Estimating and Using Individual-Level Marginal Component Effects from Conjoint Experiments

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Abstract

Conjoint experiments are quickly gaining popularity as a survey method to study multidimensional political preferences. A common way to explore heterogeneity of preferences estimated with conjoint experiments is by estimating average marginal component effects across subgroups of respondents. However, this method does not allow exploring the full variation of preferences within the studied populations as that requires estimating effects on the level of individual respondents. Currently, there is no accepted technique to obtain estimates of respondent-level preferences from conjoint experiments. In this paper, I address this gap by proposing a procedure to estimate individual preferences as respondent-specific marginal component effects. The proposed strategy does not require any additional assumptions compared to the standard conjoint analysis, although some changes to the task design are recommended. I also develop methods to account for uncertainty of resulting individual-level estimates. Using the proposed procedure, I partially replicate the conjoint experiment on immigrant admission with necessary design adjustments. Then, I demonstrate how individual-level estimates can be used to explore distributions of preferences, intercorrelations between different preference dimensions, and relationships of preferences to other variables of interest.

1 Introduction

The conjoint experiment is a survey-based method that allows estimating relative importance of more than one factor in respondents' decisions within the causal inference framework (Hainmueller, Hopkins, and Yamamoto 2014). Despite having been introduced to political science relatively recently, conjoint experiments quickly gained popularity as a powerful and flexible analytical tool. In a standard conjoint experiment, respondents are asked to make choices from sets of options described using a fixed number of attributes with randomized values. On the basis of respondents' answers, scholars can make inferences about the effects of different attribute values on the decisions of interest within the studied population. Conjoint experiments are also robust to response quality issues such as survey satisficing (Bansak et al. 2019).

A major recent development with regard to randomized experiments concerns estimation of heterogeneous treatment effects (e.g., Imai and Strauss 2011). Existing methods to account for such heterogeneity in conjoint experiments include estimation of average marginal component effects (AMCEs) by respondent subgroups (Leeper, Hobolt, and Tilley 2020), and a hierarchical Bayesian approach (Horiuchi, Smith, and Yamamoto 2018). However, these methods have limitations. Importantly, they can use only known categorizations meaning that potential latent heterogeneities cannot be identified. Furthermore, classifications of respondents into subgroups often involve questions without universally accepted answers. For instance, what is the cut point between those high vs. low in ethnocentrism? Or should party-leaning independents in the United States be treated as partisans? These are largely ad hoc decisions that may influence the results of the corresponding comparisons. Comparisons based on categorizing respondents into types also never explore the full distributions of preferences in the population—that may be of substantive interest to researchers.

Consider the following example. A conjoint study of immigration preferences has revealed that Americans prefer to admit immigrants who are educated and proficient in English whereas immigrants' origin countries do not have much impact on hypothetical admission decisions (Hainmueller and Hopkins 2015). Nevertheless, important variation in preferences within the population can still exist. Even when the average effect is positive, as it is the case for immigrants' education, preferences may vary in strength. If education is highly important for some respondents but not really important for others, it is still possible to observe an average effect that is positive and statistically reliable on a conventional level. The same is true for null results. For instance, according to the same study immigrants from Somalia are, on average, neither rewarded nor punished in terms of Americans' admission choices (when compared to immigrants from India as the baseline). This might mean, however, that some respondents strongly oppose admitting Somali immigrants whereas others strongly endorse it—for instance, for humanitarian reasons. Importantly, these potential differences in preferences do not necessarily follow known characteristics of respondents, such as ethnocentrism or partisanship. Moreover, if such heterogeneities exist but are orthogonal to the partisan conflict on immigration, that may be a substantively interesting finding.

In this paper, I develop an alternative approach to explore effects' heterogeneity in conjoint experiments. Specifically, I propose a systematic procedure for obtaining respondent-level preference estimates: individual marginal component effects (IMCEs). IMCEs represent estimated causal quantities—the effects of specific treatment components, i.e. attribute values—for each individual respondent. Obtaining them, therefore, makes it possible to estimate the full distributions of preferences within the population.[1] Similarly,

[1] This application of IMCEs is most useful with representative samples—otherwise estimated distributions may deviate from those in the general population.

IMCEs can be used to explore the interrelationships between different preference dimensions—for instance, by estimating the respective correlations.

There are additional reasons why obtaining individual-level effects from conjoint experiments is of theoretical and methodological relevance. One major benefit of obtaining IMCEs is the possibility to use them as measures of preferences in subsequent analyses, such as regression—similar to individual-level estimates from list experiments (Imai, Park, and Greene 2015). Conjoint analysis, after all, is a method of measurement: it allows assessing the direction and strength of citizens' preferences with respect to some attributes of interest. Conjoint tasks often involve hypothetical choices, and it is substantively interesting whether and, if yes, how exactly preferences estimated within such tasks can explain political behavior. As a measurement method, conjoint experiments posess a number of essential advantages vis-a-vis standard survey questions including enhanced realism, multidimensionality, and reduced social desirability concerns. Using IMCEs in regression analysis would allow researchers to move beyond describing preferences within the analyzed population (or specific subpopulations) and thus increase overall applicability of the method.

Finally, estimated IMCEs can be used in further testing the external validity of conjoint analysis. Existing studies validate conjoint experiments by contrasting their results to real-life behavioral benchmarks on the aggregate level (e.g., Hainmueller, Hangartner, and Yamamoto 2015). IMCEs, in turn, can be used to test whether conjoint experiments validly measure individual level preferences. Consider the recent study that employs eye-tracking data as a comparison benchmark for AMCE estimates from a conjoint experiment (Jenke et al. 2020). Estimation of IMCEs would allow to implement this analysis on the level of individual respondents. It can identify individuals for whom conjoint measures of attribute importance work better or worse than average—and, potentially, explore their background characteristics.

The proposed procedure to estimate IMCEs relies on the same set of assumptions as the estimation of average effects in conjoint studies. It also involves only minor adjustments to the design of conjoint tasks such that unbiased IMCE estimates can be feasibly obtained. These adjustments include using a rating (rather than choice) outcome, minimizing the number of randomized values for each attribute, and maximizing the number of rated profiles. I also develop two alternative methods to account for uncertainty of IMCEs based on, respectively, the normality assumption and nonparametric bootstrap. Computation of IMCEs, investigation of their distributions, and estimation of relationships to other variables can be implemented in commonly used statistical software, such as R and Stata. Sample scripts that illustrate data processing and reported analyses are made available with this paper as replication materials.

To demonstrate how the proposed method can be applied in practice, I run a survey study that partially replicates the conjoint experiment on immigrant admission to the U.S.—with necessary design adjustments. Then, I explore distributions and external relationships of IMCEs. I find that the distributions of preferences with respect to normatively desirable attributes of potential immigrants tend to be asymmetric: for instance, almost nobody prefers less educated immigrants whereas respondents who prefer those with college degrees do so to different extents. I also find that respondents expressing preferences for immigrants who are proficient in English also tend to prefer those with college education and no history of entry violations. Finally, I report that, even though respondents from both parties express relatively strong preferences for immigrants who have not previously violated U.S. entry rules, for Republicans this effect is almost twice as high compared to Democrats. Presented results reveal an important aspect of immigration preferences among Americans, namely asymmetric (skewed) distributions of some effects, that could not have been identified without application of IMCEs.

Overall, this paper advances the methodology of conjoint experiments as a tool for political research. It demonstrates how individual-level estimates of preferences can be obtained from conjoint tasks and used in further analyses—thus moving beyond simple descriptions of average preferences within specific populations. The proposed procedure can be easily applied in other areas where conjoint experiments have proved useful, beyond immigration preferences that serve as an empirical example in this study.

2 Formal Setup

Data that researchers obtain from conjoint experiments can be formally described in the following way. There is a sample of individuals (respondents) indexed $i = 1, \ldots, I$. Each individual rates a pre-defined number of profiles indexed $j = 1, \ldots, J$. Let $\mathbf{y} = (y_{11}, \ldots, y_{IJ})$ be the vector of length $I \times J$ containing ratings given by individuals to presented profiles. Profiles are described in terms of attributes indexed $l = 1, \ldots, L$. Let $\mathbf{x}_l = (x_{11l}, \ldots, x_{IJl})$ be the vector of length $I \times J$ containing values of attribute l from profiles presented to individuals. For simplicity and without loss of generality, assume that attribute l has only two possible values: $x_{ijl} \in \{0, 1\}$.

As soon as the assumptions of (1) stability and no carryover effects, (2) no profile-order effects, and (3) completely independent randomization of the profiles hold, average marginal component effect (AMCE) for attribute l, defined as the marginal effect of the attribute averaged over the joint distribution of the remaining attributes, can be estimated using a simple regression model of the following form (for proofs and derivations, see Hainmueller, Hopkins, and Yamamoto 2014):

$$\mathbf{y} = \alpha_l + \beta_l \, \mathbf{x}_l + \boldsymbol{\varepsilon}_l, \tag{1}$$

where α_l and β_l are regression parameters to be estimated and $\boldsymbol{\varepsilon}_l$ is the vector of errors. Define a matrix containing a vector of ones and a vector of attribute l values:

$$\mathbf{X}_l = [\mathbf{1}_{I \times J}, \mathbf{x}_l], \tag{2}$$

where $\mathbf{1}_{I \times J}$ is an all-ones vector of length $I \times J$. Then, AMCE of attribute l, denoted π_l, can be estimated as:

$$\left(\hat{\alpha}_l, \hat{\beta}_l\right) = \left(\mathbf{X}_l^{\mathrm{T}}\, \mathbf{X}_l\right)^{-1} \mathbf{X}_l^{\mathrm{T}}\, \mathbf{y}, \tag{3}$$

$$\hat{\pi}_l = \hat{\beta}_l. \tag{4}$$

AMCE as a causal quantity is conceptually related to the average treatment effect (ATE), difference in mean outcomes between units in treatment and control groups.[2] Experimental researchers have to rely on averaging across respondents due to what is known as the fundamental problem of causal inference: unit treatment effect (UTE) almost never can be recovered (Holland 1986). However, since respondents in conjoint experiments often rate multiple profiles with randomized attribute values, it is technically possible to obtain estimates for treatment effects on the unit level—i.e., for an individual respondent.[3] These quantities are of little interest when the goal is description of preferences in the general population. Nevertheless, individual-level estimates of preferences obtained from conjoint experiments can be used in further analyses. Such analyses can explore how preferences on specific dimensions expressed in conjoint tasks vary within the population and relate to broader political attitudes and behaviors.

These quantities can be operationalized and estimated from conjoint experiments using what I call the individual marginal component effect (IMCE). It relates to the

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2 AMCE and ATE are not fully equivalent since estimation of AMCEs requires averaging over the joint distribution of (remaining) attributes, in addition to averaging across respondents. It means that the choice of attributes and values for a conjoint experiment should be rooted in established theories or social reality.

3 The conjoint design does not technically require more than one choice per respondent. Sometimes researchers choose to increase the number of respondents and keep the number of rated profiles to as low as two. Under such design, IMCEs cannot be estimated.

AMCE the same way UTE relates to ATE: IMCE attempts to recover the effect of interest for each unit of analysis (i.e., the individual survey respondent) instead of relying on averages. The word "individual" in effect designation, therefore, refers to individual respondent (unit), not to individual profile, attribute, or value.

When the assumptions necessary to estimate AMCEs using simple regression hold, IMCEs can be estimated by running models similar in form to Equation 1 independently for each individual respondent. Let $\mathbf{y}_i = (y_{i1}, \dots, y_{iJ})$ be the vector of length J containing ratings given by individual i to presented profiles. Let $\mathbf{x}_{il} = (x_{i1l}, \dots, x_{iJl})$ be the vector of length J containing values of attribute l from profiles presented to individual i. Then respondent-specific regressions take the form of:

$$\mathbf{y}_i = \alpha_{il} + \beta_{il}\,\mathbf{x}_{il} + \boldsymbol{\varepsilon}_{il}, \tag{5}$$

where α_{il} and β_{il} are respondent-specific regression parameters to be estimated and $\boldsymbol{\varepsilon}_{il}$ is the vector of respondent-specific errors. Define:

$$\mathbf{X}_{il} = [\mathbf{1}_J, \mathbf{x}_{il}], \tag{6}$$

where $\mathbf{1}_J$ is an all-ones vector of length J. Then, IMCE of attribute l for individual i, denoted π_{il}, can be estimated as:

$$\left(\hat{\alpha}_{il}, \hat{\beta}_{il}\right) = (\mathbf{X}_{il}^{\mathrm{T}}\,\mathbf{X}_{il})^{-1}\,\mathbf{X}_{il}^{\mathrm{T}}\,\mathbf{y}_i, \tag{7}$$

$$\hat{\pi}_{il} = \hat{\beta}_{il}. \tag{8}$$

3 Design Requirements

As shown in the previous section, it is technically possible to obtain IMCE estimates without making any additional assumptions compared to those necessary to estimate AMCEs. Estimation of IMCEs simply requires running regression models independently for each respondent and obtaining corresponding individual-level sets of estimates.

However, there are potential difficulties with practical estimation of IMCEs that might require certain adjustments to the standard conjoint design. First, estimation of AMCEs relies on relatively large samples with effective numbers of observations equal to the number of respondents times the number of rated profiles. Estimation of IMCEs, in turn, has to rely on samples as small as the number of rated profiles per respondent that usually does not exceed two dozen. Low numbers of observations do not allow invoking large-sample theory, meaning that the estimator of IMCEs has to have good small-sample properties. One such estimator is ordinary least squares (OLS): it is unbiased in small samples given that the exogeneity assumption holds. As soon as all attribute values in a conjoint experiment are completely randomized, the exogeneity assumption holds by design and the OLS estimates of IMCEs are indeed unbiased. However, the OLS estimator is known to work most efficiently with interval dependent variables. Therefore, conjoint experiments aimed at estimating IMCEs should rely on respondents' numerical ratings of profiles rather than on discrete choice responses.

Second, there is a limitation with respect to the number of potential attribute values that can be used in a conjoint experiment aimed at estimating IMCEs. Since attribute values are randomized, there is always a chance that an individual respondent is never presented with a profile containing a specific attribute value. In this case, IMCE cannot be estimated. To minimize such occurrences, the number of potential values for each single attribute in conjoint experiments aimed at estimating IMCEs should be as low as possible. It is necessary to note that, even with minimal numbers of attribute values, respondents with no variance will likely appear in the dataset anyway—but such cases will be rare and completely at random.

The third practical aspect of running conjoint experiments when IMCEs are of interest concerns the number of profiles that respondents are asked to rate. Increasing this number decreases the probability of cases when an individual respondent is never presented with a specific attribute value. Additionally, greater numbers of rated profiles improve reliability of estimated IMCEs. At the same time, there are limits to the number of rated profiles related to both survey costs and potential negative consequences for response quality. Therefore, the number of rated profiles should be maximized—but within the boundary such that survey satisficing does not become a problem.

4 Accounting for Uncertainty

If the conjoint experiment is designed so that IMCEs can be feasibly estimated, such estimates are unbiased under complete randomization—but they are also uncertain. Since IMCE estimation relies on relatively small numbers of observations, the resulting measurement error, though random, can be relatively large. Since the ultimate goal of obtaining IMCEs is using them in consequent analyses, treating point estimates as true values can inflate reliability of estimated associations. Here, I propose a method of accounting for uncertainty of IMCE estimates: instead of using point estimates, potential IMCE values are drawn multiple times from their estimated sampling distributions.

The sampling distributions of IMCEs can be estimated either parametrically or nonparametrically. Parametric estimation relies on the normality assumption. When the errors have a normal distribution, the OLS estimator is also normally distributed even in finite samples with the mean equal to the true parameter value:[4]

$$\hat{\pi}_{il} = \hat{\beta}_{il} \sim \mathcal{N}\left(\beta_{il}, \sigma_{il}^2 \left(\mathbf{X}_{il}^{\mathrm{T}} \mathbf{X}_{il} \right)_{22}^{-1}\right). \tag{9}$$

Then, IMCE values can be drawn M times from this distribution with the OLS point estimate as the mean and standard deviation approximated using the standard error:

$$\hat{\pi}_{il1}, \ldots, \hat{\pi}_{ilM} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(\hat{\beta}_{il}, s_{il}^2 \left(\mathbf{X}_{il}^{\mathrm{T}} \mathbf{X}_{il} \right)_{22}^{-1}\right). \tag{10}$$

[4] Subscript "22" in Equation 9 and Equation 10 refers to the second row and the second column of the corresponding inverted matrix.

The alternative way of estimating the sampling distribution of IMCEs makes use of nonparametric bootstrap (Davison and Hinkley 1997). It assumes that observed values of pairs (x_{ijl}, y_{ij}) are independent draws from some underlying joint distribution denoted F_i:

$$(\mathbf{x}_{il}, \mathbf{y}_i) = \left[(x_{il1}, y_{i1}), \ldots, (x_{ilJ}, y_{iJ})\right] \overset{\text{i.i.d.}}{\sim} F_i. \tag{11}$$

Using the sample at hand, it is possible to define an estimator for F_i, empirical distribution function $\hat{F}_i$, that puts equal probabilities at each observed value:

$$\hat{F}_i(x, y) = \frac{1}{J} \sum_{j=1}^{J} \mathbb{I}\left(x_{ilj} < x, y_{ij} < y\right), \tag{12}$$

where $\mathbb{I}(\cdot)$ is an indicator function. To estimate the sampling distribution of $\hat{\beta}_{il}$, start from sampling pairs (x_{ijl}, y_{ij}) from $\hat{F}_i$ (resampling with replacement):

$$\left(\mathbf{x}^*_{ilm}, \mathbf{y}^*_{im}\right) = \left[(x^*_{il1m}, y^*_{i1m}), \ldots, (x^*_{ilJm}, y^*_{iJm})\right] \overset{\text{i.i.d.}}{\sim} \hat{F}_i, \tag{13}$$

where $m \in \{1, \ldots, M\}$. Also, define:

$$\mathbf{X}^*_{ilm} = [\mathbf{1}_J, \mathbf{x}^*_{ilm}]. \tag{14}$$

Then, plausible values of $\hat{\beta}_{ilm}$—and, respectively, $\hat{\pi}_{ilm}$—can be obtained by re-estimating the OLS regression for each of the M samples from $\hat{F}_i$:

$$\left(\hat{\alpha}_{ilm}, \hat{\beta}_{ilm}\right) = \left[(\mathbf{X}^*_{ilm})^{\mathrm{T}} \mathbf{X}^*_{ilm}\right]^{-1} (\mathbf{X}^*_{ilm})^{\mathrm{T}} \mathbf{y}^*_{im}, \tag{15}$$

$$\hat{\pi}_{ilm} = \hat{\beta}_{ilm}. \tag{16}$$

It is necessary to note that, given the random character of the bootstrap process, some resamples can result in absence of variance on specific attribute values (meaning that corresponding IMCE cannot be estimated). In such cases, resampling can be repeated as necessary to obtain the required number of complete replications.

Independently of how the sampling distributions are estimated, the plausible IMCE values can be employed in consequent analyses using the method proposed for multiple imputations (Rubin 1987). First, the quantities of interest are estimated for all datasets containing randomly drawn plausible values of IMCEs. Second, results of these estimations are aggregated using guidelines for calculating average point estimates, combined between- and within-imputation variances, and adjusted degrees of freedom.

5 Empirical Application: Immigrant Admission

To evaluate the proposed method, I designed and fielded a survey study with embedded conjoint experiment. Participants were recruited using the Lucid panel in December 2019. Lucid samples match the American National Election Study on a number of important demographic benchmarks (Coppock and McClellan 2019). The total of 970 respondents completed the questionnaire.[5] Participants' demographics were supplied by the Lucid panel. The sample characteristics were the following. Mean age was 45.4 years. Gender ratio was 48.6% male to 51.4% female. Median household income category was $40,000 to $44,999. Also, 69.8% of respondents self-identified as non-Hispanic whites. Finally, 38.6% of respondents were Democrats, 36.9% were Republicans, and 24.5% were independents.

The key part of the survey was a conjoint experiment that partially replicated the immigrant admission study (Hainmueller and Hopkins 2015), with adjustments necessary to feasibly estimate IMCEs. In the experiment, each respondent rated 15 pairs of profiles (30 total) of potential immigrants in terms of preference for being admitted to the United States. The conjoint part of the study was programmed on Qualtrics survey platform using the Conjoint Survey Design Tool (Strezhnev et al. 2014).

The conjoint experiment used a rating outcome. Respondents were asked to rate presented immigrant profiles using an 11-point scale from 0 = *Definitely not admit* to 10 = *Definitely admit*.

Profiles of hypothetical immigrants were described in terms of six attributes. Attributes were selected following the original experiment to be replicated, as well as the

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5 This number excludes 88 respondents who otherwise completed the survey but used exact same rating scores for all profiles in the conjoint experiment.

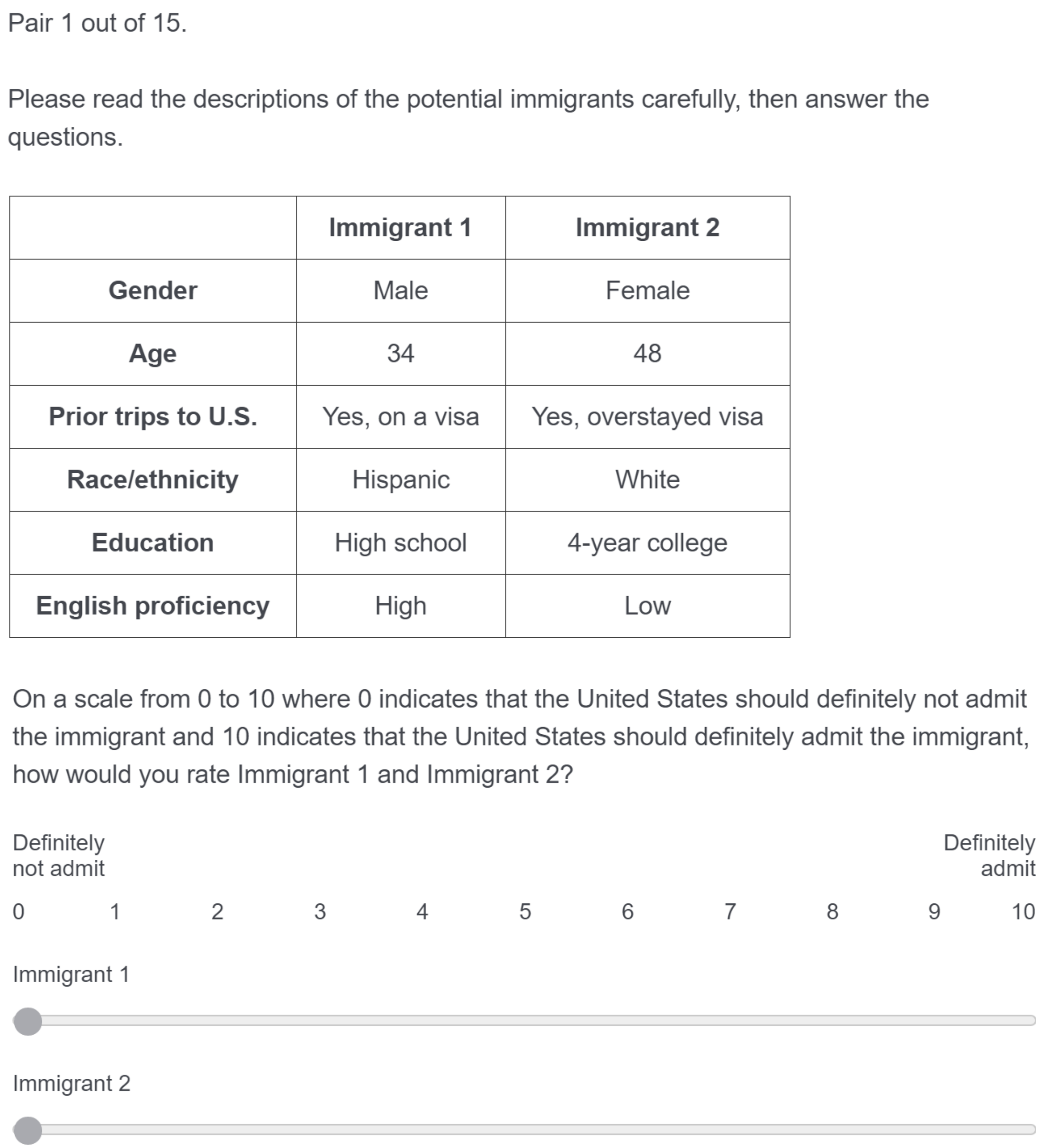
current literature on politics of immigration demonstrating potential importance of immigrants' age and gender (Ward 2019), race/ethnicity (Citrin et al. 1997; Newman and Malhotra 2018; Valentino, Brader, and Jardina 2013), education (Valentino et al. 2019), English proficiency (Hopkins 2015; Newman, Hartman, and Taber 2012), and legality of prior visits to the U.S. (Hartman, Newman, and Bell 2014; Wright, Levy, and Citrin 2016).

To make profiles look more realistic, I used more than two values per attribute in descriptions presented to respondents. However, these values were chosen in a way such that they could be easily dichotomized to feasibly estimate IMCEs. For instance, English proficiency was collapsed into categories "Good" (attribute values "Very high" or "High") and "Poor" (attribute values "Low" or "Very low"). Values for all attributes were fully and independently randomized with uniform distributions, i.e. all values of an attribute had equal probabilities of being presented. See Figure 1 for an example of conjoint profiles as presented to respondents and Table 1 for the full list of attribute values.

The survey also included a short question battery to assess respondents' ethnocentrism adapted from a longer version (Bizumic and Duckitt 2012). Respondents were asked about their agreement or disagreement with statements about general preference for their cultural in-group. Sample item: "In most cases, I like people from my culture more than I like others." Answers were given on a 7-point Likert-type scale from 1 = *Strongly disagree* to 7 = *Strongly agree*.[6]

For data manipulations and analyses, I used Stata (StataCorp 2015), and R (R Core Team 2019). Tables were produced using `esttab` exporting tool (Jann 2007). Figures were created with `ggplot2` (Wickham 2016).

[6] See Table S1 in Supplementary Material for the full ethnocentrism battery.



Pair 1 out of 15.

Please read the descriptions of the potential immigrants carefully, then answer the questions.

	Immigrant 1	Immigrant 2
Gender	Male	Female
Age	34	48
Prior trips to U.S.	Yes, on a visa	Yes, overstayed visa
Race/ethnicity	Hispanic	White
Education	High school	4-year college
English proficiency	High	Low

On a scale from 0 to 10 where 0 indicates that the United States should definitely not admit the immigrant and 10 indicates that the United States should definitely admit the immigrant, how would you rate Immigrant 1 and Immigrant 2?

Definitely not admit

Definitely admit

0 1 2 3 4 5 6 7 8 9 10

Immigrant 1

Immigrant 2

Figure 1. Experimental design

Table 1. Attributes for immigrant profiles in conjoint experiment

Attribute	Values
Age	*Older:* 40–54
	Young: 25–39
Gender	Male
	Female
Race/ethnicity	*Non-white:* Black, Hispanic, Asian
	White
Education	*Less than college:* Elementary school, Middle school, High school
	Some college or higher: 2-year college, 4-year college, Graduate degree
English proficiency	*Poor:* Low, Very low
	Good: Very high, High
Prior trips to U.S.	*Violation:* Overstayed visa, Unauthorized
	No violation: No, On a visa

Note. Age values (in years) were randomly chosen from the specified intervals

6 IMCE in the Immigrant Admission Experiment

I start from replicating the aggregate results of the immigration admission task, with the conjoint design adjusted for estimation of IMCEs. To do so, I estimate AMCEs using the standard procedure. Results are presented in Figure 2. Following the guidelines, standard errors are clustered on the level of respondents (Hainmueller, Hopkins, and Yamamoto 2014). Overall, AMCE estimates very closely replicate results of the previous immigrant admission study—given the design differences. Respondents demonstrate relatively strong preferences for admitting immigrants who have at least some college education, speak good English, and have not violated U.S. immigration rules in the past. The estimated effects of immigrants' race and age on admission preferences are extremely close to zero. Finally, respondents exhibit slight preference for immigrant women over men.[7]

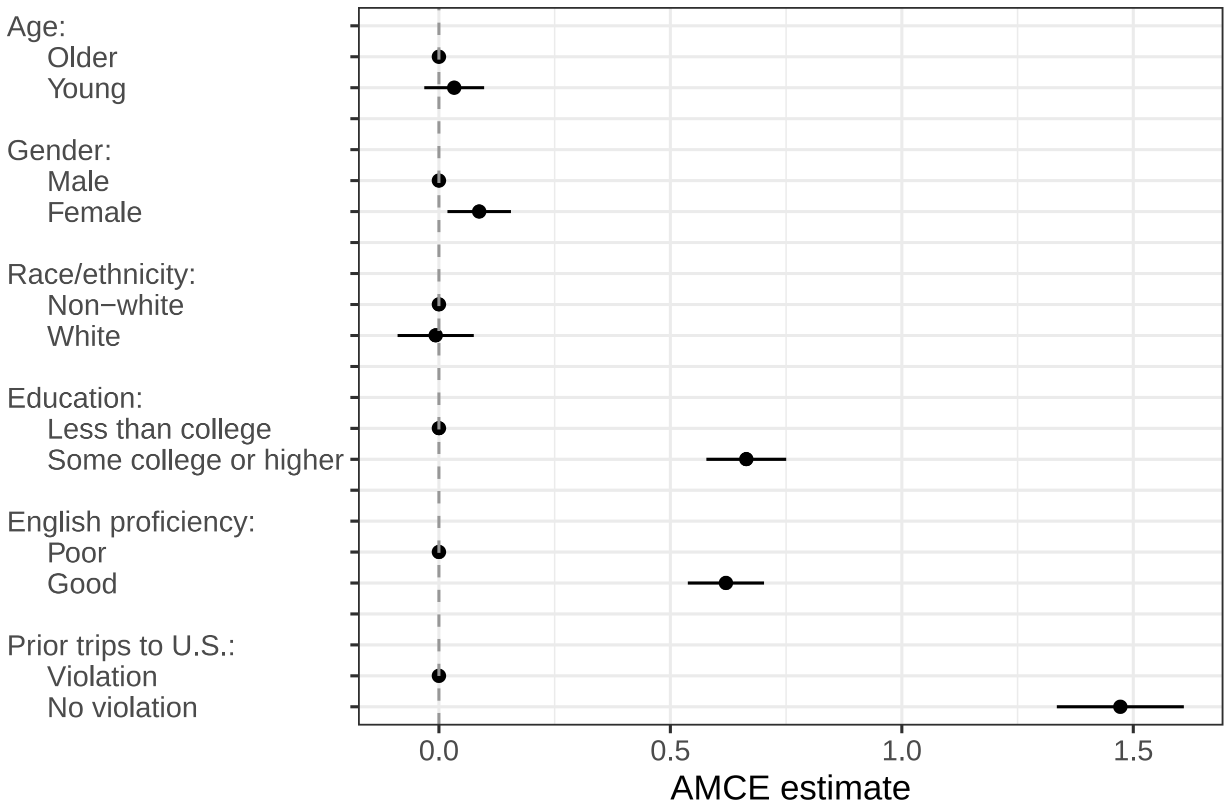


Figure 2. Effects of profile attributes on admission preference ratings

Successful replication is important because it demonstrates comparability between the standard conjoint design and the adjusted one. Adjustments necessary to feasibly estimate IMCEs involve simplifications, such as minimization of possible values per profile—at least in the analysis, if not in the task itself. However, even with this simplified design I have obtained the same substantive result: Americans prefer immigrants with

[7] As a robustness check, I obtain AMCE estimates without dichotomization of attribute values (Figure S1 in Supplementary Material). Overall, specific values for education perform similarly to when they are collapsed: college education, English proficiency, and no history of status violations all increase immigrants' admission favorability ratings. I also implement a preference stability test that shows no differences in attributes' effects between profiles presented to respondents early vs. late in the task (Figure S2 in Supplementary Material).

high-skilled occupations, good knowledge of English, and commitment to following immigration rules. Overall, a relatively simple conjoint experiment with only six attributes and minimal numbers of values per attribute successfully replicates a much more complicated study with detailed descriptions of profiles.

From the practical point, successful replication means that I can proceed with the next step of the analysis: estimating IMCEs. To do so, I obtain IMCE point estimates calculated according to Equation 7. IMCEs on all six preference dimensions are successfully estimated for 964 respondents. Due to the binary character of all analyzed attributes, IMCE estimates have straightforward interpretations. For instance, education attribute IMCE reflects direction and strength of respondent's preference for immigrants with at least some college education vis-a-vis those without college education.[8]

Figure 3 presents empirical univariate distributions of IMCE point estimates for education and race obtained using Gaussian kernel density function.[9] They reveal some interesting aspects of preference distributions. For instance, the modal IMCE of college education is zero—but, at the same time a relatively large share of respondents do prefer immigrants with at least some college to those without. Since almost nobody prefers immigrants without college degrees to college-educated ones, respondents with relatively strong preferences for highly educated immigrants contribute to the average positive effect. In other words, education IMCE distribution is asymmetric.[10]

Empirical density of IMCE point estimates for race, in turn, is mostly symmetric with both modal and mean values close to zero. However, the distribution is far from having no variance: respondents with relatively pronounced preferences for and against

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[8] See Table S2 in Supplementary Material for the precise interpretations of all estimated IMCEs.

[9] See Figure S3 in Supplementary Material for empirical densities of IMCEs for other attributes.

[10] See Table S3 in Supplementary Material for skewness statistics and the corresponding tests.

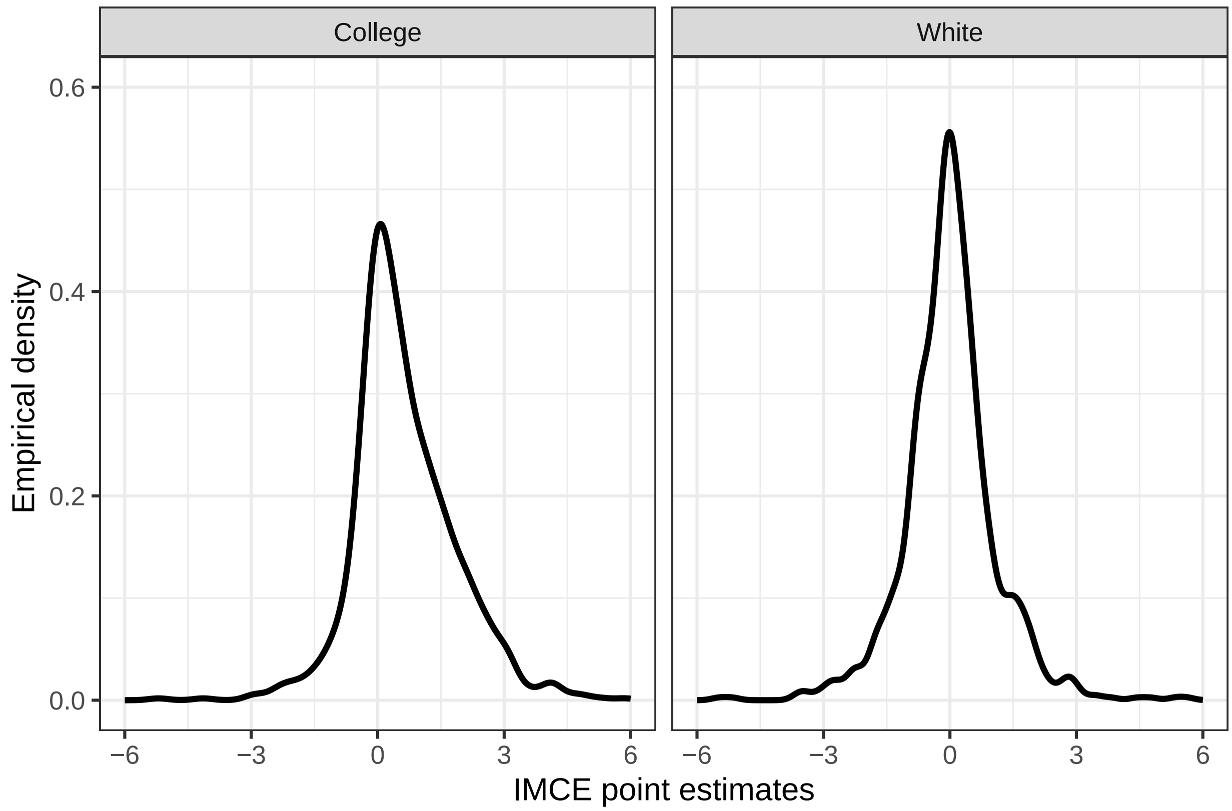

Figure 3. Empirical distributions of IMCE point estimates for education and race

whites as immigrants are present in the sample—even though ones without a strong preference for immigrant race are much more common.[11]

Since there exists essential variation in preferences estimated via IMCEs, I move to exploring how they co-vary. Correlations between different dimensions of preferences, estimated using IMCEs for the corresponding conjoint attributes, are presented in Table 2. Results suggest that preference dimensions are mostly independent from each other. At the same time, preferences with respect to some normative attributes do correlate—although magnitudes are relatively low. For instance, respondents who prefer English-proficient

[11] See Table S4 in Supplementary Material for the classifications of respondents' preferences on the basis of estimated IMCE 95% confidence intervals.

immigrants also express preferences for those with college education and no history of unauthorized presence in the United States.

Table 2. Preference correlations based on IMCE point estimates

	Young	Female	White	College	English	Legality
Young	1.00					
Female	.02	1.00				
White	.06	.03	1.00			
College	.04	.06	.01	1.00		
English	−.03	−.06	−.02	.12	1.00	
Legality	−.07	−.04	.05	−.05	.09	1.00

Finally, I turn to estimating the relationships between IMCEs and other individual-level variables of interest. For these analyses, I obtain the following sets of data, in addition to IMCE point estimates: (1) 100 plausible values for each IMCE drawn from the normal distribution according to Equation 10 and (2) 100 plausible values for each IMCE obtained using nonparametric bootstrap according to Equation 15. All bivariate relationships, therefore, are estimated with three sets of IMCE values: point estimates, imputed using the normality assumption, and imputed using nonparametric bootstrap. Point and variance estimates for analyses with imputed datasets are obtained using the guidelines for multiple imputations.

Figure 4 presents the bivariate relationships of IMCEs with ethnocentrism, education, and partisanship. These variables are used in the analysis as interval and rescaled to the 0–1 range for comparison purposes. The earlier investigation of the variation of immigration preferences across the American electorate has revealed the "hidden consensus" along all these covariates (Hainmueller and Hopkins 2015). According to my results, this finding—for the most part—seems to hold when IMCEs are used to estimate the relationships of interest. Neither education nor ethnocentrism are strongly or consistently associated with preferences for immigrant admission on any dimension. At the same time, a pronounced relationship emerges between preference for immigrants with no prior status violations and partisanship. Specifically, Republicans tend to prefer potential immigrants who do not break the rules (vs. those who do) to a greater extent than Democrats. This result might reflect the increased partisan divide over illegal/undocumented immigration over the last five years.

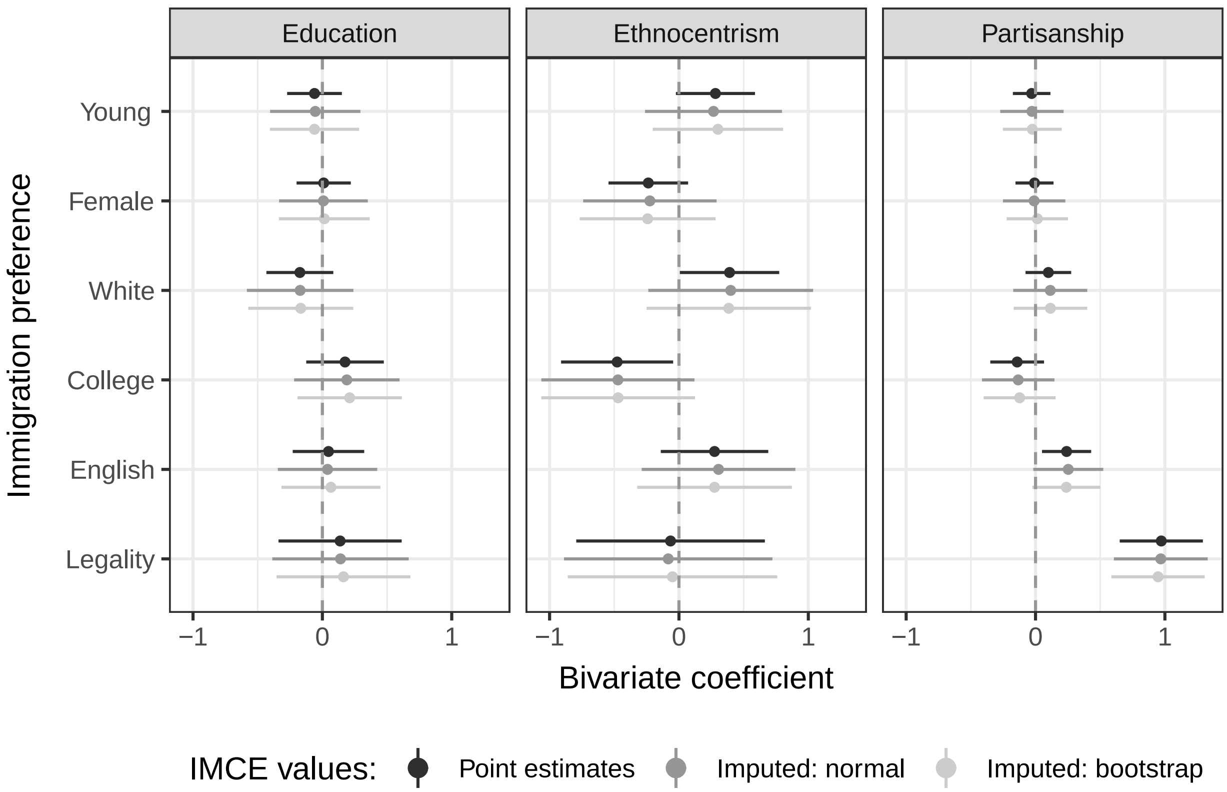

Figure 4. Bivariate relationships of IMCEs with education, ethnocentrism, and partisanship

Altogether, application of IMCEs from an immigration admission conjoint experiment allow making an important extension to the results reported previously. Specifically, respondents' preferences with respect to three attributes of potential immigrants—education, English proficiency, and previous status violations—are asymmetric. These distributions are positively skewed: non-trivial shares of respondents prefer immigrants with college degrees, good knowledge of English, and no history of unauthorized presence in the U.S. whereas almost no one does the opposite. At the same time, the corresponding IMCE distributions have well-pronounced modes located at zeros indicating no reliable effects. It suggests that respondents with clearly defined preferences on immigration are a minority—but their demands are pronounced enough to produce significant AMCEs. This finding does not fully conform to the interpretation that Americans' immigration preferences are broadly shared, although those who prefer well-educated and English-proficient immigrants do not have identifiable partisan profiles.

7 IMCE Estimation: A Brief Guide

There are several important steps that researchers need to consider when designing and analyzing conjoint experiments aimed at estimating IMCEs. First, feasible estimation of IMCEs requires a few important adjustments to the conjoint design: use of rating outcomes, minimal number of attribute values, and maximized number of rated profiles. Therefore, the decision on whether estimation of IMCEs is of interest should be made at the experiment design stage. When making this decision, potential limitations of the required design changes should be taken into account. The trade-offs involved are discussed in-depth in the next section of the paper.

Second, raw data exported from most survey platforms usually do not adhere to the format necessary to estimate IMCEs. Therefore, data may need to be reshaped whereby each conjoint profile rated by each respondent is stored in a separate row with one variable corresponding to the outcome (profile rating) and one for each attribute value. Importantly, unique respondent identifiers should be preserved in the reshaped data so that estimated IMCEs can be linked back to individual-level covariates. Sample script used to process data from the immigrant admission replication study run on Qualtrics is available as part of the replication materials.

Third, IMCEs should be estimated independently for each respondent and recorded in a separate dataset. This can be implemented using simple iterative commands, such as loops, available in all common statistical packages. Resulting IMCE estimates can be linked back to survey data using unique respondent identifiers. Sample script used to estimate and record IMCEs from the immigrant admission replication study is available as part of the replication materials. Separate scripts from the replication materials illustrate drawing probable values from IMCE sample distributions estimated using either normal approximation or non-parametric bootstrap.

Fourth, in some analyses—such as description of empirical distributions—IMCE point estimates can be used. However, uncertainty of numerical parameter estimates from many inferential analyses that employ IMCEs should account for uncertainty of IMCEs themselves. This can be done by employing multiple random draws from estimated sample distributions of IMCEs rather than point estimates. A straightforward method to use these draws in inferential analyses is by treating them as multiple imputations. Sample scripts used to estimate the relationships between IMCEs and respondent-level covariates in the immigrant admission study are available as part of the replication materials.

Fifth, even if IMCEs have been successfully estimated and used in the subsequent analyses of interest, implementation of some robustness checks is recommended. For instance, if conjoint attribute values are dichotomized at the analysis stage, it is necessary to check whether such dichotomization does not obscure any interesting value-specific effects. To run such a check, one can estimate AMCEs for all specific attribute values, rather than dichotomized ones. Additionally, estimation of IMCEs requires relatively large numbers of rated profiles per respondent. Therefore, it is important to test for the stability of measured preferences over time. This can be done by comparing estimated AMCEs in the first (earlier) and second (later) halves of conjoint scenarios.

8 Discussion of Design Requirements

Due to the recommended adjustments to the design of conjoint experiments, the proposed procedure involves important trade-offs—of which researchers should be aware. IMCE estimation relies on the OLS method with relatively small numbers of observations and, thus, conjoint tasks should use interval rating outcomes—especially, if the normality assumption is invoked to account for estimates' uncertainty. Therefore, estimation of IMCEs may be less compatible with conjoint designs that necessarily imply binary choices as outcomes due to their substantive research questions. At the same time, conjoint experiments generally allow including both rating and choice outcomes. This opportunity can be used by researchers to compare effects estimated using interval and binary dependent variables. However, inclusion of both rating and choice responses for each conjoint scenario increases overall length of the survey. In case of length limitations, maximizing the total number of rated profiles per respondent may be more important.

Additionally, the number of potential randomized values for each attribute should be minimized. This can be achieved in two ways: researchers can use relatively broad attribute values either at the design stage or at the analysis stage. Consider the immigrant admission example. Profiles of potential immigrants can be described as having low or high level of education in the task itself. Alternatively, profile descriptions can use specific education levels, such as "High school" or "4-year college." Then, these values can be collapsed into broader categories, such as "Less than college" vs. "Some college or higher," for the purpose of IMCE estimation. The latter option is preferable because it increases profiles' realism and limits potential differences in respondents' interpretations of less specific labels. Moreover, when a diverse set of attribute values is used in the conjoint task itself, it is still possible to estimate AMCEs for the specific attribute values—as a form of robustness check.

Finally, the number of rated profiles per respondent should be maximized, ideally close to 30 profiles that is the currently suggested upper boundary (Bansak et al. 2018). The absolute minimum number of profiles needed to obtain reliable IMCE estimates, and whether such number exists as a somewhat firm boundary, should be addressed in future research. As of now, a conservative recommendation would be to use no less than 20 rated profiles per respondent. It means that the conjoint task gets relatively long—possibly, limiting opportunities to include other items in the same survey for either time or cost considerations.

9 Concluding Remarks

Flexibility and power of conjoint experiments have gained them popularity among political researchers over a relatively short period of time. Currently, conjoint analysis is employed to measure average preferences within certain populations by exploring respondents' behaviors in multidimensional choices. In this paper, I move the methodological literature one step further by showing that estimates of individual-level preferences can be obtained from conjoint experiments and, then, used in consequent analyses. These estimates, that I call individual marginal component effects (IMCEs), can be estimated without making any assumptions on top of those necessary for the standard conjoint analysis. However, there are several practical recommendations for the conjoint design to ensure that IMCEs can be feasibly estimated. They include reliance on interval rating outcomes, minimizing the number of randomized values per attribute, and maximizing the number of rated profiles per respondent. Also, since the main reason of estimating IMCEs is to use them in subsequent analyses, adjustment for estimates' uncertainty is necessary. This can be achieved by drawing multiple plausible values of IMCEs from their sampling distributions that, in turn, can be estimated using either the normality assumption or nonparametric bootstrap. Importantly, IMCE estimates can be obtained and second-step analyses can be implemented in commonly used statistical software, such as R and Stata. Sample scripts that illustrate data processing and reported analyses are made available with this paper as replication materials.

I demonstrate how the proposed procedure can be used in practice by partially replicating the conjoint study of immigrant admission to the U.S.—with design adjusted to feasibly estimate IMCEs. I employ IMCEs estimated from this conjoint experiment in consequent analyses to explore distributions of preferences, correlations between preference dimensions, and relationships of preferences to other respondent-level variables. I find that preference distributions are often asymmetric, preferences intercorrelations are generally low, and relative preferences for immigrants without status violation history are greater among Republicans. Overall, application of IMCEs allows extending previous findings by revealing skewed preferences: demand for educated, English-proficient, and rule-abiding immigrants is not universal as many respondents are effectively indifferent to these attributes.

Possibly, the key benefit of the proposed strategy is the possibility of turning estimated IMCEs into individual-level measures of preferences. Carrying out such analyses lies beyond of the scope of this contribution but some potential future applications are discussed below. Consider, for instance, the conjoint analysis of public preferences with respect to the U.S. Supreme Court nominees (Sen 2017). IMCE estimation can allow investigating how these preferences translate into support for political candidates and relevant political attitudes. How does respondents' reliance on specific dimensions in evaluating potential justices relate to their trust into the Supreme Court compared to other political institutions? Do those who prioritize nominees' partisanship over credentials tend to vote for more radical candidates during the primary season? IMCEs provide researchers with a tool to answer questions like these.

Estimating and using IMCEs from conjoint experiments can also be useful for studying political phenomena other than preferences. An example is multidimensional stereotypes about politically relevant social categories that researchers have recently started to explore with conjoint analysis (Goggin, Henderson, and Theodoridis 2019; Flores and Schachter 2018). IMCEs can be applied to study political implications of such stereotypes. For instance, an influential argument connects opposition to government welfare programs in the U.S. public with stereotypes of welfare recipients as African Americans (Gilens 1999). Conjoint experiments can be used to assess prominence of race in stereotypes about welfare recipients and IMCEs can be employed to estimate the impact of race, relative to other stereotype dimensions, on welfare policy opinions. Since respondents are often hesitant to reveal sensitive stereotypes in standard survey self-reports, application of conjoint experiments as an individual-level measurement tool might be particularly useful. Altogether, researchers' ability to obtain estimates for individual-level marginal component effects and use them in consequent analyses can make conjoint experiments an even more potent and popular tool in political methodology.

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References

Bansak, Kirk, Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto. 2018. "The Number of Choice Tasks and Survey Satisficing in Conjoint Experiments." *Political Analysis* 26 (1): 112–19.

Bansak, Kirk, Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto. 2019. "Beyond the Breaking Point? Survey Satisficing in Conjoint Experiments." *Political Science Research and Methods.* Published online. https://doi.org/10.1017/psrm.2019.13.

Bizumic, Boris, and John Duckitt. 2012. "What Is and Is Not Ethnocentrism? A Conceptual Analysis and Political Implications." *Political Psychology* 33 (6): 887–909.

Citrin, Jack, Donald P. Green, Christopher Muste, and Cara Wong. 1997. "Public Opinion Toward Immigration Reform: The Role of Economic Motivations." *Journal of Politics* 59 (3): 858–81.

Coppock, Alexander, and Oliver A. McClellan. 2019. "Validating the Demographic, Political, Psychological, and Experimental Results Obtained from a New Source of Online Survey Respondents." *Research and Politics* 6 (1). https://doi.org/10.1177/2053168018822174.

Davison, Anthony C., and David V. Hinkley. 1997. *Bootstrap Methods and their Application.* Cambridge: Cambridge University Press.

Flores, Rene D., and Ariela Schachter. 2018. "Who Are the 'Illegals'? The Social Construction of Illegality in the United States." *American Sociological Review* 83 (5): 839–68.

Gilens, Martin. 1999. *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy.* Chicago: University of Chicago Press.

Goggin, Stephen N., John A. Henderson, and Alexander G. Theodoridis. 2019. "What Goes with Red and Blue? Mapping Partisan and Ideological Associations in the Minds of Voters." *Political Behavior*. Published online. doi:10.1007/s11109-018-09525-6.

Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto. 2015. "Validating Vignette and Conjoint Survey Experiments against Real-World Behavior." *Proceedings of the National Academy of Sciences of the United States of America* 112 (8): 2395–2400.

Hainmueller, Jens, and Daniel J. Hopkins. 2015. "The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants." *American Journal of Political Science* 59 (3): 529–48.

Hainmueller, Jens, Daniel J. Hopkins, and Teppei Yamamoto. 2014. "Causal Inference in Conjoint Analysis: Understanding Multidimensional Choices via Stated Preference Experiments." *Political Analysis* 22 (1): 1–30.

Hartman, Todd K., Benjamin J. Newman, and C. Scott Bell. 2014. "Decoding Prejudice Toward Hispanics: Group Cues and Public Reactions to Threatening Immigrant Behavior." *Political Behavior* 36 (1): 143–66.

Holland, Paul W. 1986. "Statistics and Causal Inference." *Journal of the American Statistical Association* 81 (396): 945–60.

Hopkins, Daniel J. 2015. "The Upside of Accents: Language, Inter-group Difference, and Attitudes toward Immigration." *British Journal of Political Science* 45 (3): 531–57.

Horiuchi, Yusaku, Daniel M. Smith, and Teppei Yamamoto. 2018. "Measuring Voters' Multidimensional Policy Preferences with Conjoint Analysis: Application to Japan's 2014 Election." *Political Analysis* 26 (2): 190–209.

Imai, Kosuke, Bethany Park, and Kenneth F. Greene. 2015. "Using the Predicted Responses from List Experiments as Explanatory Variables in Regression Models." *Political Analysis* 23 (2): 180–96.

Imai, Kosuke, and Aaron Strauss. 2011. "Estimation of Heterogeneous Treatment Effects from Randomized Experiments, with Application to the Optimal Planning of the Get-Out-the-Vote Campaign." *Political Analysis* 19 (1): 1–19.

Jann, Ben. 2007. "Making Regression Tables Simplified." *Stata Journal* 7 (2): 227–44.

Jenke, Libby, Kirk Bansak, Jens Hainmueller, and Dominik Hangartner. 2020. "Using Eye-Tracking to Understand Decision-Making in Conjoint Experiments." *Political Analysis*. Published online. https://doi.org/10.1017/psrm.2019.13.

Leeper, Thomas J., Sara B. Hobolt, and James Tilley. 2020. "Measuring Subgroup Preferences in Conjoint Experiments." *Political Analysis* 28 (2): 207–21.

Newman, Benjamin J., Todd K. Hartman, and Charles S. Taber. 2012. "Foreign Language Exposure, Cultural Threat, and Opposition to Immigration." *Political Psychology* 33 (5): 635–57.

Newman, Benjamin J., and Neil Malhotra. 2018. "Economic Reasoning with a Racial Hue: Is the Immigration Consensus Purely Race Neutral?" *Journal of Politics* 81 (1): 153–66.

R Core Team. 2019. *R: A Language and Environment for Statistical Computing.* Vienna: R Foundation for Statistical Computing.

Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys.* New York: Wiley.

Sen, Maya. 2017. "How Political Signals Affect Public Support for Judicial Nominations: Evidence from a Conjoint Experiment." *Political Research Quarterly* 70 (2): 374–93.

StataCorp. 2015. *Stata Statistical Software*. College Station, TX: StataCorp LLC.

Strezhnev, Anton, Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto. 2014. "Conjoint Survey Design Tool: Software Manual." https://scholar.harvard.edu/files/astrezhnev/files/conjoint_sdt_manual.pdf.

Valentino, Nicholas A., Ted Brader, and Ashley E. Jardina. 2013. "Immigration Opposition Among U.S. Whites: General Ethnocentrism or Media Priming of Attitudes About Latinos?" *Political Psychology* 34 (2): 149–66.

Valentino, Nicholas A., Stuart N. Soroka, Shanto Iyengar, Toril Aalberg, Raymond Duch, Marta Fraile, Kyu S. Hahn, Kasper M. Hansen, Allison Harell, Marc Helbling, Simon D. Jackman, and Tetsuro Kobayashi. 2019. "Economic and Cultural Drivers of Immigrant Support Worldwide." *British Journal of Political Science* 49 (4): 1201–26.

Ward, Dalston G. 2019. "Public Attitudes toward Young Immigrant Men." *American Political Science Review* 113 (1): 264–69.

Wickham, Hadley. 2016. *ggplot2: Elegant Graphics for Data Analysis*. 2nd ed. New York: Springer.

Wright, Matthew, Morris Levy, and Jack Citrin. 2016. "Public Attitudes Toward Immigration Policy Across the Legal/Illegal Divide: The Role of Categorical and Attribute-Based Decision-Making." *Political Behavior* 38 (1): 229–53.

Estimating and Using Individual-Level Marginal Component Effects from Conjoint Experiments

Supplementary Material

Kirill Zhirkov

Table S1. Full ethnocentrism battery

(Preamble) Below are items that relate to different cultures and ethnic groups. Work quickly and record your first reaction to each item. There are no right or wrong answers. Please indicate the degree to which you disagree or agree with each item.
(1) In most cases, I like people from my culture more than I like others.
(2) I don’t think I have any particular preference for my own cultural or ethnic group over others. (reversed)
(3) The world would be a much better place if all other cultures and ethnic groups modelled themselves on my culture.
(4) The values, way of life, and customs of most other cultures are probably just as good as those of my own. (reversed)
(5) Our culture would be much better off if we could keep people from different cultures out.
(6) I like the idea of a society in which people from completely different cultures, ethnic groups, and backgrounds mix together freely. (reversed)
(7) We need to do what's best for our own people, and stop worrying so much about what the effect might be on other peoples.
(8) We should always show consideration for the welfare of people from other cultural or ethnic groups even if, by doing this, we may lose some advantage over them. (reversed)

Note. Respondents were randomly presented with four statements, one from each following pair: (1) and (2), (3) and (4), (5) and (6), (7) and (8). Answers were given on a 7-point Likert-type scale from 1 = *Strongly disagree* to 7 = *Strongly agree*

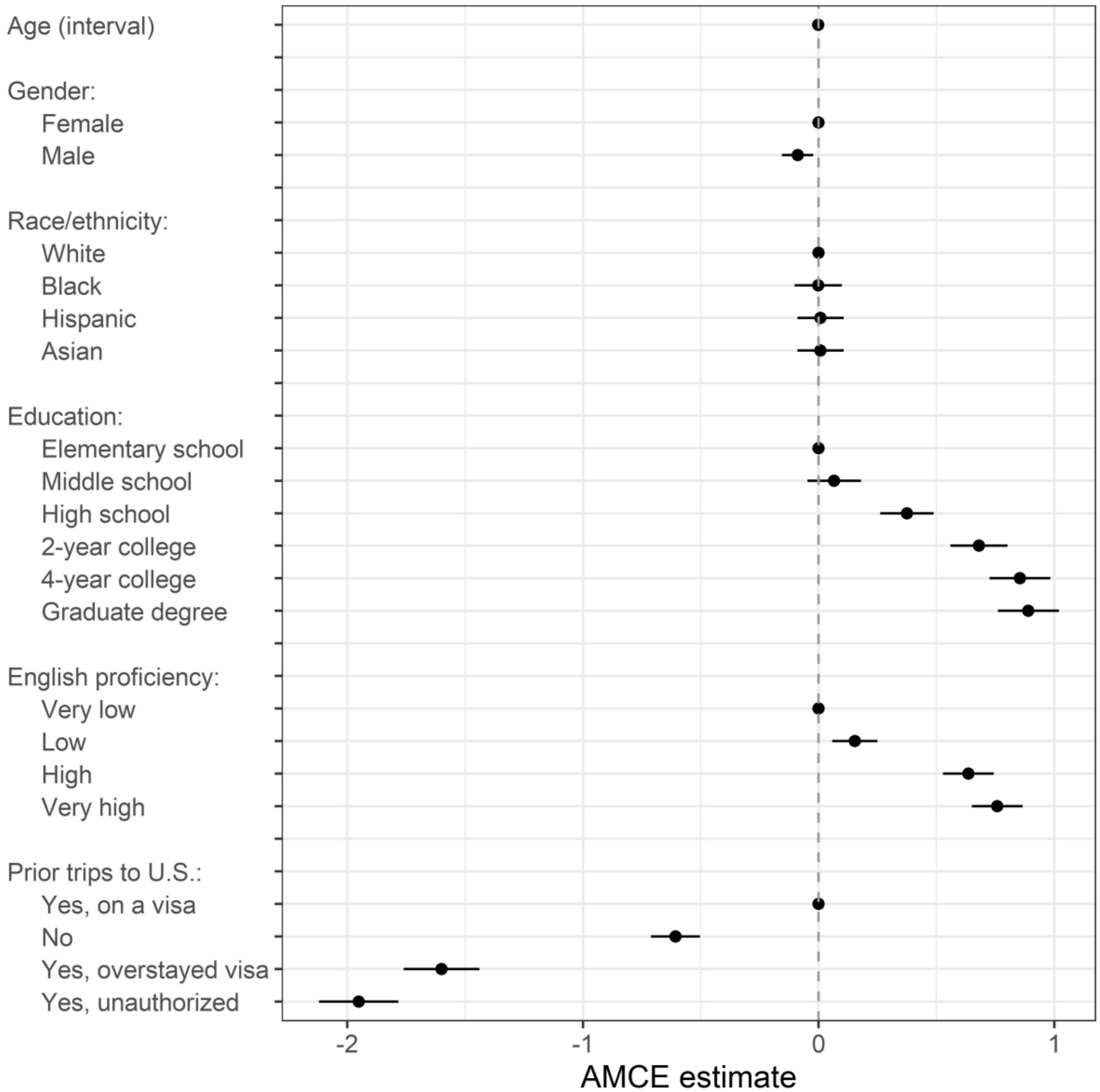

Figure S1. Effects of profile attributes on admission preference ratings: no dichotomization

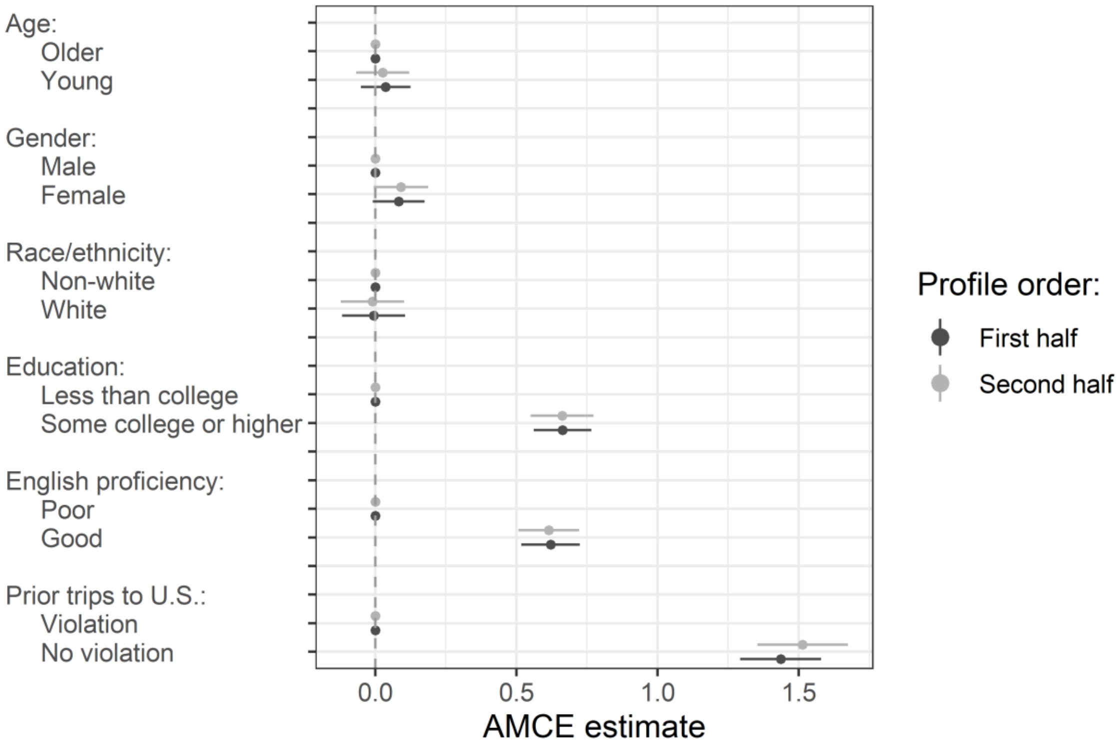

Figure S2. Effects of profile attributes on admission preference ratings: early vs. late profiles

Table S2. IMCE interpretations

IMCE	Interpretation
Young	Relative preference for young immigrants; estimated difference in admission ratings between immigrants aged 39 years or younger vs. immigrants aged 40 years or older
Female	Relative preference for female immigrants; estimated difference in admission ratings between female immigrants vs. male immigrants
White	Relative preference for white immigrants; estimated difference in admission ratings between white immigrants vs. non-white immigrants
College	Relative preference for college-educated immigrants; estimated difference in admission ratings between immigrants with some college education vs. immigrants without college education
English	Relative preference for English-proficient immigrants; estimated difference in admission ratings between immigrants with good English vs. immigrants with poor English
Legality	Relative preference for immigrants without history of status violations; estimated difference in admission ratings between immigrants with no status violations vs. immigrants with status violations

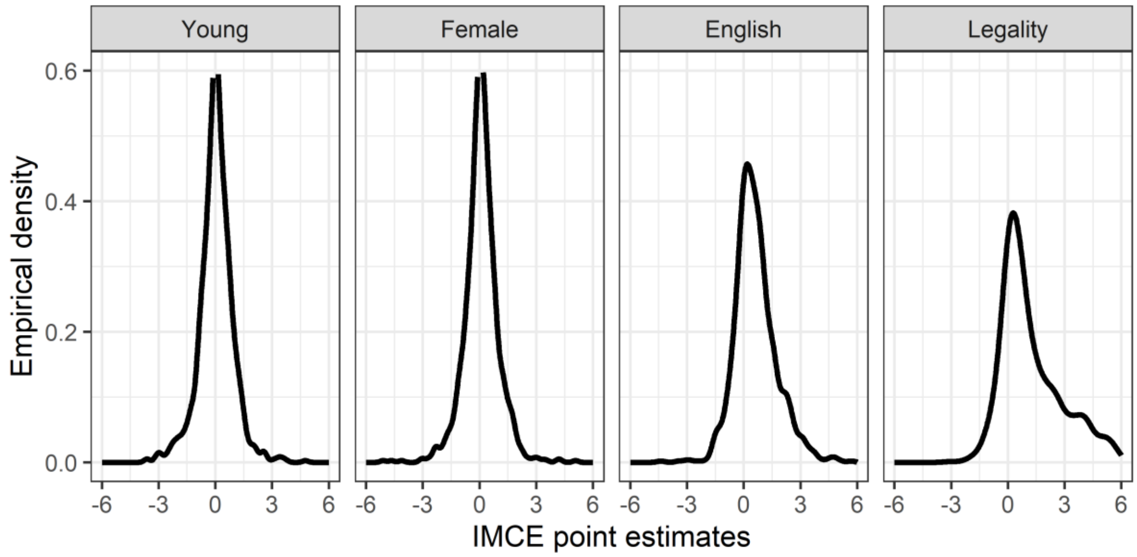

Figure S3. Empirical distributions of IMCE point estimates for age, gender, English proficiency, and prior trips to U.S.

Table S3. IMCE distribution skewness statistics by attribute

	Skewness	*p*-value
Young	-0.01	.926
Female	-0.07	.373
White	-0.15	.060
College	0.42	<.001
English	1.25	<.001
Legality	1.42	<.001

Note. *p*-values for the H_0 that skewness is zero (D’Agostino, Belanger, and D’Agostino 1990)

Table S4. Respondents' preferences by IMCE 95% confidence intervals

	Count	Percentage
Young		
Negative	33	3.4
Indifferent	894	92.7
Positive	37	3.8
Female		
Negative	30	3.1
Indifferent	907	94.1
Positive	27	2.8
White		
Negative	35	3.6
Indifferent	885	91.8
Positive	44	4.6
College		
Negative	16	1.7
Indifferent	721	74.8
Positive	227	23.6
English		
Negative	13	1.4
Indifferent	751	77.9
Positive	200	20.8
Legality		
Negative	8	0.8
Indifferent	558	57.9
Positive	398	41.3

References

D'Agostino, Ralph B., Albert Belanger, and Ralph B. D'Agostino, Jr. 1990. "A Suggestion for Using Powerful and Informative Tests of Normality." *American Statistician* 44 (4): 316--21.