Identification of Preferences in Forced-Choice Conjoint Experiments: Reassessing the Quantity of Interest

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SUPPLEMENTAL INFORMATION

A REVIEW OF FORCED-CHOICE CONJOINT EXPERIMENTS IN POLITICAL SCIENCE

In this supplemental information, I review papers implementing forced-choice conjoint experiments appearing in major political science journals since the publication of Hainmueller et al.'s (2014) foundational paper. In particular, I specify for each of them the kind of questions there are asking—preference-related or selection-process—and the estimation framework they are using. I carry out a systematic review of all conjoint papers published or forthcoming in the *American Journal of Political Science* (AJPS), in the *American Political Science Review* (APSR), in the *Journal of Politics* (JOP), in *Political Behavior* (PB), in *Political Science Research and Methods* (PSRM), and in the *British Journal of Political Science* (BJPS), which have published the majority of conjoint studies in political science and are also the most influential in doing so. I exclude methodological articles as well as articles which conjoint design does not involve a forced-choice component.

These selection criteria leave me with 61 articles, which I classify along two dimensions. The first dimension is the type of question that they are asking, based on the typology developed in this paper. I classify as "selection-process" those papers in which the selection process implemented in the experimental design mirrors the selection process of interest, and in which the interest in the actual outcome of this process is expressed and supported by a reflection on compositional effects. I classify as "preference-related" the papers in which the selection process implemented does not mirror any existing selection process, or in which the selection process it mirrors is not of interest in the paper. This essentially covers articles that focus on respondents' preferences studied for themselves. Finally, I construct a "mixed" category for the ambiguous cases. The second dimension identifies whether each paper is using the AMCE framework explicitly or implicitly, that is, whether each one estimates and reports AMCEs or derivatives thereof (such as marginal means).

The literature review is summarized in Table A1. As it turns out, I was not able to find a single paper seeking to answer a purely selection-process question. It is remarkable that the recent methodological discussion around conjoint experiments mostly focuses on selection-process questions (de la Cuesta et al. 2021; Abramson et al. 2019, 2020; Bansak et al. 2020), while most scholars use conjoint experiments with an interest in respondents' preferences. Arguably, a substantial number of articles belong to the "mixed" category; in these papers—all voting conjoint experiments—the broader research agenda seems indeed to be about explaining patterns of election outcomes. However, in all of theses cases, the specific questions asked in the papers are unambiguously preference-related questions, and none of them is concerned with compositional effects. The beginning of Carnes and Lupu's (2016) abstract provides a quintessential example. They write, "In most democracies, lawmakers tend to be vastly better off than the citizens who elect them. Is that because voters prefer more affluent politicians over leaders from working-class background?" Although the first sentence suggests a research agenda raising a selection-process question—explaining the underrepresentation of working-class elected officials in the United States—the second sentence indicates that the specific mechanism explored in the paper pertains to people's preferences, which the authors aim to study independent of other potential (compositional) mechanisms.

Table A1: Literature Review of Forced-Choice Conjoint Experiment Papers since 2014 in Six Major Political Science Journals

Reference	Journal	Topic	Question	Estimation
Franchino and Zucchini (2015) . .	PSRM	Political candidates	Preferences	CLogit
Hainmueller and Hopkins (2015) .	AJPS	Immigration	Preferences	AMCE
Hansen et al. (2015)	PB	Policy evaluation	Preferences	CLogit
Carnes and Lupu (2016)	APSR	Political candidates	Mixed	AMCE
Ballard-Rosa et al. (2016)	JOP	Tax policy	Preferences	AMCE
Mummolo (2016)	JOP	News selection	Preferences	AMCE
Mummolo and Nall (2017)	JOP	Residential mobility	Preferences	AMCE
Kirkland and Coppock (2018) . . .	PB	Political candidates	Preferences	AMCE
Auerbach and Thachil (2018) . . .	APSR	Clientelism	Preferences	AMCE
Hankinson (2018)	APSR	Housing policy	Preferences	AMCE
Teele et al. (2018)	APSR	Political candidates	Mixed	AMCE
Eggers et al. (2018)	JOP	Political candidates	Preferences	AMCE
Peterson and Simonovits (2018) . .	JOP	Political candidates	Preferences	AMCE
Ward (2019)	APSR	Immigration	Preferences	AMCE
Bechtel et al. (2019)	BJPS	Climate policy	Preferences	AMCE
Campbell et al. (2019)	BJPS	Political candidates	Preferences	AMCE
Chauchard et al. (2019)	JOP	Political candidates	Preferences	AMCE
Doherty et al. (2019)	JOP	Political candidates	Mixed	AMCE
Blackman and Jackson (2019) . . .	PB	Political candidates	Preferences	AMCE
Mummolo et al. (2019)	PB	Political candidates	Preferences	AMCE

Ono and Burden (2019)	PB	Political candidates	Mixed	AMCE
Liu (2019)	PSRM	Political elite	Preferences	AMCE
Auerbach and Thachil (2020) . . .	AJPS	Clientelism	Preferences	AMCE
Hartman and Morse (2020)	BJPS	Immigration	Preferences	AMCE
Rodon and Sanjaume-Calvet (2020)	JOP	Policy fairness	Preferences	AMCE
Schneider (2020)	JOP	Political candidates	Preferences	AMCE
Atkeson and Hamel (2020)	PB	Political candidates	Preferences	AMCE
Berinsky et al. (2020)	PB	Immigration	Preferences	AMCE
Crowder-Meyer et al. (2020)	PB	Political candidate	Preferences	AMCE
Hobolt et al. (2020)	PB	Brexit negotiations	Preferences	AMCE
Leeper and Robison (2020)	PB	Political candidate	Preferences	AMCE
Horiuchi et al. (2020)	PSRM	Political candidate	Preferences	AMCE
Mares and Visconti (2020)	PSRM	Political candidate	Preferences	AMCE
Ono and Yamada (2020)	PSRM	Political candidate	Mixed	AMCE
Costa (2021)	AJPS	Political representation	Preferences	AMCE
Kertzer et al. (2021)	BJPS	International resolvesfran	Preferences	AMCE
Broockman et al. (2021)	BJPS	Political candidates	Preferences	AMCE
Bakker et al. (2021)	JOP	Political candidates	Preferences	AMCE
Clayton et al. (2021)	PB	Immigration	Preferences	AMCE
Shafranek (2021)	PB	Affective polarization	Preferences	AMCE
Barnett et al. (Forthcoming)	AJPS	Job candidates	Preferences	AMCE
Becher and Brouard (Forthcoming)	AJPS	Executive candidates	Preferences	AMCE
Poertner (Forthcoming)	AJPS	Political candidates	Preferences	AMCE
Spater (Forthcoming)	AJPS	Spatial proximity	Preferences	AMCE
Hobolt et al. (Forthcoming)	BJPS	Affective polarization	Preferences	AMCE
Hübscher et al. (Forthcoming) . . .	BJPS	Political candidates	Mixed	AMCE
Incerti et al. (Forthcoming)	BJPS	International compromise	Preferences	AMCE
Rogowski and Stone (Forthcoming)	BJPS	Judicial candidates	Preferences	AMCE
Magni and Reynolds (Forthcomingb)	JOP	Political candidates	Mixed	AMCE
Tellez (Forthcoming)	JOP	Peace agreements	Preferences	AMCE
Weaver (Forthcoming)	JOP	Political candidates	Preferences	AMCE
Funck and McCabe (Forthcoming) .	PB	Political candidates	Preferences	AMCE
Magni and Reynolds (Forthcominga)	PB	Political candidates	Preferences	AMCE
Manento and Testa (Forthcoming) .	PB	Political candidates	Preferences	AMCE
Martin and Blinder (Forthcoming) .	PB	Political candidates	Mixed	AMCE
Neuner and Wratil (Forthcoming) .	PB	Political candidates	Preferences	AMCE
Rehmert (Forthcoming)	PB	Political candidates	Mixed	AMCE
Saha and Weeks (Forthcoming) . .	PB	Political candidates	Preferences	AMCE
Schwarz et al. (Forthcoming) . . .	PB	Sex crimes	Preferences	AMCE
Jensen et al. (Forthcoming)	PSRM	Political candidates	Preferences	AMCE
Kaslovsky et al. (Forthcoming) . . .	PSRM	Judicial candidates	Preferences	AMCE

In spite of the overwhelming dominance of preference-related studies in the empirical literature, almost all reviewed papers have adopted the AMCE framework, explicitly or implicitly, and are thus estimating and reporting selection-process estimands. A couple of papers published at the very beginning of the review period use condition logistic regressions—more commonly used in the marketing literature—but it makes no doubt that Hainmueller et al.'s (2014) AMCE framework has become the standard framework for analyzing forced-choice conjoint experiments in political science, regardless of the question asked.

To be sure, this review is not exhaustive of all conjoint studies published or forthcoming in political science, and one may find counterexamples—conjoint experiments used to answer a genuinely selection-process question, or preference-related studies analyzed with preference-related estimands. However, the journals considered in this review and the overwhelming pattern suffice to make the point that the use of the AMCE framework in preference-related studies is a widespread reality in political science.

B COMPARING PREFERENCE DISCRIMINATORY POWER ACROSS ATTRIBUTES

Scholars who rely on forced-choice experiments are usually primarily interested in exploring patterns of preferences within attributes, between the modalities of each attribute. However, we may also want to ask questions about the relative importance of attributes, that is, to compare the discriminatory power of preferences across attributes. What is the strongest determinant of preferences? Is gender more important than education in the determination of favorability towards immigrants? Although we could get a sense of the relative importance of attributes by visually inspecting patterns of ACPs (or AMCEs) and their absolute values, the methodological literature on conjoint experiments has yet to propose formalized quantity specifically designed to answer these questions. In this appendix, I propose two such estimands and calculate them on the immigrant experiment data.

The most straightforward indicator of an attribute's discriminatory power is the range of the distribution of the measures of preferences for that attribute. The range of ACPs for attribute ℓ is simply

$$\iota_\ell \equiv \max_{t_\ell} \pi_\ell(t_\ell; w_{t_\ell}) - \min_{t_\ell} \pi_\ell(t_\ell; w_{t_\ell}) \tag{B1}$$

which measures the largest variation in preferences that we can find for attribute ℓ. Provided that measures of preferences are fully comparable (within and across attributes, that is), the comparison of the coefficients of $(\iota_\ell)_{\ell\in\{1,\ldots,L\}}$ allows us to rank and compare the relative importance of attributes. The range, however, does not exploit all the information available; in particular, it exploits information from the most and least preferred levels but omits the remaining levels. Therefore, it is not clear if the attribute importance measured by the range is due to a limited number of levels, or to the high dispersion of all levels.

An alternative—in fact complementary, as I will show—measure is thus the average absolute deviation from the situation of indifference (where all ACPs are zero), that is, the average absolute ACP:

$$\sigma_\ell \equiv \frac{2}{|\mathcal{T}_\ell|} \sum_{t_\ell \in \mathcal{T}_\ell} |\pi_\ell(t_\ell; w_{t_\ell})| \tag{B2}$$

which is a dispersion measure because the ACPs for a given attribute are centered in 0. I actually define σ_ℓ as twice the average of absolute ACPs so that $\iota_\ell = \sigma_\ell$ when all the absolute ACPs for ℓ are equal. In other words, the difference between ι_ℓ and σ_ℓ reflects information on the ACP distribution: the closer (farther) both measures, the more polarized (more spread out) the distribution. Arguably, this information can be obtained by directly looking at the distribution of ACPs, but my goal is here to propose standalone measures that summarize information on the dispersion of ACPs. Finally, both of these measures can be straightforwardly generalized to conditional ACPs.

Figure B1's first panel reports ι_ℓ (range) and σ_ℓ (variability) for all attributes of the immigrant experiments. For conditionally independently randomized attributes, I took the ACPs conditional on unrestricted levels. In this figure, I estimated confidence intervals by simulation, using the ACP variance-covariance matrix. Regardless of the measure of attribute importance, job plans appears as the most determinant attribute for preferences, and gender as the least determinant. The remaining attributes are relatively close; if anything, the reason for application and job experience tend to be slightly less important that language skills and education; and occupation has an ambiguous position that depends on the indicator considered. In sum, this graph provides

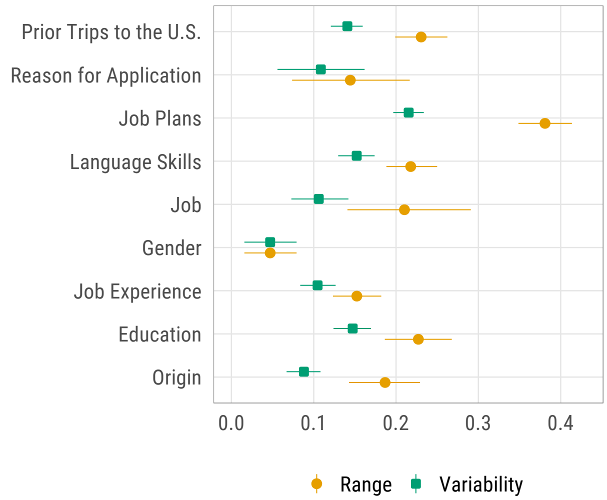

Figure B1: Within-attribute range and variability of ACPs associated with immigrants' characteristics. Conditional ACPs are calculated conditional on the the unrestricted levels of the condition attribute. Bars represent 95% confidence intervals with clustering at the respondent level, obtained from 1,000 simulations.

an efficient summary of the relative importance of the attributes included in the experiment.

One concern is that ACPs and, a fortiori, functions of ACPs, are not directly comparable across attributes when attributes are not completely independently randomized. For example, in Figure B1, the range and variability for occupation are conditional on profiles who have a college degree, while the range and variability for job plans are unconditional. Figure B2 reports range and variability measures all conditional on the unrestricted levels of all non-completely independently randomized attributes, successively. For example, in the first panel, all range and variability measures are conditional on profiles with a college degree.

This panel is useful to compare the range and variability of ACPs for job to the range and variability for other attributes. Here, in particular, I just want to make sure that the relative dominance of job plans and the low importance of gender with respect to job are not driven by low-educated profiles. In this case, the hierarchy holds when one considers ranges, but the variability for occupation is indistinguishable from the variability for gender (probably because gender matters more in preferences for high-educated profiles than for low-educated ones). Similar checks can be performed for each non-completely independently randomized attribute, using

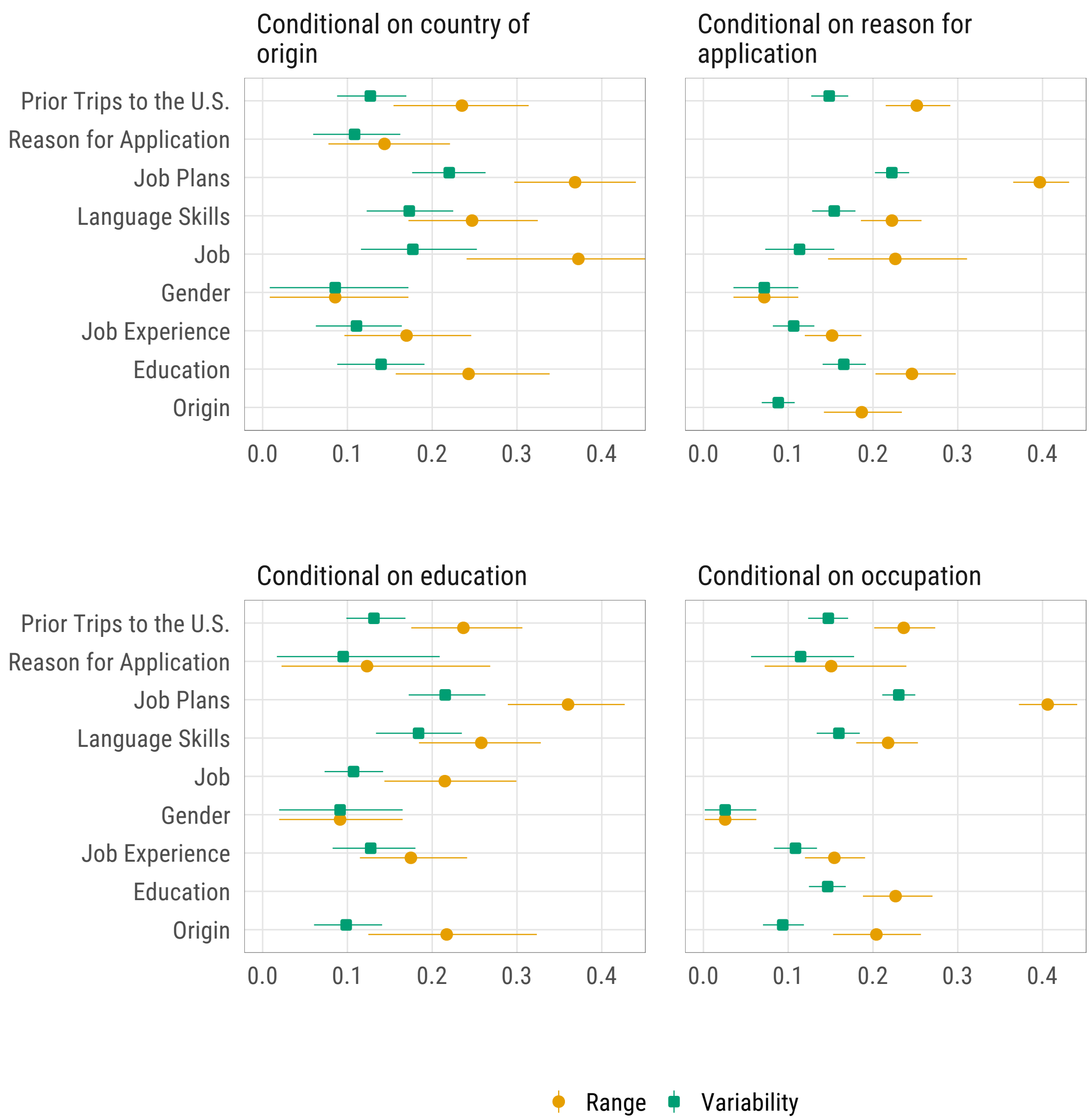

Figure B2: Within-attribute range and variability of ACPs associated with immigrants' characteristics, for different conditions. Conditional ACPs are calculated conditional on the the unrestricted levels of the condition attribute. Bars represent 95% confidence intervals with clustering at the respondent level, obtained from 1,000 simulations.

the subsequent panels. They confirm the overall pattern obtained in Figure B1.

C PROOFS

C.1 *Bounds of the AMCE*

By virtue of independent randomization (or conditionally independent randomization), the AMCE can be estimated on data from conjoint experiments, and expressed with observed outcomes (Hainmueller et al. 2014). As a result, Equation 2 can be rewritten as:[1]

$$
\begin{aligned}
\hat{\tau}_\ell(t_{\ell 1}, t_{\ell 0}) = \sum_{t_\ell \in \mathcal{T}_\ell} & \mathbb{P}\left(T_{i[-j]\ell} = t_\ell \middle| t_\ell \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
& \times \Big\{ \mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 1}, T_{i[-j]\ell} = t_\ell, (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \{t_\ell\}))^2\right] \\
& \quad - \mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 0}, T_{i[-j]\ell} = t_\ell, (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \{t_\ell\}))^2\right] \Big\}
\end{aligned}
\tag{C1}
$$

by linearity of the expectation.

When $T_{i[-j]\ell} = t_{\ell 1}$, the first expectation in the curve brackets is equal to .5; when $T_{i[-j]\ell} = t_{\ell 0}$, the second expectation in the curve brackets is equal to .5. We can distinctly write the terms that depends on the data, and those that do not, and aggregate the former following the law of total

[1] I establish the proof with the expression of the AMCE that uses observed outcome, not potential outcomes, to overcome the fact that the potential outcome $Y_{ij}(t_\ell, t_\ell, \mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]})$ is not defined.

expectation:

$$
\begin{aligned}
\hat{\tau}_\ell(t_{\ell 1}, t_{\ell 0}) = \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 1} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
\times \mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 1}, T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell),\right. \\
\left. (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell))^2\right] \\
- \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 0} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
- \mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 0}, T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell),\right. \\
\left. (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell))^2\right] \\
+ .5 * \mathbb{P}\left(T_{i[-j]\ell} = t_{\ell 1} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
- .5 * \mathbb{P}\left(T_{i[-j]\ell} = t_{\ell 0} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right)
\end{aligned} \tag{C2}
$$

In particular, the last two lines are equal to:

$$
\begin{aligned}
.5 * \left(1 - \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 1} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right)\right) \\
- .5 * \left(1 - \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 0} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right)\right)
\end{aligned} \tag{C3}
$$

Developing this expression, the terms in $.5 * 1$ cancel out, and the remainder can be reintegrated in the first part of the expression of the AMCE by factorization, so that

$$
\begin{aligned}
\hat{\tau}_\ell(t_{\ell 1}, t_{\ell 0}) = \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 1} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
\times \left\{\mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 1}, T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell) \setminus \{t_{\ell 1}\},\right.\right. \\
\left.\left. (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell))^2\right] - .5\right\} \\
- \mathbb{P}\left(T_{i[-j]\ell} \neq t_{\ell 0} | T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)\right) \\
\times \left\{\mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 0}, T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell) \setminus \{t_{\ell 0}\},\right.\right. \\
\left.\left. (\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]}) \in (\mathcal{T}_{[-\ell]} \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell))^2\right] - .5\right\}
\end{aligned} \tag{C4}
$$

In the AMCE expression, the expectations are positive, hence the AMCE reaches its maximum when the first expectation is equal 1 ($t_{\ell 1}$ is systematically chosen when compared to a different level) and the second expectation is equal to 0 ($t_{\ell 0}$ is never chosen when compared to a different level). In this case, the first term in curve brackets is .5 and the second term is $-.5$, and the expression can be rearranged to obtain

$$1 - 1/2 * \left(\mathbb{P}(T_{ij\ell} = T_{i[-j]\ell} = t_{\ell 1}) + \mathbb{P}(T_{ij\ell} = T_{i[-j]\ell} = t_{\ell 0})\right) \tag{C5}$$

where I implicitly condition on $T_{i[-j]\ell} \in \mathcal{T}_\ell \cap \mathbb{T}_\ell(\{t_{\ell 1}, t_{\ell 0}\}, \mathcal{T}_\ell)$. This is the upper bound of interval 3; the lower bound is obtained similarly, by setting the first expectation to 0, and the second expectation to 1.

Under uniform randomization,

$$\mathbb{P}(T_{ij\ell} = T_{i[-j]\ell} = t_{\ell 1}) + \mathbb{P}(T_{ij\ell} = T_{i[-j]\ell} = t_{\ell 0}) = \frac{1}{|\mathcal{T}_\ell|} \tag{C6}$$

and the bounds simplify to $\pm[1 - 1/|\mathcal{T}_\ell|]$.

C.2 *AMCE under uniform randomization*

In Equation C4, both probabilities are equal to $1 - \frac{1}{|\mathcal{T}_\ell|}$, and the conditions on $T_{i[-j]\ell}$ and on $(\mathbf{T}_{ij[-\ell]}, \mathbf{T}_{i[-j][-\ell]})$ can be omitted by independence, so that

$$\begin{aligned}\hat{\tau}_\ell(t_{\ell 1}, t_{\ell 0}) \overset{\mathcal{U}}{=} & \left(1 - \frac{1}{|\mathcal{T}_\ell|}\right)\left\{\mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 1}, T_{i[-j]\ell} \in \mathcal{T}_\ell \setminus \{t_{\ell 1}\}\right] - .5\right\} \\ & - \left(1 - \frac{1}{|\mathcal{T}_\ell|}\right)\left\{\mathbb{E}\left[Y_{ij} \middle| T_{ij\ell} = t_{\ell 0}, T_{i[-j]\ell} \in \mathcal{T}_\ell \setminus \{t_{\ell 0}\}\right] - .5\right\}\end{aligned} \tag{C7}$$

which simplifies into

$$\hat{\tau}_\ell(t_{\ell 1}, t_{\ell 0}) \overset{\mathcal{U}}{=} \left(1 - \frac{1}{|\mathcal{T}_\ell|}\right)\left\{\mathbb{E}\left[Y_{ij} | T_{ij\ell} = t_{\ell 1}, T_{i[-j]\ell} \in \mathcal{T}_\ell \setminus \{t_{\ell 1}\}\right] - \mathbb{E}\left[Y_{ij} | T_{ij\ell} = t_{\ell 0}, T_{i[-j]\ell} \in \mathcal{T}_\ell \setminus \{t_{\ell 0}\}\right]\right\}. \tag{C8}$$

C.3 *Consistency of the ACP and CACP estimators*

Developing the definition of $\hat{\delta}_{t_\ell t'_\ell}$ (consistently estimated by OLS) gives

$$\begin{aligned}
\hat{\delta}_{t_\ell t'_\ell} &= \sum_{i\in\{1,\ldots,n\}} [Z_i 1\{T_{i1\ell} = t_\ell, T_{i2\ell} = t'_\ell\} + (1 - Z_i)1\{T_{i1\ell} = t'_\ell, T_{i2\ell} = t_\ell\}] - .5 \\
&= \sum_{i\in\{1,\ldots,n\}} [Y_{i1} 1\{T_{i1\ell} = t_\ell, T_{i2\ell} = t'_\ell\} + Y_{i2} 1\{T_{i1\ell} = t'_\ell, T_{i2\ell} = t_\ell\}] - .5 \\
&= \sum_{\substack{i\in\{1,\ldots,n\}\\ j\in\{-1,1\}}} Y_{ij} 1\{T_{ij\ell} = t_\ell, T_{i[-j]\ell} = t'_\ell\} - .5 \\
&= \hat{\mathbb{E}}\left[Y_{ij} | T_{ij\ell} = t_\ell, T_{i[-j]\ell} = t'_\ell\right] - .5
\end{aligned}$$

where $\hat{\mathbb{E}}[\cdot]$ refers to the sample analogue of the expectation. Plugging the final expression of $\hat{\delta}_{t_\ell t'_\ell}$ in Equation **??** gives the sample analogue of $\hat{\pi}_\ell(t_\ell; w_{t_\ell})$ (Equation **??**), which is itself equal to the ACP under independent attribute randomization. The consistency of the CACP estimator can be obtained in the exact same way.

D MONTE-CARLO SIMULATIONS

In this section, I report evidence from Monte-Carlo simulations that ACPs correctly identify preferences, and that inference obtained from the proposed estimation method is correct. I also use Monte-Carlo simulation to illustrate how the ACP allows to recover the vector of preferences P, and to check that the estimators are correctly implemented in the R function I make available online.

I simulate data from an imaginary forced-choice conjoint experiment with four attributes: one continuous attribute (e.g. age, $\ell = \ell_\infty$), one binary attribute (e.g. gender, $\ell = \ell_2$), and two four-category attributes (e.g. education and occupation, $\ell = \ell_4$ and $\ell = \ell'_4$). The first two are completely independently randomized, but the last two are only conditionally independently randomized. In fact, randomization is set such that the fourth level of the third attribute is never associated with the third or the fourth levels of the fourth attribute. One can think about it as a way to avoid profiles of doctors with no formal education. A pair of profile is assigned to each "respondent," who has to make a decision about whom they prefer. The imaginary experiment is run on two groups of respondents of size 2,000 (e.g. Republicans and Democrats) and each respondent is presented with only one pair of profiles.

In this section, I start by constructing a vector of preferences, which I then use to simulate fake data. Specifically, I simulate 5,000 data sets, which correspond to 5,000 samples that would be observed if a forced-choice conjoint experiment would be conducted on a population whose preferences could be summarized by P. For each sample, I estimate ACPs and compare their distributions to their theoretical values. I also show that the proposed estimation method is able to estimate direct pairwise preferences, and thereby to recover P—the target of most studies relying on forced-choice conjoint experiments. Given the analytical elements provided earlier, these results are not surprising, but simulations make them more concrete.

D.1 *Data-Generation Process*

The first step is to define a vector of preferences P, that is, a series of coefficients $p_{t_\ell t'_\ell}$ which represent direct pairwise preferences. The coefficients correspond to the deviation of the selection probability from the situation of indifference when a t_ℓ-profile is compared to a t'_ℓ-profile. For the continuous attribute, the coefficient p_{ℓ_∞} corresponds to the first derivative (slope) of the selection probability with respect to this attribute. I set P to arbitrary values (under constraint that selection probabilities, defined in the next paragraph, remain in the $[0; 1]$ interval) and define it separately for each group of respondents. Both vectors are reported in Table D1, where the rows of each matrix represent the t_ℓ and the columns the t'_ℓ. P is defined either by the coefficients above or below the diagonal, which are the same in absolute values but of opposite sign. For the continuous attribute, one additional unit increases the selection probabilities by .1 percentage point in both group. In the first categorical variable, the selection probability of level 2 when compared to level 1 is 55% $(.5 + .050)$ in the first group, but only 45% $(.5 - .050)$ in the second group.

Table D1: Preference Parameters for the Monte Carlo Simulation

		Binary		Categorical 1				Categorical 2			
		1	2	1	2	3	4	1	2	3	4
	Group 1										
Continuous:	.001										
Binary:											
Level 1			.100								
Level 2		−.100									
Categorical 1:											
Level 1					−.050	−.120	−.100				
Level 2				.050		−.030	−.100				
Level 3				.120	.030		.010				
Level 4				.100	.100	−.010					
Categorical 2:											
Level 1									.100	−.080	−.100
Level 2								−.100		.000	−.040
Level 3								.080	.000		−.060
Level 4								.100	.040	.060	
	Group 2										
Continuous:	.001										
Binary:											
Level 1			−.100								
Level 2		.100									
Categorical 1:											
Level 1					.000	.050	.030				
Level 2				.000		−.030	.100				
Level 3				−.050	.030		.000				
Level 4				−.030	−.100	.000					
Categorical 2:											
Level 1									.100	−.080	.020
Level 2								−.100		−.050	−.100
Level 3								.080	.080		−.030
Level 4								−.020	.050	.030	

Note.—The parameters are the deviations of the selection probability of a profile defined in rows when compared to a profile defined in columns.

For each simulation $s \in \{1, \dots, 5000\}$, I randomly assign to each respondent two independent sets of attributes, each made of one continuous variable drawn from a uniform distribution on $[18; 65]$ (rounded to the closest integer), and three categorical variables. The first categorical variable has two levels and the last two four levels. These variables are independently drawn, except the four-level variables, which I constraint the fourth level of the first one not to be drawn at the same time as the third and fourth levels of the second one. I then use Table D1 to calculate the selection probability of each profile:

$$p_i^s = .5 + p_{\ell_\infty}(T_{i1\ell_\infty} - T_{i2\ell_\infty}) + p_{t_{\ell_2}t'_{\ell_2}} V_{i\ell_2 t_{\ell_2} t'_{\ell_2}} + \sum_{\ell \in \{\ell_4, \ell'_4\}} \sum_{(t_\ell, t'_\ell) \in \mathcal{T}_\ell^2} p_{t_\ell, t'_\ell} V_{i\ell t_\ell t'_\ell} \tag{D1}$$

As an example, consider a pair of profiles for whom the continuous attribute is $(20; 34)$, the binary attribute $(1, 1)$, and the two categorical attributes $(2, 3)$ and $(4, 1)$. If this pair is assigned to a respondent from the first group, the selection probability of the first profile is .556 $(.5 + (20 - 34) * .001 + 0 - .030 + .100)$. Finally, for each respondent, I simulate selection by drawing from a Bernoulli distribution:

$$Y_{i1} \sim \mathcal{B}(p_i^s) \tag{D2}$$

The selection decision of the second profile is entirely determined by the selection decision made for the first profile:

$$Y_{i2} = 1 - Y_{i1}. \tag{D3}$$

D.2 *Results*

The results of the Monte-Carlo simulations are reported in Tables D2, D3 and D4 respectively for ACPs, differences in ACPs, and for the parameters of the vector of preferences defined in Table D1. For each estimand, I implement the estimation method presented in the paper for each iteration of the simulation, setting uniform weights for all levels of categorical attributes. Each table reports the target value analytically calculated from Table D1 as well as the mean and the standard deviation of the estimator's distribution, the estimated bias, mean absolute error, the average standard error, and the 95% coverage rate. The average and the bias provide information about the overall accuracy of the estimators; the average is expected to be as close to the target as possible and the bias to 0. The standard deviation of the distribution of estimates and the mean absolute error give a sense of the variability of the estimates. The average standard error indicates the average estimated level of precision of the estimation, and the coverage rate allows to evaluate whether this precision is correctly estimated. The target value should fall in the estimate's confidence interval 95% of the time, so that the target coverage rate is expected to be .95.

The simulation results indicate that the estimation method proposed in this article performs very well. For all quantities, the average estimated value matches the target value, or a value that differs from the target by at most .001, .002 if one considers the preference parameters. This confirms that the proposed estimator is unbiased. The estimated values are distributed around the target with relatively small standard deviations—typically less than .03 for ACPs, .045 for differences in ACPs, and .055 for preference parameters. The precision of the estimations is similarly correctly estimated; the coverage rate is very close to .95 in all cases, and never out of the $[.942; 954]$ interval.

In the standard setting described earlier, ACPs estimated conditional on unrestricted levels and ACPs estimated conditional on comparable pairs are the same (Table D2, panels 3 and 4). This is the expected result since there is no interactions between the categorical attributes 1 and 2 in terms of preferences. To see what happens when there are such interactions, I ran additional Monte-Carlo simulations considering that preferences for the second categorical attribute were conditional on the first attribute. Specifically, I set $p_{1_{\ell'_4} 2_{\ell'_4}} = .1$ when $(T_{i1\ell_4}, T_{i2\ell_4}) \in \{1, 2, 3\}^2$, $p_{1_{\ell'_4} 2_{\ell'_4}} = -.1$ when $(T_{i1\ell_4}, T_{i2\ell_4}) = (4, 4)$, $p_{1_{\ell'_4} 2_{\ell'_4}} = 0$ when $(T_{i1\ell_4}, T_{i2\ell_4}) \in \{1, 2, 3\} \times \{4\}$, and $p_{1_{\ell'_4} 2_{\ell'_4}} = -.05$ when $(T_{i1\ell_4}, T_{i2\ell_4}) \in \{4\} \times \{1, 2, 3\}$. Results are reported in Table D2's last panel. ACPs for levels 3 and 4 are unchanged, while ACPs for levels 1 and 2 correctly reflect the interaction in preferences.

The main conclusion of this simulation exercise is that the estimation method proposed allows to identify respondents' preferences. In fact, it is able to estimate a precise summary of these

Table D2: ACPs from the Monte-Carlo Simulation (Group 1; 2,000 observations; 5,000 simulations)

	Target	Mean	SD	Bias	MAE	Avg. SE	Covg.
	Continuous						
Slope	0.001	0.001	0.001	0.000	0.000	0.001	0.948
	Binary						
Level 1	0.100	0.100	0.016	0.000	0.012	0.015	0.945
Level 2	−0.100	−0.100	0.016	0.000	0.012	0.015	0.945
	Categorical 1						
Level 1 (conditional)	−0.090	−0.091	0.031	−0.001	0.025	0.032	0.951
(comparable pairs)	−0.090	−0.090	0.022	0.000	0.018	0.022	0.947
Level 2 (conditional)	−0.027	−0.027	0.031	0.000	0.025	0.032	0.952
(comparable pairs)	−0.027	−0.027	0.022	0.000	0.018	0.022	0.945
Level 3 (conditional)	0.053	0.053	0.032	−0.001	0.025	0.032	0.946
(comparable pairs)	0.053	0.053	0.023	−0.001	0.018	0.022	0.940
Level 4	0.063	0.065	0.032	0.001	0.025	0.032	0.950
	Categorical 2						
Level 1 (conditional)	−0.027	−0.027	0.021	0.000	0.017	0.021	0.949
(comparable pairs)	−0.027	−0.027	0.019	0.000	0.015	0.019	0.953
Level 2 (conditional)	−0.047	−0.047	0.021	0.000	0.017	0.021	0.953
(comparable pairs)	−0.047	−0.047	0.020	0.000	0.016	0.020	0.952
Level 3	0.007	0.007	0.021	0.000	0.017	0.021	0.948
Level 4	0.067	0.067	0.021	0.000	0.017	0.021	0.954
	Categorical 2 (interaction with Categorical 1)						
Level 1 (conditional)	−0.027	−0.026	0.021	0.000	0.017	0.021	0.946
(comparable pairs)	−0.046	−0.046	0.020	0.000	0.016	0.019	0.945
Level 2 (conditional)	−0.047	−0.046	0.021	0.000	0.017	0.021	0.948
(comparable pairs)	−0.027	−0.027	0.020	0.000	0.016	0.020	0.946
Level 3	0.007	0.006	0.021	0.000	0.017	0.021	0.945
Level 4	0.067	0.066	0.021	0.000	0.017	0.021	0.946

Notes.—Target values represent the ACPs analytically calculated from the parameters of the simulation (Table D1). The MAE is the mean absolute error.

Table D3: Differences in ACPs from the Monte-Carlo Simulation between Groups 1 and 2 (4,000 observations; 5,000 simulations)

	Target	Mean	SD	Bias	MAE	Avg. SE	Covg.
	Continuous						
Slope	0.000	0.000	0.001	0.000	0.001	0.001	0.949
	Binary						
Level 1	0.200	0.200	0.022	0.000	0.017	0.022	0.948
Level 2	−0.200	−0.200	0.022	0.000	0.017	0.022	0.948
	Categorical 1						
Level 1	−0.097	−0.097	0.045	0.000	0.036	0.045	0.950
Level 2	−0.050	−0.050	0.045	0.000	0.036	0.045	0.952
Level 3	0.060	0.059	0.045	−0.001	0.036	0.045	0.944
Level 4	0.087	0.088	0.046	0.001	0.036	0.045	0.947
	Categorical 2						
Level 1	−0.040	−0.040	0.030	0.000	0.024	0.030	0.951
Level 2	0.037	0.037	0.030	0.000	0.024	0.030	0.947
Level 3	−0.027	−0.026	0.030	0.000	0.024	0.030	0.952
Level 4	0.030	0.030	0.030	0.000	0.024	0.030	0.951

NOTES.—Target values represent the differences ACPs analytically calculated from the parameters of the simulation (Table D1). The MAE is the mean absolute error.

Table D4: Estimated Preference Parameters from the Monte-Carlo Simulation (Group 1; 2,000 observations; 5,000 simulations)

	Target	Mean	SD	Bias	MAE	Avg. SE	Covg.
	Continuous						
Slope	0.001	0.001	0.001	0.000	0.000	0.001	0.948
	Binary						
Levels 1 vs. 2	0.100	0.100	0.016	0.000	0.012	0.015	0.945
	Categorical 1						
Levels 1 vs. 2	−0.050	−0.049	0.055	0.001	0.044	0.055	0.946
Levels 1 vs. 3	−0.120	−0.121	0.054	−0.001	0.043	0.054	0.951
Levels 1 vs. 4	−0.100	−0.102	0.054	−0.002	0.043	0.054	0.944
Levels 2 vs. 3	−0.030	−0.029	0.055	0.001	0.044	0.055	0.948
Levels 2 vs. 4	−0.100	−0.101	0.054	−0.001	0.043	0.054	0.943
Levels 3 vs. 4	0.010	0.008	0.057	−0.002	0.045	0.055	0.942
	Categorical 2						
Levels 1 vs. 2	0.100	0.099	0.036	−0.001	0.029	0.036	0.954
Levels 1 vs. 3	−0.080	−0.080	0.037	0.000	0.029	0.037	0.946
Levels 1 vs. 4	−0.100	−0.100	0.035	0.000	0.028	0.036	0.953
Levels 2 vs. 3	0.000	0.000	0.037	0.000	0.029	0.037	0.954
Levels 2 vs. 4	−0.040	−0.041	0.037	−0.001	0.030	0.037	0.949
Levels 3 vs. 4	−0.060	−0.060	0.037	0.000	0.029	0.037	0.944

Notes.—Target values represent the parameters of the simulation (Table D1). The MAE is the mean absolute error.

preferences—the ACP—and even to recover the vector of average preferences P itself.

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