Analyzing conjoint experiments in Stata

The **-conjoint-** command

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Goals and contribution of -conjoint-

- Conjoint analysis itself is not overly complicated
- For most, can simply use -regress-
- ‘Constraints’ make it a bit more complex
- There are commands available in R (and potentially other software):
    - cjoint (Barari et al., 2018)
    - cregg (Leeper and Barnfield, 2020)
- Shared bits of Stata code:
    - e.g. in Hainmueller et al. 2013
- No simple command in Stata
- -conjoint- was made for Stata-only (or preferring) users, to maintain a consistent workflow...
- I am looking to maintain but also improve it in the future!

Outline

- Conjoint experiments
- Analysis
- The -conjoint- command
- Two examples
- What it cant do

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Conjoint Experiments

- Developed in mathematical psychology (e.g. Luce and Tukey, 1964)
- Popular in various disciplines
    - Including in political science (e.g. Hainmueller et al., 2014, Ghosn et al., 2021a)
    - But also market research, environmental economics, health care, etc.
- Share alot of similarities with discrete choice experiments (e.g. see Louviere et al., 2010)
- Choice-based conjoints (but there are other types)

Conjoint Experiments

- Survey experiment tool to elicit how people choose between different options (alternatives) that vary in different (multidimensional) ways?
- How much do people value different attributes (of alternatives) and the trade-off between them
- Measuring preferences without directly asking them
- Can estimate the causal impact of different levels (of attributes) on choices (Hainmueller et al. 2014)

Conjoint Experiments

- Survey experiment tool to elicit how people choose between different options (alternatives) that vary in different (multidimensional) ways?
- How much do people value different attributes (of alternatives) and the trade-off between them
- Measuring preferences without directly asking them
- Causal impact of different levels (of attributes) on choices (Hainmueller et al. 2014)

	A	B

Colour	Green	Orange
Skin texture	Smooth	Rough
Price per kg	£2.70	£2.25
Vitamin C content	Low	High
Calcium content	Low	High

Conjoint Experiments

- Another fictional example (semi-based on an ‘Apple vs Samsung’ patent trial in 2012)

Conjoint Experiments

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- Use a paired-profile design (each participant shown two profiles at a time)

Mobile Phone A	Mobile Phone B

Conjoint Experiments

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- Use a paired-profile design (each participant shown two profiles at a time)
- Describe each profile (alternative) by some attributes

	Mobile Phone A	Mobile Phone B
Screen size		
Weight		
Internal memory		
Slide to unlock		
Autocorrect		
Price		

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Conjoint Experiments

- Another fictional example (semi-based on an ‘Apple vs Samsung’ patent trial in 2012)
- Use a paired-profile design (each participant shown two profiles at a time)
- Describe each profile (alternative) by some attributes
- Decide potential levels of those attributes

	Mobile Phone A	Mobile Phone B
Screen size		
Weight		
Internal memory		
Slide to unlock		
Autocorrect		
Price		

	Levels
Screen size	4.7’’, 5.5’’, 6.7’’
Weight	150g, 175g, 200g
Internal memory	32gb, 64gb, 128gb
Slide to unlock	No, Yes
Autocorrect	No, Yes
Price	£150, £300, £500

Conjoint Experiments

- Another fictional example (semi-based on an 'Apple vs Samsung' patent trial in 2012)
- Use a paired-profile design (each participant shown two profiles at a time)
- Describe each profile (alternative) by some attributes
- Decide potential levels of those attributes
- Present each participant with randomized combinations of levels

Task 1

	Mobile Phone A	Mobile Phone B
Screen size	4.7"	5.5"
Weight	175g	200g
Internal memory	64gb	64gb
Slide to unlock	Yes	Yes
Autocorrect	No	Yes
Price	£300	£300

	Levels
Screen size	4.7", 5.5", 6.7"
Weight	150g, 175g, 200g
Internal memory	32gb, 64gb, 128gb
Slide to unlock	No, Yes
Autocorrect	No, Yes
Price	£150, £300, £500

Conjoint Experiments

- Another fictional example (semi-based on an ‘Apple vs Samsung’ patent trial in 2012)
- Use a paired-profile design (each participant shown two profiles at a time)
- Describe each profile (alternative) by some attributes
- Decide potential levels of those attributes
- Present each participant with randomized combinations of levels

Task 2

	Mobile Phone A	Mobile Phone B
Screen size	6.7”	5.5”
Weight	150g	150g
Internal memory	32gb	128gb
Slide to unlock	Yes	Yes
Autocorrect	Yes	Yes
Price	£500	£150

	Levels
Screen size	4.7”, 5.5”, 6.7”
Weight	150g, 175g, 200g
Internal memory	32gb, 64gb, 128gb
Slide to unlock	No, Yes
Autocorrect	No, Yes
Price	£150, £300, £500

Conjoint Experiments

- Another fictional example (semi-based on an 'Apple vs Samsung' patent trial in 2012)
- Use a paired-profile design (each participant shown two profiles at a time)
- Describe each profile (alternative) by some attributes
- Decide potential levels of those attributes
- Present each participant with randomized combinations of levels

Task 3

	Mobile Phone A	Mobile Phone B
Screen size	6.7''	6.7''
Weight	150g	150g
Internal memory	128gb	128gb
Slide to unlock	No	Yes
Autocorrect	No	Yes
Price	£150	£150

	Levels
Screen size	4.7'', 5.5'', 6.7''
Weight	150g, 175g, 200g
Internal memory	32gb, 64gb, 128gb
Slide to unlock	No, Yes
Autocorrect	No, Yes
Price	£150, £300, £500

Average marginal component effect (Hainmueller et al., 2014)

Without constraints

- Complete randomization
  - Every level for every attribute is independent of the levels of all other attributes
- Difference in the average choice probabilities between the ‘treatment’ and ‘control’ (two levels)
- AMCE can be computed simply by a regression of the observed choices on D-1 dummy variables for the levels of each attribute
- Estimated coefficient is the difference in probabilities of a profile being selected (relative to the baseline)

Average marginal component effect (Hainmueller et al., 2014)

With constraints

- With constraints - levels of one attribute are restricted on the basis of another

Average marginal component effect (Hainmueller et al., 2014)

With constraints

- With constraints - levels of one attribute are restricted on the basis of another
- e.g. phone weight and screen size -- it might be infeasible for a 6.7” screen on a 150g phone
- Distribution of (phone) weight is dependent on the screen size, but conditionally independent of all other attributes (e.g. internal memory)

	Mobile Phone A	Mobile Phone B
Screen size	6.7’’	4.7’’
Weight	150g	150g
Internal memory	32gb	128gb
Slide to unlock	Yes	Yes
Autocorrect	Yes	Yes
Price	£500	£150

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Average marginal component effect (Hainmueller et al., 2014)

With constraints

- AMCE can be computed by:
  - For each level, take the combinations with other levels where they (and the baseline level) appear
  - Calculate the overall difference in choice outcomes across these strata

	Mobile Phone A	Mobile Phone B
Screen size	6.7’’	4.7’’
Weight	150g	150g
Internal memory	32gb	128gb
Slide to unlock	Yes	Yes
Autocorrect	Yes	Yes
Price	£500	£150

- E.g. for effect of 6.7’’ relative to 4.7’’ screen:

  (6.7’’#175g – 4.7’’#175g) + (6.7’’#200g – 4.7’’#200g)

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Average marginal component effect (Hainmueller et al., 2014)

With constraints

- AMCE can be computed by:
  - For each level, take the combinations with other levels where there are conditional independence
  - Calculate the overall difference in choice outcomes across these strata

	Mobile Phone A	Mobile Phone B
Screen size	6.7’’	4.7’’
Weight	150g	150g
Internal memory	32gb	128gb
Slide to unlock	Yes	Yes
Autocorrect	Yes	Yes
Price	£500	£150

- E.g. for effect of 6.7’’ relative to 4.7’’ screen:

  (6.7’’#175g – 4.7’’#175g) + (6.7’’#200g – 4.7’’#200g)

- But for effect of 5.5’’ relative to 4.7’’ screen:

  (5.5’’#150g – 4.7’’#150g) + (5.5’’#175g – 4.7’’#175g) + (5.5’’#200g – 4.7’’#200g)

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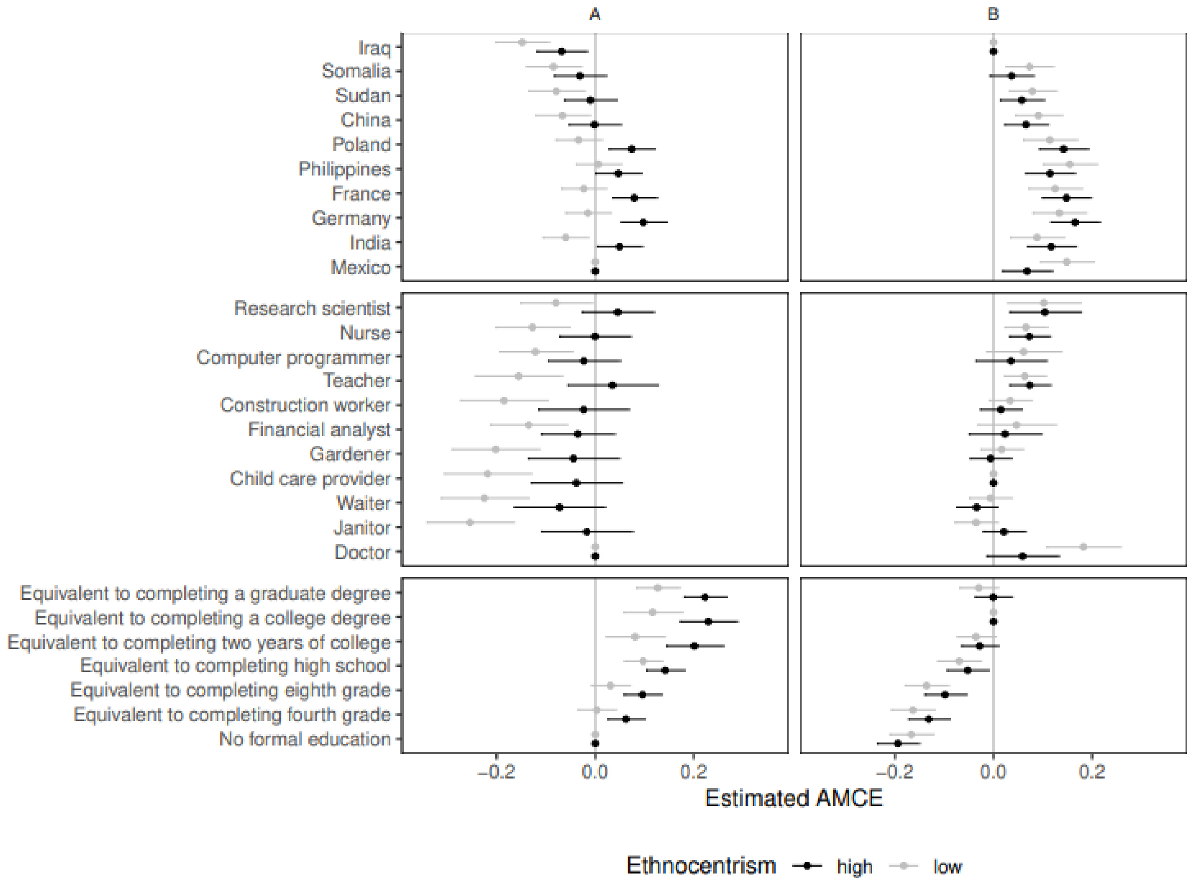
Average marginal component effect (Hainmueller et al., 2014)

- AMCEs are the effect relative to the baselevel (control)
- No constraints: choice of baselevel can impact the visualization of the results
- With constraints, can directly impact the results
- With subgroups, e.g. males versus females, becomes a bit more complicated
    - Particularly when preferences for reference level diverges
    - Interpretation has to be careful

Figure 4: Comparison of AMCEs for Low- and High-Ethnocentrism Respondents Using Two Alternative Reference Categories Choices for Three Features from Hainmueller et al.'s (2014) Immigration Experiment



From Leeper et al., 2020

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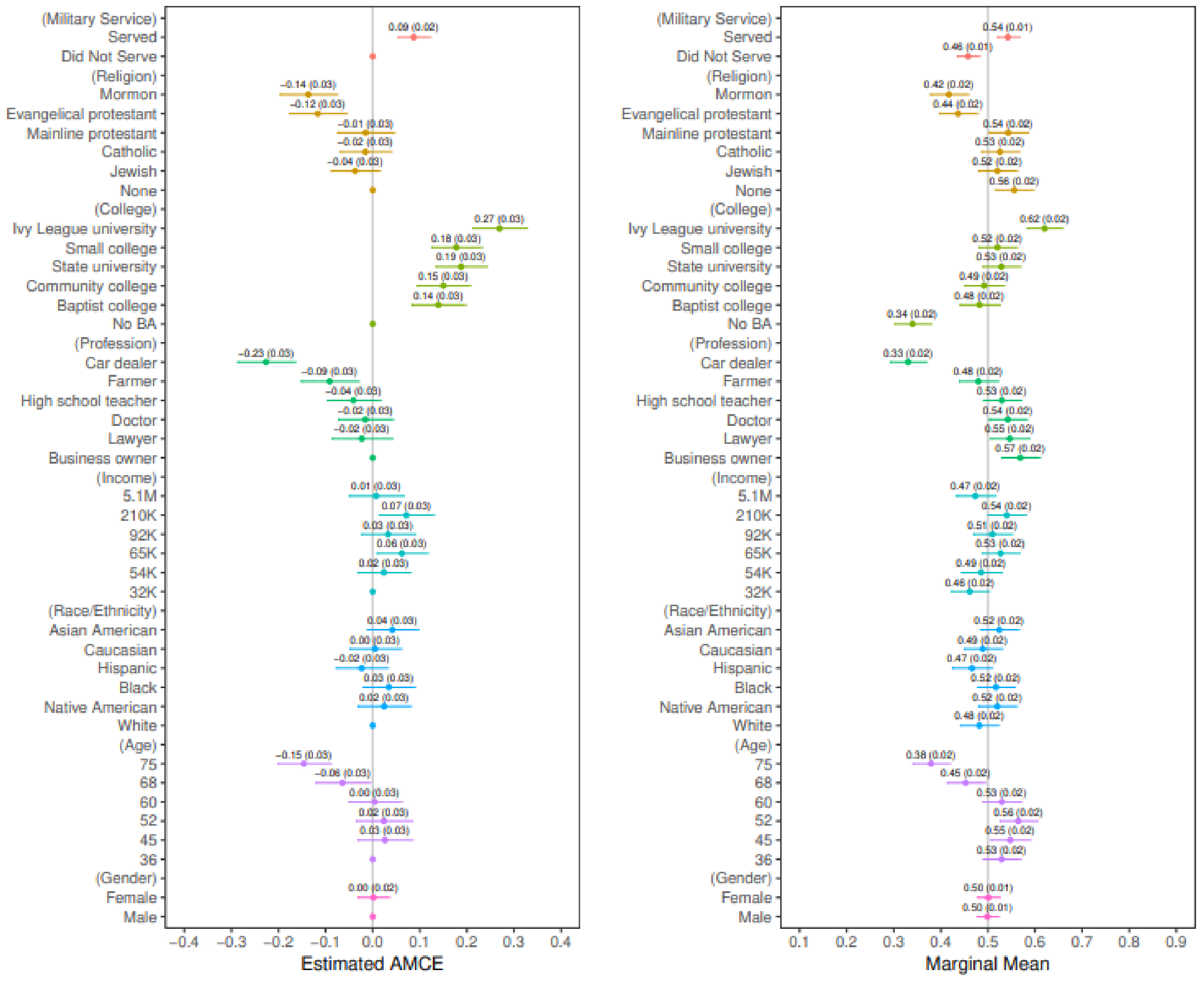
Marginal Means (Leeper et al., 2020)

- Rather than marginal effect of one level relative to another (AMCE)
- Represent as the (marginal) mean effect
- The average probability of a profile being selected given an attribute level, the level of favorability
- Does not depend on the choice of base or reference level
- Can be estimated using -regress- and -margins- commands

Figure 1: Replication of Hainmueller et al. (2014) Candidate Experiment using AMCEs and MMs



From Leeper et al., 2020

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Analysing conjoints

- Two well known R packages:

- **cjoint** (Barari et al., 2018)
  - Estimate AMCEs
  - Lots of other functionality
  - Two-way constraints between each pair of levels must be specified

- **cregg** (Leeper and Barnfield, 2020)
  - Estimate AMCEs and MMs
  - Two-way constraints between levels are automatically detected
  - Lots of other functionality

- No ‘simple’ function in Stata (as far as I know)

-conjoint-

Replicate conjoint analysis functionality in a simple command

✓Can estimate AMCEs and MMs

✓(Theoretically) can include unlimited-way constraints between levels

✓The combinations of constrained levels are automatically detected through **conjoint…constraint(x#y)**

✓Can pass the results to **-coefplot-** for plotting

❌ Limited other functionality…

- ❌Comparisons of effects of baselevel choices
- ❌Comparing attribute-levels
- ❌…

Title

conjoint — Analysis and visualisation of conjoint (factorial) experiments

Syntax

```
conjoint depvar indepvars [if] [in] , estimate(estimate_options) [options display_options]
```

Options	Description
Estimate Options	
amce	estimate average marginal component effects (AMCEs)
mm	estimate marginal means (MMs)
Options	
id(*varname*)	variable identifying respondents for calculating clustered standard errors
subgroup(*varname*)	variable identifying subgroups to be analysed
baselevels(*numlist*)	list of the baselevels for each variable (if **amce** are estimated)
constraints(*varlist*)	list of sets of variables to identify profile constraints (if **amce** are estimated)
h0(#)	null hypothesis value (if **mm** are estimated)
Display Options	
notable	suppress coefficient table
graph[(#)]	plot coefficients and type of plot

cjoint (Barari et al., 2018)
- Estimate AMCEs
- Lots of other functionality
- Two-way constraints between pairs of levels must be specified

cregg (Leeper and Barnfield, 2020)
- Estimate AMCEs and MMs
- Two-way constraints between levels are automatically detected
- Lots of other functionality

-conjoint-

- Relatively simple
- Has a replay function
- Cleaning/preparation function
- Split into a ‘estimate mm’ (marginal means) and ‘estimate amce’ (average marginal component effects) functions
- A display function
- **How amazing Statalist is (e.g. the optional arguments code)!**

```
program conjoint, eclass
    version 16

    if replay() {
    else {
        syntax varlist(min=2) [if] [in], ESTimate(string) [ID(varname) ///
        SUBgroup(varname) BASElevels(numlist int) CONstraints(varlist fv) ///
        h0(real -1) NOtable graph GRAPH2(integer -1)]
        marksample touse
        gettoken depvar xvars: varlist

        /* prepare and check inputs */
        conjoint_prep , xvars(`xvars') estimate(`estimate') h0(`h0') ///
        constraints(`constraints') baselevels(`baselevels') rawcmd(`0') ///
        subgroup(`subgroup') graph("`graph'") graph2("`graph2'")

        /* estimate effects */
        if "`estimate'" == "mm" {
            conjoint_est_mm, depvar(`depvar') xvars(`xvars') ///
            resmat_size(`e(resmat_size)') subgroup(`subgroup') h0(`h0') ///
            id(`id') touse(`touse')
        }
        else if "`estimate'" == "amce" {
            conjoint_est_amce, depvar(`depvar') xvars(`xvars') ///
            resmat_size(`e(resmat_size)') regress_xvars(`e(regress_xvars)') ///
            baselevels(`e(baselevels)') subgroup(`subgroup') id(`id') ///
            touse(`touse')
        }
    }

    /* display results, allowed for replay */
    conjoint_disp , subgroup(`subgroup') xvars(`xvars') notable("`notable'") ///
    graph("`graph'") graph2("`graph2'") estimate("`estimate'") rawcmd(`0') ///
    depvar(`depvar') clustvar(`id') constraints(`constraints') ///
    baselevels(`e(baselevels)') h0(`h0')
end
```

-conjoint-

conjoint Chosen_Immigrant Country_of_Origin Reason_for_Application Education, est(amce) id(CaseID) constraint(Country_of_Origin#Reason_for_Application Education#**Job**)

conjoint_prep

- Checks for various issues
- Cleans constraint list (variables in constraint list do need to be an IV and vice versa)

```
/* check constraints */
/* error if full-factorial interaction (in constraints) */
if strpos("`rawcmd'","##") {
    di as error "full-factorial interactions (##) not allowed in constraints"
    exit 198
}
/* error if spaces are found in constraints */
if strpos("`rawcmd'"," #") | strpos("`rawcmd'","# ") {
    di as error "spaces between # and variables not allowed in constraints"
    exit 198
}
/* ensures constraints is suitably formatted */
local constraints: subinstr local constraints "i." "", all
local constraints_cln: subinstr local constraints "#" " ", all
if strpos("`constraints_cln'",".") {
    di as error "unary operators not allowed in constraints"
    exit 198
}
/* checks for multiple occurrences of the same var in constraints */
local dup_constraints : list dups constraints_cln
if "`dup_constraints'" != "" {
    di as error "repeated variables in constraints not allowed"
    exit 198
}
/* find non-constrained vars, add them to constraint list */
local missing_xvars : list xvars - constraints_cln
local regress_xvars : list constraints | missing_xvars
```

-conjoint-

conjoint Chosen_Immigrant Country_of_Origin Reason_for_Application Education, est(amce) id(CaseID) constraint(Country_of_Origin#Reason_for_Application Education#**Job**)

conjoint_amce

- Uses -regress-
- Uses r(error) table to identify constraints/empty cells (combinations of levels)
- Uses -lincom- when constraints to calculate difference
- String can be too long – **can be calculated manually in future version**

```
quietly regress `depvar' i.(`regress_xvars') if `if_condition', cluster(`id')
quietly margins `regress_xvars'
mat reg_errors = r(error)

local xvar_count : word count `xvars'
forvalues i = 1/`xvar_count' {
    local focal_xvar : word `i' of `xvars'
    local focal_xvar_baselevel : word `i' of `baselevels'
```

```
//compares coefficients and collects results into differences matrix
forvalues rownum = 1/`rows' {
    local cdiff = results2[`rownum',1] - results1[`rownum',1]
    local pooledse = sqrt(results2[`rownum',2]^2 + results1[`rownum',2]^2)
    local tstat = (results2[`rownum',1] - results1[`rownum',1])/`pooledse'
    local tfactor = invttail(`pooleddf', 0.025)
    local pvalue = 2*ttail(`pooleddf',abs(`tstat'))
    local lb = `cdiff' - `pooledse'*`tfactor'
    local ub = `cdiff' + `pooledse'*`tfactor'
    matrix diff[`rownum',1]=`cdiff', `pooledse', `tstat', `pvalue', `lb', `ub'
}
```

-conjoint-

conjoint Chosen_Immigrant Country_of_Origin Reason_for_Application Education, est(amce) id(CaseID) constraint(Country_of_Origin#Reason_for_Application Education#**Job**)

conjoint_disp

- Displays results table
- Sends a string to -coefplot- if graph option specified
- ereturns some results

```
/* display graph if specified */
if "`graph'`graph2'" != "-1" {
    /* if one plot */
    if "`graph'"=="graph" | "`graph2'"=="0" | "`subgroup'"=="" {
        /* if one model */
        if ("`subgroup'"=="") local graph_code "(matrix(results[,1])) "
        /* multiple models (one plot) */
        else {
            foreach sub of local subgroups {
                local subgroup_label : label (`subgroup') `sub'
                local subgroup_label = strtoname("`subgroup_label'")
                local graph_code ///
                "`graph_code' (matrix(results_`subgroup_label'[,1]), label(`subgroup_label')) "
            }
        }
        /* plot the single plot */
        quietly coefplot `graph_code', ci((5 6)) keep(*:) xline(`plotxline', ///
        lpattern(-) lcolor(black)) coeflabels(`plot_level_labels') ///
        eqlabels(`plot_var_labels', asheadings) graphregion(col(white)) ///
        scale(0.7) xtitle({bf:`plottitle'})
```

Conjoint Example #1

Refugee resettlement preferences conjoint (Simon et al., 2021, Braithwaite et al., 2020)

- 402 Syrian refugees asked for their relocation preferences
- Two alternatives, "Country A" and "Country B"
- Varied by:
    - Level of abuse
    - Ease of finding work
    - Size of diaspora
    - Legality (of move)
- Completely randomised

Table 4: Attributes and Levels

Attributes	Levels
Level of abuse	No verbal or physical
	Some verbal
	Some physical and verbal
	Frequent physical and verbal
Ease of finding work	Easy
	Moderate
	Difficult
Size of diaspora Syrian diaspora	Syrian diaspora
	Only Middle Eastern diaspora
	No Middle Eastern or Syrian diaspora
Legality	Resettlement for you and your family
	Resettlement for you only
	No legal resettlement so would have to make your own way
	No legal resettlement so would have to use a smuggler

From Simon et al., 2021

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Conjoint Example #1

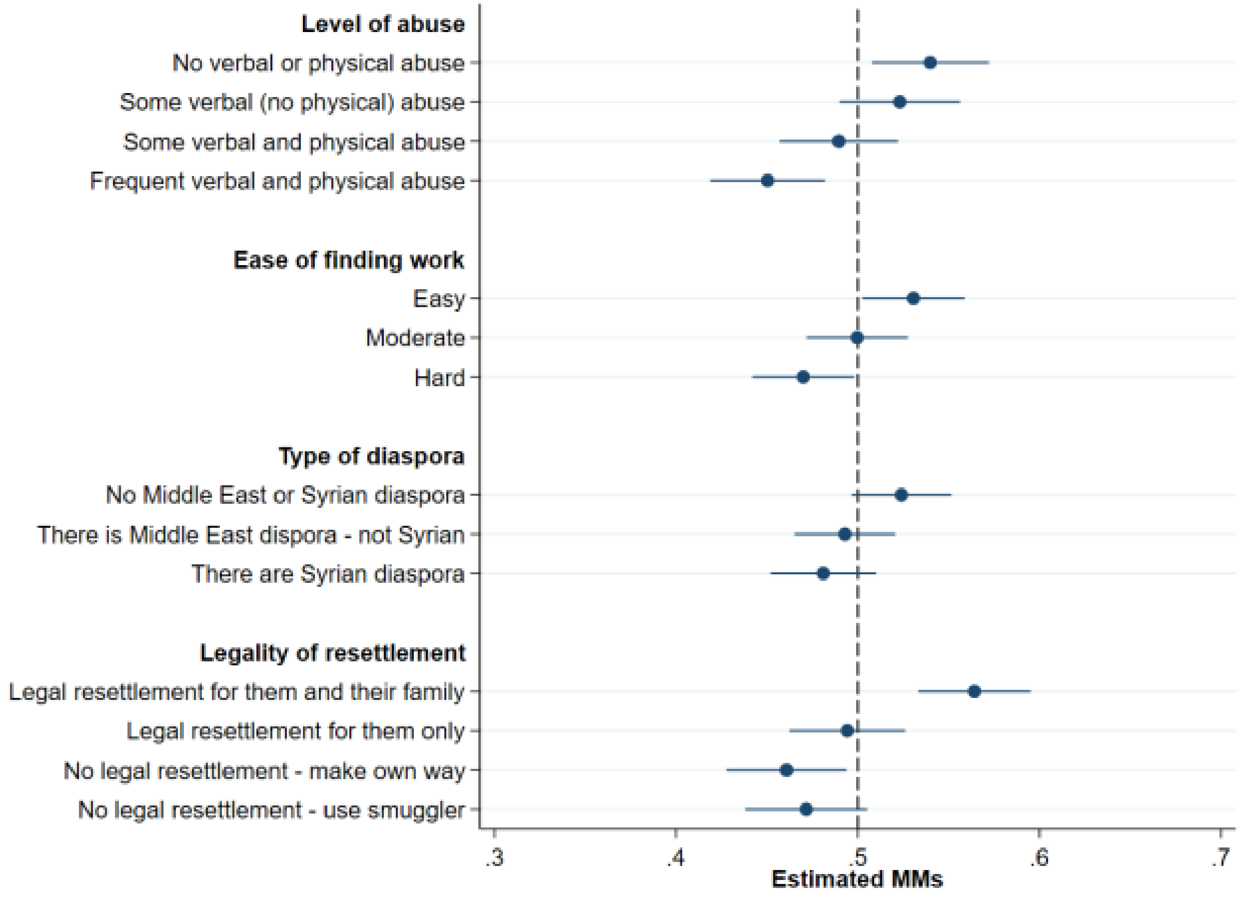
Refugee resettlement preferences conjoint (Simon et al., 2021, Braithwaite et al., 2020)

- cjoint (R)
  - amce(chosen ~ abuse + easework + diaspora + legality, cluster=TRUE, respondent.id="ID" data=resettle_conjoint)

- cregg (R)
  - cj(data=resettle_conjoint, chosen ~ abuse + easework + diaspora + legality, id = ~ ID, **estimate = "amce")**
  - cj(data=resettle_conjoint, chosen ~ abuse + easework + diaspora + legality, id = ~ ID, **estimate = "mm")**

- conjoint (Stata)
  - conjoint chosen abuse easework diaspora legality, **est(amce)** id(ID)
  - conjoint chosen abuse easework diaspora legality, **est(mm)** id(ID)

Figure 1: Marginal mean estimates of preferences for relocation destinations



From Simon et al., 2021

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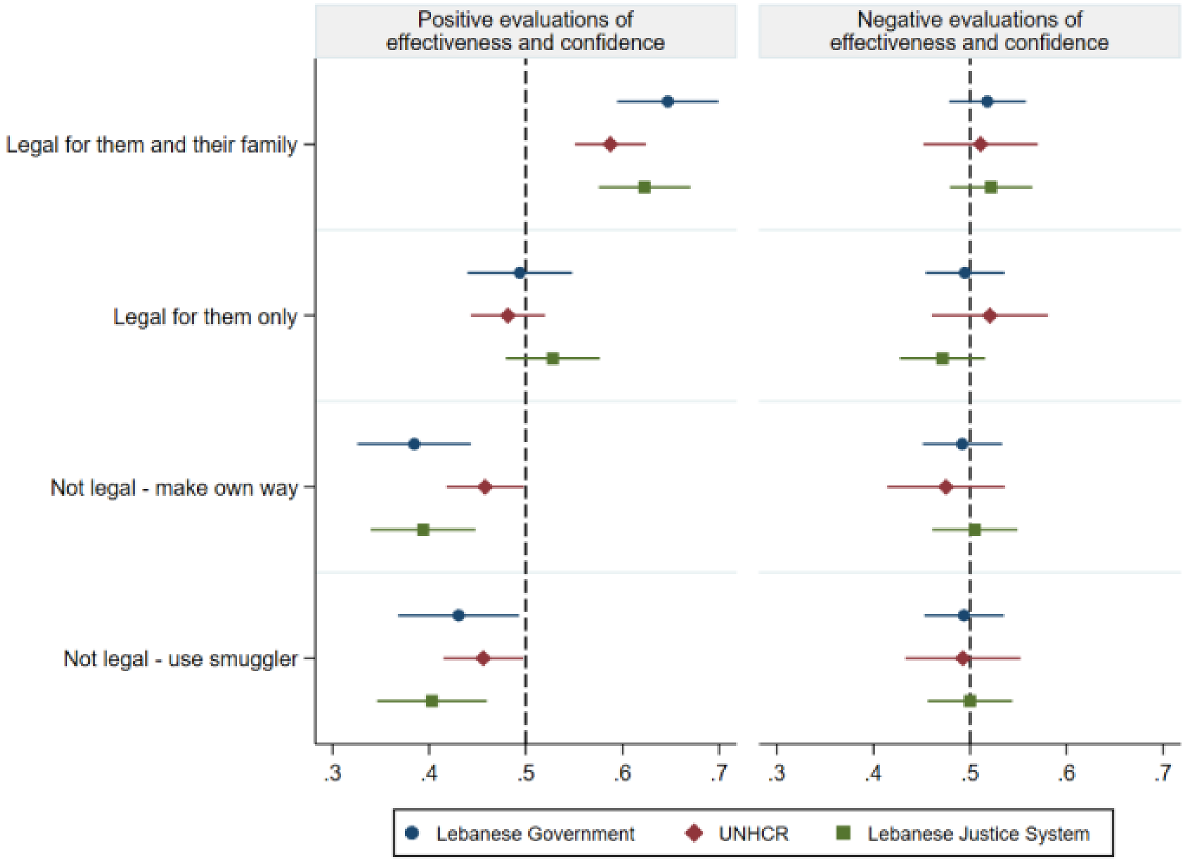
Conjoint Example #1

Refugee resettlement preferences conjoint (Simon et al., 2021, Braithwaite et al., 2020)

- cjoint (R)
  - amce(chosen ~ abuse + easework + diaspora + legality, cluster=TRUE, respondent.id=“ID" data=resettle_conjoint)
- cregg (R)

And when adding subgroups (here 3 models depending on their evaluations of different agencies) and a little bit of extra code to merge the plots

- conjoint (Stata)
  - conjoint chosen abuse easework diaspora legality, **est(amce)** id(ID)
  - conjoint chosen abuse easework diaspora legality, **est(mm)** id(ID)



From Simon et al., 2021

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Conjoint Example #2

Immigration conjoint (Hainmueller et al., 2014)

- Asked between 2 immigrants, which they would prefer to be admitted to the United States
  - Prior trips to the US
  - Reason for application
  - Country of origin
  - English skills
  - Profession
  - Job Experience
  - Employment Plans
  - Education Level
  - 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
If you had to choose between them, which of these two immigrants should be given priority to come to the United States to live?	○	○

From Hainmueller et al 2014

Conjoint Example #2

Immigration conjoint (Hainmueller et al., 2014)

Defining the constraints for cjoint (R)

- cjoint (R)

```
attribute_list <- list()
attribute_list[["Country of Origin"]] <- ("Germany"
"Mexico", "Philippines", "Poland", "India", "China", "Sudan",
"Somalia", "Iraq")
attribute_list[["Reason for Application"]] <- c("reunite with family",
"seek better job", "escape persecution")

constraint_list<-list()
constraint_list[[1]] <- list()
constraint_list[[1]][["Reason for Application"]] <- c("escape
persecution")
constraint_list[[1]][["Country of Origin"]] <- c("Germany", "France",
"Mexico", "Philippines", "Poland", "India")
immigrationdesign <- makeDesign(type='constraints',
attribute.levels=attribute_list, constraints=constraint_list)


immigrationdesign <- makeDesign(type='constraints',
attribute.levels=attribute_list, constraints=constraint_list)
```

- cjoint (R)
  - amce(Chosen_Immigrant ~ Country_of_Origin + Reason_for_Application + data=immigrationconjoint, cluster=TRUE, respondent.id="CaseID“, design=immigrationdesign)
- cregg (R)
  - cj(data= immigrationconjoint, Chosen_Immigrant ~ Country_of_Origin * Reason_for_Application, id = ~ CaseID, estimate = "amce“)
- conjoint (Stata)
  - conjoint Chosen_Immigrant Country_of_Origin Reason_for_Application, est(amce) id(CaseID) constraint(Country_of_Origin#Reason_for_Application)

Conjoint Example #2

Immigration conjoint (Hainmueller et al., 2014)

Defining the constraints for cjoint (R)

- cjoint (R)

```
attribute_list <- list()
attribute_list[["Country of Origin"]] <- ("Germany"
"Mexico", "Philippines", "Poland", "India", "China", "Sudan",
"Somalia", "Iraq")
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"seek better job", "escape persecution")

constraint_list<-list()
constraint_list[[1]] <- list()
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persecution")
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"Mexico", "Philippines", "Poland", "India")
immigrationdesign <- makeDesign(type='constraints',
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immigrationdesign <- makeDesign(type='constraints',
attribute.levels=attribute_list, constraints=constraint_list)
```
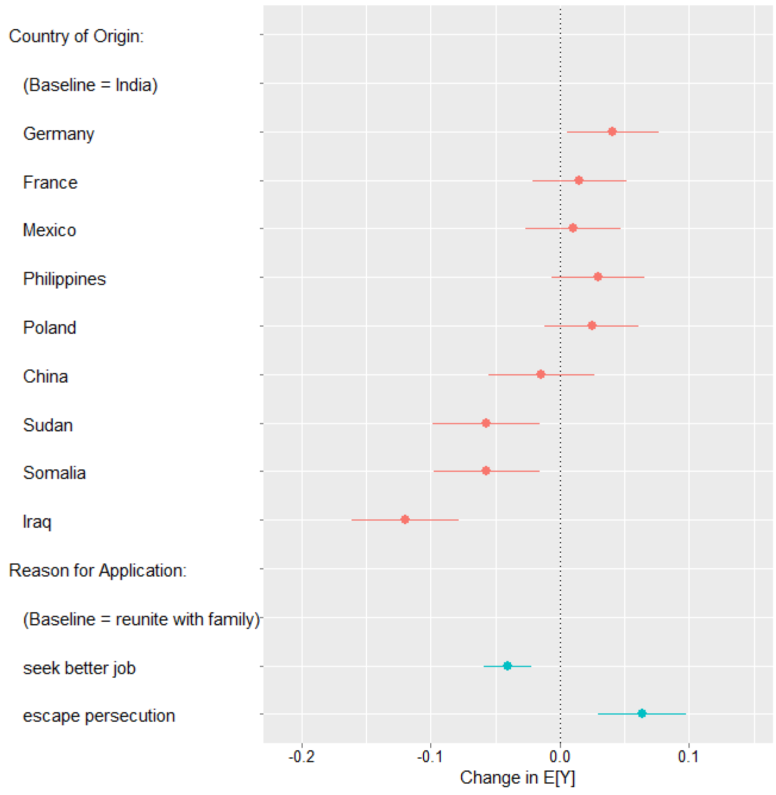

- cjoint (R)
  - amce(Chosen_Immigrant ~ Country_of_Origin + Reason_for_Application + data=immigrationconjoint, cluster=TRUE, respondent.id="CaseID“, design=immigrationdesign)
- cregg (R)
  - cj(data= immigrationconjoint, Chosen_Immigrant ~ Country_of_Origin * Reason_for_Application, id = ~ CaseID, estimate = "amce“)
- conjoint (Stata)
  - conjoint Chosen_Immigrant Country_of_Origin Reason_for_Application, est(amce) id(CaseID) constraint(Country_of_Origin#Reason_for_Application)

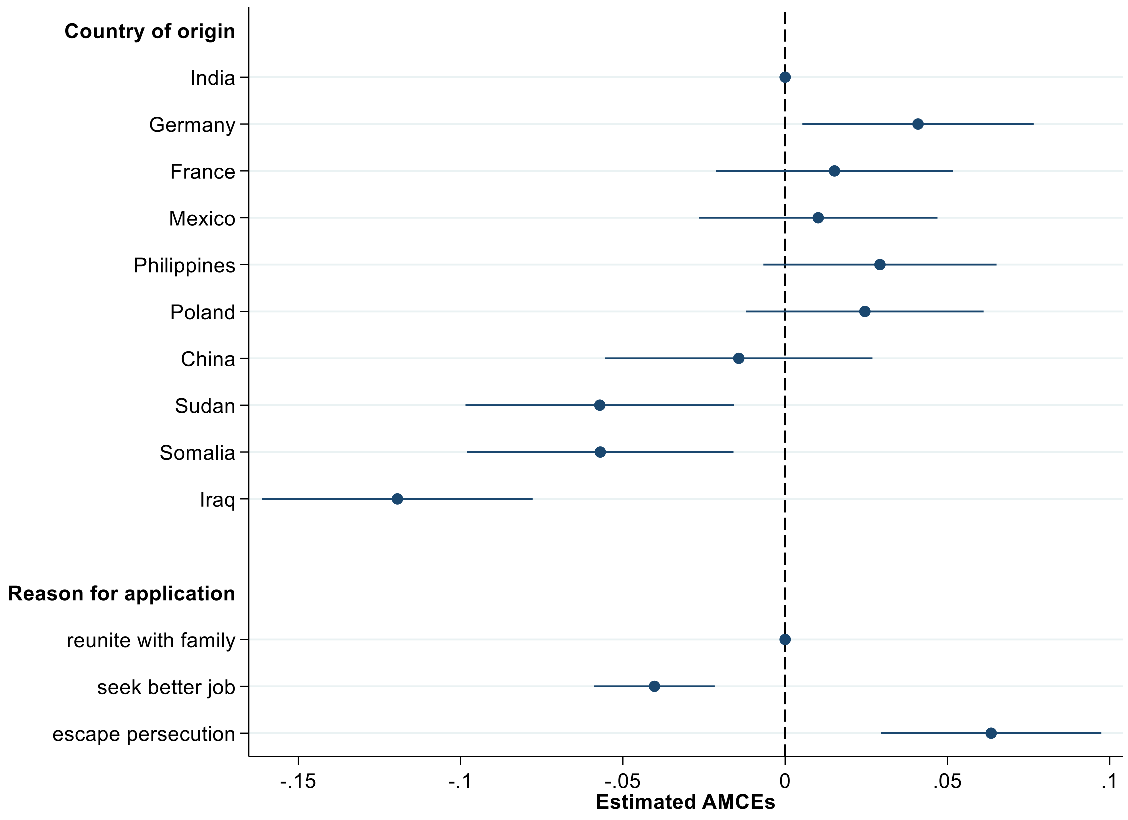
Conjoint Example #2

Immigration conjoint (Hainmueller et al., 2014)

cjoint (R) - plot(results)



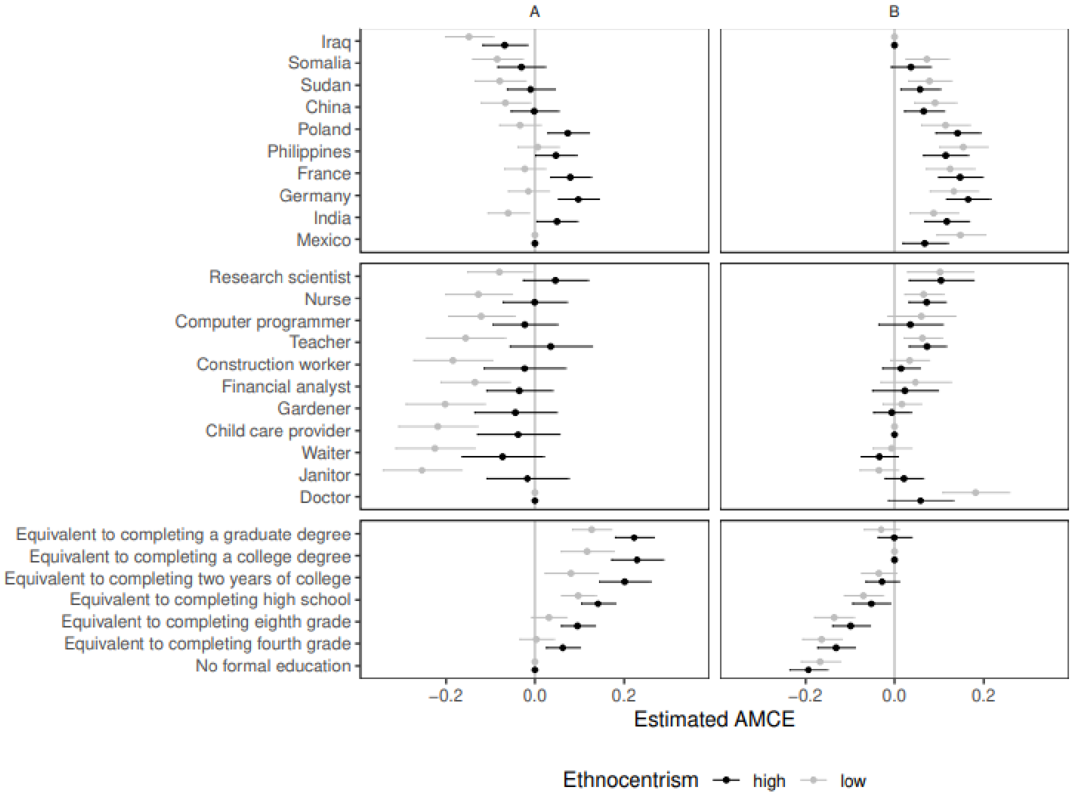
Conjoint (Stata) - conjoint, graph



What -conjoint- cant do (yet)

- ❌ Limited extra functionality…
  - ❌ Comparisons of effects of baselevel choices
  - ❌ Comparing attribute-levels
  - ❌ Compare model (fits)
  - ❌ Customizability of plots
  - ❌ Manually specify constraints
  - ❌ Weights
  - ❌ Passing results to e(b) and e(V)
  - ❌ …
- ❌ Reliance on lincom where string can be too long (can be fixed soon)
- ❌ Integrate with survey software (e.g. Kobo Toolbox and equivalents)
- ❌…

Figure 4: Comparison of AMCEs for Low- and High-Ethnocentrism Respondents Using Two Alternative Reference Categories Choices for Three Features from Hainmueller et al.'s (2014) Immigration Experiment



From Leeper et al., 2020

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