What Do We Learn About Voter Preferences From Conjoint Experiments?

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Conjoint experiments have become a standard tool in political science

Forced choice factorial experiments

Randomize features of profiles, ask respondents to choose most preferred

Conjoint experiments have become a standard tool in political science

	Candidate 1	Candidate 2
Number of Children	3	3
Gender	Female	Male
Number of Years in Politics	3 years	8 years
Current Occupation	Mayor	Corporate Lawyer
Age	65	65
Spouse's Occupation	Farmer	Farmer

Based on the limited information above, which of the two candidates would you be more likely to support in the congressional primary?

Candidate 1Candidate 2

Teele, Kalla, and Rosenbluth — APSR (2018)

Conjoint experiments have become a standard tool in political science

Forced choice factorial experiments

Randomize features of profiles, ask respondents to choose most preferred

The target estimand:

- The *Average Marginal Component Effect* (AMCE): the effect of varying a feature on the probability a profile is chosen, averaging over all other attributes

Hainmueller, Hopkins, and Yamamoto (2014) — 400+ citations

Researchers interpret AMCEs to make statements about aggregate preferences

"respondents prefer candidates who have an Ivy League education and who are not car dealers, Mormon, or fairly old."

Hainmueller, Hopkins, and Yamamoto - PA (2014)

Researchers interpret AMCEs to make statements about aggregate preferences

“Americans express a pronounced preference for immigrants who are well educated, are in high-skilled professions, and plan to work upon arrival”

Hainmueller and Hopkins - AJPS (2015)

Researchers interpret AMCEs to make statements about aggregate preferences

"In contrast to the observed attributes of actual politicians, voters do not prefer older politicians or celebrities, and are indifferent with regard to dynastic ties and gender."

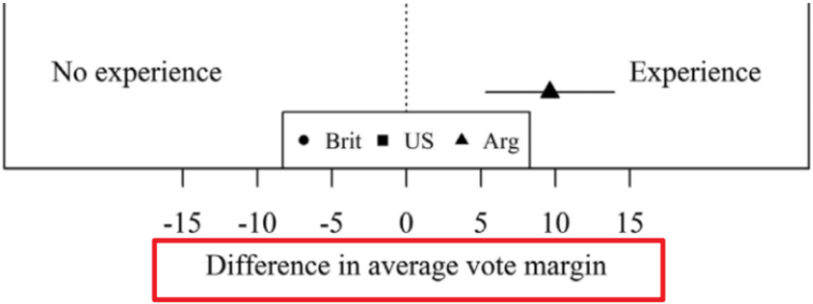
Horiuchi, Smith, and Yamamoto - PSRM (2018)

Researchers interpret AMCEs to make statements about aggregate preferences

"voters and legislators do not seem to hold female candidates in disregard; all else equal, they prefer female to male candidates"

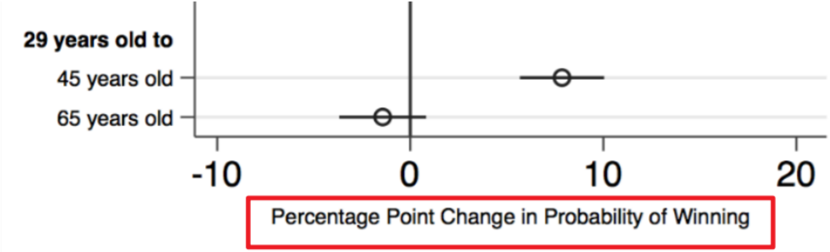
Teele, Kalla, and Rosenbluth - APSR (2018)

Researchers interpret AMCEs in the context of elections



Carnes and Lupu - APSR (2016)

Researchers interpret AMCEs in the context of elections



Teele, Kalla, and Rosenbluth - APSR (2018)

Key takeaway

Without additional assumptions on the distribution of preferences, a positive AMCE of X over X' does not imply:

- A majority of respondents prefer X to X'
- A randomly drawn voter prefers X to X', all else equal
- X beats X' in most elections

We describe:

- What the AMCE estimates using a simple example
- AMCE as a preference aggregation rule

We provide:

- Analytic bounds on proportion who prefer X to X'
- Conditions when AMCE corresponds to majority preference

An Example

Primitives

Preferences over candidate profiles are constructed from:

- Rankings of features (researchers' quantities of interest)
- Weights (e.g., how much an individual cares about party ID relative to gender)

Agnostic about content of preferences

Assume individual rankings over features complete and transitive

Definitions

- Without these assumptions, issues persist

Rankings of features

5 voters

2 binary attributes:

- Party ID (Democrat or Republican)
- Gender (Male or Female)

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

Weights of attributes

V1, V2, and V3 place more weight on candidates' parties

- $P >> G$

V4 and V5 place more weight on candidates' genders

- $G >> P$

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

Preference orderings over candidate profiles

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

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

Preference orderings over candidate profiles

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

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

Preference orderings over candidate profiles

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

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

Preference orderings over candidate profiles

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

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

Preference orderings over candidate profiles

V1	V2	V3	V4	V5
$M \succ F$	$M \succ F$	$M \succ F$	$\mathbf{F} \succ \mathbf{M}$	$\mathbf{F} \succ \mathbf{M}$
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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

Preference orderings over candidate profiles

V1	V2	V3	V4	V5
$M \succ F$	$M \succ F$	$M \succ F$	$\mathbf{F} \succ \mathbf{M}$	$\mathbf{F} \succ \mathbf{M}$
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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

Preference orderings over candidate profiles

V1	V2	V3	V4	V5
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$\mathbf{R} \succ \mathbf{D}$	$\mathbf{R} \succ \mathbf{D}$	$\mathbf{R} \succ \mathbf{D}$	$D \succ R$	$D \succ R$

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

Pairwise races between candidates

Tally the number of votes each candidate would receive:

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR						

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR	MR					

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR	MR	MR				

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR	MR	MR	MR			

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR	MR	MR	MR	FR		

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
MR, FR	MR	MR	MR	FR	FR	

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
$\mathbf{MR}, FR$	MR	MR	MR	FR	FR	3, 2

Pairwise races between candidates

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

Comparison	V1	V2	V3	V4	V5	Tally
$\mathbf{MR}, FR$	MR	MR	MR	FR	FR	3, 2
$\mathbf{MR}, FD$	MR	MR	MR	FD	FD	3, 2
$\mathbf{MR}, MD$	MR	MR	MR	MD	MD	3, 2
$MD, \mathbf{FR}$	FR	FR	FR	FR	FR	0, 5
$\mathbf{MD}, FD$	MD	MD	MD	FD	FD	3, 2
$\mathbf{FR}, FD$	FR	FR	FR	FD	FD	3, 2

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

$$\underbrace{\bar{Y}(MR, MD)}_{MR\text{'s vote share against } MD} - \underbrace{\bar{Y}(FR, MD)}_{FR\text{'s vote share against } MD} =$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

Comparison	$V1$	$V2$	$V3$	$V4$	$V5$	Tally
$\mathbf{MR}, FR$	MR	MR	MR	FR	FR	$3, 2$
$\mathbf{MR}, FD$	MR	MR	MR	FD	FD	$3, 2$
$\mathbf{MR}, MD$	MR	MR	MR	MD	MD	$3, 2$
$MD, \mathbf{FR}$	FR	FR	FR	FR	FR	$0, 5$
$\mathbf{MD}, FD$	MD	MD	MD	FD	FD	$3, 2$
$\mathbf{FR}, FD$	FR	FR	FR	FD	FD	$3, 2$

$$3/5 \qquad - \quad \bar{Y}(FR, MD) \quad =$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

Comparison	$V1$	$V2$	$V3$	$V4$	$V5$	Tally
$\mathbf{MR}, FR$	MR	MR	MR	FR	FR	$3, 2$
$\mathbf{MR}, FD$	MR	MR	MR	FD	FD	$3, 2$
$\mathbf{MR}, MD$	MR	MR	MR	MD	MD	$3, 2$
$MD, \mathbf{FR}$	FR	FR	FR	FR	FR	$0, 5$
$\mathbf{MD}, FD$	MD	MD	MD	FD	FD	$3, 2$
$\mathbf{FR}, FD$	FR	FR	FR	FD	FD	$3, 2$

$$3/5 \quad - \quad 5/5 \quad = \quad -2/5$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

Comparison	$V1$	$V2$	$V3$	$V4$	$V5$	Tally
$\mathbf{MR}, FR$	MR	MR	MR	FR	FR	$3, 2$
$\mathbf{MR}, FD$	MR	MR	MR	FD	FD	$3, 2$
$\mathbf{MR}, MD$	MR	MR	MR	MD	MD	$3, 2$
$MD, \mathbf{FR}$	FR	FR	FR	FR	FR	$0, 5$
$\mathbf{MD}, FD$	MD	MD	MD	FD	FD	$3, 2$
$\mathbf{FR}, FD$	FR	FR	FR	FD	FD	$3, 2$

$$\begin{aligned} \bar{Y}(MR, MD) &- \bar{Y}(FR, MD) &= -2/5 \\ \bar{Y}(MR, FD) &- \bar{Y}(FR, FD) &= \end{aligned}$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

$$
\begin{array}{lclcr}
\bar{Y}(MR, MD) & - & \bar{Y}(FR, MD) & = & -2/5 \\
3/5 & - & 3/5 & = & 0
\end{array}
$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

$$
\begin{aligned}
\bar{Y}(MR, MD) &- \bar{Y}(FR, MD) &= -2/5 \\
\bar{Y}(MR, FD) &- \bar{Y}(FR, FD) &= 0 \\
\bar{Y}(MR, MR) &- \bar{Y}(FR, MR) &= 1/10 \\
\bar{Y}(MR, FR) &- \bar{Y}(FR, FR) &= 1/10
\end{aligned}
$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

$$
\begin{array}{lcllr}
\hline
\bar{Y}(MR, MD) & - & \bar{Y}(FR, MD) & = & -2/5 \\
\bar{Y}(MR, FD) & - & \bar{Y}(FR, FD) & = & 0 \\
\bar{Y}(MR, MR) & - & \bar{Y}(FR, MR) & = & 1/10 \\
\bar{Y}(MR, FR) & - & \bar{Y}(FR, FR) & = & 1/10 \\
\bar{Y}(MD, MD) & - & \bar{Y}(FD, MD) & = & 1/10 \\
\bar{Y}(MD, FD) & - & \bar{Y}(FD, FD) & = & 1/10 \\
\bar{Y}(MD, MR) & - & \bar{Y}(FD, MR) & = & 0 \\
\bar{Y}(MD, FR) & - & \bar{Y}(FD, FR) & = & -2/5 \\
\hline
\end{array}
$$

AMCE of Male (Proposition 3 of Hainmueller, Hopkins, and Yamamoto (2014))

$$
\begin{array}{rcrcr}
\hline
\bar{Y}(MR, MD) & - & \bar{Y}(FR, MD) & = & -2/5 \\
\bar{Y}(MR, FD) & - & \bar{Y}(FR, FD) & = & 0 \\
\bar{Y}(MR, MR) & - & \bar{Y}(FR, MR) & = & 1/10 \\
\bar{Y}(MR, FR) & - & \bar{Y}(FR, FR) & = & 1/10 \\
\bar{Y}(MD, MD) & - & \bar{Y}(FD, MD) & = & 1/10 \\
\bar{Y}(MD, FD) & - & \bar{Y}(FD, FD) & = & 1/10 \\
\bar{Y}(MD, MR) & - & \bar{Y}(FD, MR) & = & 0 \\
\bar{Y}(MD, FR) & - & \bar{Y}(FD, FR) & = & -2/5 \\
\hline
 & & & & -2/5
\end{array}
$$

Normalizing this, we get an AMCE of $-1/15$

AMCE contradicts the majority preference

We have a negative AMCE of being male

Yet we know majority of voters prefer men

And we know men win most elections

Why?

- AMCE combines direction and strength of preferences
- Correlation between prioritizing gender and a preference for women ANES

Such a correlation structure pervades politics ANES

This is not a sampling issue Distribution of AMCE estimates

What does the AMCE tell us about preferences?

AMCE is a summary statistic that gives us an "average voter"

Majorities are decided by median voters, not average

AMCE changes when new features are added

Same 5 voters, same preferences as before

Include a third feature, $A \in \{O, Y\}$

- Voters 1, 2, and 3 have the weights $P >> G >> A$
- Voters 4 and 5 have the weights $A >> G >> P$

No interactions

Produces an AMCE of Male of 1/14

- Opposite sign of AMCE of Male without Age

Some important insights about the AMCE

1) May indicate the opposite of majority preference
2) Depends on the randomization scheme, even when no interactions

Preference Aggregation

We need a mapping from individual to aggregate preferences

In other words, a preference aggregation rule

- A large literature devoted to study of social choice

AMCE is a preference aggregation rule related to the Borda Count

This connection helps us place bounds on the proportion who prefer a feature

Proposition 1: Borda scores are proportional to AMCE.

Sketch of Proof

Borda scores of each candidate:

- Borda: Assign last choice a score of zero
- Penultimate choice: score of one

  $\vdots$

- Top choice: $K - 1$
  ($K :=$ number of profiles)

V1	Borda score
MR	3
FR	2
MD	1
FD	0

Proposition 1: Borda scores are proportional to AMCE.

Sketch of Proof

Borda scores of each candidate:

- Borda: Assign last choice a score of zero
- Penultimate choice: score of one

  $\vdots$

- Top choice: $K - 1$
  ($K :=$ number of profiles)

All pairwise comparisons made:

- Last choice never picked when one of the options
- Penultimate choice picked once

  $\vdots$

- Top choice picked against all others: $K - 1$ times

A candidate's Borda score $=$ # of times that candidate is picked

Proposition 1: Borda scores are proportional to AMCE.

Borda score of a feature $:=$ sum of Borda scores of all profiles with that feature

A feature's Borda score $=$ number of times profiles with that feature picked

$$\implies \text{Borda score of feature } t_1 - \text{Borda score of feature } t_0$$

$$=$$

$$\#\text{ of times } t_1 \text{ picked} - \#\text{ of times } t_0 \text{ picked}$$

Revisiting the example

$$
\begin{array}{lcl c r}
\bar{Y}(MR, MD) & - & \bar{Y}(FR, MD) & = & -2/5 \\
\bar{Y}(MR, FD) & - & \bar{Y}(FR, FD) & = & 0 \\
\bar{Y}(MR, MR) & - & \bar{Y}(FR, MR) & = & 1/10 \\
\bar{Y}(MR, FR) & - & \bar{Y}(FR, FR) & = & 1/10 \\
\bar{Y}(MD, MD) & - & \bar{Y}(FD, MD) & = & 1/10 \\
\bar{Y}(MD, FD) & - & \bar{Y}(FD, FD) & = & 1/10 \\
\bar{Y}(MD, MR) & - & \bar{Y}(FD, MR) & = & 0 \\
\bar{Y}(MD, FR) & - & \bar{Y}(FD, FR) & = & -2/5 \\
\hline
19/5 & - & 21/5 & = & -2/5
\end{array}
$$

Proposition 1: Borda scores are proportional to AMCE.

Borda score of a feature $:=$ sum of Borda scores of all profiles with that feature

A feature's Borda score $=$ number of times profiles with that feature picked

$$\implies \text{Borda score of feature } t_1 - \text{Borda score of feature } t_0$$

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$$\#\text{ of times } t_1 \text{ picked} - \#\text{ of times } t_0 \text{ picked}$$

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A feature's Borda score $=$ number of times profiles with that feature picked

$$\implies \text{Borda score of feature } t_1 - \text{Borda score of feature } t_0$$
$$=$$
$$\#\text{ of times } t_1 \text{ picked} - \#\text{ of times } t_0 \text{ picked}$$
$$=$$
$$\text{AMCE} \times \text{some constant} \qquad \square$$

Insights from the connection between AMCE and Borda

1) Borda fails to indicate the majority preference
2) Borda fails the independence of irrelevant alternatives

Analytical Bounds

Analytical bounds

Bounds on fractions of people who prefer a feature as a function of:

- The AMCE estimate
- Number of possible profiles

Proposition 2: Bounds on the fraction who prefer t_1 to t_0.

Given AMCE of $\pi(t_1, t_0)$, fraction who prefer t_1 to t_0 lies in interval

$$\left[\max\left\{0, \frac{\pi(t_1,t_0)2(K-1)+2}{K+2}\right\}, \min\left\{1, \frac{\pi(t_1,t_0)2(K-1)+K}{K+2}\right\}\right]$$

Sketch of proof for lower bound: (symmetric for upper bound)

- Suppose respondents who prefer t_1 give highest weight and those who prefer t_0 give lowest weight
- Leads to maximum possible Borda score for t_1 and minimum possible Borda score for t_0

Proposition 2: Bounds on the fraction who prefer t_1 to t_0.

Those who prefer t_1 maximally give $\left(\frac{K}{2}\right)^2$ more points to t_1 than t_0 Why?

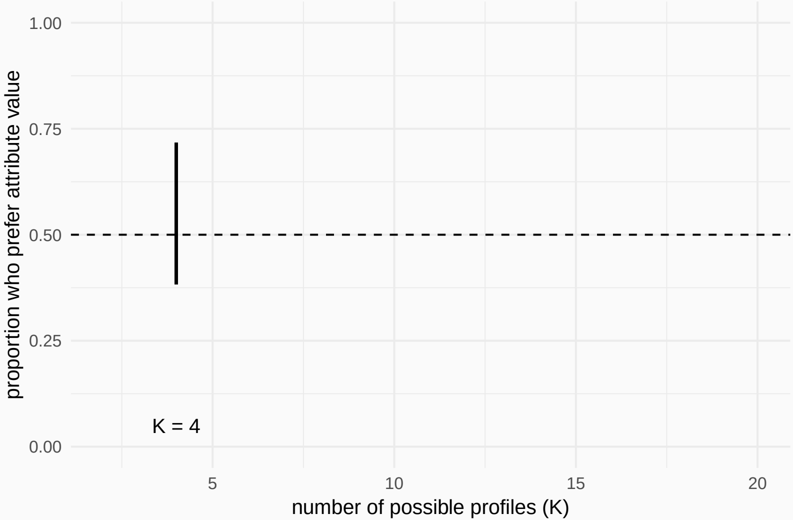
Those who prefer t_0 minimally give $\frac{K}{2}$ more points to t_0 than t_1 Why?

$$\text{AMCE} \propto (\text{fraction who prefers } t_1)\left(\frac{K}{2}\right)^2 + (\text{fraction who prefers } t_0)\left(-\frac{K}{2}\right)$$

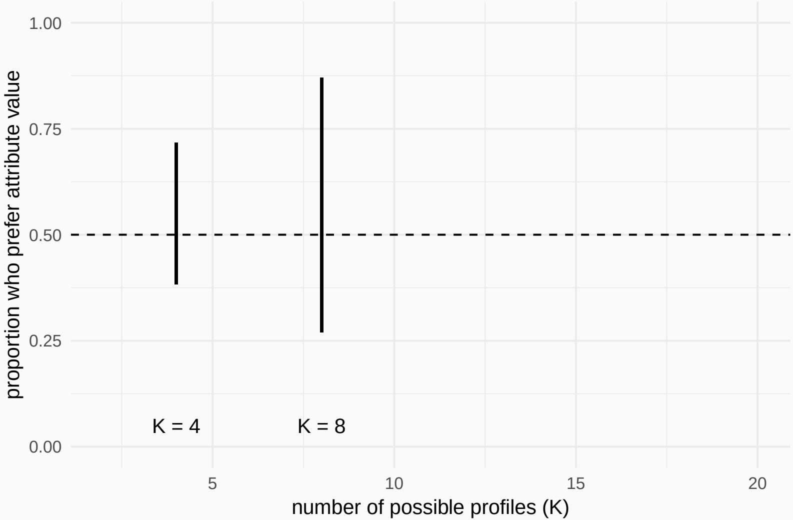
Inverting this yields the lower bound. $\square$

General bounds

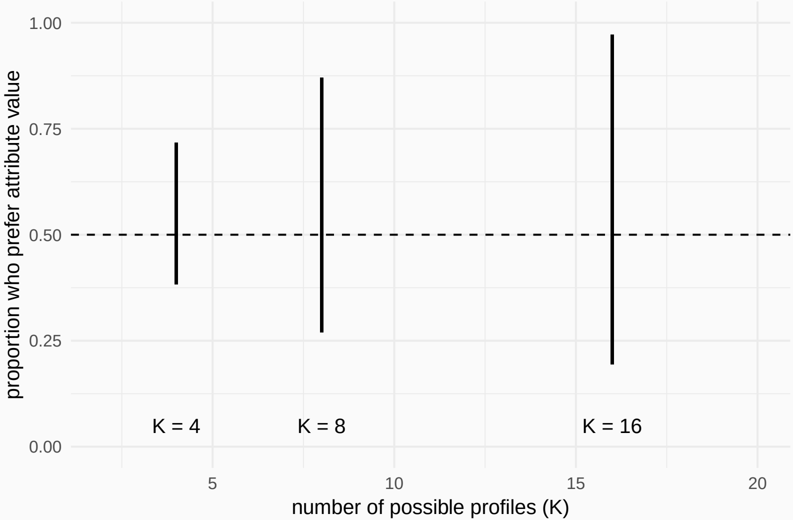
Example: Binary attribute, AMCE = 0.05



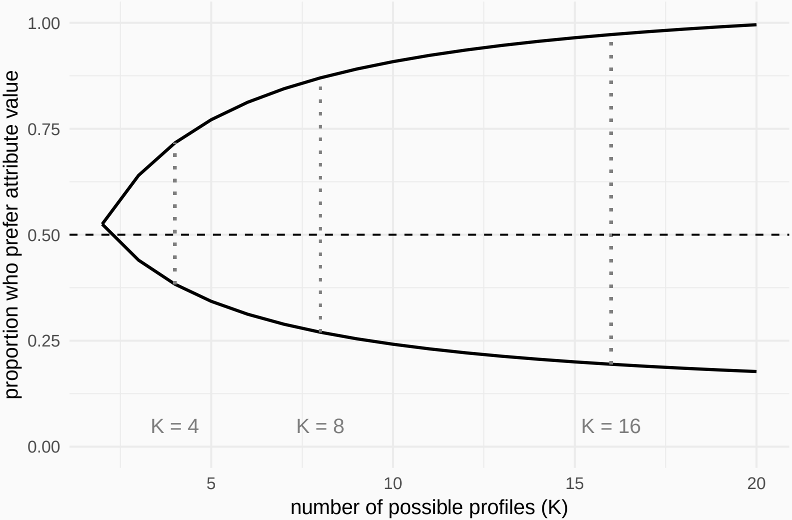
Example: Binary attribute, AMCE = 0.05



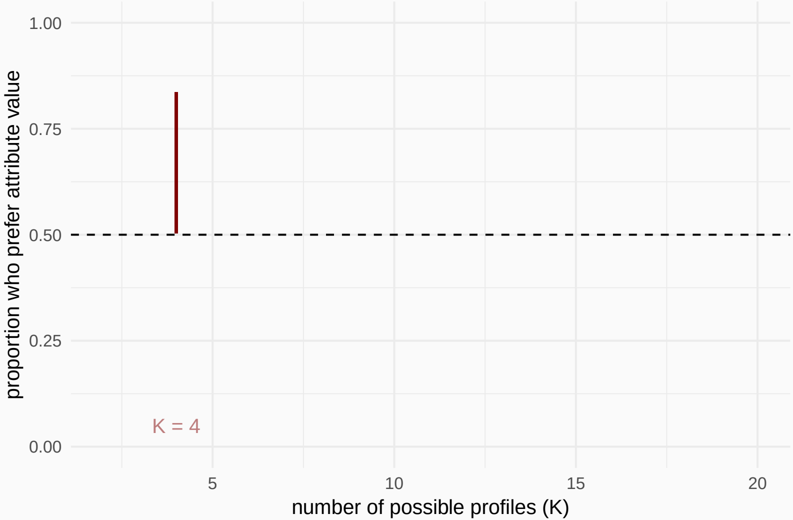
Example: Binary attribute, AMCE = 0.05



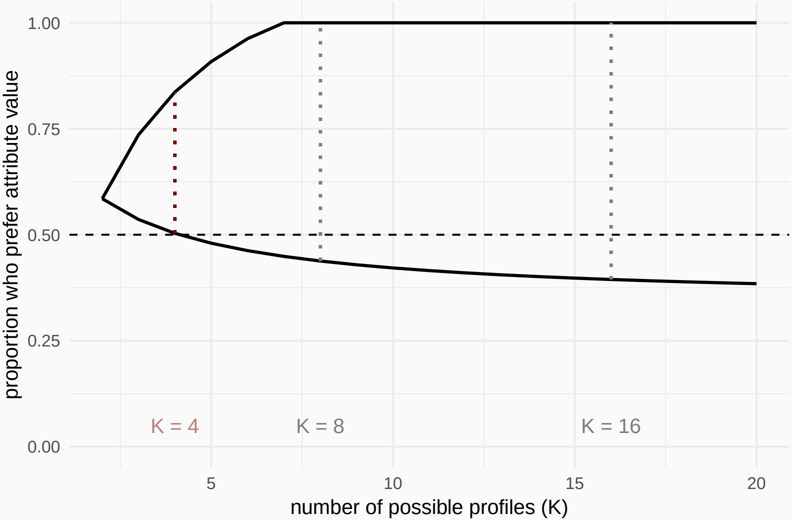
Example: Binary attribute, AMCE = 0.05



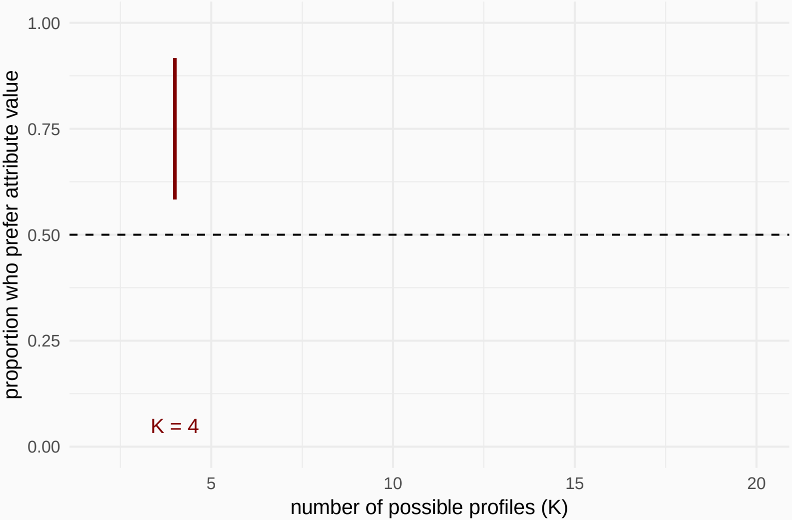
Example: Binary attribute, AMCE = 0.17



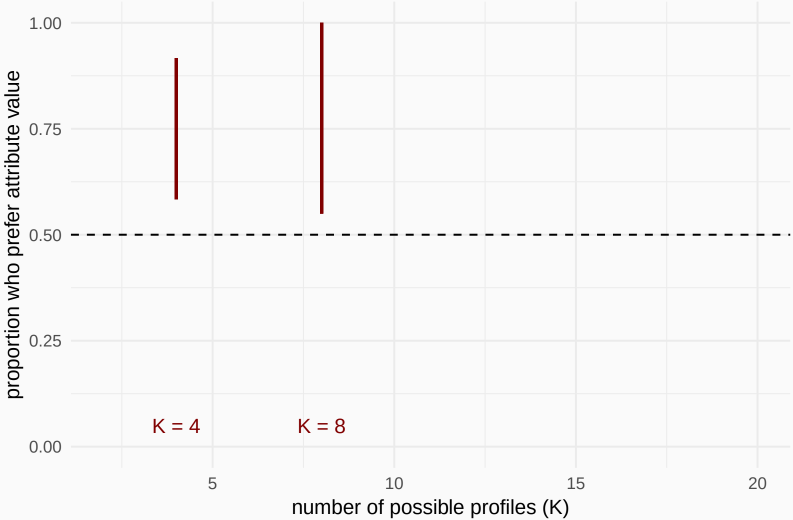
Example: Binary attribute, AMCE = 0.17



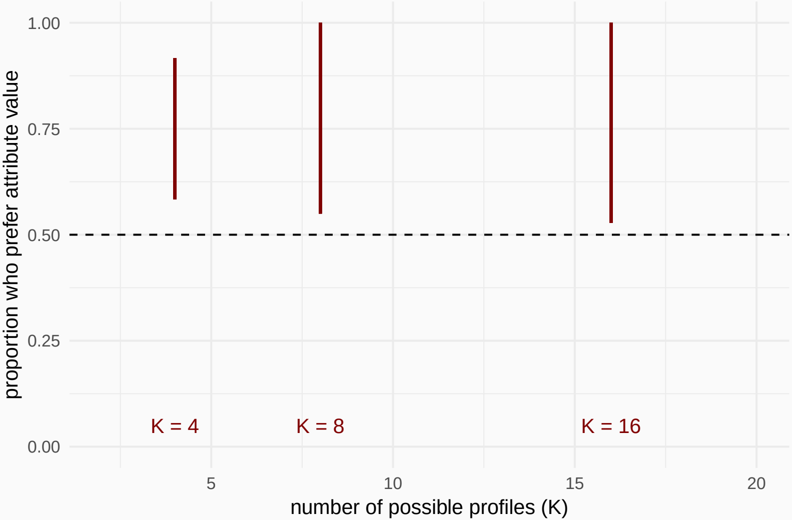
Example: Binary attribute, AMCE = 0.25



Example: Binary attribute, AMCE = 0.25



Example: Binary attribute, AMCE = 0.25



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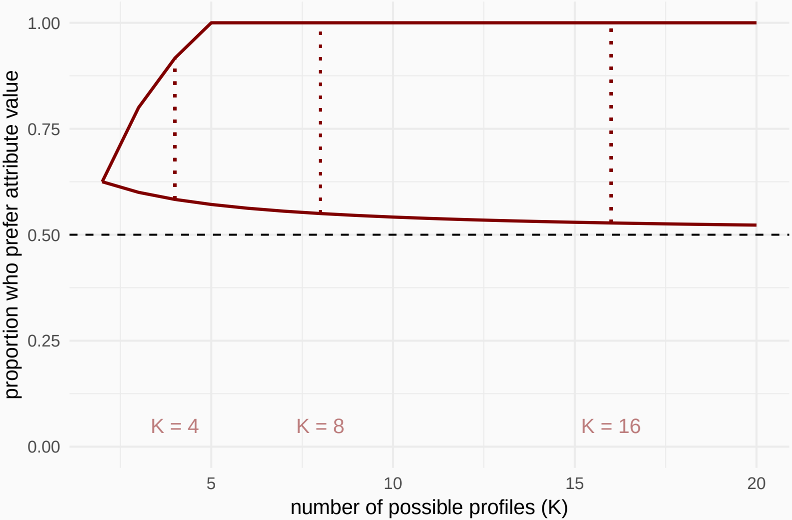
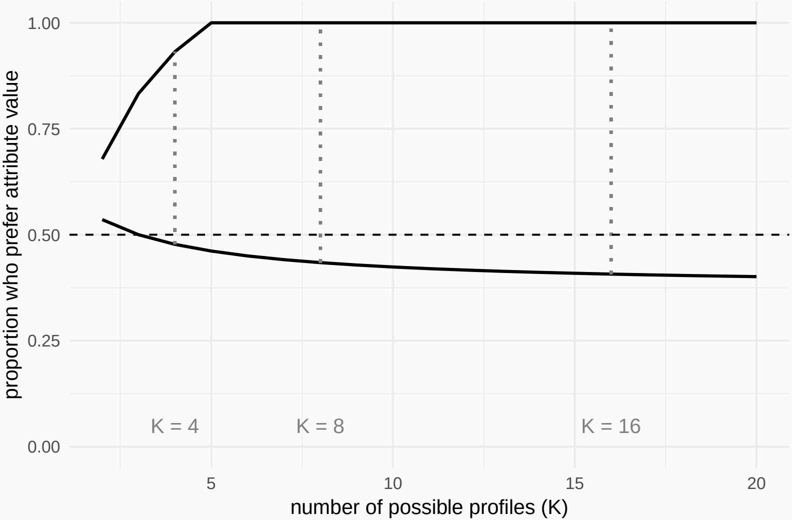


Example: Ternary attribute, AMCE = 0.25



Analytical Bounds APSR/AJPS/JOP

Paper	AMCE (π)	K	τ	Bounds
APSR				
Ward (2019)	-0.18	6,840	5	[0, 0.77]
Auerbach and Thachil (2018)	0.13	1,296	3	[0.20, 1]
Hankinson (2018)	-0.09	6,144	4	[0, 0.88]
Teele, Kalla, and Rosenbluth (2018)	0.15	864	4	[0.20, 1]
Carnes and Lupu (2016)	0.09	32	2	[0.22, 1]
JOP				
Newman and Malhotra (2018)	0.35	120,960	9	[0.39, 1]
Ballard-Rosa, Martin, and Scheve (2016)	-0.24	38,400	4	[0, 0.68]
Mummolo and Nall (2016)	0.11	3,456	4	[0.15, 1]
Mummolo (2016)	0.30	6	2	[0.63, 1]
AJPS				
Hemker and Rink (2017)	0.33	155	2	[0.66, 1]
Huff and Kertzer (2017)	0.19	108,000	6	[0.23, 1]

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When can the AMCE capture majority preference?

Proposition 3: Under uncorrelated weights, AMCE captures majority preference.

Sketch of Proof

Suppose weights are distributed identically across supporters and opponents

In expectation, each t_1 supporter gives as many more points to t_1 than t_0 as an opponent takes away from it

Thus, we can write

$$\text{AMCE} \propto \text{fraction who prefers } t_1 - \text{fraction who prefers } t_0$$

Takeaways

AMCE combines intensity and direction of preferences to give an “average voter”

In many applications, we want to discern the two

To capture electoral majorities:

- Attributes binary
- Total number of profiles low
- But note that small effect sizes still won’t detect majorities

External validity requires inclusion of all relevant attributes

Directions for future work

Recover weights assigned to attributes

- Evaluate homogeneous weights assumption

Develop approaches that decouple direction from intensity

- Estimate a model of voting
- Uncover marginal willingness to pay

Use social choice theory to inform our understanding of empirical estimands

Thank you

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asyam@mit.edu

Maximal points to t_1

$$\underbrace{\underbrace{t_1\alpha\beta\gamma}_{K-1} \succ \underbrace{t_1\alpha'\beta\gamma}_{K-2} \succ \ldots \succ \underbrace{t_1\alpha'\beta'\gamma'}_{\frac{K}{2}} \succ \underbrace{t_0\alpha\beta\gamma}_{\frac{K}{2}-1}}_{\frac{K}{2}} \succ \underbrace{t_0\alpha'\beta\gamma}_{\frac{K}{2}-2} \succ \ldots \succ \underbrace{t_0\alpha'\beta'\gamma'}_{0}$$

$$\underbrace{t_1\alpha\beta\gamma}_{K-1} \succ \underbrace{\underbrace{t_1\alpha'\beta\gamma}_{K-2} \succ \ldots \succ \underbrace{t_1\alpha'\beta'\gamma'}_{\frac{K}{2}} \succ \underbrace{t_0\alpha\beta\gamma}_{\frac{K}{2}-1} \succ \underbrace{t_0\alpha\beta\gamma}_{\frac{K}{2}-2}}_{\frac{K}{2}} \succ \ldots \succ \underbrace{t_0\alpha'\beta'\gamma'}_{0}$$

$\frac{K}{2}$ such comparisons

Back

Minimal points to t_0

$$\underbrace{\underbrace{t_0\alpha\beta\gamma}_{K-1} \succ \underbrace{t_1\alpha\beta\gamma}_{K-2}}_{1} \succ \underbrace{t_0\alpha'\beta\gamma}_{K-3} \succ \underbrace{t_1\alpha'\beta\gamma}_{K-4} \succ \ldots \succ \underbrace{t_0\alpha'\beta'\gamma'}_{1} \succ \underbrace{t_1\alpha'\beta'\gamma'}_{0}$$

$$\underbrace{t_0\alpha\beta\gamma}_{K-1} \succ \underbrace{t_1\alpha\beta\gamma}_{K-2} \succ \underbrace{\underbrace{t_0\alpha'\beta\gamma}_{K-3} \succ \underbrace{t_1\alpha'\beta\gamma}_{K-4}}_{1} \succ \ldots \succ \underbrace{t_0\alpha'\beta'\gamma'}_{1} \succ \underbrace{t_1\alpha'\beta'\gamma'}_{0}$$

$\frac{K}{2}$ such comparisons

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General Analytical Bounds

Fraction of respondents who prefer t_1 over t_0, given an AMCE estimate of $\pi(t_1, t_0)$, must be in the interval

$$y \in \left[\max\left\{ \frac{\pi(t_1,t_0)\tau(K-1)+\tau}{K(\tau-1)+\tau}, 0 \right\}, \right.$$
$$\left. \min\left\{ \frac{\pi(t_1,t_0)\tau(K-1)+K(\tau-1)}{K(\tau-1)+\tau}, 1 \right\} \right]$$

where τ is the number of distinct values the attribute of interest can take.

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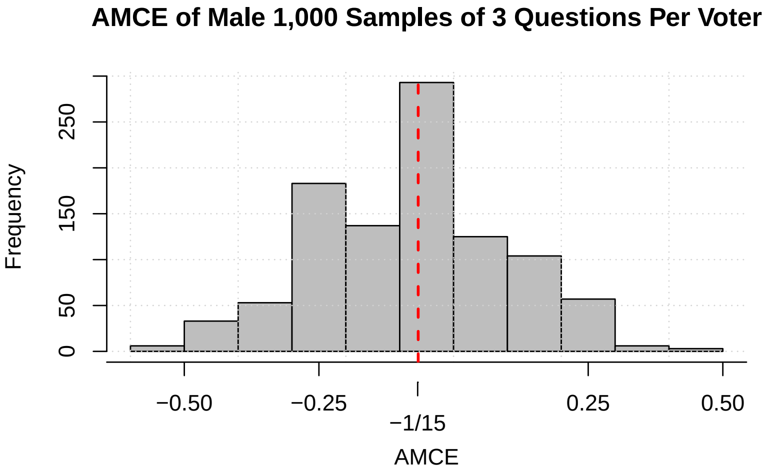
This is not a sampling issue!



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Assumptions

- Complete ($x \succsim y$, $y \succsim x$ or both)
- Transitive (if $x \succsim y$ & $y \succsim z$, then $x \succsim z$)

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The Borda winner profile is comprised of Borda winner features

Lemma 2: With no interactions and binary attributes, a profile has the highest Borda score if and only if all its features have the highest Borda scores for their respective attributes.

Sketch of proof

Definition: (No interactions) Voter i's preferences have no interactions when for all $t_1, t_0, \alpha, \beta, \alpha'$, and β', we have

$$t_1\alpha\beta \succ t_0\alpha\beta \iff t_1\alpha'\beta' \succ t_0\alpha'\beta'.$$

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Borda winner profile is comprised of Borda winner features

No interactions $\implies b_i(t_1\alpha\beta) - b_i(t_1\alpha'\beta') = b_i(t_0\alpha\beta) - b_i(t_0\alpha'\beta')$

$$\iff \sum_{i\in N} b_i(t_1\alpha\beta) - \sum_{i\in N} b_i(t_0\alpha\beta) = \sum_{i\in N} b_i(t_1\alpha'\beta') - \sum_{i\in N} b_i(t_0\alpha'\beta')$$

Suppose $t_1\alpha\beta$ is the profile with the highest Borda score

$$\iff \sum_{i\in N} b_i(t_1\alpha\beta) - \sum_{i\in N} b_i(t_0\alpha\beta) \geq 0$$

$\iff \sum_{i\in N} b_i(t_1\alpha'\beta') - \sum_{i\in N} b_i(t_0\alpha'\beta') \geq 0$ for all α', β'

Recall $B_i(t_1) = \sum_{\alpha,\beta} \sum_{i\in N} b_i(t_1\alpha\beta)$

$$\iff B_i(t_1) \geq B_i(t_0)$$

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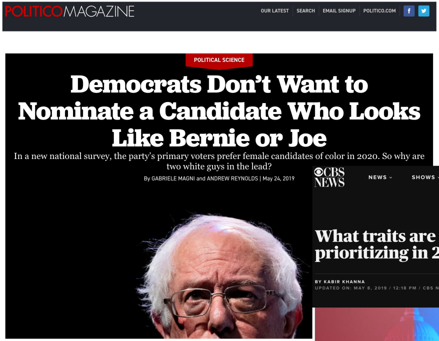
Journalists also interpret conjoints in the context of elections



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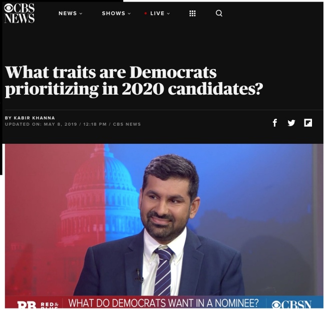
POLITICAL SCIENCE

Democrats Don't Want to Nominate a Candidate Who Looks Like Bernie or Joe

In a new national survey, the party's primary voters prefer female candidates of color in 2020. So why are two white guys in the lead?

By GABRIELE MAGNI and ANDREW REYNOLDS | May 24, 2019

Brendan Smialowski/Getty Images



CBS NEWS

NEWS SHOWS LIVE

What traits are Democrats prioritizing in 2020 candidates?

BY KABIR KHANNA

UPDATED ON: MAY 8, 2019 / 12:18 PM / CBS NEWS

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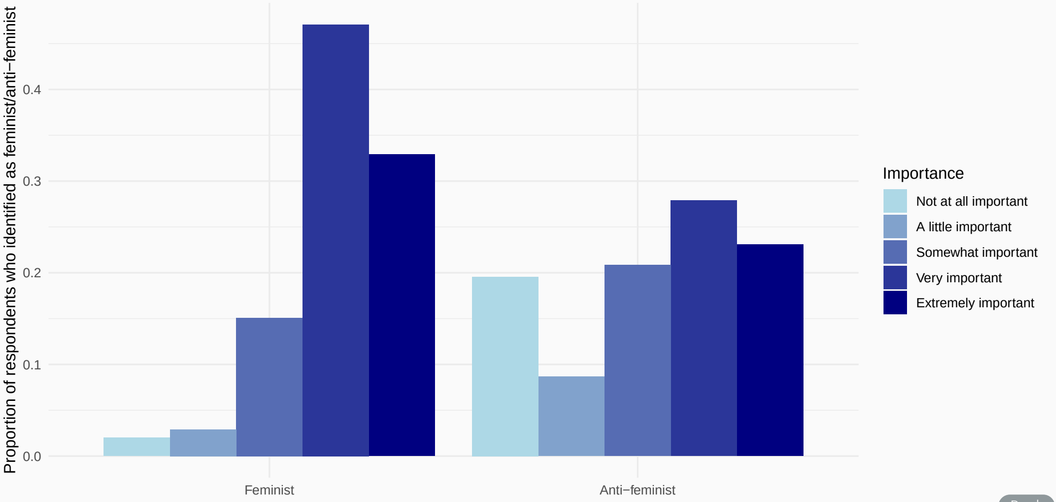
Direction and intensity: Feminism



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Question	Correlation	χ^2	# of categories
Favor allowing use of bathrooms of identified gender	-0.258 (0.000)	309.2 (0.000)	3
Favor torture for suspected terrorists	-0.246 (0.000)	147.8 (0.000)	3
Favor allowing Syrian refugees into US	-0.246 (0.000)	203.6 (0.000)	3
Favor 2010 health care law	-0.182 (0.000)	125.4 (0.000)	3
Support preferential hiring/promotion of blacks	-0.173 (0.000)	104.9 (0.000)	2
Favor building a wall with Mexico	-0.129 (0.000)	73.6 (0.000)	3
Favor affirmative action in universities	-0.098 (0.000)	15.7 (0.000)	2
Favor sending troops to fight ISIS	-0.080 (0.000)	21.7 (0.000)	3
Think economy has gotten better since 2008	-0.065 (0.000)	13.1 (0.000)	2
Agree that children brought illegally should be sent back	-0.025 (0.103)	2.7 (0.260)	3
Think government should make it harder to own a gun	-0.024 (0.289)	7.1 (0.069)	4
Approve of House incumbent	-0.013 (0.472)	0.5 (0.497)	2
Favor ending birthright citizenship	-0.011 (0.550)	1.6 (0.459)	3
Favor requiring provision of services to same-sex couples	0.020 (0.199)	8.8 (0.012)	3
Favor laws protecting gays against job discrimination	0.110 (0.000)	49.9 (0.000)	2
Think government should take more action on climate change	0.132 (0.000)	66.2 (0.000)	3
Favor requiring employers to give paid leave to new parents	0.149 (0.000)	29.1 (0.000)	2
Favor vaccines in schools	0.174 (0.000)	97.7 (0.000)	3
Support requiring equal pay for men and women	0.201 (0.000)	145.2 (0.000)	3
Favor the death penalty	0.211 (0.000)	184.2 (0.000)	2
Believe benefits of vaccination outweigh risks	0.275 (0.000)	251.4 (0.000)	3
The term ‘feminist’ describes you extremely/very well	0.328 (0.000)	115.3 (0.000)	5

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- Conjoints in media
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