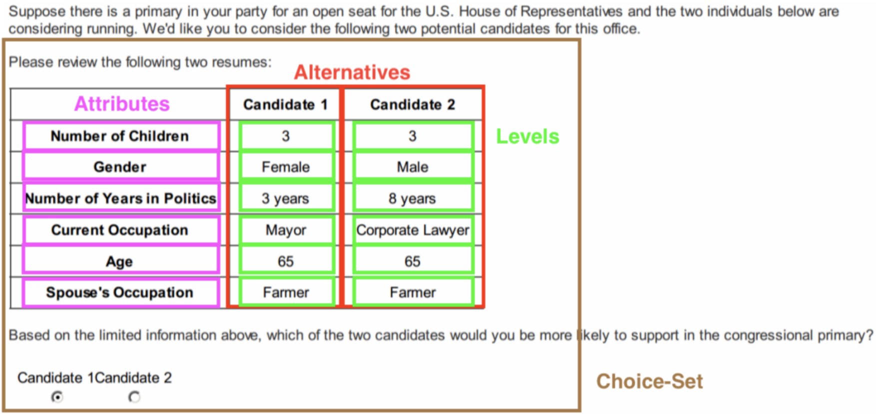
Section 7

Terminology

Basic terminology in Choice Based Conjoint (1/2)

1. Alternative
   1. The two (or more) profiles that a respondent will have to choose from (Candidate A, Candidate B)
2. Attributes
   1. AKA independent variables, explanatory variables, treatments or treatment combinations, features
   2. Characteristics of the different alternatives (policies, age, gender)
3. Attribute levels
   1. The discrete values that an attribute can take in a given alternative
   2. That is, the value that the independent variables can take (Age: 20, 30, 40, 50)
4. Choice-sets: a combination of two or more alternatives (progressive candidates VS conservative candidates)
   1. Relevant if we want to analyse a subset of profile (e.g. only female candidates)

Basic terminology in Choice Based Conjoint (2/2)



Suppose there is a primary in your party for an open seat for the U.S. House of Representatives and the two individuals below are considering running. We'd like you to consider the following two potential candidates for this office.

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Gender	Female	Male
Number of Years in Politics	3 years	8 years
Current Occupation	Mayor	Corporate Lawyer
Age	65	65
Spouse's Occupation	Farmer	Farmer

Based on the limited information above, which of the two candidates would you be more likely to support in the congressional primary?

Candidate 1 Candidate 2

Q: What the research is controlling (and manipulating) and what not?

Section 8

The challenge of Design

Why a Challenge?

- Why is it called design?
  1. Manipulation of the treatment conditions occurs **by design**
  2. That is, the researcher controls to specific treatment conditions
- Design is the most relevant elements of any experiment approach and the greater barrier in answering your research question
- It allow us to understand the decision rules used to select a profile instead of another

Three type of design in a CJ

1. **Attributes Design**
    1. Our Independent Variables
2. **Choice-Set Design**
    1. The Conjoint Profiles
3. Information/Context Design (unfortunately, we are not going to cover it)
    1. Priming, framing . . . .

Attributes Design: Attributes

1. Identify and define the **attributes**
    1. Which attributes should be included in order to answer my RQ?
    2. Define a universal but finite list of attributes that are theoretically relevant
        1. Usually 10-15 attributes
    3. Reduce the attributes
        1. Less then 10 attributes is considered acceptable
    4. Avoid double-barrel attributes
        1. E.g., "Expertise" of a candidate

Attributes Design: levels

1. Identify and define the **levels**
    1. Which levels are suitable for the decision task?
    2. Are the levels ordinal, nominal or continuous?
    3. Select theoretically relevant start- and end-points for each attributes
        1. Q: What is a sensible range for the age of a candidate?
    4. Define a finite list of levels that have discriminant power.
        1. Keep the from 2 to 8
        2. Q: What age levels should we include for a candidate?
        3. Q: Does a year difference make any difference in accuracy?
    5. If the design is too big and you assume linearity, use only start- and end-point designs
        1. e.g., Instead of ordinal age use “Young” and “Old”
    6. Avoid attributes ambiguity
        1. E.g., “High level of integrity” of a candidate VS “Never committed for corruption”

Attributes Design: Garbage in Garbage out I

2. Validity concerns: **garbage in, garbage out"**
   2. **Masking** or inter-attributes correlation (Verlegh, Schifferstein, and Wittink 2002)
      1. Perceived association between an attribute included in the design and an omitted one
      2. E.g. Including policy positions but excluding PID
   3. **Satisficing** (Bansak et al. 2018)
      1. Disregard substantive informations due to high cognitive complexity.
      2. E.g., Inferring from PID policy positions and attributes
   4. Unrealistic trade-off(s) between attributes
      1. A doctor (Attribute=Profession) without an academic degree (Attribute=Education)
   5. **"Range effect"** (Verlegh, Schifferstein, and Wittink 2002)
      1. Using specific level combinations could lead to implicit associations
      2. E.g., A white Democratic candidate of age 78 from Vermont
3. Modelling concerns
   1. **"Number-of-levels effect"**
      1. Too many levels could make the interpretation difficult
      2. Statistical power might be insufficient

Choice-Set Design: Profiles, Tasks, Outcome

1. Number of Alternative **Profiles**
   1. Single Profiles (1)
   2. Paired Profiles (2)
   3. Multi Profiles (up to 4)
2. Number of conjoint choice **Tasks** per respondent
   1. Ranges from 2 to 20
3. Outcome measures
   1. Discreet Choice (better for Trade-offs)
   2. Individual rating (better for detecting extreme response style)
4. Randomization (**VERY RELEVANT STATISTICALLY**)
   1. Position of the attributes in our CJ
   2. Levels

Choice-Set Design: Sample size and complexity

1. Sample size = Number of choices per individual + Number of participant in the study
    1. Trade off between Power and Cognitive Burden
2. Dimensional Complexity = Number of Attributes X Number of Attributes' Levels X Number of Tasks
    1. It is a trade-off between cognitive burden and experimental conditions
3. Data quality = Power (Sample size) - Dimensional Complexity - Cognitive Burden

Exercise

- RQ: **Do citizens vote for candidates that are spatially closer to their policy positions?**
- Q: Does it makes sense just to focus on policy position?
  - Think about voting behaviour, how voters make up their mind?
- Q: What should I manipulate and how should I operationalize them? (Attributes design)
  - PID
  - Left-Right
  - Several Policy
  - ...?
- Q: What kind of trade offs should I include in the design?
  - Do the trade-offs make sense? (Choice-set design)
  - E.g., does it makes sense to include both left-right and policies?
- Q: Should I exclude some trade-offs (Choice-set design)
  - Does it make sense to include L-R=Extremely Left, Policy=Liberalization of health care ?

Section 9

Profiles construction

Profiles construction

1. Full Factorial
   1. All possible combinations of levels
2. Fully randomized design
   1. **Fully randomized uniform design**
      1. Equal probability of all levels in a given attribute
      2. E.g., Female 33%, Male 33%, Non-Binary 33%
   2. **Randomized weighted design**
      1. Unequal probability of certain levels in a given attribute
      2. Marginal distribution of levels departs from uniform distribution
      3. E.g. Female 50% and Male 49%, Non-Binary 1%
   3. **Restricted Randomization (or nested design)**
      1. Certain combinations or attributes are not allowed to happen
      2. E.g., Doctor without academic degree
3. Orthogonal and fractional factorials
   1. Not used in the social science with the exception of Franchino and Zucchini (2015)
4. and many more (!!)
   1. Block Designs
   2. Optimal Designs

Section 10

Full Factorial Design

Factorial Design (1/2)

1. Full Factorial
    1. Preferable design
    2. Shows every attributes level with every other attribute level
    3. All the combination are included in the design
    4. It grows geometrically with each attribute
    5. Potentially we would like to assign respondents (n=30) to each combination
2. Example
    1. Age= 30s, 40s, 50s
    2. Education= Elementary School, High School, Academic Degree
    3. Years in Congress= More than 5, between 5 and 10, more than 10
    4. Q: How many combinations?
    5. Q: What would be a reasonable sample size?

Full Factorial Design (2/2)

Age	Education	Expertise	Combinations
30s	Elementary	<5	1
40s	Elementary	<5	2
50s	Elementary	<5	3
30s	High School	<5	4
40s	High School	<5	5
50s	High School	<5	6
30s	Academic	<5	7
40s	Academic	<5	8
50s	Academic	<5	9
30s	Elementary	>5 <10	10
40s	Elementary	>5 <10	11
50s	Elementary	>5 <10	12
30s	High School	>5 <10	13
40s	High School	>5 <10	14
50s	High School	>5 <10	15
30s	Academic	>5 <10	16
40s	Academic	>5 <10	17
50s	Academic	>5 <10	18
30s	Elementary	>10	19
40s	Elementary	>10	20
50s	Elementary	>10	21
30s	High School	>10	22
40s	High School	>10	23
50s	High School	>10	24
30s	Academic	>10	25
40s	Academic	>10	26
50s	Academic	>10	27

Full Factorial Design: Combinations

1. In fact, we have many more combinations
2. Q: Why is it the case?
3. We can calculate all the combination using the formula
4. L is the number of levels, M the number of alternatives, and A the number of attributes

$$Combinations = L^{M^A} \quad = 3^{2^3} = 729$$

5. The number of alternative is thus 729
6. If we assign approximately 20 respondents per each combination
7. $729 * 20 = 14000$

Section 11

Fully randomized design

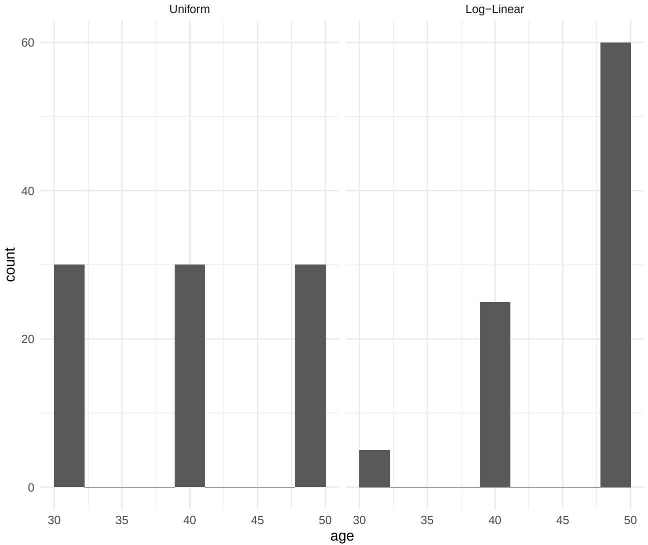
Fully randomized design

1. Developed by Hainmueller, Hopkins, and Yamamoto (2014) relaying upon the Potential Outcome Framework
2. It creates a CJ tasks sampling each level independently
3. That is, it sample a n number of rows for the full factorial

Randomized weighted design (1/2)

1. Level sampling performed in the same way as the fully randomized design
2. **BUT** we can control the probability of a given level to appear in the CJ table
3. That is, we specify a marginal distribution for certain levels
4. The marginal distribution of certain level should correspond to the one found in the target population
5. Some levels appears more, some appears less
6. This increase the **external validity** of the CJ experiment
7. Q: Why is this the case?

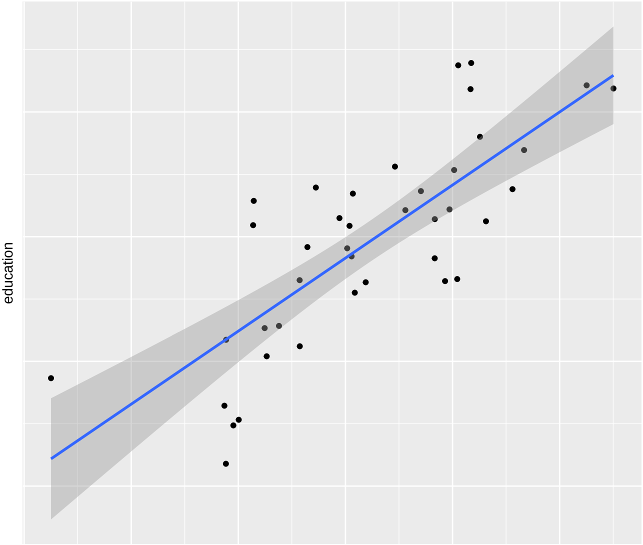
Randomized weighted design (2/2)



Restricted Randomization (or nested design) (1/2)

1. Sampling performed in the same way as the fully randomized design
2. **BUT** we impose limitation on the combination of certain attributes within a profile.
3. Technically, we set the conditional probability of the co-occurrence of two attributes/levels equal to zero
4. Meaning, we deny that two (or more) unlikely or contrasting combination of attributes/levels from appearing together
5. This improves the the **internal validity** of our CJ experiment
6. Q: Why is this the case?

Restricted Randomization: Education Income (2/2)



Assumption of the Fully Randomized Designs

1. Stability and no-carry over (aka SUTVA)
    1. Respondents DO NOT use the information from previous questions or tasks in evaluation the profiles
    2. If two profiles in two subsequent different tasks had identical attributes the respondents would choose the same profile.
2. No profile-order effects:
    1. The ordering of profiles within a choice task does not affect responses
    2. Meaning that it is possible to to pool information across profiles when estimating causal quantities of interest
3. Randomization of the profiles
    1. The potential choice behaviour can never be systematically related to what profiles they will actually see in the experiment.
    2. Individual choices are statistically independent of the profiles

Section 12

Implementation

What do you need I

1. A well though trough design
    1. Attributes
    2. Levels per Attributes
    3. Number of Profiles per Task
    4. Number of Tasks per respondent
    5. Outcome measure (Discrete Choice, Rating . . .)
2. A PHP script
    1. Define all of the possible Levels
    2. Randomly sample from those values
    3. Specify the marginal distribution
    4. Impose constrains
3. A server to host the PHP script
    1. We cannot relay on the respondent's browser
    2. The displayed profiles should be unaffected by any refreshes or browser error
4. A Qualtrics Account
    1. Collect demographic and moderators
    2. Display profile to the respondents
    3. Save the sampled values for later use in analysis

What do you need II

5. A survey design for R
   1. Import levels and attributes
   2. Take into account marginal distribution and constrains

Section 13

Design

My Design I

1. An experiment in Belgium, Brussels (Saint-Gilles)
2. RQ1: Are candidates with a minority background more likely to be voted?
3. RQ2: Which type of cognitive mechanisms are used by voters when it comes to vote choice?
    1. Proximity (Policy Positions)
    2. Valence (Competence)
    3. Symbolic representation (Same Ethnic Background)
4. Attributes
    1. Age (Symbolic)
    2. Years in Politics (Valence)
    3. Ethnicity (Symbolic)
    4. Party (Proximity)
5. Levels distribution
    1. Age: 30s (10%), 40s (30%) , 50s (60%)
    2. Years in Politics: 5 (33%), 10 (33%), 20 (33%)
    3. Main Language: French (40%), Turkish (30%), Italian (20%), Portuguese (5%), Dutch (5%)

My Design II

4. PID: Radical Left (12%), Green (18%), Left (34%), Liberal (20%), Right (14%), Radical-Right (2%)

6. Restrictions
   1. Age 30, Years in Politics 20
7. Outcome
   1. Forced Choice
8. Profiles
   1. 2 per each task
9. Tasks
   1. 5 per each respondent

Section 14

Conjointsdt

Conjointsdt

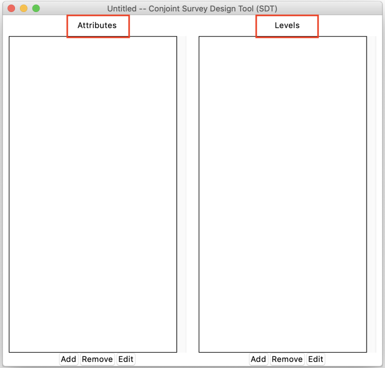
1. We use a python program developed by Anton Strezhnev (NYU) called **Conjointsdt**
2. Deals with several aspects of out CJ design
   - The PHP script for randomization
   - The Qualtrics Tables
   - The survey design in R (in fact, it does not)
3. Sometimes it bugs. Try to close and open the program if something is not properly working!
4. In any case, cheers to him!

Section 15

PHP Script

PHP Script: Attributes and Levels in Conjointsdt

1. Download the program (you did it already, right?)
2. (if you did not here is the link https://github.com/astrezhnev/conjointsdt)
3. Feed the program with Attributes and Levels



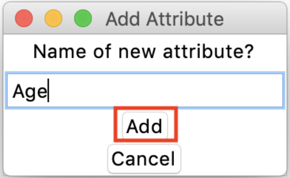


Figure 3: Conjointsdt Attributes and Levels

PHP Script: Save the baseline 1

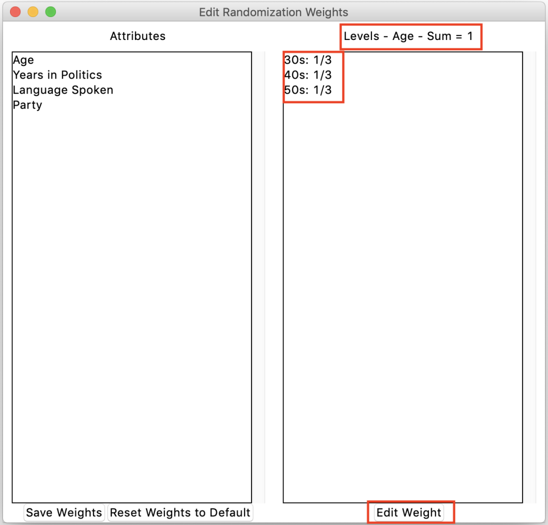
....

1. Let's save the design in case something get lost
2. File -> Save -> name_of_the_design.sdt

PHP Script: Implement Weights for the marginal distribution

1. File -> Randomization Weights
2. Impute the proportion from 0 to 1
3. If a levels appear 20% of the time, 0.20
4. **The sum of the weights should be equal to 1**
5. Rememberer to save: File -> Save -> name_of_the_design.sdt

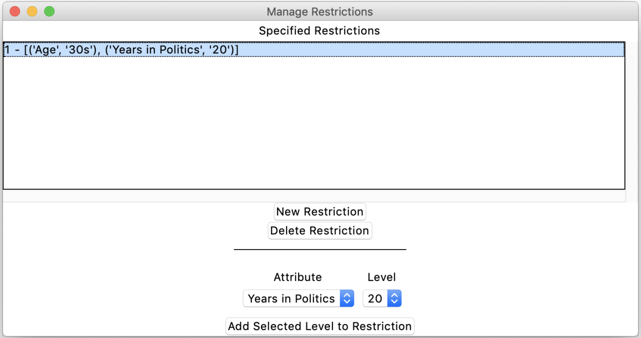
PHP Script: Implement Weights in Conjointsdt



PHP Script: Implement Restrictions

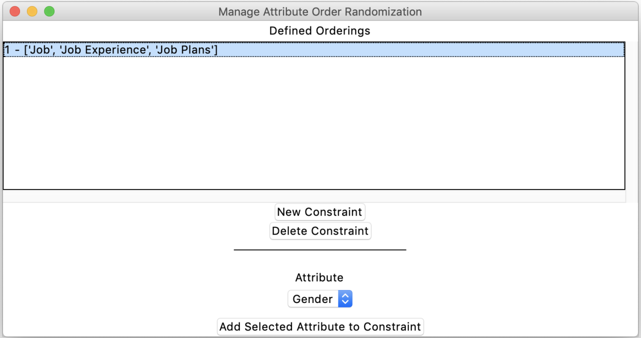
1. Q: Is it realistic that a candidate in its 30s has 20 years of political experience?
2. Set the conditional probability of displaying Age=30 AND Experience=20 equal to 0
3. Edit -> Restrictions -> Add Selected levels to Restriction
4. Rememberer to save: File -> Save -> name_of_the_design.sdt

PHP Script: Implement Restrictions in Conjointsdt



PHP Script: Attribute Order Constrains

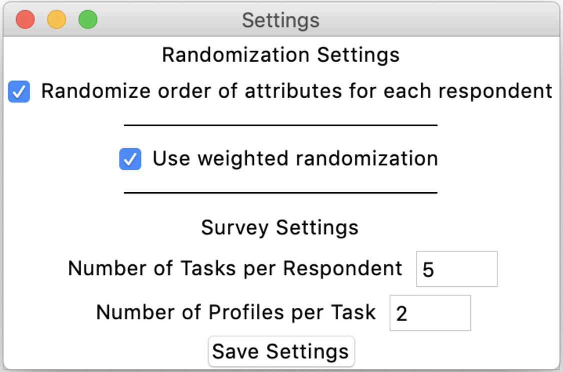
1. Group together similar Attributes (e.g. all attributes related to Job in Hainmueller, Hopkins, and Yamamoto (2014))
2. Usually, used in big designs to reduce the cognitive burden of the respondent
3. Edit -> Restrictions -> Attribute Order Constrains



PHP Script: Tuning the choice-design

1. Edit -> Settings
2. Randomized Order of attributes per each respondent
    1. That is, we keep the attribute order the same per each respondent
    2. Ease the cognitive load
3. Use Weighted Randomization
    1. Essential to use a specific marginal distribution for the levels
4. Number of Tasks
    1. How many times a single respondents performs a CJ task
5. Number of Profiles
    1. Usually two Profile at time
    2. Q: Can you think of a design where 3 profiles make sense?

PHP Script: Tuning the choice-design



PHP Script: Export the Design

1. Menu -> Edit -> Export to PHP
   1. THis is going to be on a server for the randomization
   2. php_script_name_of_the_design.php
2. Menu -> Edit -> Export to Qualtrics
   1. HTML tables that will be fed by the PHP script
   2. Task_1_name_of_the_design.html
3. Menu -> Edit -> Export to R
   1. Used in the Modelling Part
   2. design_R_name_of_the_design.dat

Exercise: Build a CJ Design

1. **Think theoretically !!**
   1. What is my RQ (and hypotheses) ?
   2. Alternative design:
      1. Select the alternatives
      2. Select the levels
   3. Choice-set design:
      1. Uniform or non-Uniform distribution?
      2. Restrictions on combination of certain attributes/levels (please include!)
      3. Attribute order constrains?
      4. How many profiles per choice-sets? (let's stick to two)
      5. How many comparisons to include (sample size)?

Section 16

Upload on the PHP script on a Server

Load the PHP on a server

1. We need a server that host and run PHP code on demand
2. Every free PHP server works
   1. https://www.freehosting.com/
   2. https://www.000webhost.com/
   3. https://aws.amazon.com/
   4. https://www.cloudways.com/
   5. . . . .
3. We are going to use 000webhost
   1. Easy to use
   2. ZERO costs
   3. Expires after 3 months

Load the PHP on a server: 000webhost

4. Create an Account (you did already right?)

00webhost - Create a New Website

5. Select Create a New Website
   1. Use a reasonable name
   2. Leave the PSW untouched

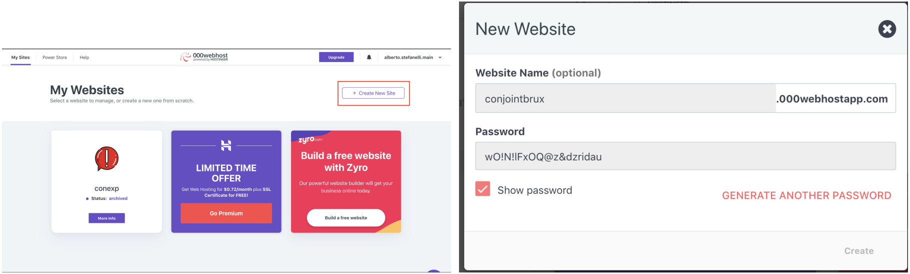


Figure 4: Conjointsdt Attributes and Levels

000webhost - File Manager

5. Select File Manager

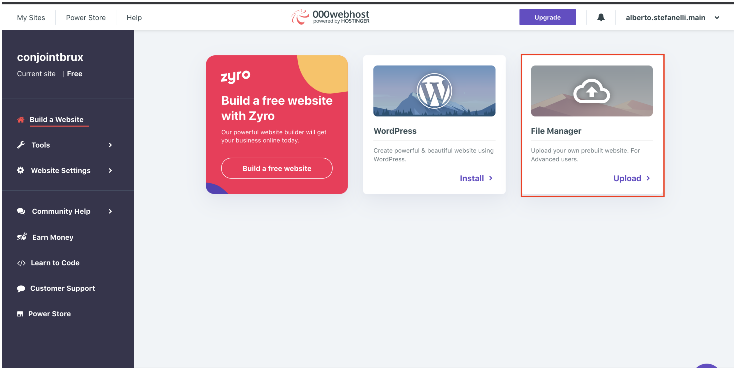


Figure 5: Conjointsdt Attributes and Levels

000webhost - Upload

6. Upload the PHP file from Conjointsdt

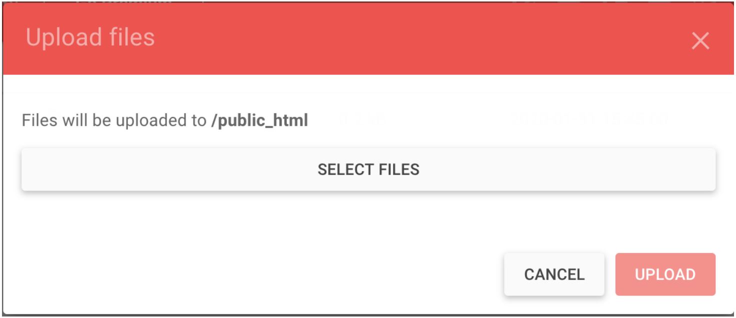


Figure 6: Conjointsdt Attributes and Levels

000webhost - Get the Link

7. Right click on the file -> View
8. Copy the web address and store it somewhere
    9. https://cjbrux.000webhostapp.com/belgian_experiment_php_script.php
9. If you change the design remember to UPLOAD AGAIN the PHP

Exercise: Upload the PHP on the server

1. Follow the steps in the previous page
2. Store the link where the PHP script is upload

Section 17

Deploy on Qualtrics

Why Qualtrics

1. Quite flexible
2. Does not require programming
3. Excellent support
4. Widely used in Academia
5. Widely used by survey companies
6. Other options are not there yet
    1. Check out Lime Survey if are willing to learn JS.

How to Deploy on Qualtrics

1. Create an account (you should have done it already)
2. Create a new survey
    2. Create your Own -> Survey
    3. Project Name -> Get Started
3. Organize the survey in blocks
    1. Changing block means changing page
    2. Each block should correspond to a part of the survey (Demographics, Controls, Experiments. . .)
4. Insert questions in each blocks
    1. Click on each block to add text and change options
    2. Use the right panel to modify the type of questions and their behaviour
    3. Use the left panel for the randomization of the questions' options
5. Survey Flow tab
    1. Randomization
    2. PHP Script

Flow of the Survey

1. Consent Form (Forced Choice + Conditional)
2. Mediators to condition on
    1. ONLY in case you are playing with framing
3. CJ Blocks
    1. Text
    2. Tables
    3. Choice
4. Additional Controls (if needed)
    1. Education
    2. SES
    3. ....
5. Main IVs of interests
    1. PID
    2. Language
    3. Age
6. Conclusion and follow-up

CJ Blocks: HTML Table

1. Open the .html file using a text editor
    1. textEdit on Mac
    2. notepad on Windows
    3. Sublime
2. Modify according to your need
3. Copy the content

CJ Blocks: Qualtrics

2. On Qualtrics: Create a new multiple choice question
3. On the text area select “HTML View”
4. Copy the content of each .html file generated by Conjointsdt
5. Modify the text if necessary
6. Add a binary Multiple Choice Options (e.g. Candidate 1, Candidate 2)
    7. Validation Options -> Request Choice
    8. Position -> Horizontal
    9. Answer -> Single Answer
7. Insert a Page Break
8. Repeat for all the CJ tasks

CJ Blocks: Image

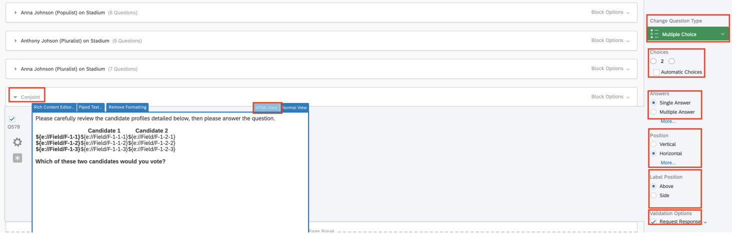
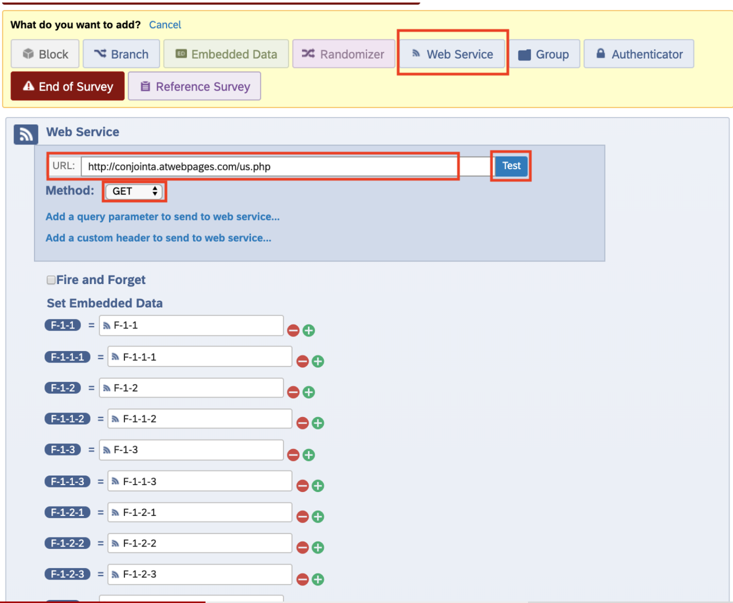


Figure 7: Conjointsdt Attributes and Levels

Survey Flow

1. Menu -> Survey Flow
2. Add **Web Service**
3. Paste the link with the PHP script
4. Test that the link is working with the method GET
5. Move the Web Service plug-in at the very beginning of the flow
6. Check that everything is in order
7. OPTIONAL: Include attention checks

Survey Flow

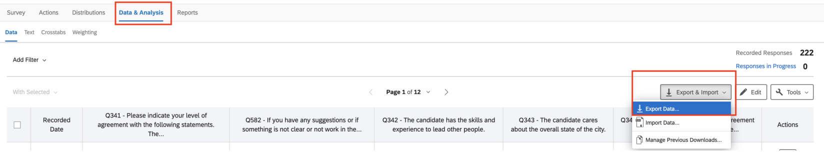

What do you want to add? Cancel
Block
Branch
Embedded Data
Randomizer
Web Service
Group
Authenticator
End of Survey
Reference Survey
Web Service
URL: http://conjointa.atwebpages.com/us.php
Test
Method: GET
Add a query parameter to send to web service...
Add a custom header to send to web service...
Fire and Forget
Set Embedded Data
F-1-1 = F-1-1
F-1-1-1 = F-1-1-1
F-1-2 = F-1-2
F-1-1-2 = F-1-1-2
F-1-3 = F-1-3
F-1-1-3 = F-1-1-3
F-1-2-1 = F-1-2-1
F-1-2-2 = F-1-2-2
F-1-2-3 = F-1-2-3

Preview, test and deploy the survey

1. Preview the survey
2. Let someone take the survey
    1. Distribution -> Anonymous Link (it is on the right)
3. Fill the survey with fake responses
    1. Review
    2. Generate test responses
    3. 500 or 1000 responses
4. Check that there is nothing strange in the generated data
    1. Export the data in R
    2. Check for questions that are filled with just NA
    3. Check quotas if you have experiments
5. Cancel the test responses
    1. Data & Analysis
    2. Tools
    3. Delete Data
    4. Decrement Quotas
6. Data collection
    1. ALWAY check that the initial 100 responses are OK!!

Export Qualtrics data

1. Data & Analysis
2. Export Data
3. .csv format



Have fun with Qualtrics

1. Use the survey that you have been invited by Levi
2. Change it according to your CJ
3. Steps:
    1. Change HTML tables
    2. Change Web Service with the one that you uploaded
    3. Change IVs
    4. Feed the survey with test responses

Section 18

Analysing a CJ experiment

In General

1. Conjoint analysis belongs to the part-worth model family
2. The aim is NOT to estimate the Average Treatment Effect
3. BUT analyse the impact that each treatment/features/attribute has on the likelihood to select a certain profile

Challenges

1. Break down the effect of each Attribute/Level
2. Take into account the possibility that multiple respondents perform multiple tasks
3. Model the possible interactions between Attributes
4. Model the possible interactions between respondent's characteristics and Attributes
5. Take into account the constrains between different Attributes (if implemented)

Estimands

1. Binomial distributions (2 profiles with discrete choice)
    1. Nested Logit
    2. Mixed Logit Model
    3. **Average Marginal Component Effect AMCE** Hainmueller, Hopkins, and Yamamoto (2014)
    4. Marginal Means
2. Gaussian distribution (1 or 2 profiles with ratings)
    1. Nested OLS
    2. Finite mixture models
    3. **Average Marginal Component Effect AMCE** Hainmueller, Hopkins, and Yamamoto (2014)
    4. Marginal Means
3. Multinomial distribution (more than 2 profiles)
    1. Nested multinomial logit
    2. Mixed multinomial Logit Model

Section 19

Challenge 1: Break down the effect using the AMCE

Challenge 1: Break down the effect using the AMCE

1. Used in most applications of conjoint survey experiments in political science.
2. **Formally:** The effect of a particular attribute value of interest against another value of the same attribute while holding equal the joint distribution of the other attributes
3. **Layman terms:** A measure of the overall effect of an attribute after taking into account the possible effects of the other attributes by averaging over effect variations caused by them
4. **Example:** The average causal effect of being a female candidate as opposed to a male candidate on the respondents' candidate ratings when they are also given information about the candidates' age, race/ethnicity.

How does this work ?

1. Simple Mean difference
   1. Calculate the average rating (or probability to be chosen) of all female candidates
   2. Calculate the average rating (or probability to be chosen) of all male candidates
   3. Take the difference between the two averages
2. AMCE averages over both the sign and the magnitude of the individual-level causal effects
3. All the attributes but the one of interest are treated as pre-treatment covariates and averaged over

A numerical Example

1. Toy example
   1. 5 Voters
   2. 6 Tasks
   3. 2 Profiles
   4. Forced choice
2. Attributes and Levels
   1. Gender: Female, Male
   2. Party: Republican, Democrat
3. Every possible pairwise comparison
4. Votes candidate would obtain in a head to head competition

Calculations AMCE for Male Candidates

1. Count how many times a candidate would have won in a head to head competition
2. Per each competition, compare how male candidates perform against female
3. Calculate the fraction of vote for male VS female candidates
4. Sum over all possible opponents
5. Normalize by (# of profiles - 1) X (# of features -1) X # of values of gender

A numerical Example: Table

1. Votes that each candidate would take for every possible pairwise comparison
2. Men win 3 out of 4 election when they face a woman and 4 out of 6 total contests
3. For instance, for the comparison *Male Republican VS Female Republican*, male candidates win 3 times, female candidates win 2 times

Comparison	Voter 1	Voter 2	Voter 3	Voter 4	Voter 5	Sum Tally
MR,FR	MR	MR	MR	FR	FR	3,2
MR,FD	MR	MR	MR	FD	FR	3,2
MR,MD	MR	MR	MR	MD	FR	3,2
MD,FR	FR	FR	FR	FR	FR	0,5
MD,FD	MD	MD	MD	FD	FD	3,2
FR,FD	FR	FR	FR	FD	FD	3,2

Calculation table (2/2)

Profile 1	Profile 2
Y(MR,MD)	Y(FR,MD)
Y(MR,FD)	Y(FR,FD)
Y(MR,MR)	Y(FR,MR)
Y(MR,FR)	Y(FR,FR)
Y(MD,MD)	Y(FD,MD)
Y(MD,FD)	Y(FD,FD)
Y(MD,MR)	Y(FD,MR)
Y(MD,FR)	Y(FD,FR)

Calculation table (1/2)

Profile 1	Profile 2	Male	Female	Male - Female
Y(MR,MD)	Y(FR,MD)	3/5	5/5	-2/5
Y(MR,FD)	Y(FR,FD)	3/5	3/5	0
Y(MR,MR)	Y(FR,MR)	5/10	2/5	1/10
Y(MR,FR)	Y(FR,FR)	3/5	5/10	1/10
Y(MD,MD)	Y(FD,MD)	5/10	2/5	1/10
Y(MD,FD)	Y(FD,FD)	3/5	5/10	1/10
Y(MD,MR)	Y(FD,MR)	2/5	2/5	0
Y(MD,FR)	Y(FD,FR)	0/5	2/5	-2/5
Sum				-2/5

Calculation AMCE

$$
\begin{aligned}
&= (profile - 1) \cdot (features - 1) \cdot gender \\
&= (2 - 1) \cdot (4 - 1) \cdot 2 \\
&= 1 \cdot 3 \cdot 2 \\
&= 6
\end{aligned}
$$

$$
\begin{aligned}
AMCE &= \frac{2}{5}/6 \\
&= -\frac{1}{15}
\end{aligned}
$$

What the AMCE really means

1. **Interpretation:** The average effect of varying one attributes of a profile on the probability that that profile will be chosen by a respondent
2. **Interpretation:** Shifting a candidate's gender from Male to Female increase the favourability (or likelihood of choosing a candidate) by X percentage points
3. The range of value depends on the number of level of a feature and the probability of co-occurrence of the same attribute levels (Female Candidate VS Female Candidate)
    1. With 5 levels $(1/5) - 1 = 0.8$ and thus the bound is -0.8 to 0.8
    2. Q: What about gender: Female and Male?
4. Take home message:
    1. **CAUTION in comparing the relative size of features with different levels !!!**
    2. As in any regression, the AMCE is a relative quantity. Favourability is higher or lower **relative to the attribute baseline**.

What the AMCE is NOT

1. **NOT** a general measure of preference of certain attributes
   2. **NOT** that the majority of the respondents prefer a profile with feature A versus candidate with feature B
   3. **NOT** that respondents prefers candidate with feature A versus candidate with feature B
2. **NOT** that candidates with feature A beat candidates with feature B in most elections
3. Example:
   1. A large majority of the respondents can have a preference for female candidates but the AMCE is positive for male candidates
   2. Q: Why?

Section 20

Challenge 2: Take into account the clustering

Challenge 2: Take into account the clustering

1. In the above example, each respondent perform 6 pairwise comparisons
2. So we have more observations than respondents
3. Q: What are the units of observation in CJ analysis?

Clustering structure

1. In the above example, each respondent perform 6 pairwise comparisons
2. So we have more observations than respondents
3. Q: What are the units of observation in CJ analysis?
4. A: The units of analysis are the CJ tasks **NOT** the respondents
5. Recall that:
    1. DV: Choice Profile A VS Profile B
    2. IV: Profile Attributes
6. In order to correctly estimate the Standard Error we need to take into account the clustered nature of the data

Clustering structure: Conjoint Data

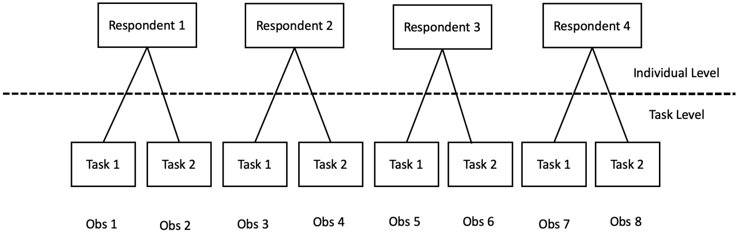


Figure 9: Conjointsdt Attributes and Levels

Clustering structure: Modelling Approaches

1. **Sandwich estimators** (also called robust variance estimator)
   1. OLS: residuals variance is assumed to be independent
   2. OLS: Meaning residual variance is constant across observations
   3. CJ: Due to the nested structure, the variance can vary between individuals.
   4. OLS for CJ: P-values for hypothesis tests and confidence intervals do not perform as they should
   5. Sandwich: Take into account the variance heterogeneity
2. Choice Models
3. Multilevel models
   1. Level 1: CJ tasks
   2. Level 2: Individuals
4. Bootstrapping

Section 21

Lab Sessions - 1: Basic AMCEs

Challenges: What we still need to address

1. ~~Break down the effect of each Attribute/Level~~
2. ~~Take into account the possibility that respondents perform multiple tasks~~
3. Model possible interactions between Attributes
4. Model possible interactions between respondent's characteristics and Attributes
5. If implemented by design, take into account the constrains between different Attributes

Section 22

Challenge 3: Interactions between Attributes

Challenge 3: Interactions between Attributes

1. The decision of choosing a particular profile could be the results of a particular combination of features.
2. The causal effect of one attribute (say candidate's income) may vary depending on what value another attribute (e.g., ideology) is held at.
3. We may want to quantify the magnitude of such interactions.
4. ACIE: Average component interaction effect
5. ACIE: Difference in the AMCEs of a given attributes between the value a pro Medicare candidate and a candidate against it

Interactions between Attributes: an example

1. Voters might value the **programmatic coherence** of a candidate policy positions
   2. A voter might be in favour of a reduction of governmental intervention in the economy and as such would support a candidate in favour of cutting unemployment benefits
   3. What would happen if a candidate is in favour of cutting unemployment benefits but – at the same time – is pro Medicare?
   4. ACIE: the percentage point difference in the AMCEs of cutting unemployment benefits between a pro Medicare candidate and a candidate against it
2. Q: Can you came up with another example of attribute interaction? (**think theoretically!**)

Section 23

Challenge 4: Interactions between Attributes and Respondent's Characteristics

Challenge 4: Interactions between Attributes and Respondent's Characteristics

1. Also called sub-groups analysis
2. We are searching for **causal effect heterogeneity**
3. Attribute's marginal effect conditional on the respondent characteristic of interest (e.g. socio-economic background)
4. E.g. The effect of the candidate's income as a function of the respondent's income.

Section 24

Challenge 5: AMCE with Restricted Randomization

Challenge 5: AMCE with Restricted Randomization

1. Restricted Randomization means that we have constrains between profile features
2. E.g. Doctors without an academic education
3. AMCE is a weighted average across each combination of the constrained features
4. The effect of being a doctor on candidate favourability is marginalized only across higher level of educations
5. Take home:
    1. Be clear about what features are being marginalized over
    2. Analysing only the complete and comparable subset of the design

Section 25

Lab Sessions - 2: Interaction and Restricted Randomization

Section 26

Robustness Checks

Essential steps

1. Display Frequencies and Proportions
    1. Check if randomization went well by checking that frequencies of conjoint features are balanced
2. Carryover and Left/Right Diagnostics
    1. Any preference for the left-hand or right-hand profile.
    2. Fatigue
    3. Preference bias
    4. Bot
3. Ordering effects
    1. If respondents experience cognitive fatigue they might only pay attention to the part of each task that is easiest to process (e.g., the top of the table, only the first task).
    2. Then the attributes should exhibit order effects.

Section 27

Lab Sessions - 3: Plotting and Diagnostics

Section 28

Advance topics in CJ Analysis

What people are working on

1. Marginal Means
2. Design based for non-uniform distribution
3. Power Analysis
4. Advances in preference heterogeneity

Section 29

Marginal Means

Challenges for interactive effects

1. Most of the time, sub-groups analysis is interpreted descriptively and not causally
    1. "The pattern of support are generally similar for respondents irrespective of their level of ethnocentrism"
2. Ceiling effect
    1. Smaller effect in difference in the AMCE for a given feature because a group has already a strong preference for a given attributes
    2. AMCE difference is valid only when preferences toward profiles with the reference category are equivalent across groups.
    3. E.g. Political Experience (No Experience, 3 Years, 6 years) X PID (Republican, Democrats): Republican might experience a small effect because their preference towards candidate experience is already very high and ash such, a large positive effect for Democrats occurs despite Democrat being less supportive in every experimental conditions
3. Paper to read: Leeper, Hobolt, and Tilley (2019)

Marginal Means: A tabular representation

	Caucasian	African.American	Marginal Means
Evangelical	10	7.0	8.5
Catholic	15	18.0	16.5
Jewish	8	NA	8.0
Marginal Means	11	12.5	NA

Marginal Means

1. Marginal Means can resolves problems especially when dealing with interactions since they DO NOT require a **reference category**
   1. Descriptively: They express favorability on the scale of the outcome over alternative values of each feature
   2. causally: Difference in marginal means across two levels of a feature
2. They can be estimated using the R package cregg

Marginal Means: comparison with AMCE

Figure 4: Estimated Preference Differences between Inequity Averse and Non-Averse Respondents from Ballard-Rosa et al. (2016) Tax Preference Experiment for Each Possible Reference Category

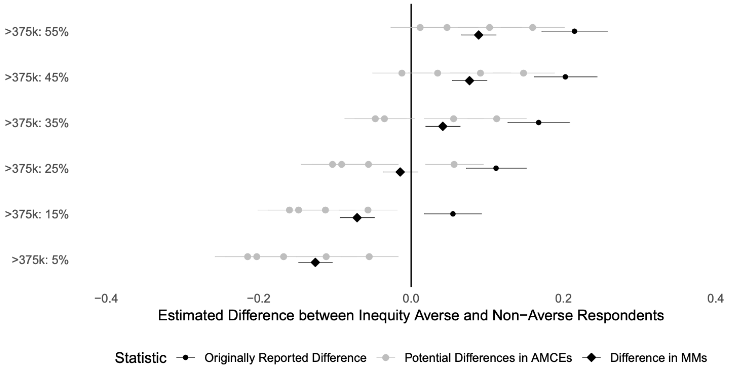


Figure 10: Conjointsdt Attributes and Levels

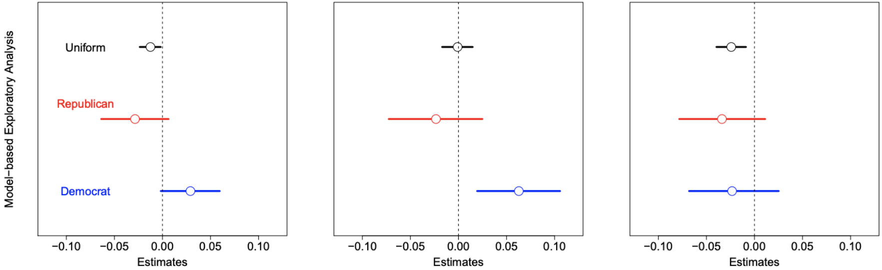
Section 30

Improving external validity with non-uniform distribution

Improving external validity with non-uniform distribution

1. the actual distribution of profiles in the real world and the distribution of theoretical interest are often far from uniform.
2. However, we are using a distribution that does not match the real world distribution (e.g. uniform)
3. It compromise the external validity of conjoint analysis.
    1. Design-based confirmatory analysis, incorporates the target profile distribution in the design
    2. Model-based exploratory analysis, takes into account the target profile distribution at the analysis stage, after randomizing profiles and collecting data
4. Paper to read: Improving the External Validity of Conjoint Analysis: The Essential Role of Profile Distribution Brandon de la Cuesta, Naoki Egami, Kosuke Imai (Working paper, 2020)

Non-uniform distribution example



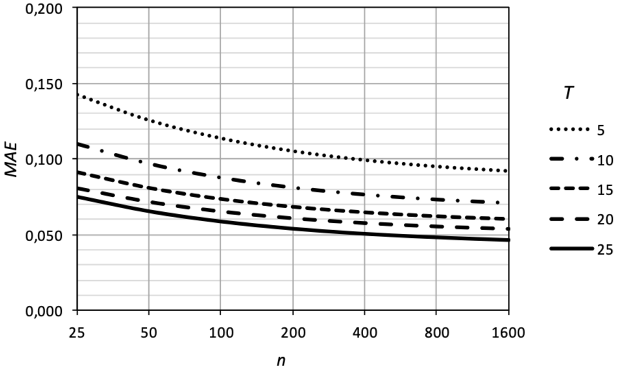
Section 31

Power Analysis Conjoint experiment

Power Analysis Conjoint experiment

1. Properly designed experiments must ensure that power will be reasonably high to be able to detect significant results
2. Meaning, the higher the power of the statistical test, the less likely you can make a type II error.
3. You might have a coefficients that point out in the hypothesised direction but they are non-significant due to a small sample size.
4. Type II error is related to
   - Difference magnitude between the samples — Effect size
   - the number of observations
   - the spread of data (SD)
5. Take a look at http://www.robertkubinec.com/post/conjoint_power_simulation/

Power simulation



Graph 2. Results for a scenario based on typical study parameters A = 6, La = 6, M = 4, C = 1, β = 0.4, e = 0 and no "none option" with *T* in the range of 5 to 25.

Section 32

Preference heterogeneity

Preference heterogeneity

1. Subgroup analysis is done using interaction with manifest variables (or latent factors)
2. We can better model preference heterogeneity using:
   1. LCA Ramaswamy and Cohen (2001)
   2. Mixture Models: Martin can you tell us something about it?

Section 33

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