

Intro to Conjoint Experiments

Session 5

Alberto Stefanelli

Session 4: Recap

① AMCE

- Effect decomposition
- Advantages
- Calculation
- Interpretation

② Marginal Means

- Purpose and interpretation
- Relation with the AMCE

Session 5: Outline

- ① Sub-group analysis
- ② Attributes interaction
- ③ Power Analysis for CJ
- ④ Restricted Randomization
- ⑤ Weighted Randomization
- ⑥ Conjoint mixture model

Materials

- Lecture's PDF
- Lab
- Exercise
- Solutions

Where to find the material:

- On my [GitHub/conjoint_class](#)

Sub-group analysis

- ① Subgroup analyses of conjoint experiments in order to discover preference heterogeneity.
- ② Increasingly common feature of experimental analysis
- ③ e.g., AMCE of male and female political candidates among male and female respondents ([Teele, Kalla, and Rosenbluth 2018](#))
- ④ **Technically:** Attribute's marginal effect conditional on the respondent characteristic of interest
- ⑤ 2 quantities of interest
 - Causal effects of profile features within each subgroup (Hainmueller, Hopkins, and Yamamoto ([2014](#)) term “conditional AMCEs”)
 - Difference between two conditional AMCEs across subgroups

Common issues in sub-group analysis (1)

- ① Most of the time, difference-in-AMCEs is interpreted descriptively and not causally
 - Difference-in-AMCEs are used to descriptively interpret apparent differences in favorability toward objects with a given feature (e.g., immigrants from Syria) between the two groups (low and high ethnocentrism respondents) ([Hainmueller, Hopkins, and Yamamoto 2014](#))
 - However, differences-in-preferences (that is to say, the difference in degree of favorability toward profiles containing a given feature) are not directly reflected in differences-in-AMCEs.
 - That is, difference-in-AMCEs do not provide inference into difference between subgroups' favorability toward a conjoint feature

Common issues in sub-group analysis (2)

- ② Reason: difference between subgroups (low and high ethnocentrism respondents) diverge in the reference category ([Leeper, Hobolt, and Tilley 2019](#))
 - Lack of differences when another (meaningful) baseline category is chosen
 - Smaller/Larger effect in difference-in-AMCEs for a given feature because a group has already a weak/strong preference for a given attribute
 - AMCE difference is valid only when preferences toward profiles with the reference category are equivalent across groups.
 - 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 as such, a large positive effect for Democrats occurs despite Democrat being less supportive in every experimental conditions
- ③ **Take Home:** Differences in the sign/size of causal effects should not be interpreted as differences in preferences

Solutions for difference-in-AMCEs

- ① Unadjusted marginal means
 - AMCE is very sensitive to which reference category you choose (as we have seen in Lab 4?) but MM are not
 - They express favorability on the scale of the outcome over alternative values of each feature
- ② An omnibus F-test, measuring differences therein.
 - **Model 1:** Model estimating only marginal effects of a given attribute
 - **Model 2:** Same as Model 1 with additional interactions between the sub-grouping covariate and the features
 - F-test for the model comparison between two models
- ③ Other approaches? Check out Ratkovic and Tingley ([2017](#)) on Bayesian Lasso for sparse estimation and uncertainty in subgroup analysis

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

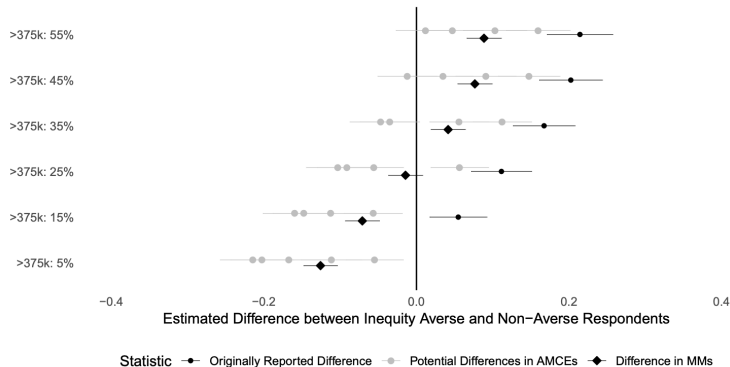


Figure 1: Conjointsdtd Attributes and Levels

Interactions between attributes (ACIE)

- 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 attribute between conditional on another attribute

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 social spending
 - ③ What would happen if a candidate is in favour of increasing social spending but – at the same time – is pro Medicare?
 - ④ ACIE: the percentage point difference in the AMCEs of cutting social spending between a pro Medicare candidate and a candidate against it
- ② Q: Can you come up with another example of attribute interaction? (**think theoretically**)

AMCE with Restricted Randomization

- ❶ Restricted randomization means that we have constraints between profile features
- ❷ E.g., Doctor without an academic education
- ❸ AMCE is a weighted average across each combination of the constrained features
- ❹ The effect of being a doctor on candidate favourability is marginalized **only** across higher level of educations
- ❺ Recommendations
 - Check the frequencies to be sure that the conditional probability between two attributes/levels is actually 0
 - Analysing only the complete and comparable subset of the design. This needs to be implemented while analysing the CJ in R or other software
 - Be clear about what features are being marginalized over

Non-uniform distribution

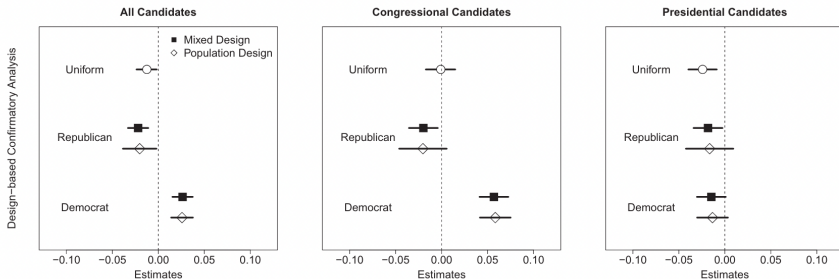
- ❶ The actual distribution of profiles in the real world and the distribution of theoretical interest are often far from being uniform.
- ❷ We should match the real world distribution
- ❸ It compromise the external validity of conjoint analysis.
 - ❶ Design-based confirmatory analysis: incorporates the target profile distribution in the design
 - ❷ Model-based exploratory analysis: takes into account the target profile distribution at the analysis stage, after randomizing profiles and collecting data
- ❹ **Paper to read:** Improving the External Validity of Conjoint Analysis: The Essential Role of Profile Distribution ([de la Cuesta, Egami, and Imai 2022](#))

Assumptions design with non-uniform distribution

Table 3. Data requirements and assumptions of design-based and model-based approaches.

Approach	Data requirement	Assumption	Note
Design-based confirmatory analysis			
• Joint population randomization	Joint distribution over all profile attributes	None	
• Marginal population randomization	Marginal distributions of each profile attribute	Absence of three-way or higher order interaction	Relax the assumption with partial joint distributions
• Mixed randomization	Joint distribution over control factors	None	Efficient when focus on one or two main factors
Model-based exploratory analysis			
• Linear probability model	Marginal distributions of each profile attribute	Absence of three-way or higher order interaction	Relax the assumption with partial joint distributions

Non-uniform distribution example

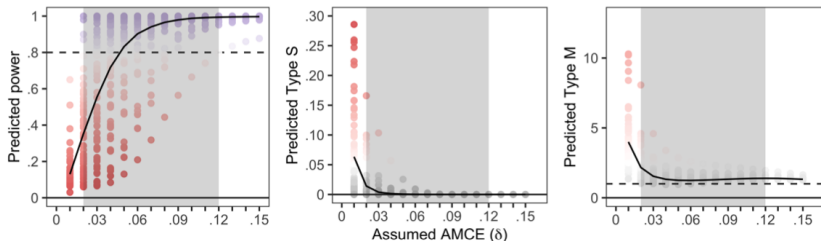


Power Analysis for conjoint experiments

- ❶ Experiments must ensure that statistical power is be reasonably high
 - Type I error: Successfully rejecting the null hypothesis when it is false (false-positive)
 - Type II error: Fails to reject a null hypothesis that is actually false (false-negative)
 - Type S error: opposite direction of the true effect size, given that the statistic is statistically significant (sign) ([Gelman and Carlin 2014](#))
 - Type M error: magnitude of your effect is overestimated (size) ([Gelman and Carlin 2014](#))
- ❷ Calculating the required minimal sample size for a conjoint experiment is not a trivial exercise.
 - Multiple profiles
 - Multiple tasks
 - High numbers of attributes
 - High numbers of levels

Retrospective statistical power, Type M and Type S error rates.

- Scholars think that conjoint designs “free us from the power constraints that limit traditional factorial experiments” (Kertzer, Renshon, and Yarhi-Milo 2019, 7)
- This results in conjoint studies that are under-powered and thus are likely to result in biased estimates, both in terms of direction and magnitude
- Stefanelli, A., & Lukac, M. (2020, November 18). Subjects, Trials, and Levels: Statistical Power in Conjoint Experiments.
<https://doi.org/10.31235/osf.io/spkcy>



Power calculation tool

- Shiny App for power calculations in CJ
- <https://mblukac.shinyapps.io/conjoints-power-shiny/>

Conjoint Experiments: Power Analysis Tool

Respondents

1000

500 1,000 3,000

Tasks

3

1 3 9

Effect size (%)

0.05

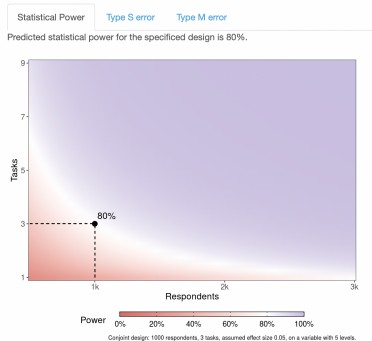
0.01 0.05 0.2

Variable levels

5

2 5 30

About Help



Mixture Modelling for conjoint data: Limitation of the AMCE

- ① The AMCE can be swayed both by **intensity** as well as **prevalence** of some preferences (Abramson et al., 2019).
- ② Existence of subgroups with distinct preferences and different responses to the treatment.
- ③ Existence of unobserved subgroups with extreme preferences and their prevalence in one of the groups can seriously bias the results of a conjoint experiment
- ④ Presence of heterogeneity within observed subgroups and not only between subgroups (i.e. strong VS weak party identifiers).

Mixture Modelling for conjoint data: Rationale

- We should first investigate the heterogeneity itself and then try to explain where it comes from.
 - Subgroups as unobserved (latent) classes in the population.
 - Investigate differences in the effects between unobserved groups.
 - The effects of the attributes are allowed to differ in magnitude or direction across the extracted unobserved groups.

Mixture Modelling for conjoint data: Equation

The diagram shows the equation $y_i | \mathbf{x}, k = \beta_{0k} + \sum_{p=1}^P \beta_{pk} x_{ip} + \epsilon_{ik}$ with several annotations:

- P attributes** ($\mathbf{x} = (x_1, x_2, \dots, x_P)$) points to \mathbf{x} .
- Selection of a profile for each individual i** points to y_i .
- β_{0k} is a class K specific intercept** points to β_{0k} .
- Latent membership is denoted by C , where $C = 1, 2, \dots, K$.** points to k .
- Values x_{ip} for subject i for attribute p .** points to x_{ip} .
- β_{pk} is a class-specific effect of attribute p for class k** points to β_{pk} .
- and $\epsilon_{ik} \sim N(0, \sigma_k^2)$ with σ_k^2 as a residual variance/covariance matrix for class k .** points to ϵ_{ik} .

$$y_i | \mathbf{x}, k = \beta_{0k} + \sum_{p=1}^P \beta_{pk} x_{ip} + \epsilon_{ik}$$

Mixture Modelling for conjoint data: advantages

- 1 Subgroups are allowed to emerge even if they are not correlated to observed covariates.
- 2 Well-defined framework to test the presence of subgroups
- 3 Misclassification of the subjects within the unobserved subgroups can be investigated and taken into account

Session 5: Recap

- ① Sub-group analysis
 - Issues
 - Solutions (MM)
- ② Attributes interaction
 - ACIE
- ③ Power Analysis for CJ
 - Underpowered studies
 - Shiny app
- ④ Restricted Randomization
 - Design-based approaches
 - Model-based approaches
- ⑤ Conjoint mixture model
 - Limitations AMCE
 - Rationale
 - Advantages

References I

- Cuesta, Brandon de la, Naoki Egami, and Kosuke Imai. 2022. "Improving the External Validity of Conjoint Analysis: The Essential Role of Profile Distribution." *Political Analysis* 30 (1): 19–45. <https://doi.org/10.1017/pan.2020.40>.
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- Leeper, Thomas J., Sara B. Hobolt, and James Tilley. 2019. "Measuring Subgroup Preferences in Conjoint Experiments." *Political Analysis*, August, 1–15. <https://doi.org/gh6p77>.

References II

- Ratkovic, Marc, and Dustin Tingley. 2017. "Sparse Estimation and Uncertainty with Application to Subgroup Analysis." *Political Analysis* 25 (1): 1–40. <https://doi.org/10.1017/pan.2016.14>.
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