

Experimental Methods: Lecture 5

Discrete Choice Experiments

Raymond Duch

May 25, 2023

University of Oxford

Road Map to Lecture 5

- Conjoint Experiments Overview
- External Validity of Conjoint Experiments
- Conjoint Experiments Heterogeneity

Conjoint Experiments Overview

Conjoint Experiments

- Typical survey experiments test uni-dimensional causal effect
 - Treatment versus Control
- Typical vignette experiments: immigration, candidate, racial cue
- But what components of manipulation produce observed effect?
 - Why does immigration status matter?

- Political Analysis 2013 Causal Inference in Conjoint Analysis
- Understanding Multidimensional Choices via State Preference Experiments
- The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes towards Immigrants
- Validating Vignette and Conjoint Survey Experiments Against Real-World Behaviour

Example: Candidates

- Respondents chose between/rank 2 candidates
 - $J=2$ (choices)
 - $K=6$ choices/evaluations
- Each candidate has a profile
 - Each profile has a set of L discretely valued attributes, or a treatment composed of L components
 - We use D to denote the total number of levels for attribute l
 - $L=8$ (candidate attributes, $D(1)...D(6)$ (total number of levels for candidate's age, education, etc.), and $D(7)...D(8)=2$ (for military service and gender)

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

Immigrant 1		Immigrant 2				
<p>If you had to choose between them, which of these two immigrants should be given priority to come to the United States to live?</p>		<input type="radio"/>				
<p>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?</p>						
Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<p>Using the same scale, how would you rate Immigrant 2?</p>						
Absolutely Not Admit 1	2	3	4	5	6	Definitely Admit 7
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Fig. 1 Experimental design: Immigration conjoint. This figure illustrates the experimental design for the conjoint analysis that examines immigrant admission to the United States.

Respondent's JK Profiles

$$\sum_{j=1}^J Y_{ijk}(\bar{\mathbf{t}}) = 1$$

Stability Assumption

- Potential outcomes always take on the same value as long as all the profiles in the same choice task have identical sets of attributes

$$Y_{ijk}(\bar{T}_i) = Y_{ijk^t}(\bar{T}_i)$$

$$\text{if } \bar{T}_{ik} = \bar{T}_{ik^t}$$

$$\text{for any } j, k, k^t$$

No Profile Order Effect

$$Y_{ij}(T_{ik}) = Y_{ij'}(T'_{ik})$$

$$\text{if } T_{ijk} = T'_{ij'k}$$

$$\text{and } T_{ij'k} = T'_{ijk}$$

for any i, j, j', k

Randomisation of Profiles

$$Y_i(\mathbf{t}) \perp T_{ijkl} \text{ for any } i, j, k, l$$

- Pairwise independence between all elements of $Y_i(t)$ and T_{ijkl} and $0 < p(t) = p(T_{ik} = t) < 1$

Basic Profile Effects

$$\pi(t_1, t_0) = Y_i(t_1) - Y_i(t_0)$$

Profiles	Candidate	Service	Income	Eduction
t_0	1	military	rich	college
	2	no service	poor	college
t_1	1	military	rich	college
	2	military	poor	college

Estimate Profile Effects

- Unit-level causal effects are difficult to identify
 - Involve counterfactuals and hence fundamental problem of causal inference
- Average Treatment Effects (ATE)?
 - If there are a large number of attributes with multiple levels the number of observations in each conditioning set will be virtually zero rendering estimation difficult if not impossible

Average Marginal Component Effect

$$\begin{aligned}\hat{\pi}_1(t_1, t_0, p(\mathbf{t})) = & \sum_{(\mathbf{t}, \mathbf{t}) \in \tilde{\tau}} \{ \mathbb{E}[Y_{ijk} | T_{ijkl} = t_1, T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t}] \\ & - \mathbb{E}[Y_{ijk} | T_{ijkl} = t_0, T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t}] \} \\ & \times p(T_{ijk[-l]} = t, \mathbf{T}_{i[-j]k} = \mathbf{t} | (T_{ijk[-l]}, \mathbf{T}_{i[-j]k}) \in \tilde{\tau})\end{aligned}$$

- The marginal effect of attribute l averaged over the joint distribution of the remaining attributes

Estimating AMCE

- For any attribute of interest T_{ijkl} the subclassification estimate of the AMCE can be computed simply by dividing the sample into the strata defined by T_{ijk}
- Typically the attributes on which the assignment of the attribute of interest is restricted
- Calculate the difference in the average observed choice outcomes between the treatment ($T_{ijkl} = 1$) and control ($T_{ijkl} = 0$) groups within each stratum
- Take the weighted average of these differences in means, using the known distribution of the strata as the weights

Regression Estimation

- The linear regression estimator is fully nonparametric, even though the estimation is conducted by a routine typically used for a parametric linear regression model
- Regress the outcome variable on the L sets of dummy variables
- Interaction terms for the attributes that are involved in any of the randomization restrictions used in the study
- Take the weighted average of the appropriate coefficients

Variance Estimation

- Observed choice outcomes within choice tasks strongly negatively correlated
- Both potential choice and rating outcomes within respondents are likely to be positively correlated because of unobserved respondent characteristics influencing their preferences
- Point estimates of the AMCE can be coupled with standard errors corrected for within respondent clustering
- Obtain cluster-robust standard errors for the estimated regression coefficients by using the cluster option in Stata
- Block bootstrap where respondents are resampled with replacement and uncertainty estimates are calculated based on the empirical distribution of the AMCE over the resamples

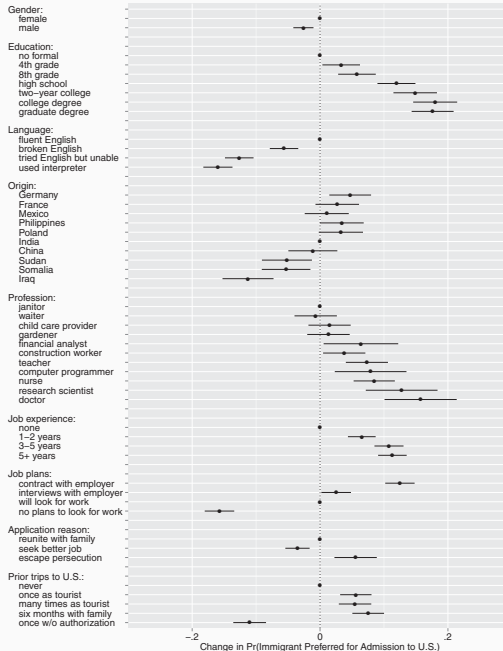
Example: Candidate Experiment

- 3,466 rated profiles - 1,733 pairings
- 311 respondents
- Design yields 186,624 possible profiles - far exceeds number of completed tasks
- Respondents rated each candidate profile on a seven-point scale, where 1 indicates that the respondent would "never support" the candidate and 7 indicates that she would "always support" the candidate
- Rescaled to 0 and 1

AMCE for candidate age levels

$$\text{rating}_{ijk} = \beta_0 + \beta_1[\text{age}_{ijk} = 75] + \beta_2[\text{age}_{ijk} = 68] + \\ \beta_3[\text{age}_{ijk} = 60] + \beta_4[\text{age}_{ijk} = 52] + \\ \beta_5[\text{age}_{ijk} = 45] + \epsilon$$

- The reference category is 36 years old
- β s are estimators for AMCE for ages 68, 75, etc. compared to 36



Conjoint External Validity

CACE External Validity

- Hypothetical versus Behavioural choices
- Treatment versus Control
- Hainmueller et al 2015 PANS
- Behavioural data from Swiss referendum
- Results matched to conjoint experiment

Swiss Behavioural Data

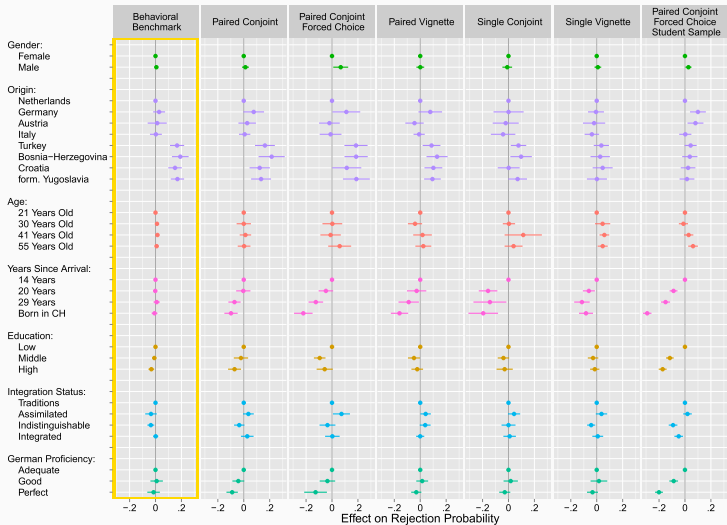
- Municipalities used referendums to vote on the naturalization applications of immigrants
- Voters received a voting leaflet with a short description of the applicant, including information about attributes, such as age, sex, education, origin, language skills, and integration status
- Voters then cast a secret ballot to accept or reject individual applicants
- These voting data yield an accurate measure of the revealed preferences of the voters what components of manipulation produce observed effect

Conjoint Experiment Data

- Respondents are presented with profiles of immigrants and then asked to decide on their application for naturalization
- List of attributes matches attributes voters saw on the voting leaflets distributed for the referendums - presented in same order as on the original leaflets
- Each respondent is randomly assigned to one of five different designs and asked to complete 10 choice tasks

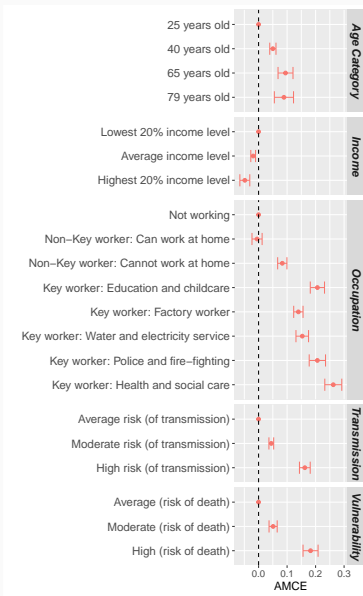
Experimental Designs

Designs	Profiles
single-profile vignette	accept/reject single profile
paired-profile vignette	accept/reject two profiles
single-profile conjoint	name/value of attributes
paired-profile conjoint	accept/reject 2 applicants
paired-profile conjoint	accept/reject 1 of 2 applicants

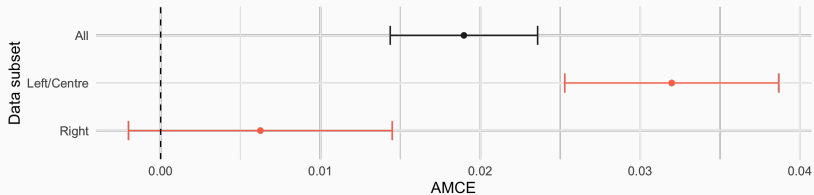


Conjoint Heterogeneity

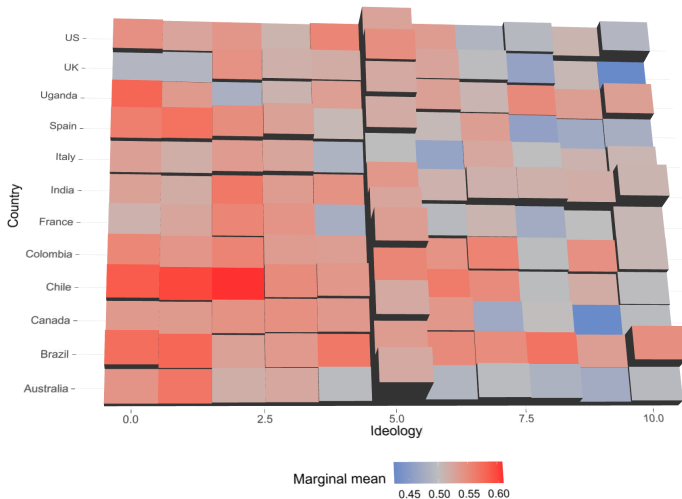
Duch et al CANDOUR Vaccination Prioritization



Subset Data on Ideology (AMCE for Income)



Selected profiles with “Lowest 20% income”



Nested Conjoint Causal Quantities

Table 1. Nested causal quantities in a conjoint experiment

Subject	Round	Profile	Attribute	...	y	y'	
1	1	1	A	...	1	0	} OMCE
1	1	2	B	...	0	1	
1	2	1	A	...	0	0	
1	2	2	A	...	1	0	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	} RMCE
N	2	1	B	...	0	1	
N	2	2	A	...	1	1	
							} IMCE
							} AMCE

Estimation: Step 1

Use BART to model potential heterogeneity in the observed experimental data defined as:

$$P(Y_{ijk} = 1 | T_{ijk}, X_i) = f(T_{ijk}, X_i) \approx \hat{f}(T_{ijk}, X_i),$$

where

- Y_{ijk} is the observed binary outcome
- T_{ijk} is the vector of treatment assignments across the L attributes,
- X_i is the vector of covariate information for subject i considering profile j in round k of the experiment. f is some unknown true data generating process,
- \hat{f} is an estimated model of that function.

Estimation Step 2

Using the final trained model (\hat{f}), we predict counterfactual outcomes (i.e. whether the profile was selected or not) changing the value of attribute-levels.

- Specifically, to recover a vector of OMCE estimates of attribute-level l_1 ,
- we take z draws from the predicted posterior using a “test” matrix which is identical to the training dataset,
- except each element in the column corresponding to attribute l is set to the value l_1

Finally, therefore, to recover a parameter estimate of the OMCE, we simply average these z predictions for each observation to yield a vector of observation-level effects:

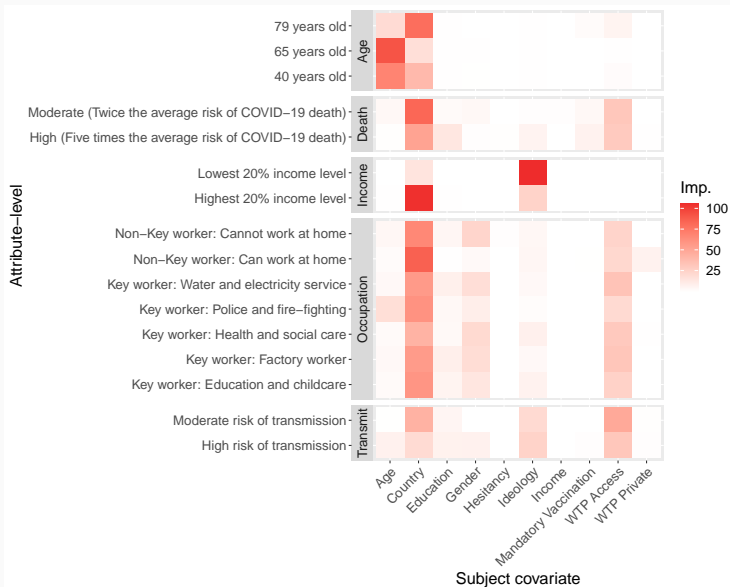
$$\text{OMCE} = \hat{\tau}_{ijkl} = \frac{1}{z} \left(\hat{f}(T_{ijkl} = l_1, X_i) - \hat{f}(T_{ijkl} = l_0, X_i) \right).$$

Step 3

Finally, the IMCE estimates can then be calculated by averaging the OMCEs for each individual i :

$$\text{IMCE} = \hat{\tau}_{il} = \frac{1}{J \times K} \sum^K \sum^J \hat{\tau}_{ijkl}.$$

Influence Heat Map



COVID Ideology Income

