Survey Experiments

Research Programs and Conjoint Analysis

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The Margin of Error and Sample Size

List Experiments

Conjoint Experiments

Conjoint Interpretation

The Margin of Error and Sample Size

Margin of Error and Sample Size

In survey sampling, we sometimes refer to the *margin of error* (MoE). This is a component of the confidence interval calculation:

$$\Big[\text{Estimate } - \underbrace{\text{Critical Value} \cdot SE}_{\text{Margin of Error}}, \quad \text{Estimate } + \underbrace{\text{Critical Value } \cdot SE}_{\text{Margin of Error}}\Big]$$

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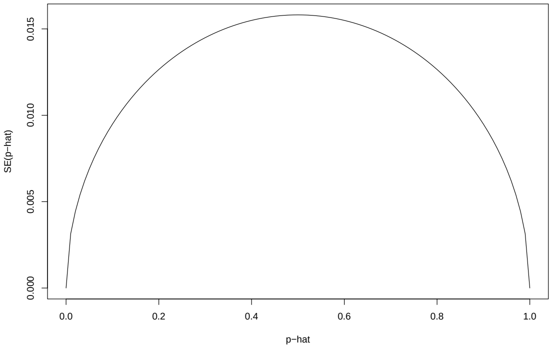

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So, find n given other parameters:

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$$\begin{aligned} \text{MoE} &= \text{Critical Value } \cdot SE \\ 0.03 &= 1.96 \cdot \sqrt{\frac{.5(1-0.5)}{n}} \end{aligned}$$

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n &= 1.96^2 \cdot \frac{.5(1-0.5)}{0.03^2} \\
n &\approx 3.8416 \cdot 277.8 \\
n &\approx 1067
\end{aligned}
$$

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If a survey experimental treatment effect $= 0.02$, MoE of 0.03 *not* likely to detect it.

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```
power.prop.test(n = 1067 / 2, p1 = 0.5, p2 = 0.52)
```

```
##
##      Two-sample comparison of proportions power calc
##
##               n = 533.5
##              p1 = 0.5
##              p2 = 0.52
##       sig.level = 0.05
##           power = 0.09564109
##     alternative = two.sided
##
## NOTE: n is number in *each* group
```

Power and Sample Size

For continuous outcomes, everything matters that is in

$$SE(\widehat{ATE}) = \sqrt{\frac{1}{N-1}\left[\frac{m\text{Var}(Y_i(0))}{N-m} + \frac{(N-m)\text{Var}(Y_i(1))}{m} + 2\text{Cov}(Y_i(0), Y_i(1))\right]}$$

Power and Sample Size

For continuous outcome,

```
power.t.test(n = 100, delta = 1.5, sd = 1)
```

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```r
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## NOTE: n is number in *each* group
```

Power and Sample Size

(See `code/03-power.R`.)

Power and Sample Size

(We often use simulation to get power, sample size, MDE for complex assignments or estimation strategies.)

List Experiments

Split the class!

- I have read George Orwell's *1984*.
- I am currently enrolled in a doctoral program (PhD).
- I purchased groceries this week.

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Let X be the number of items agreed with.

$X_{\text{Group1}} = \underline{\hspace{2em}}$
$X_{\text{Group2}} = \underline{\hspace{2em}}$

1991 US National Race and Politics Survey

Now I'm going to read you three things that sometimes make people angry or upset. After I read all three, just tell me HOW MANY of them upset you. (I don't want to know which ones, just how many.)

(1) the federal government increasing the tax on gasoline
(2) professional athletes getting million-dollar-plus salaries
(3) large corporations polluting the environment

How many, if any, of these things upset you?

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(2) professional athletes getting million-dollar-plus salaries

(3) large corporations polluting the environment

(4) a black family moving next door to you

How many, if any, of these things upset you?

Assumptions

Blair and Imai (2012) formalise analysis.

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Let τ = true ATE. Let

$$\hat{\tau} = \frac{1}{n_{\text{Tr}}} \sum_{i=1}^{n} T_i Y_i - \frac{1}{n_{\text{Co}}} \sum_{i=1}^{n} (1 - T_i) Y_i$$

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Then

$$E(\hat{\tau}) = \tau$$

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Count of (3) control items is constant:

$$\sum_{j=1}^{J} Z_{ij}(0) = \sum_{j=1}^{J} Z_{ij}(1)$$

or, (count under Tr) = (count under Co) + (0/1 for sensitive item):

$$Y_i(1) = Y_i(0) + Z_{i,J+1}(1)$$

Assumptions

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$$Z_{i,J+1}(1) = Z^*_{i,J+1}$$

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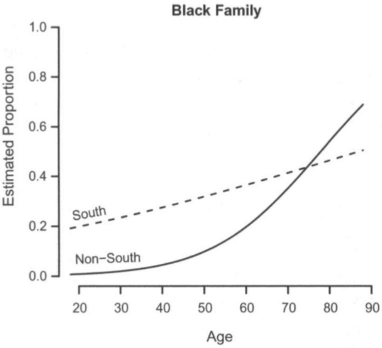
As with prior diff-in-means, can calculate it via regression.

Interpretation



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What is *social desirability bias* in surveys?

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$$S(x) = Pr(Z_{i,J+1}(0) = 1 | X_i = x) - Pr(Z^*_{i,J+1} = 1 | X_i = x)$$

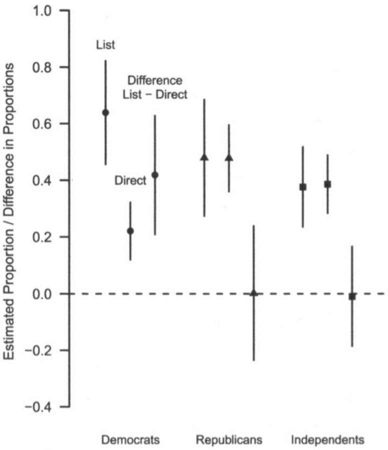
Interpretation

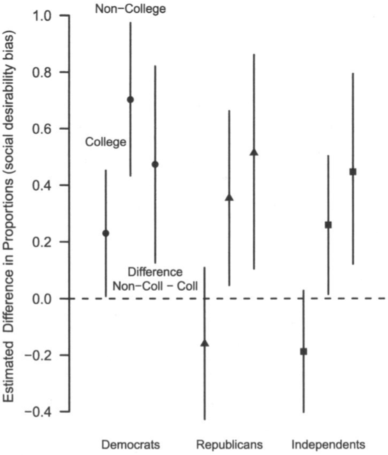
What is *social desirability bias* in surveys?

$$S(x) = Pr(Z_{i,J+1}(0) = 1 | X_i = x) - Pr(Z^*_{i,J+1} = 1 | X_i = x)$$

(First term: shown control, then asked *directly*)

Interpretation





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Conjoint experiments ...

- ask participants to select between hypothetical profiles, with their attributes randomized;
- are a way to address multidimensionality – many factors, but only one vote;
- can randomly assign attributes, or randomly assign them conditional on some restrictions;
- can be a little tricky to interpret.

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?	○	○

```r
load("../data/03-candidate.RData")
cand <- x
head(cand)
```

```
##            resID   atmilitary           atreligion
## 1 A2NEN4NSNS208S Did Not Serve              Mormon Commu
## 2 A2NEN4NSNS208S        Served                None
## 3 A2NEN4NSNS208S Did Not Serve            Catholic     S
## 4 A2NEN4NSNS208S        Served Mainline protestant     S
## 5 A2NEN4NSNS208S        Served                None   Bap
## 6 A2NEN4NSNS208S        Served Mainline protestant
##                atprof atinc          atrace atage atmale
## 1          Car dealer  5.1M           White    75 Female
## 2 High school teacher   65K  Asian American    60   Male
## 3              Farmer   32K Native American    68 Female
## 4              Doctor   54K           White    75   Male
## 5              Doctor  5.1M Native American    45 Female
## 6              Lawyer   54K           White    52   Male
```

```r
load("../data/03-immigrant.RData")
immig <- x
head(x)
```

```
##   CaseID contest_no
## 1      4          1       Equivalent to completing high
## 2      4          1                                    No
## 3      4          2 Equivalent to completing a graduate
## 4      4          2      Equivalent to completing fourth
## 5      4          3       Equivalent to completing high
## 6      4          3  Equivalent to completing a college
##   FeatGender FeatCountry
## 1       male        Iraq                        Seek be
## 2     female      France                        Seek be
## 3     female       Sudan         Escape political/relig
## 4     female     Germany Reunite with family members alr
## 5     female Philippines                        Seek be
## 6       male       Sudan                        Seek be
##                FeatJob
## 1                Nurse More than five years of job traini
```

Notation

Indices

- i respondent
- j alternative (candidate 2)
- k task (3rd task)
- l component of profile

Notation

Treatments

- T_{ijkl} a component shown
- T_{ijk} a profile shown (from $\mathcal{T}$)
- $\mathbf{T}_{ik}$ all profiles shown for task k
- $\bar{\mathbf{T}}_i$ all profiles hypothetically shown $(J \cdot K)$
- $\mathbf{t}$ all profiles actually shown, in sequence

Notation

Potential outcomes

- $Y_{ik}(\bar{\mathbf{t}})$ pot outcomes **observed** under full seq of profiles (J-dim)
- $Y_{ik} \equiv Y_{ik}(\bar{\mathbf{T}}_i)$ pot outcomes under hypothetical full seq of profiles (J-dim)
- $Y_{ijk}(\bar{\mathbf{T}}_i)$ component of $Y_{ik}(\bar{\mathbf{T}}_i)$
- $Y_i(\mathbf{t})$ pot outcomes under observed seq of profiles (given Assumption 1)

Assumptions

1. Stability, no carryover: if $\mathbf{T}_{ik} = \mathbf{T}'_{ik'}$,

$$Y_{ijk}(\bar{\mathbf{T}}_i) = Y_{ijk'}(\bar{\mathbf{T}}'_i)$$

   If treatments in task 1 same as treatments in task 6, same potential outcomes.

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3. Randomization:

$$Y_i(\mathbf{t}) \text{ indep of } T_{ijkl}$$

   Profiles don't disprop go to those who like them, e.g.

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The Fundamental Problem of Causal Inference

An Estimand: AMCE

$$
\begin{aligned}
\bar{\pi}_l(t_1, t_0, p(\mathbf{t})) \quad \equiv \quad & E\left[Y_i\left(t_1, T_{ijk[-l]}, T_{i[-j]k}\right)\right. \\
& \left. -Y_i\left(t_0, T_{ijk[-l]}, T_{i[-j]k}\right) \mid \left(T_{ijk[-l]}, T_{i[-j]k}\right) \in \widetilde{\mathcal{T}}\right]
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The Fundamental Problem of Causal Inference

The AMCE in 2×2 Designs

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The AMCE in 2×2 Designs

- Collapsing into 2 groups $\rightsquigarrow$ AMCE
- Weight by probs from joint dist'ns of other attribute

Estimation: Calculating the AMCE

See `code/03-amce-simple.R`.

Related Findings

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See Bansak et al. (2021).

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See Bansak et al. (2018).

Strange things can happen . . .

Strange things can happen ...

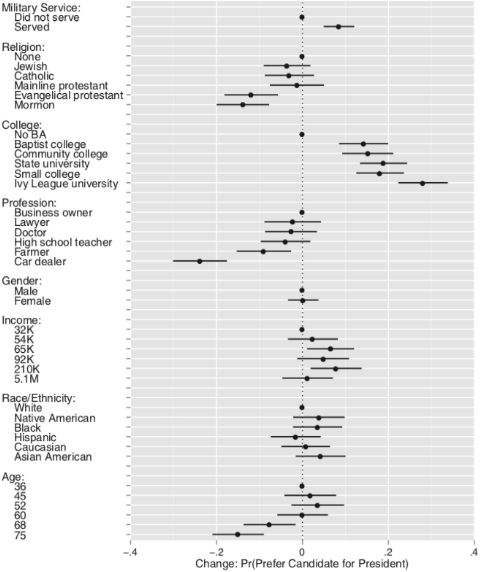
```r
cand |>
  filter(atprof == "High school teacher") |>
  count(atinc)
```

```
##   atinc   n
## 1   32K 107
## 2   54K  77
## 3   65K 111
## 4   92K  97
## 5  210K  99
## 6  5.1M 100
```

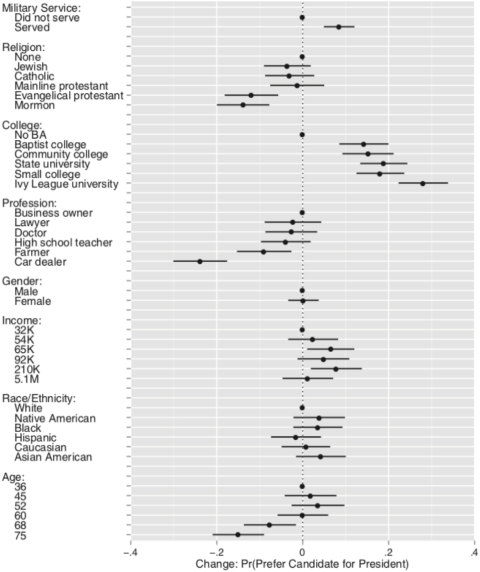
Strange things can happen . . . (“atypical profiles”)

```r
cand |> filter(atprof == "High school teacher",
               atinc == "5.1M",
               ated == "No BA") |>
  dim()
```

```
## [1] 16 11
```



Military Service:
Did not serve
Served
Religion:
None
Jewish
Catholic
Mainline protestant
Evangelical protestant
Mormon
College:
No BA
Baptist college
Community college
State university
Small college
Ivy League university
Profession:
Business owner
Lawyer
Doctor
High school teacher
Farmer
Car dealer
Gender:
Male
Female
Income:
32K
54K
65K
92K
210K
5.1M
Race/Ethnicity:
White
Native American
Black
Hispanic
Caucasian
Asian American
Age:
36
45
52
60
68
75
-.4
-.2
0
.2
.4
Change: Pr(Prefer Candidate for President)


Military Service:
Did not serve
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None
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Community college
State university
Small college
Ivy League university
Profession:
Business owner
Lawyer
Doctor
High school teacher
Farmer
Car dealer
Gender:
Male
Female
Income:
32K
54K
65K
92K
210K
5.1M
Race/Ethnicity:
White
Native American
Black
Hispanic
Caucasian
Asian American
Age:
36
45
52
60
68
75
-.4
-.2
0
.2
.4
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Atypical Profiles

- "groups of respondents exposed to different numbers of atypical profiles"

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- “groups of respondents exposed to different numbers of atypical profiles”
- (A reasonable conditional-effect diagnostic)

Atypical Profiles

- “groups of respondents exposed to different numbers of atypical profiles”
- (A reasonable conditional-effect diagnostic)
- Alternative: how atypicality affects AMCEs/ACIEs

Atypical Profiles

- “groups of respondents exposed to different numbers of atypical profiles”
- (A reasonable conditional-effect diagnostic)
- Alternative: how atypicality affects AMCEs/ACIEs
- E.g., if *high inc* usually appears in atypical profiles, then AMCE of *high inc* vs. *low inc* not internally valid (?)

Conjoint Interpretation

Interpreting the AMCE

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Interpreting the AMCE

AMCE is avg (mean) effect of varying attribute l in profile.

E.g., from l_0 to l_1.

But – AMCE does **not** give ...

- "majority prefer l_1 to l_0"
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- "l_1 candidates tend to beat l_0 candidates"

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  $$cor(\text{intensity}, \text{direction})$$

  more misleading AMCE is.
- If voters with *strong* prefs all prefer same *direction*, then AMCE misleading. (E.g., if strong gender pref is always for `female`, AMCE misleading.)

V1	V2	V3	V4	V5
$M \succ F$	$M \succ F$	$M \succ F$	$F \succ M$	$F \succ M$
$R \succ D$	$R \succ D$	$R \succ D$	$D \succ R$	$D \succ R$

Table 1—: Preferences over attributes

Rank	V1	V2	V3	V4	V5
1.	MR	MR	MR	FD	FD
2.	FR	FR	FR	FR	FR
3.	MD	MD	MD	MD	MD
4.	FD	FD	FD	MR	MR

Table 2—: Preferences over candidate profiles

Comparison	V1	V2	V3	V4	V5	Tally
MR,FR	MR	MR	MR	FR	FR	3, 2
MR,FD	MR	MR	MR	FD	FD	3, 2
MR,MD	MR	MR	MR	MD	MD	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

Table 3—: Aggregate preferences over candidate profiles

Abramson, Koçak, and Magazinnik (2022)

Comparison	V1	V2	V3	V4	V5	Tally
MR,FR	MR	MR	MR	FR	FR	3, 2
MR,FD	MR	MR	MR	FD	FD	3, 2
MR,MD	MR	MR	MR	MD	MD	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

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But, AMCE for `M` is negative!

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- Need homogeneity of pref *intensity* for majoritarian interpretations
- Suggest small number of binary attributes ...
  - but still have IIA concerns

Bansak et al. (2022)

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- Incorporating direction *and* intensity is realistic (*ceteris paribus* is not)
- AMCE is an effect on candidate/party's *expected vote share*
- Can translate this into effect on probability of winning (given voting system)

Another Critique of the AMCE

Ganter (2023) argues for the *average component preference*:

- AMCE suited for “selection-process” questions: how would outcome obtain?
  - How likely is a male immigrant to get a visa?
  - Are female immigrants more or less likely to get a visa than male immigrants?
- ACP suited for “preference-related” questions: which is preferred?
  - Do people prefer male or female immigrants?
  - Is gender more determinant than countries of origin in people’s choices?
  - How do these preferences differ across subgroups?

What should we do tomorrow?

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Let’s vote!

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Let's vote!

PollEv.com/rmoore952

Select ≤ 3 topics to inform our discussion for tomorrow! (You may "Skip" registration.)

Next:
Multiarm Bandits

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