Conjoint experiments workshop

Theory, implementation, and analysis

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Outline

Plan for today:

1. Why conjoint experiments?
2. Estimation properties
3. Break (create Qualtrics account)
4. Implementation in Qualtrics
5. Analysis in R

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I'll provide everything necessary for this

Why use conjoint experiments?

What does a conjoint look like?

On this and the next screens you will see pairs of candidates who are competing for a Congressional seat. For each pair, please choose the candidate that you prefer.

Candidate A	Candidate B
Male	Male
43	75
Member of Congress	Mayor
Democrat	Democrat
Says lockdowns should continue until there are fewer COVID-19 deaths	Says lockdowns should continue until there are fewer COVID-19 deaths
Says that a president should work with Congress even if it is obstructing his/her policies to combat a pandemic	Says that a president should work with Congress even if it is obstructing his/her policies to combat a pandemic
Says economic aid to address the COVID-19 crisis should mostly be given to businesses	Says economic aid to address the COVID-19 crisis should ensure a basic income of $1,000 per month for everyone

Which candidate do you prefer?

Candidate A

Candidate B

Terminology

Following Hainmueller et al. 2014:

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- Any given attribute l has D_l distinct values

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And each of these moving parts implies a decision

Applying terminology

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2. Cost-effective: allows to test multiple hypothesized effects
3. Easy comparisons of explanatory power of different hypotheses
4. Reduced potential for social desirability bias

Estimation properties

QoI

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- More info: Abramson, Kocak, and Magazinnik

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Democrat	0.56	0
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Party	MM	AMCE
Democrat	0.56	0
Republican	0.44	-0.12

- Comparing AMCEs across subgroups: distortion due to reference level (Leeper, Hobolt, and Tilley 2020)

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Two things to note:

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- Dataset gets large quickly: 2,000r x 6t x 2p = 24,000 profiles

Assumption 1: Stability/no carry-over

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Diagnostics:

- Produce task-specific AMCEs and compare

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Diagnostics:

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- Formal test (using `cregg` package)

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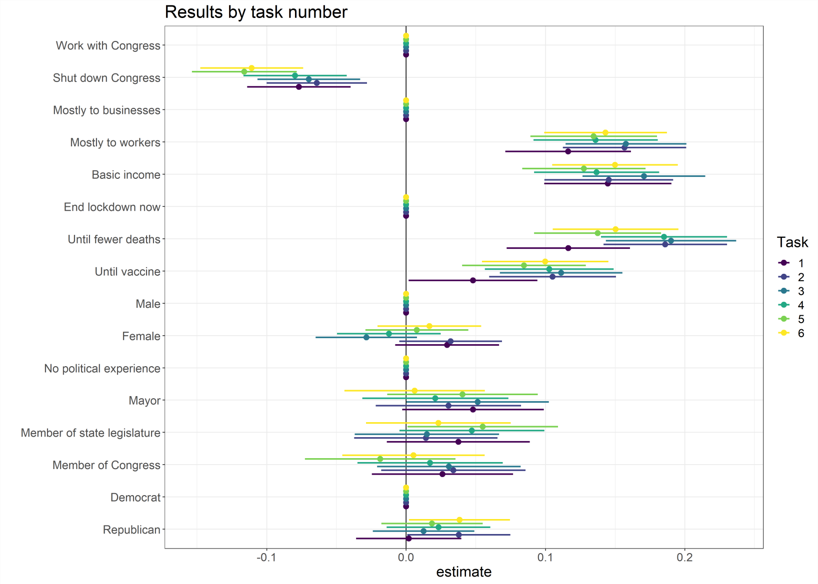

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```r
load("survey.Rdata")
library(cregg)
cj_anova(data = conjoint_congress,
         formula = selected ~ cand_gender + cand_age +
           experience + party + policy1 + policy2 + democracy,
         id = ~id,
         by = ~profile)
```

```
## Analysis of Deviance Table
##
## Model 1: selected ~ cand_gender + cand_age + experience + party + policy1 +
##     policy2 + democracy
## Model 2: selected ~ cand_gender + cand_age + experience + party + policy1 +
##    policy2 + democracy + profile + cand_gender:profile + cand_age:profile +
##    experience:profile + party:profile + policy1:profile + policy2:profile +
##     democracy:profile
##   Resid. Df Resid. Dev Df Deviance      F    Pr(>F)
## 1     16314     3895.6
## 2     16294     3884.7 20   10.908 2.2875 0.0008829 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Assumption 2: No profile-order effects

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- In a given task, choice should be the same regardless of profile-order

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No fix for profile-order effects; sample quality is paramount!

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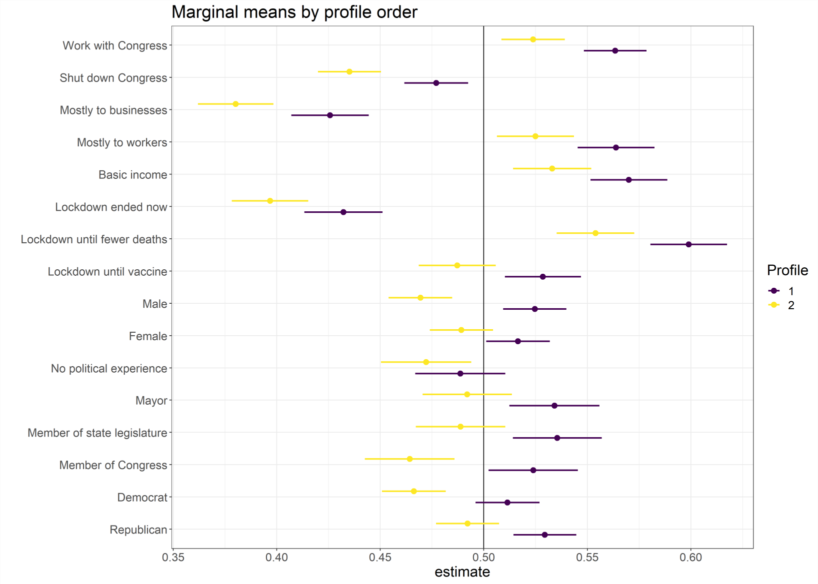

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```
library(dplyr)
model <- lm(lockdown_support_scale ~ cand_gender + cand_age +
           experience + party + policy1 + policy2 + democracy,
   data = conjoint_congress) %>% summary()

model$fstatistic
```

```
##       value       numdf       dendf
## 8.70601e-01 1.90000e+01 1.62880e+04
```

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Diagnostics: visual inspection, formal test

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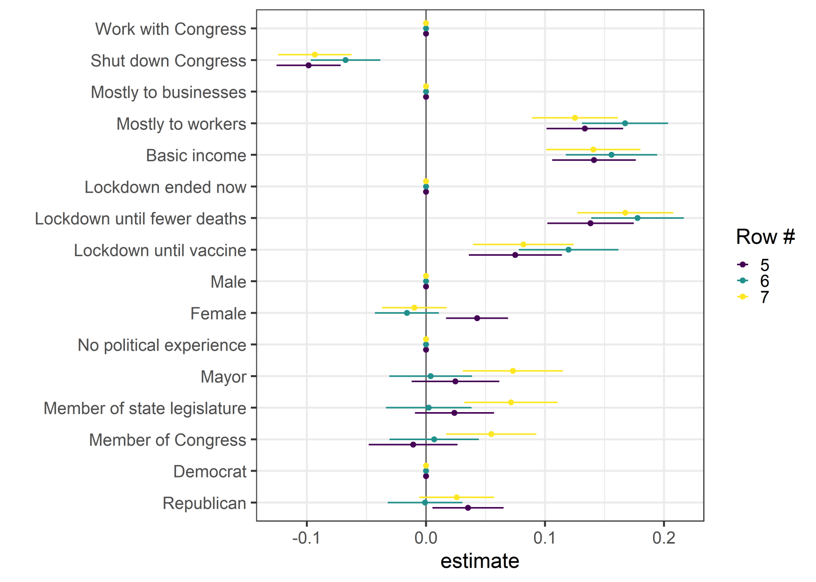

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cj_anova(data = conjoint_courts,
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##   Resid. Df Resid. Dev Df Deviance      F Pr(>F)
## 1     16348     3925.8
## 2     16308     3914.6 40   11.261 1.1729 0.2104
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- No “bias” in the traditional sense: “It is important to recognize that masking is distinct from omitted variable bias in that an estimate of an effect might be masking another while remaining a valid causal estimate. In the presence of masking, it is not that the researcher is getting an incorrect answer so much as she is asking a different question. If B is omitted, researchers get a valid estimate of the AMCE of A defined as the causal effect of A conditional on the design excluding B. If B is included, researchers still recover a valid estimate of A’s AMCE, but that AMCE has a different meaning because it is now defined as the causal effect of A conditional on the design including B.” (Bansak et al. 2019)
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- 6 to 8 attributes is generally reasonable
- Modest increases in satisficing as # of attributes increases
- My take: don’t ask too much of respondents and consider the “difficulty” of attributes

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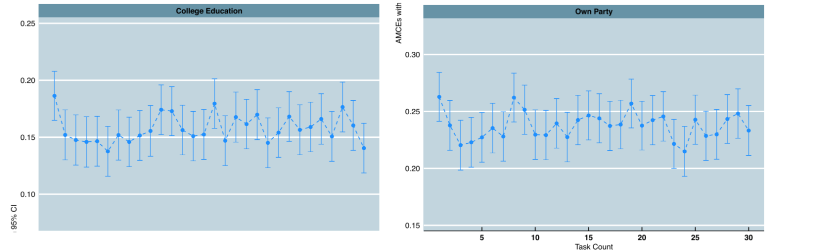

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Design: inattentiveness

- To make assumptions more plausible, have a quality sample
- Not much advice that's specific to conjoint experiments
- One solution: iteratively exclude respondents based on time

```
dem_estimate <- data.frame(restriction = seq(0, 7, .25),
                           estimate_congress = NA,
                           lwr_congress = NA,
                           upr_congress = NA)
for(i in 0:28){
  conjoint_restricted_congress <- filter(conjoint_congress, task_time > i*0.25)
  dem_estimate[i+1,2:4] <- cregg::cj(conjoint_restricted_congress,
          formula = f1,
          id = ~id) %>%
    filter(level == "Shut down Congress") %>%
    dplyr::select(estimate, lower, upper) %>%
    as.vector() %>%
    as.numeric()
}
```

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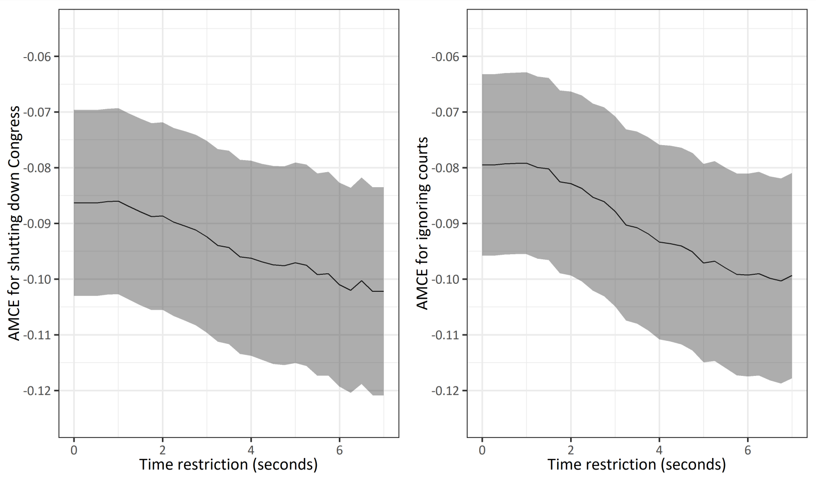

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- e.g. ethnicity of political candidates
- modify javascript code to do this
- Hainmueller et al. 2014: don't do this unless there's a "strong substantive reason"
- de la Cuesta, Egami, and Imai (forthcoming in PA): improve external validity by mimicking target profile distribution

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- Example: attribute A is "party" and attribute B is "position on healthcare"
- Hainmueller et al. 2014: atypical vs meaningless
- Restrictions on randomness complicate the estimation procedure

Implementation in Qualtrics

Our example today

Attributes for today

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Sex	Male	Female				
Age	3 months	6 months	1 year	3 years	7 years	11 years
Color	Black	Light brown	White	Light grey		
Fur type	Long hair	Short hair				
Breed	Bengal	Maine Coon	Persian	Moggie		
Character	Energetic/cuddly	Energetic/solitary	Sleepy/cuddly	Sleepy/solitary		

2x6x4x2x4x4 = 1,536 distinct profiles

Workflow

1. Create our survey in Qualtrics
2. Modify the HTML template according to your design
3. Modify the Javascript template according to your design
4. Set embedded data to save observed profiles
5. Set up the randomizer in "Survey Flow"
6. Use the HTML code as the question content
7. Insert Javascript code