Supplemental Information: The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants

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Abstract

This appendix provides additional analyses referenced in the main paper.

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I. Appendix A: Data Description

A. *Current Population Survey Data*

Table A.1 shows data from the Current Population Surveys to estimate the share of immigrants from each of our ten national-origin groups with some college education or a bachelor's degree. It confirms that the population of immigrants to the U.S. is large and diverse, and that even seemingly atypical profiles in our conjoint likely correspond to significant numbers of actual immigrants.

	Number	% of All Immigrants	% with Some Coll.	% with BA
Mexico	26,693	0.243	0.170	0.061
Somalia	450	0.004	0.262	0.076
Iraq	426	0.004	0.498	0.270
Sudan	216	0.002	0.532	0.278
China	3,875	0.035	0.558	0.427
Poland	1,077	0.010	0.564	0.341
Germany	3,015	0.027	0.667	0.369
Philippines	5,577	0.051	0.709	0.443
France	531	0.005	0.727	0.463
India	4,806	0.044	0.840	0.760

Table A.1: This table reports estimates obtained from the Current Population Surveys from September 2011 through March 2012. In total, these surveys had 1,060,286 respondents, 109,763 of whom were immigrants who provided their levels of education.

B. *Survey Administration*

The Knowledge Networks (KN) panel covers both the online and offline U.S. populations aged 18 years and older. Panel members are randomly selected using either random-digit dialing or address-based sampling. A detailed report about KN's recruitment methodology and survey administration is available at

`http://www.knowledgenetworks.com/ganp/docs/knowledge-networks-methodology.pdf`.

The first wave of our survey contained 1,714 completed interviews. After a three-week wash-out period, we re-interviewed respondents in a second survey containing the conjoint experiment described in the manuscript. The second wave yielded 1,407 completed interviews, so attrition within the panel was limited to 18% of the original respondents. The calculation of response rates using online panels is complicated by the fact that panelists are recruited and have the potential to leave the panel at different times. See Callegaro and DiSogra (2008) for an extended description of how to compute response metrics for online panels. Here, we note that of those originally invited to join the KN panel, 9.8% did so. 42.2% of these panelists were retained by the KN panel at the time of our survey. 2,499 KN panelists were invited to complete the first wave of our panel, for an initial panel recruitment rate of 68.6%. Of the 1,714 respondents who completed first-wave interviews, 1,407 completed the second wave, yielding a retention rate within our study of 82.1%. The cumulative response rate as defined by AAPOR is 2.8% for the first wave and 2.3% for the second. There is no evidence that attrition was worse among relevant demographic or attitudinal groups, as Table A.2 illustrates using t-tests.

Note that for the main tests the unit of analysis is the immigrant profile. Each profile is rated either as preferred or not preferred for admission (or supported for admission if the other outcome question is used; see below). There are 1,407 unique respondents that completed the second wave, each of whom was asked to rate five pairings with two immigrant profiles each bringing the total expected sample size to $1407 \cdot 5 \cdot 2 = 14,070$. Due to the fact that three respondents did not complete all the ratings the total number of rated profiles is slightly below that at 14,018 for the *Immigrant Preferred* and 14,060 for the *Immigrant Supported* measure.

For the analysis, we use post-stratification weights to adjust the final respondent data for common sources of survey error (non-response, coverage error, etc.). The weights adjust the sample to the demographic and geographic distributions from the March Supplement of the 2010 Current Population Survey (CPS). The results are substantively similar for both outcomes (*Immigrant Preferred* and *Immigrant Supported*) without using these weights.

C. Survey Wording and Questions

- *Introduction*: "This study considers immigration and who is permitted to come to the United States to live. For the next few minutes, we are going to ask you to act as if you were an immigration official. We will provide you with several pieces of information

Table A.2: T-tests on wave 1 and 2 respondent characteristics to examine attrition.

	Mean, 1st Wave	Mean 2nd Wave	P-Value
Male	0.498	0.511	0.478
Some College or More	0.564	0.576	0.472
High Income	0.548	0.568	0.262
Hispanic	0.108	0.108	0.993
Black	0.103	0.095	0.415
White	0.732	0.742	0.512
Republican	0.447	0.449	0.925
Independent	0.027	0.024	0.637
Democrat	0.521	0.525	0.845
Conservative	0.366	0.370	0.854
Liberal	0.267	0.269	0.864
ZIP % Foreign Born	0.086	0.085	0.778
Increase Immigration	2.188	2.187	0.992
Ethnocentrism	17.878	17.431	0.651
Self-Monitoring	6.803	6.746	0.474

Note: This table presents the means for key variables for all 1,714 respondents to wave one (column 1) as well as for the subset of 1,407 respondents who completed wave 2 (column 2). The third column presents the p-value from a two-sided t-test comparing the means in columns 1 and 2. Support for increasing immigration varies from 1 ("decrease a lot") to 5 ("increase a lot"). Ethnocentrism varies between -100 and 100, while self-monitoring varies between 3 and 15.

about people who might apply to move to the United States. For each pair of people, please indicate which of the two immigrants you would personally prefer to see admitted to the United States. This exercise is purely hypothetical. Please remember that the United States receives many more applications for admission than it can accept. Even if you aren't entirely sure, please indicate which of the two you prefer."

- *Immigrant Preferred*: "If you had to choose between them, which of these two immigrants should be given priority to come to the United States to live?"
- *Immigrant Supported*: "[o]n a scale from 1 to 7, where 1 indicates that the United States should absolutely not admit the immigrant and 7 indicates that the United States should definitely admit the immigrant, how would you rate Immigrant 1?"[1]

[1] This second outcome variable is coded as 1 for immigrant profiles that the respondent rates as above the midpoint of the seven-point scale, meaning that the respondent supports admission of this immigrant. In

- *Ethnocentrism*: "Next, we would like to know whether you have warm or cold feelings toward a number of well-known groups. We'll tell you a group and ask you to rate it from zero (0) to one hundred (100). The higher the number, the warmer or more favorably you feel toward it. If you have very warm or positive feelings, you might give it 100. If you have very cold or negative feelings, give it a zero. If you feel neither warm nor cold toward it, give it a 50. You can use all the numbers from zero to 100."

  The groups, in randomized order are: Latino or Hispanic Americans, Immigrants, Asian Americans, Whites, Blacks.

- *Self Monitoring*: Following Berinsky and Lavine (2011), we use three items from the self-monitoring scale (Snyder; 1974). The items are:

  - "When you're with other people, how often do you put on a show to impress or entertain them?" Response categories: Always, Most of the time, About half the time, Once in a while, Never.
  - "How good or bad of an actor would you be?" Response categories: Excellent, Good, Fair, Poor, Very poor.
  - "When you are in a group of people, how often are you the center of attention?" Response categories: Always, Most of the time, About half the time, Once in a while, Never.

  We randomized both the order of the questions and also the polarity of the response options. The three items are then aggregated into the self-monitoring index. The Cronbach's alpha for the items is 0.69.

- *Increase Immigration*: "Do you think the number of immigrants to America nowadays should be increased a lot, increased a little, remain the same as it is, reduced a little, or reduced a lot?" Response options: Be increased a lot, Be increased a little, Remain the same as it is, Be reduced a little, Be reduced a lot.

separate robustness checks, we also use the full seven-point ratings and find substantively similar results.

II. Appendix B: Additional Results

A. Benchmark Regression Model

Here we report the full regression results for the benchmark regression used to compute the average marginal component effects (AMCEs) visualized in the manuscript's Figure 2. The dependent variable is the binary variable *Immigrant Preferred*, which takes the value of one if the immigrant profile is preferred by the respondent and zero if not. This outcome is regressed on sets of indicator variables that measure the levels of each immigrant attribute (omitting one reference category as the baseline level) and the full set of pairwise interactions for the attributes that are linked through our restrictions on the randomization (eduction and occupation; origin and application reason).

As explained in Hainmueller et al. (2014), the AMCEs for these linked attributes need to be estimated as the weighted average of the effect of a specific attribute averaged over the valid strata of the other linked attribute. For example, since education and occupation are linked attributes, we compute the effect of going from a "Janitor" to a "Waiter" in each valid education stratum and then average across these education strata to arrive at the AMCE. The valid education strata are those education levels that are allowed with both "Janitor" and "Waiter", so in this case all education strata are valid because these occupations are allowed with all education levels. In contrast, because "Doctor" is restricted to have high eduction levels, the effect of going from "Janitor" and "Doctor" is defined and averaged over the high education levels only.

Attribute	Coef	SE
male	-0.024*	(0.010)
4th grade	0.106*	(0.049)
8th grade	0.193*	(0.047)
high school	0.116*	(0.052)
two-year college	0.183*	(0.054)
college degree	0.125*	(0.052)
graduate degree	0.204*	(0.055)
waiter	0.007	(0.047)
child care provider	0.077	(0.049)
gardener	0.013	(0.046)
financial analyst	0.089	(0.065)
construction worker	0.087	(0.047)
teacher	0.146*	(0.048)
computer programmer	0.062	(0.061)
nurse	0.144*	(0.048)
research scientist	0.085	(0.066)
doctor	0.171*	(0.061)
4th grade × waiter	-0.032	(0.072)
4th grade × child care provider	-0.049	(0.072)
4th grade × gardener	-0.026	(0.066)
4th grade × construction worker	-0.053	(0.070)
4th grade × teacher	-0.158*	(0.069)
4th grade × nurse	-0.086	(0.070)
8th grade × waiter	-0.077	(0.064)
8th grade × child care provider	-0.223*	(0.068)
8th grade × gardener	-0.091	(0.068)
8th grade × construction worker	-0.154*	(0.070)
8th grade × teacher	-0.203*	(0.071)
8th grade × nurse	-0.199*	(0.067)
high school × waiter	0.045	(0.073)
high school × child care provider	-0.039	(0.074)
high school × gardener	0.004	(0.071)
high school × construction worker	0.050	(0.071)
high school × teacher	-0.064	(0.074)
high school × nurse	-0.005	(0.073)
two-year college × waiter	-0.015	(0.078)
two-year college × child care provider	-0.078	(0.073)
two-year college × gardener	0.025	(0.080)
two-year college × financial analyst	-0.058	(0.090)
two-year college × construction worker	-0.066	(0.074)
two-year college × teacher	-0.060	(0.078)
two-year college × computer programmer	0.038	(0.086)
two-year college × nurse	-0.074	(0.075)
two-year college × research scientist	0.044	(0.088)
two-year college × doctor	-0.023	(0.086)
college degree × waiter	0.124	(0.074)
college degree × child care provider	0.122	(0.076)
college degree × gardener	0.100	(0.074)
college degree × financial analyst	0.028	(0.091)
college degree × construction worker	0.063	(0.074)
college degree × teacher	0.042	(0.076)
college degree × computer programmer	0.070	(0.089)
college degree × nurse	0.045	(0.078)
college degree × research scientist	0.134	(0.086)
college degree × doctor	0.065	(0.083)
graduate degree × waiter	-0.014	(0.078)
graduate degree × child care provider	-0.090	(0.077)
graduate degree × gardener	0.065	(0.077)
graduate degree × construction worker	-0.079	(0.080)
graduate degree × teacher	-0.066	(0.076)
graduate degree × nurse	-0.065	(0.074)
broken English	-0.064*	(0.014)
tried English but unable	-0.130*	(0.014)
used interpreter	-0.162*	(0.014)
Germany	0.048	(0.030)
France	0.038	(0.031)
Mexico	0.002	(0.031)
Philippines	0.051	(0.031)
Poland	0.035	(0.031)
China	-0.034	(0.037)
Sudan	-0.038	(0.036)
Somalia	-0.071*	(0.036)
Iraq	-0.117*	(0.034)
seek better job	-0.036	(0.032)
escape persecution	0.055	(0.038)
Germany × seek better job	-0.017	(0.045)
France × seek better job	-0.020	(0.044)
Mexico × seek better job	0.037	(0.046)
Philippines × seek better job	-0.036	(0.046)
Poland × seek better job	-0.033	(0.047)
China × seek better job	0.046	(0.049)
China × escape persecution	0.001	(0.055)
Sudan × seek better job	0.024	(0.051)
Sudan × escape persecution	0.010	(0.053)
Somalia × seek better job	0.075	(0.049)
Somalia × escape persecution	0.004	(0.053)
Iraq × seek better job	0.022	(0.049)
1-2 years job experience	0.064*	(0.014)
3-5 years job experience	0.100*	(0.014)
+5 years job experience	0.123*	(0.014)
contract with employer	0.118*	(0.015)
interviews with employer	0.020	(0.015)
no plans to look for work	-0.151*	(0.015)
once as tourist	0.074*	(0.016)
many times as tourist	0.057*	(0.016)
six months with family	0.085*	(0.016)
once w/o authorization	-0.108*	(0.016)
Constant	0.343*	(0.043)
Observations	14,018	

Table B.1: This table reports regression coefficients (column 2) and robust standard errors clustered by respondent (column 3) for the benchmark regression used to compute the average marginal component effects visualized in Figure 2 in the manuscript. $* \ p < 0.05$.

B. Other Moderators

The following section presents results when we replicate the baseline model for different subgroups of respondents, including subgroups differentiated by the percentage of immigrant workers in the respondent's industry (Figure B.1)[2] as well as the respondent's household income (Figure B.2),[3] fiscal exposure to immigration (Figure B.3),[4] ZIP-code demographics (Figure B.4), racial/ethnic background (Figure B.5), Hispanic ethnicity (Figure B.6), ideology (Figure B.7), immigration attitudes (Figure B.8), gender (Figure B.9), and age (Figure B.10). The key finding here is that the estimates for the effects of the immigrant attributes on the probability of being preferred for admission are similar across these subsets of respondents. That is, the AMCEs are similar regardless of whether we consider rich or poor respondents, old or young respondents, or many other subgroups.

The main manuscript presents results when dividing respondents based on their levels of ethnocentrism (Figure 5). The median value in the low-ethnocentrism group is about 0, indicating that these respondents rated the out-groups just as favorably as their own group. The median value in the high-ethnocentrism group is 39, indicating that these respondents rated the out-groups much less favorably than their own group. Our primary measure of ethnocentrism is very highly correlated with a separate measure that considers only the difference between in-group affect and affect toward Hispanics, with a correlation of 0.92. Also, for our analyses of ethnocentrism alone, we exclude respondents of Hispanic panethnicity since Hispanics are a heavily immigrant group likely to think about immigrants in distinctive ways. KN does not ask about Asian American panethnicity, but we exclude respondents who indicate "other" from that particular analysis for similar reasons.

Our handling of the demographics of the ZIP code requires additional explanation. Local demographics are another moderator consistent with the claim that immigration attitudes are

[2]We coded each self-reported occupation using the O-Net 2010 Occupational Listings (available online at: `http://www.onetcenter.org/taxonomy/2010/list.html` [accessed June 6, 2012]). Following Hainmueller et al. (2011), we used the March 2010 Supplement to the Current Population Survey to estimate the share of foreign-born workers by industry using 3-digit NAICS codes.

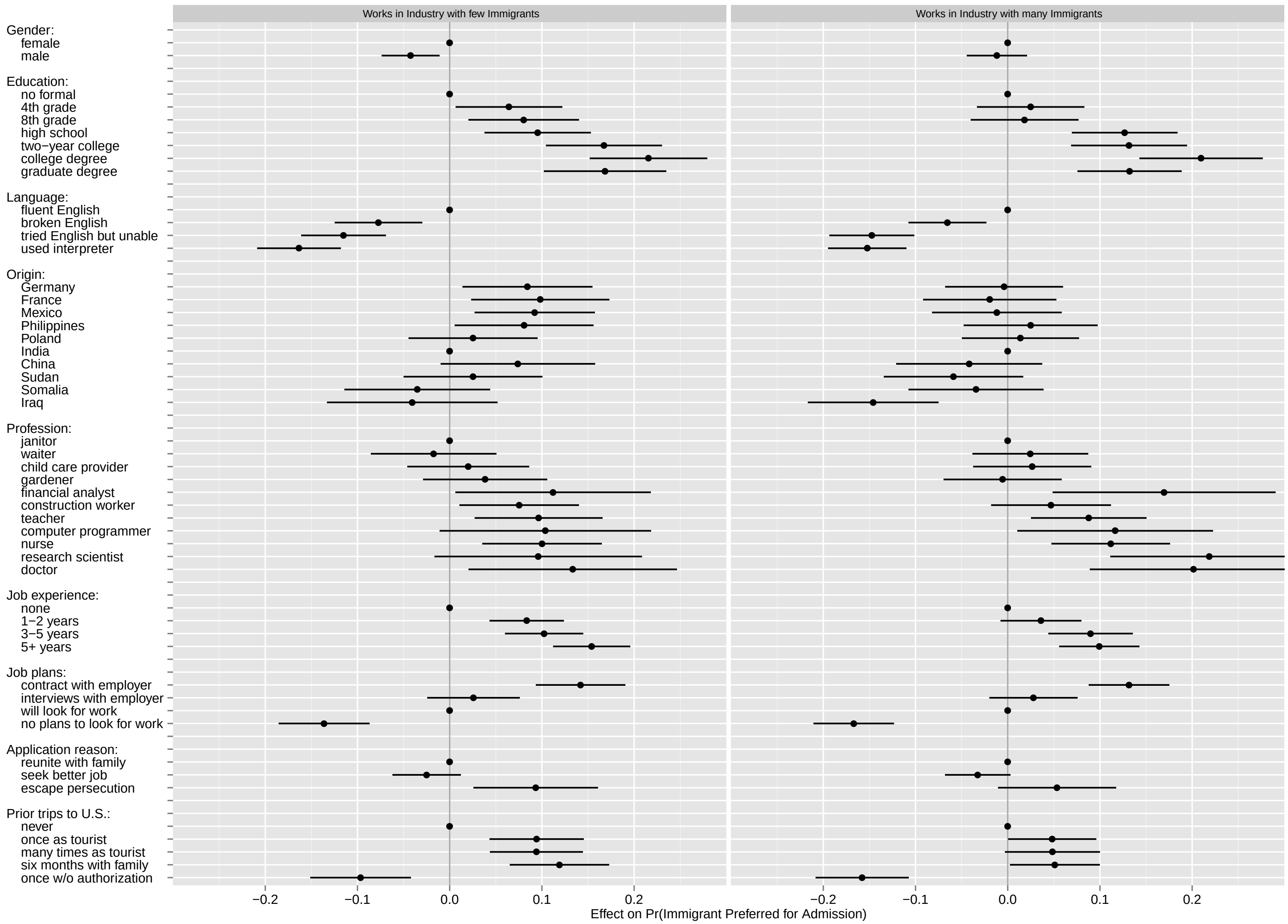
[3]High-income respondents are those whose households earn more than $50,000.

[4]We code 29.4% of the respondents as having high fiscal exposure based on the ratio of immigrant households receiving cash forms of public assistance to the total number of native households in their state. See Hanson et al. (2007) and Hainmueller and Hiscox (2010) for details of this measure, called Fiscal Exposure II. It codes the following states as high fiscal exposure: MA, RI, NY, NJ, FL, WA, CA, and HI.

to an important extent attitudes toward racial or ethnic out-groups. It is plausible that how our respondents evaluate these choices hinges not on their own racial or ethnic background but on those of their neighbors. For a respondent in a community with a significant population of Mexican immigrants, seeing a Mexican immigrant's profile might evoke different considerations than would a less typical Sudanese immigrant. To examine this possibility, we sorted our respondents into three groups based on their ZIP codes. The first group, those with little local exposure to immigrants, includes the 781 respondents in ZIP codes where fewer than 5% of residents are immigrants. The second group includes 319 respondents whose ZIP codes are more than 5% foreign born and where the foreign-born are mostly from Latin America. The final group of 429 respondents is also exposed to immigrants regularly, but in these ZIP codes, the immigrants are mostly from regions other than Latin America. Figure B.4 presents the results, and illustrates that the basic results across the attributes hold in all three of these contexts, albeit with increased uncertainty. Perceptions of who constitutes a desirable immigrant appear quite stable across residential contexts. It is plausible that those with many Hispanic immigrants as neighbors are more negative toward Iraqi immigrants (-19.6) than are those living near other immigrant groups (-2.6), but the associated 95% confidence intervals overlap widely.

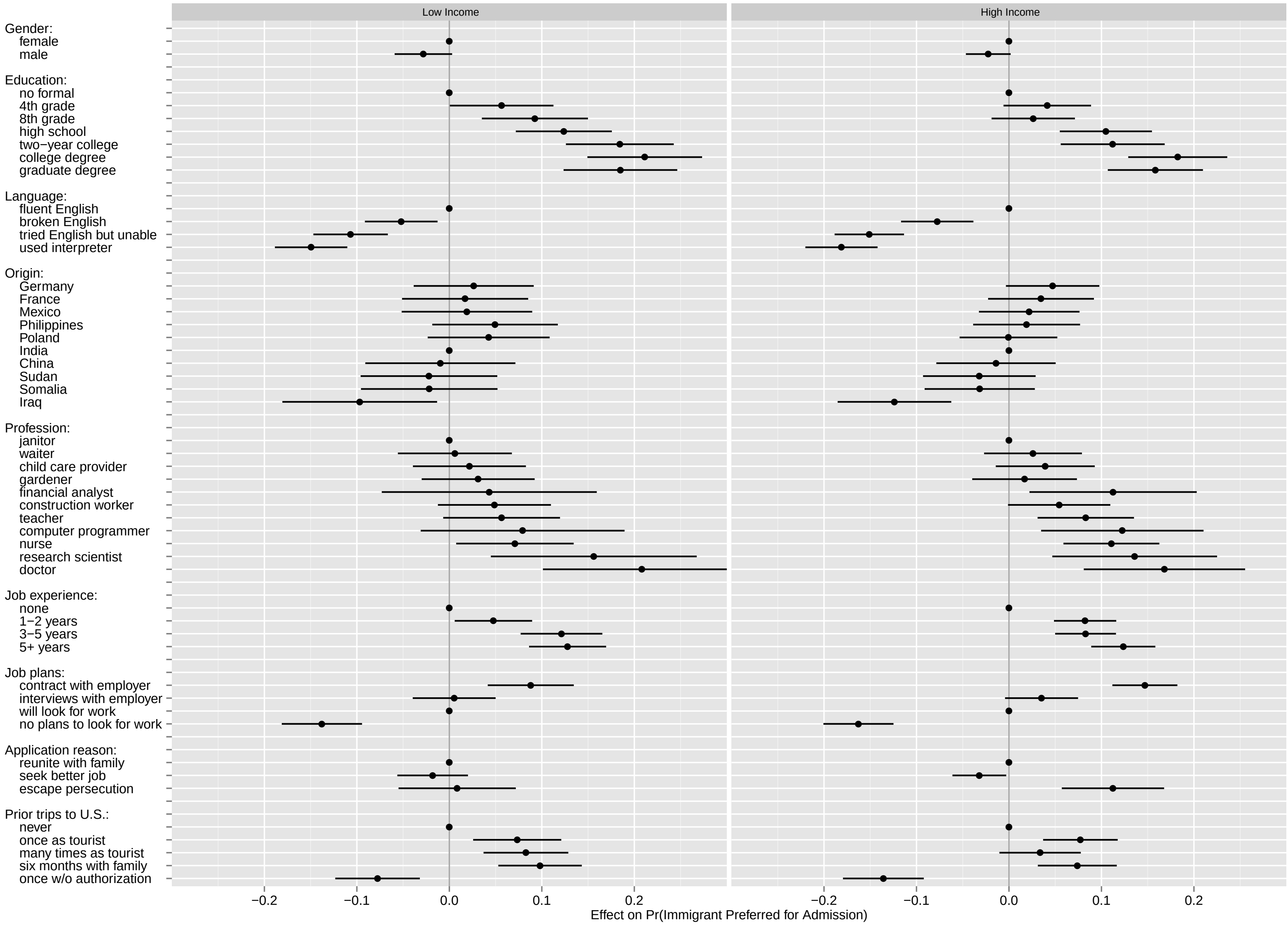
As Figure B.7 illustrates, the same pattern of stable responses holds true for self-reported political ideology. While conservative respondents penalize immigrants with no plans to work (-15.3), liberal respondents do as well (-13.2). The penalty for entering without authorization is slightly larger for conservatives (-14.5, SE=2.9) than for liberals (-9.4, SE=2.7). But even this is a difference of degree, and the general pattern across groups is highly consistent.

Figure B.1: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Percent of Immigrant Workers in Industry



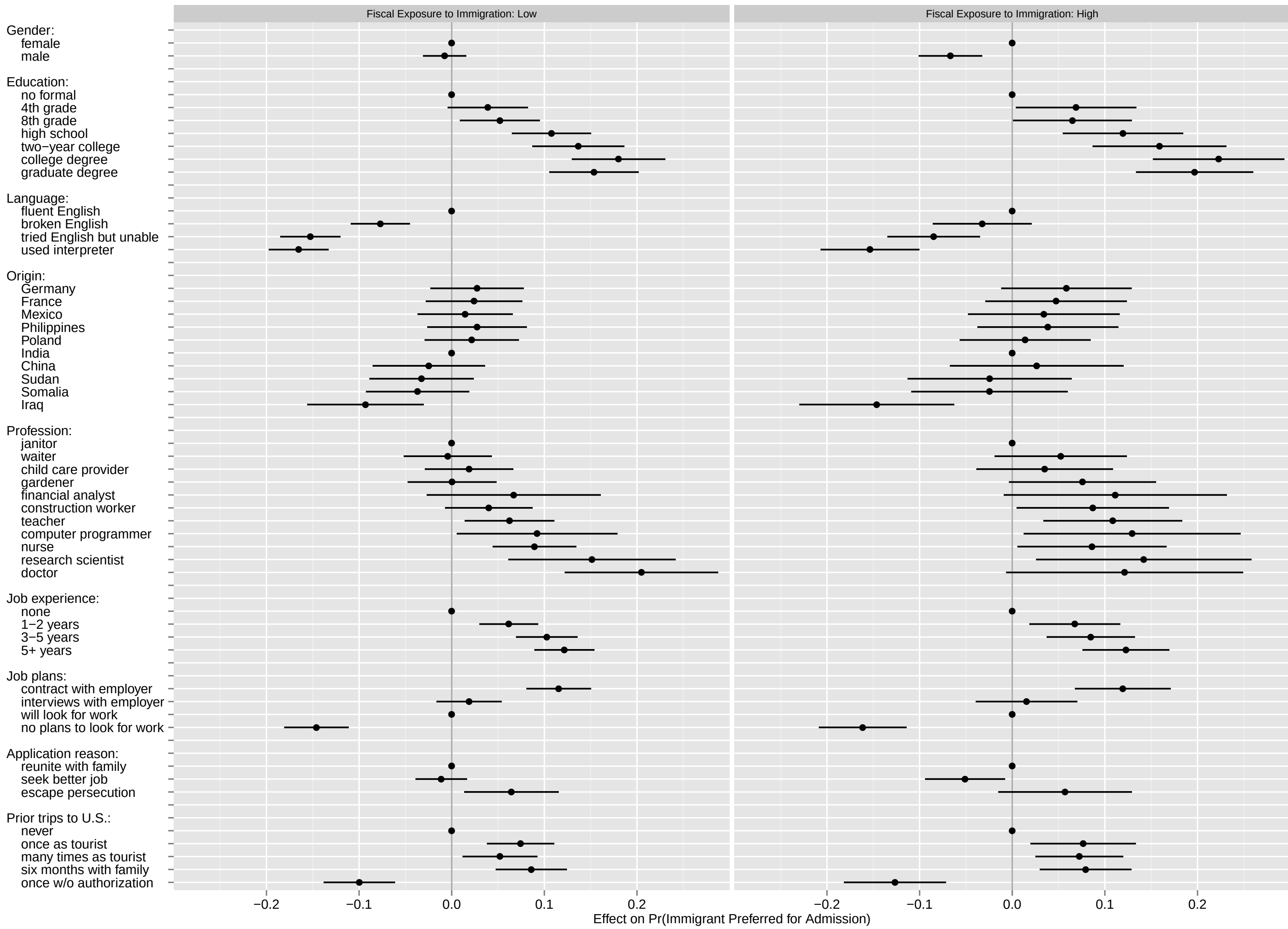
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents that work in industries with a low or high share of immigrant workers respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. The cutpoint for many/few immigrants is a 13% share of foreign-born workers.

Figure B.2: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Household Income



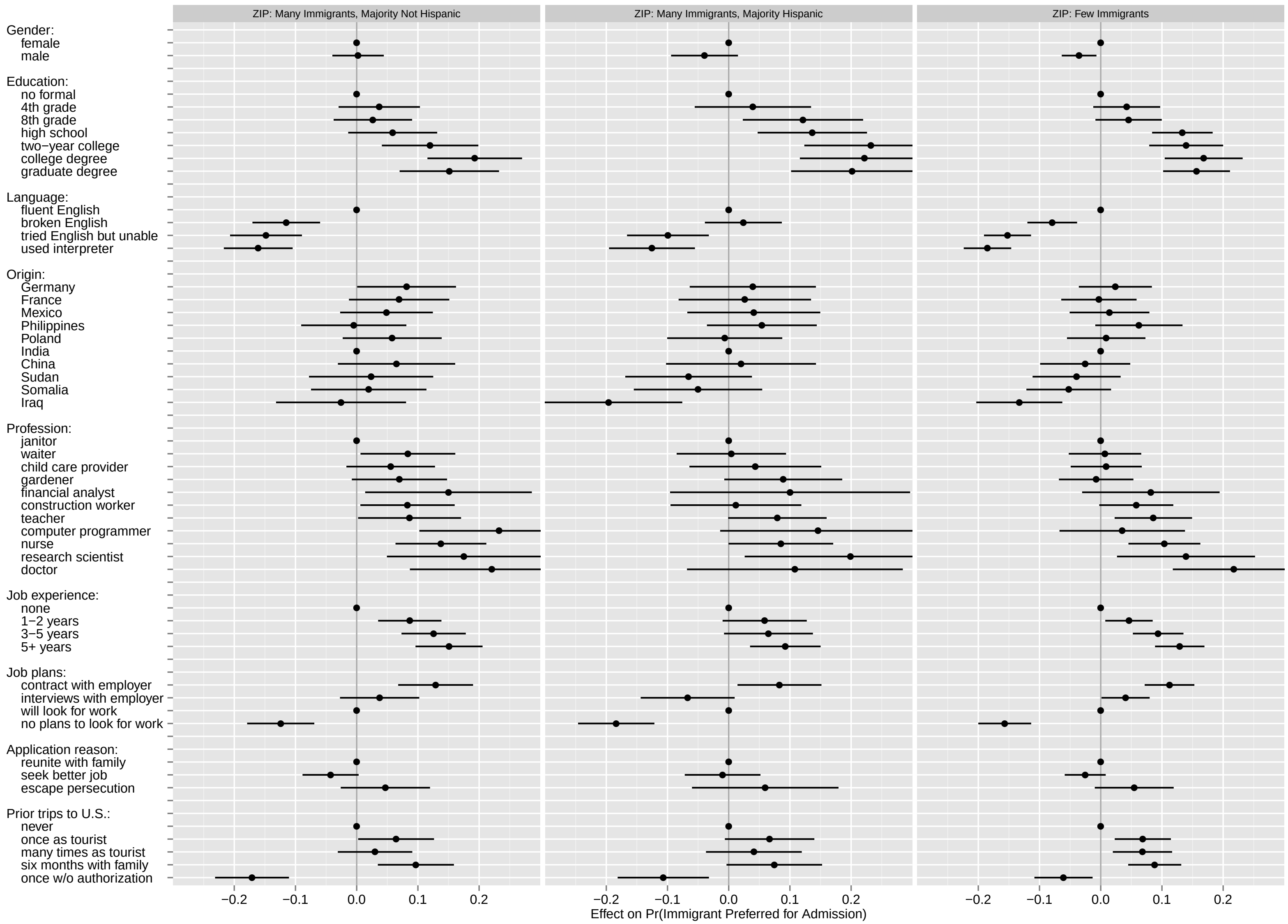
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents with household incomes below (n=608) and above \$50,000 (n=799), respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.3: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Fiscal Exposure to Immigration



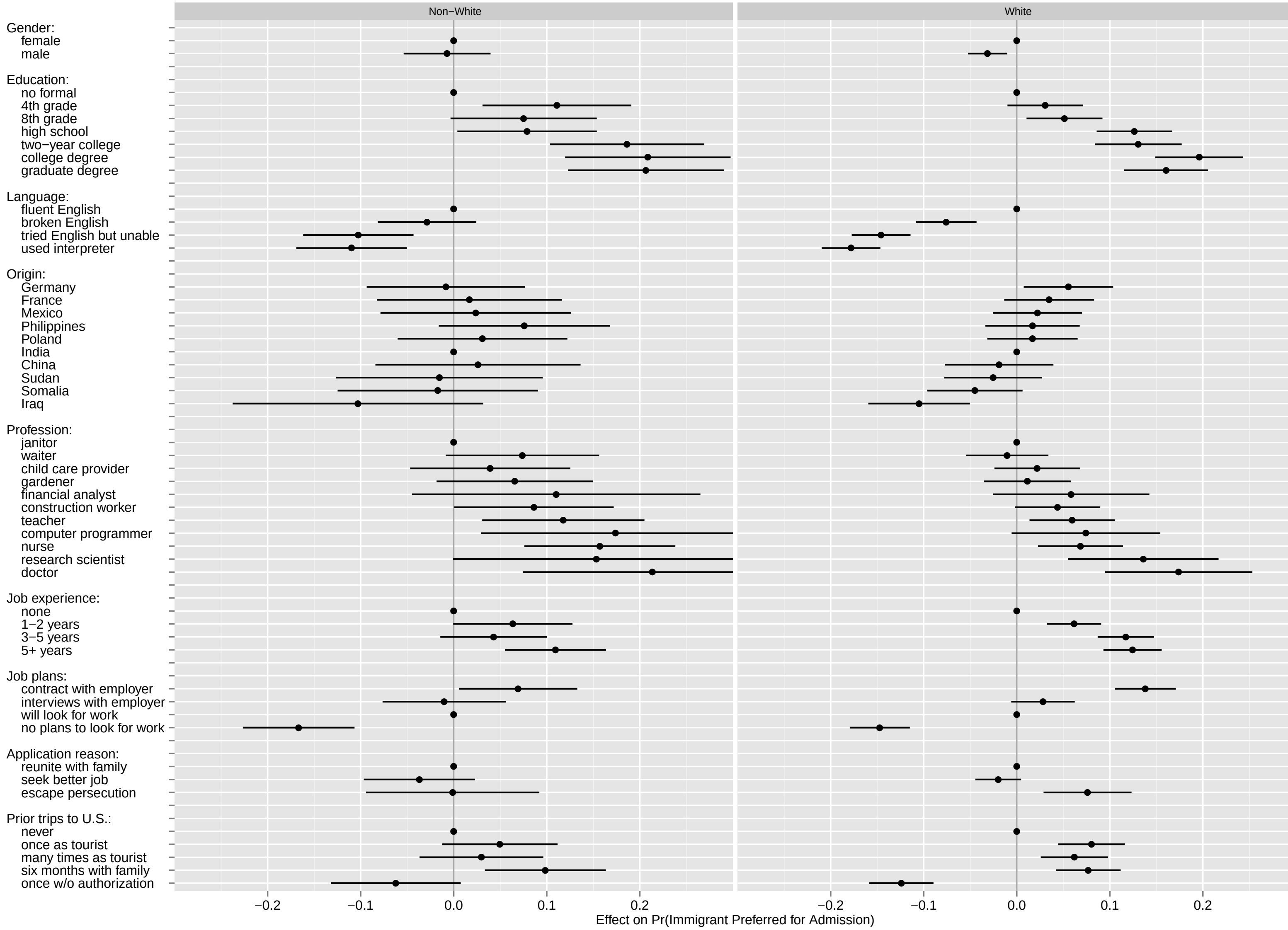
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents that live in states with low and high fiscal exposure to immigration, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. The fiscal exposure level is coded based on the number of immigrant households that receive welfare benefits divided by number of native-born households (see the text, Hainmueller and Hiscox (2010), and Hanson et al. (2007) for details).

Figure B.4: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Demographics of Respondents' ZIP Codes



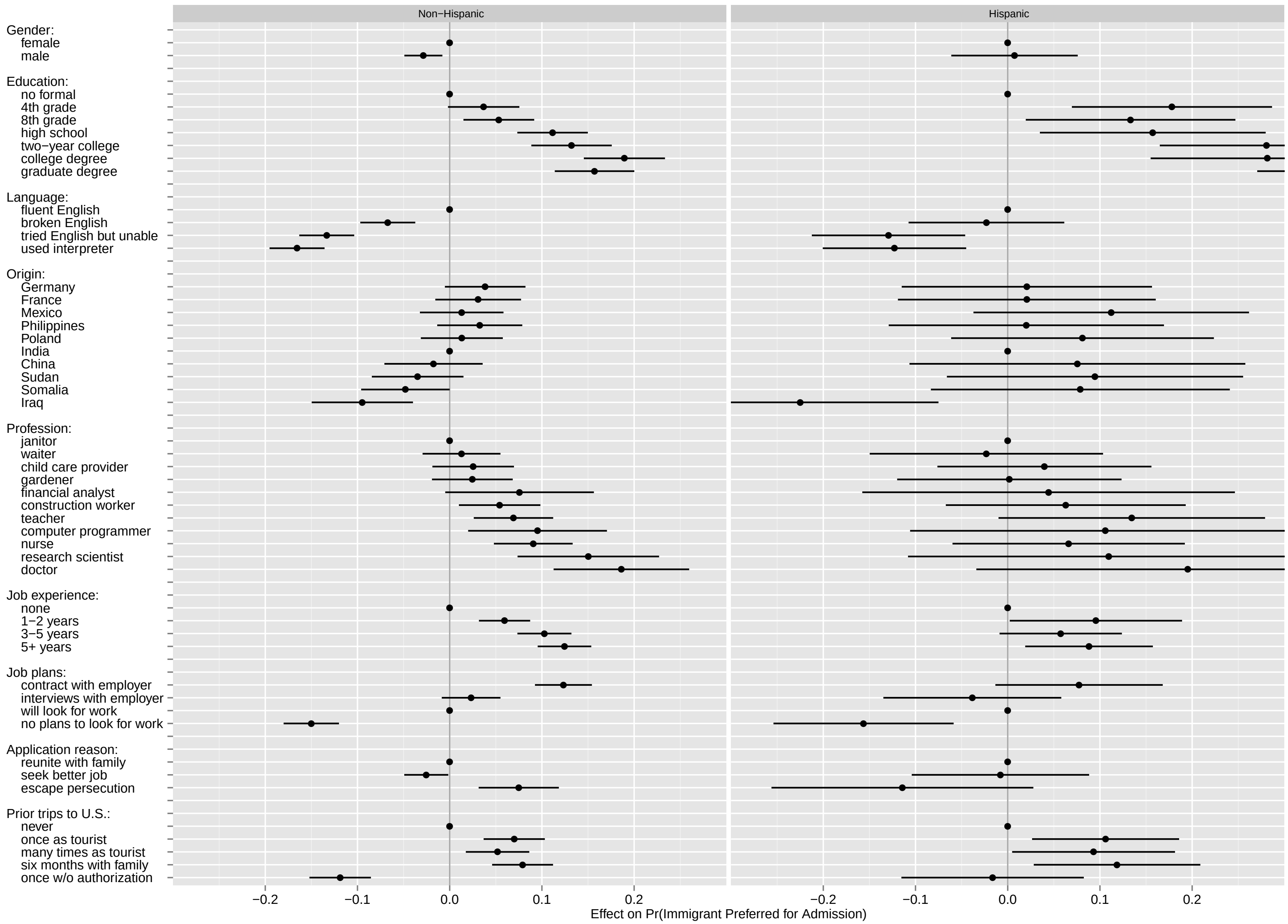
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for respondents residing in a ZIP code with: many immigrants, a majority of whom are Hispanic (n=319); many immigrants, a majority of whom are not Hispanic (n=429); and few immigrants (n=781), respectively. The cutpoint for many/few immigrants is a 5% foreign-born population share. The horizontal bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.5: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Ethnicity of Respondent



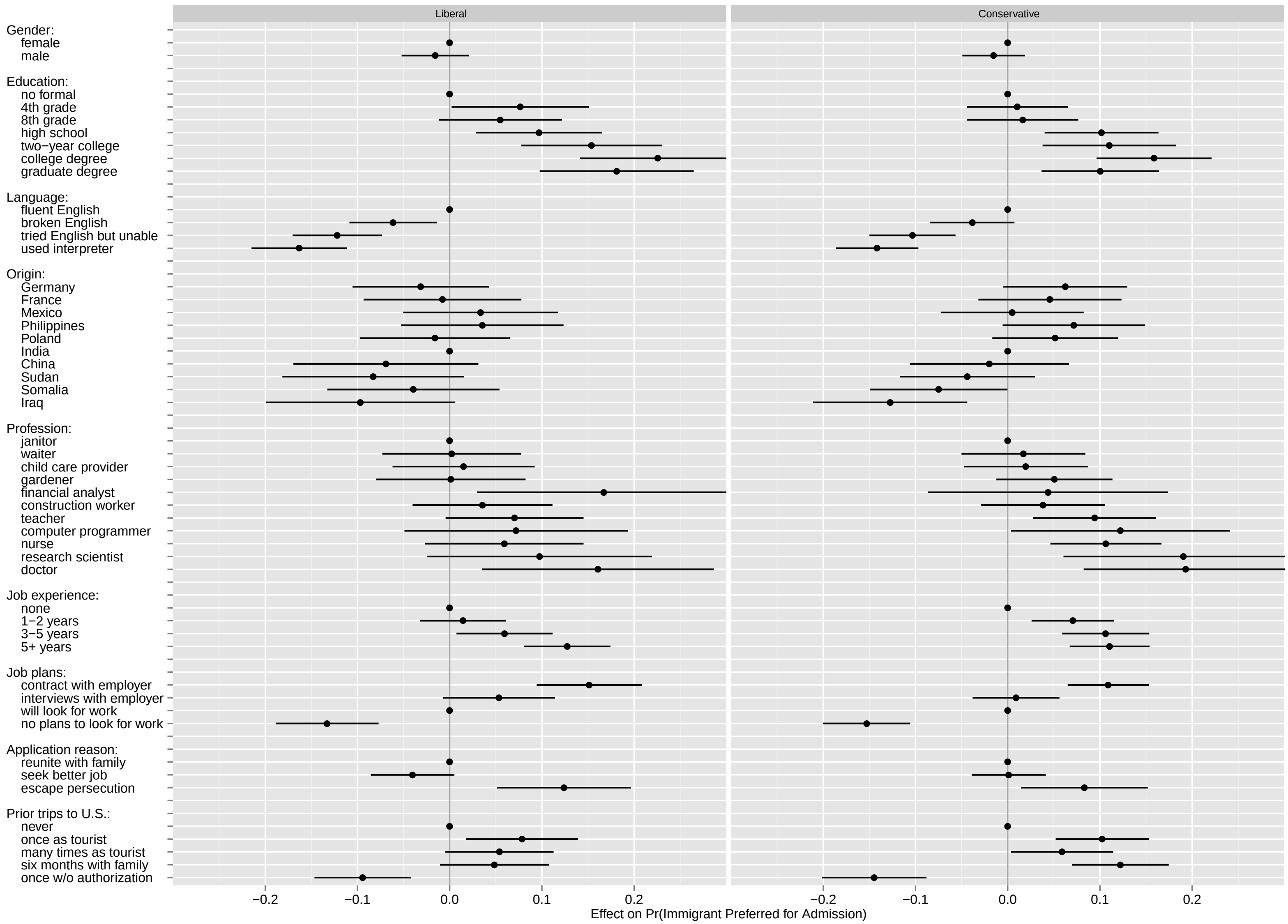
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of non-white (n=339) and white respondents (n=1,044), respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.6: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Hispanic Ethnicity



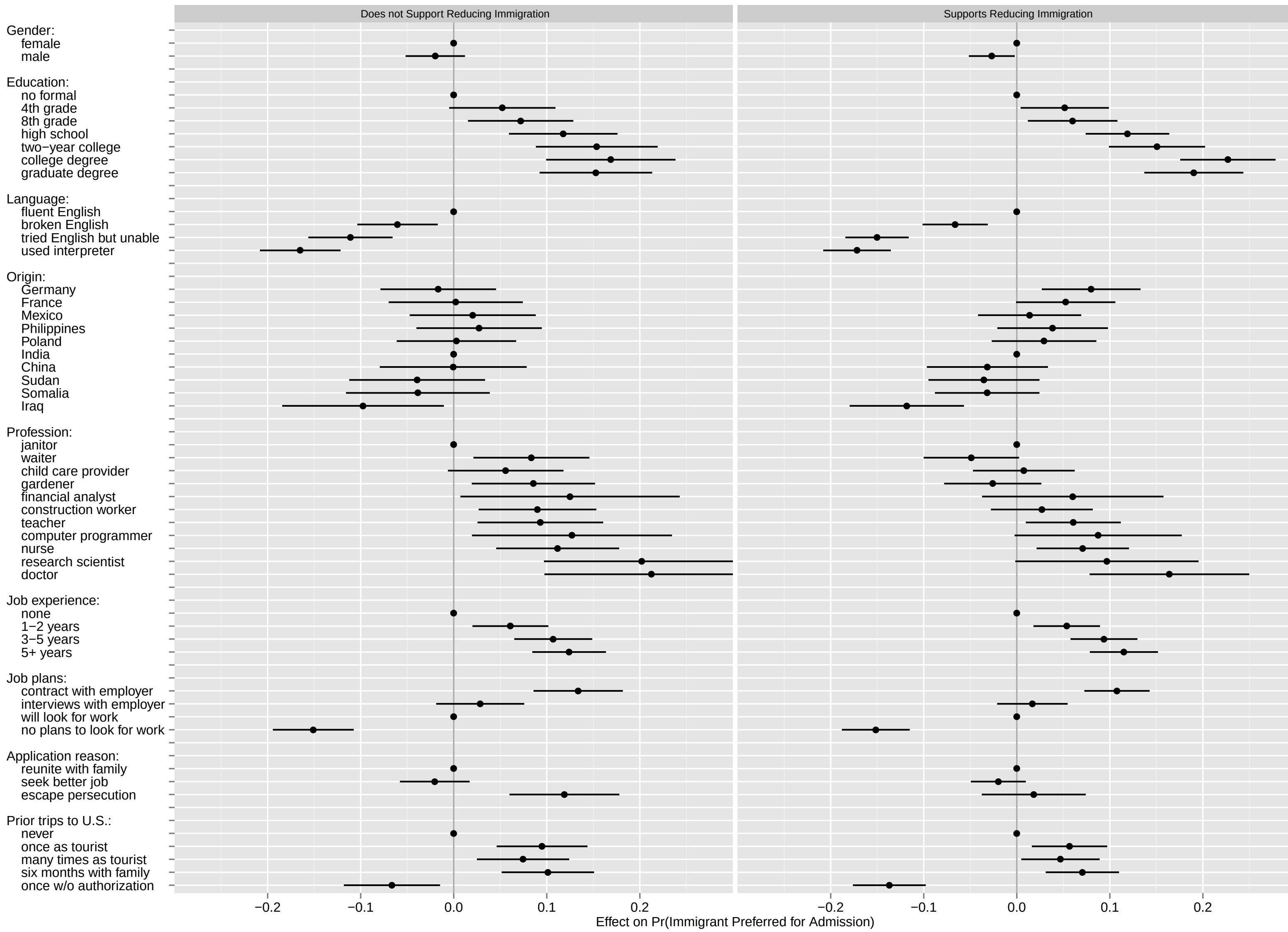
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of non-Hispanic (n=1,231) and Hispanic respondents (n=152), respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.7: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Respondents' Ideology



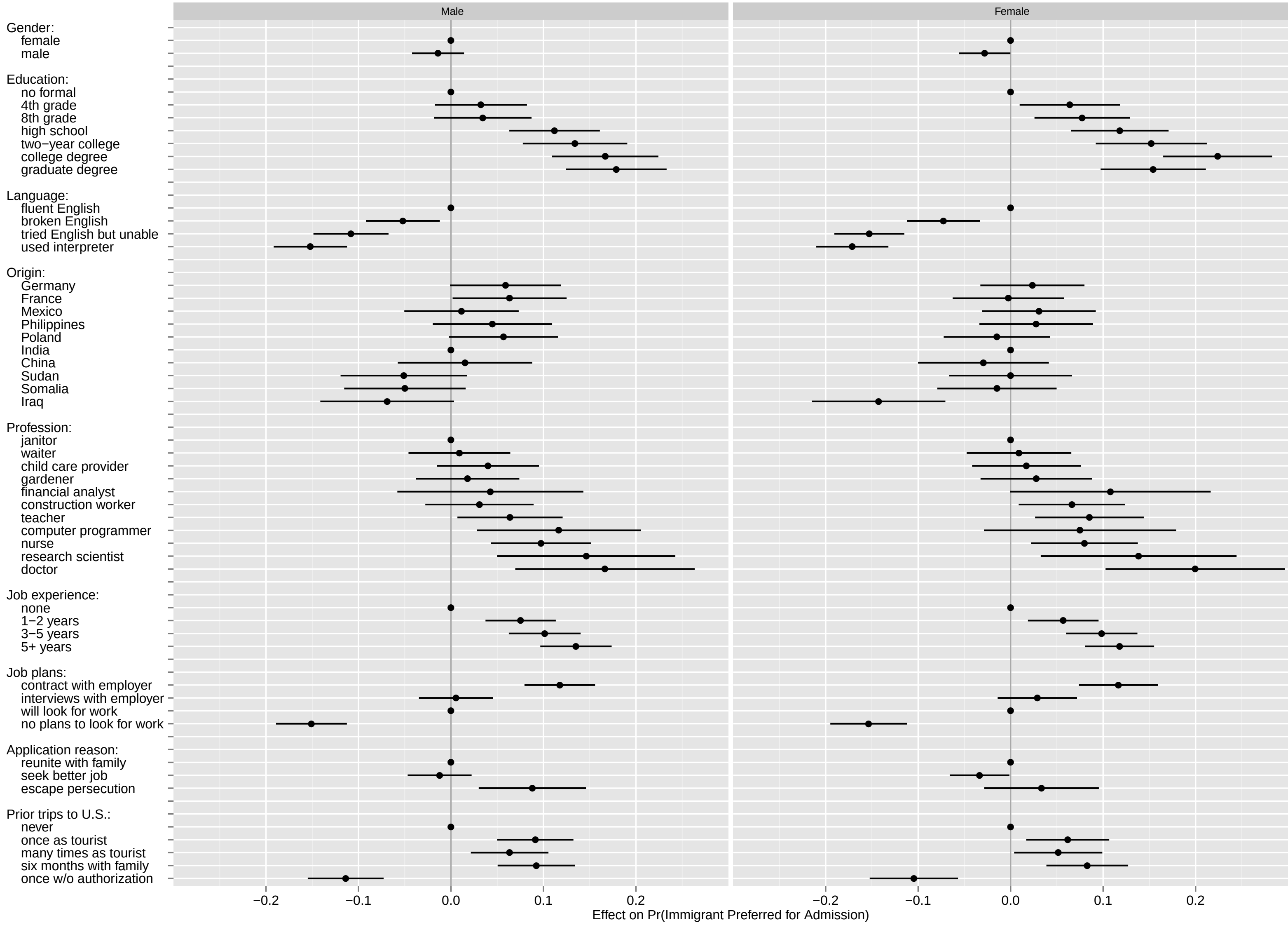
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents who self-identify as liberal (n=379) or conservative (n=520), respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.8: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Immigration Attitude of Respondent



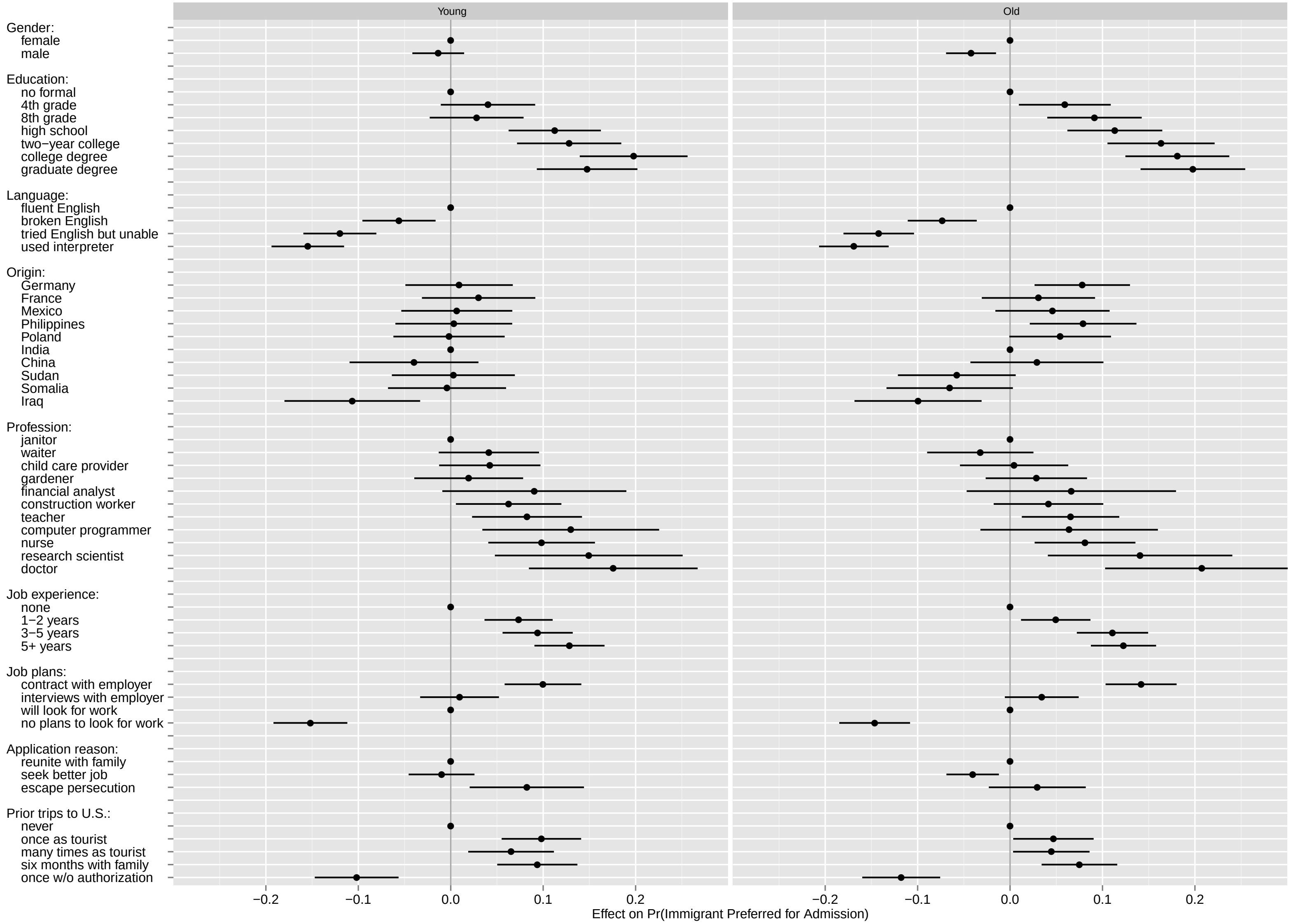
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents who do not support reducing immigration (n=605) or do (n=789), respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.9: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Gender of Respondent



Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of male (n=719) and female (n=688) respondents, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure B.10: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Age of Respondent



Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of young and old respondents, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. Median age is 38 years in the younger group and 64 in the older group.

C. Match between the Immigrant's Profession and the Respondent's Profession

Here we report the test of whether respondents are more likely to oppose an immigrant who shares their profession. In particular, we augment our benchmark model to include an indicator variable for whether the immigrant's listed profession matched that of the respondent. The results are shown in Table B.2 below. We find that respondents are not less likely to prefer or support an immigrant who shares their profession—the point estimates are very close to zero and highly insignificant.

Table B.2: Effect of a Match between the Immigrant's Profession and the Respondent's Profession

Model No:	(1)	(2)	(3)
Outcome:	Immigrant Preferred (0/1)	Immigrant Supported (0/1)	Immigrant Rating (1/7)
Match (1/0)	-0.008	-0.014	0.036
	(0.043)	(0.045)	(0.167)
Observations	12,064	12,100	12,100

Note: This table reports the effect of the binary indicator Match that measures whether there is a match between the immigrant's profession and the respondent's profession. The dependent variables are: a binary indicator for whether the immigrant profile was chosen or not (model 1), a binary indicator for whether the immigrant profile is supported for admission (model 2), and a seven-point rating of the immigrant profile ranging from "definitely admit" to "definitely not admit." All models include the covariates from the benchmark model and dummy variables for all immigrant attributes and also dummy variables for the respondents' professions (coefficients not shown here). The unit of observation is the immigrant profile; standard errors are clustered by respondent.

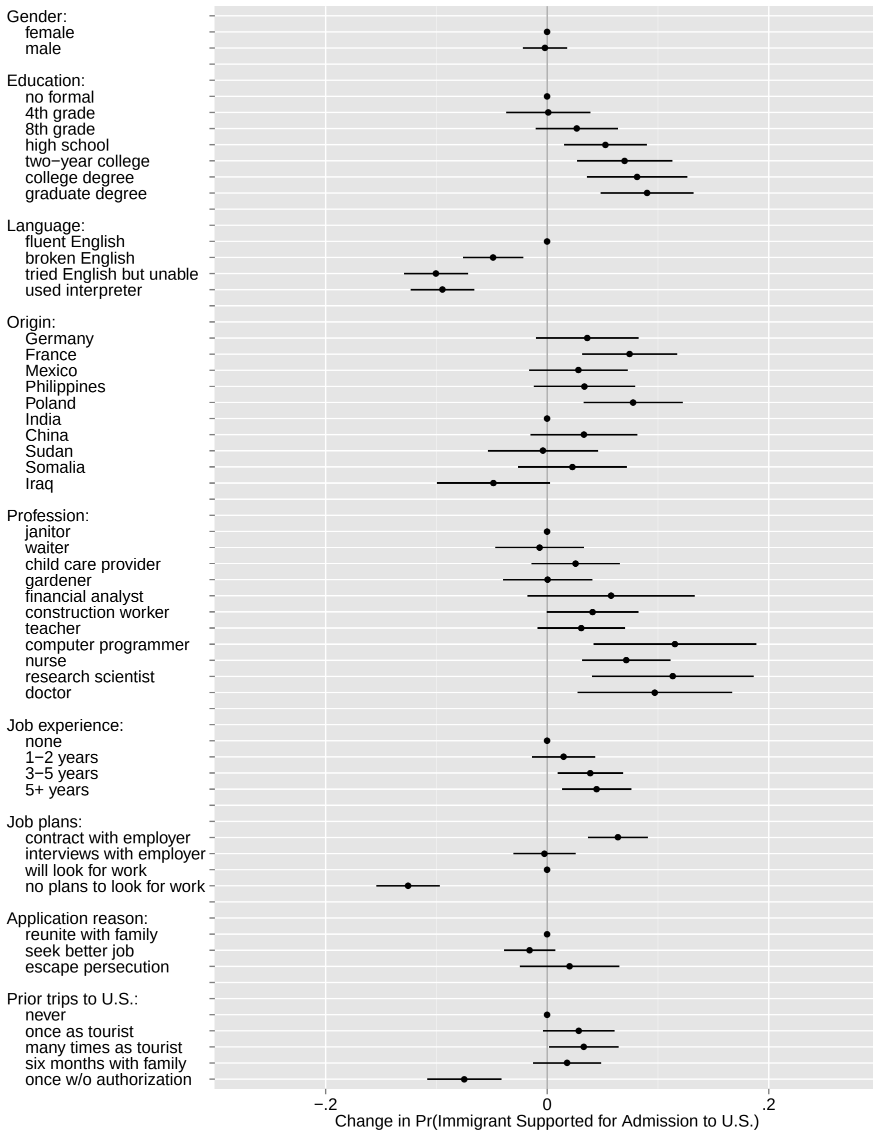
III. Appendix C: Robustness Checks

Here, we provide details for the robustness checks referenced in the manuscript.

A. Immigrant Supported Outcome

Our primary analyses focus on the *Immigrant Preferred* outcome, in which respondents are forced to choose between one of two immigrants. By specifying the dependent variable as a forced choice, we can set aside attitudes about how many immigrants to admit and isolate attitudes about what types of immigrants to admit. Nonetheless, it is important to test whether the results differ substantially when respondents are not forced to choose between two immigrants. After indicating which immigrant the respondent preferred for admission, each respondent rated each immigrant on a seven-point scale, with one indicating that the U.S. should "absolutely not admit" the immigrant and seven indicating that it "definitely should admit" the immigrant. Using these ratings of each immigrant profile, we can replicate the benchmark model using the *Immigrant Supported* outcome, which is coded as 1 if the 7-point rating is above the midpoint and zero otherwise. The effects of the attributes on this outcome are displayed in Figure C.1. The results are highly similar to the ones we obtain when using the *Immigrant Preferred* outcome variable.

Figure C.1: Effects of Immigrant Attributes on Support for Admission



Note: This plot shows estimates of the effects of the randomly assigned immigrant attributes on the probability of being supported for admission to the U.S. Estimates are based on the benchmark OLS model with clustered standard errors; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. The baseline probability of being supported for admission is 0.43.

B. Respondent Fixed and Random Effects

Here, we replicate the benchmark model while adding respondent fixed effects and then again while adding respondent random effects. The results, displayed in Figures C.2 and C.3 respectively, are almost identical to those from the benchmark model. This confirms that the random assignment of the immigrant attributes was successful so that they are orthogonal to respondent characteristics—and thus that modeling choices such as these have little effect on the estimated effects of each attribute.

C. Panel Effects, Spillover, and Self Monitoring

One concern about choice-based conjoint analysis relates to external validity and to the potential effects of survey administration on our respondents. Among respondents who completed the survey's second wave, the median amount of time as part of the KN panel was 2.9 years, meaning that our respondents have extensive experience with surveys, and might differ from the general population from which they were initially drawn. Given that possibility, Figure C.4 is reassuring, as it shows essentially identical results for respondents above and below the median time in the KN panel.

In a similar vein, it is plausible that the experience of repeatedly deciding between pairs of immigrants might change the pattern of responses, perhaps as respondents increasingly satisfice (Krosnick; 1999) or use different subsets of immigrant attributes to make their determinations. It is also plausible that the effect of viewing immigrant profiles will be to personalize the issue (Ostfeld and Mutz; 2011), temporarily shifting respondents' views. The survey was designed to limit respondents' ability to satisfice, as respondents were not able to submit responses about a given pairing until it had been visible on their screen for at least 30 seconds. Even so, it is valuable to consider whether the results change as respondents become familiar with the survey, which we do in Figure C.5. It plots the results separately for profiles that were seen first, second, third, fourth, or fifth. The pattern of results is very similar across each of the five pairings, with no clear evidence of increased satificing or other adaptations by the respondents.

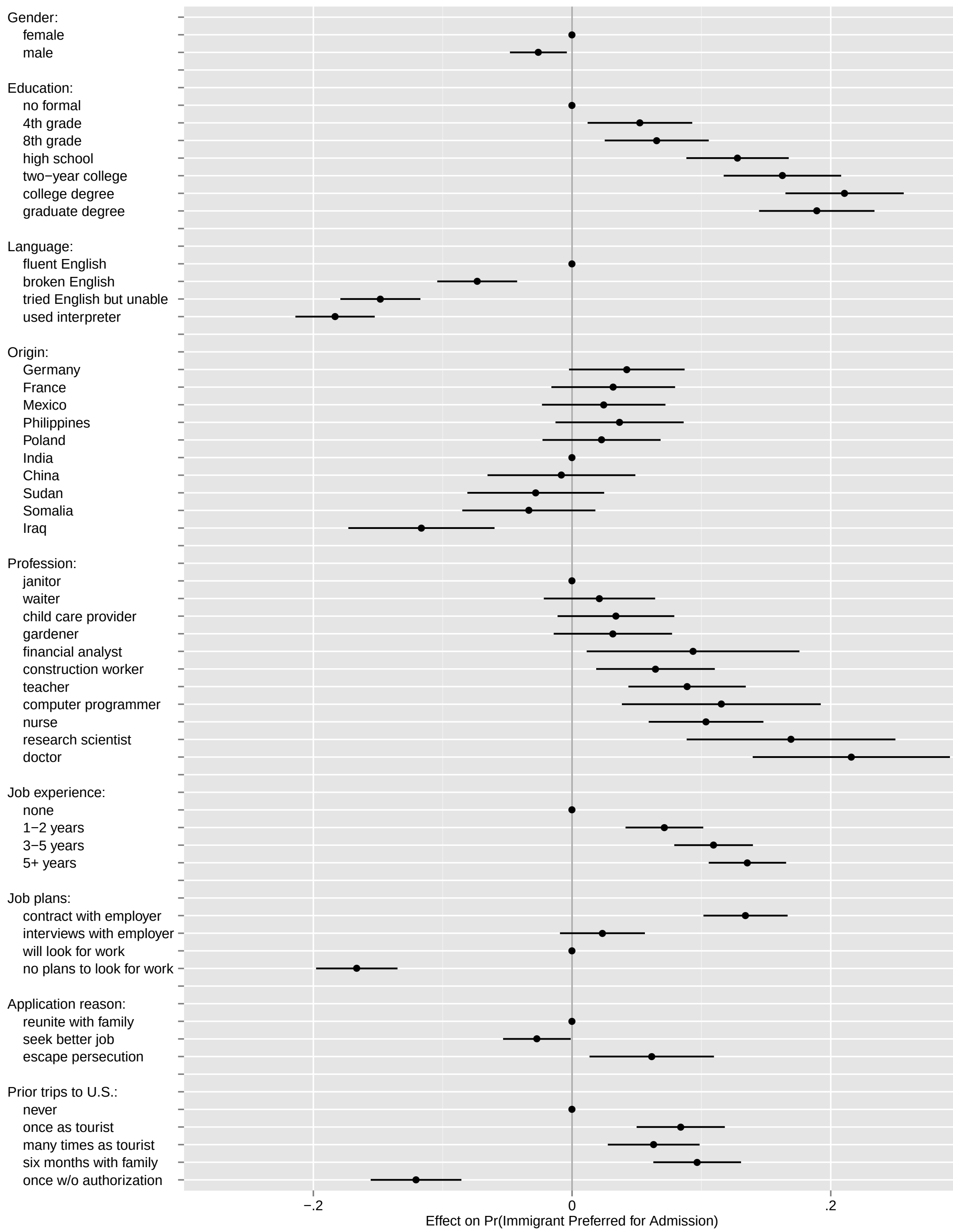
Next, we consider the extent to which responses are shaped by social desirability. Following Berinsky and Lavine (2011), we do so using three wave-one questions to measure self-monitoring, one aspect of self-presentation that is closely connected to social desirability. Respondents high in self-monitoring have been shown to exert more effort to present themselves in an appealing way. In Figure C.6, we re-estimate the marginal effects while separating respondents into those who are low or high in self-monitoring,[5] and find that any differences are generally minor.

Another concern is that respondents who are exposed to atypical immigrant profiles might react differently. To check this possibility, we identified immigrant profiles that may be considered atypical (for example, female and construction worker, etc.). This list of atypical profiles is of course somewhat arbitrary, but to err on the side of caution we included a rather expansive list of profiles; the results are not sensitive to the specific coding.[6] We then broke down the respondents into three roughly equally sized groups including respondents who were exposed to a low (0-3; 43%), medium (4-5; 43%), or high (6-9; 14%) number of atypical profiles. We replicated the baseline model for each group, and display the results in Figure C.7. Again, the pattern of results is fairly similar across all three groups, indicating that respondents are not easily distracted by seeing atypical profiles.

[5]We divide the sample at the median of the self-monitoring scale, which is an additive index of the three self-monitoring questions.

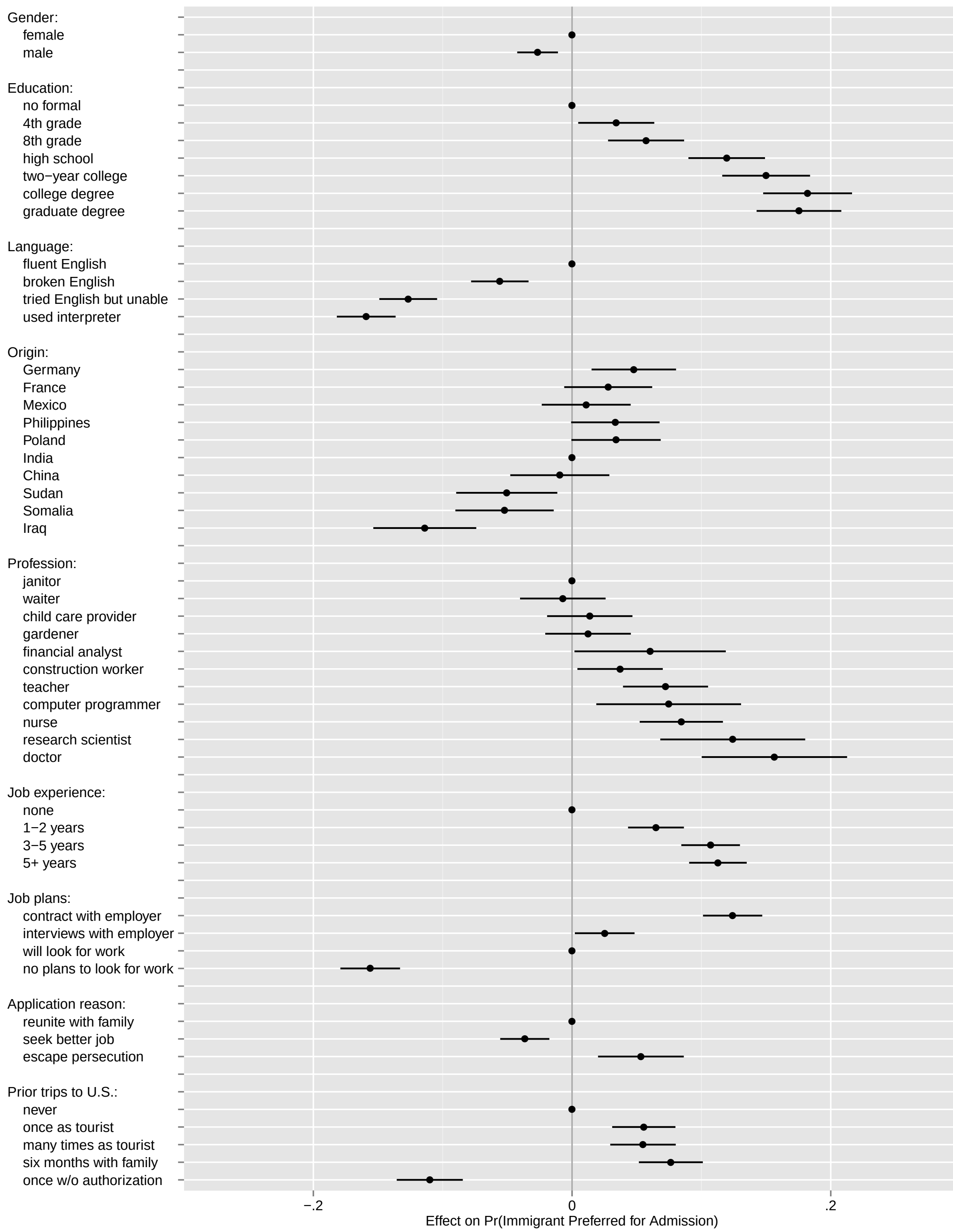
[6]The full list of atypical profiles is as follows: Mexico and some college or college degree or graduate degree; Mexico and doctor or research scientist or computer programmer or financial analyst; Somalia and some college or college degree or graduate degree; Somalia and doctor or research scientist or computer programmer or financial analyst; Sudan and research scientist or computer programmer or financial analyst; Iraq and research scientist or computer programmer or financial analyst; Germany and no formal education or 4th grade education or 8th grade education; Germany and janitor or waiter or child care provider or gardener; France and no formal education or 4th grade education or 8th grade education; France and janitor or waiter or child care provider or gardener; India and no formal education or 4th grade education or 8th grade education; India and janitor or waiter or child care provider or gardener; India and tried English but unable or used interpreter; Germany and unauthorized; France and unauthorized; Female and construction worker; Male and child care provider; seek better job and no plans to look for work.

Figure C.2: Effects of Immigrant Attributes on Probability of Being Preferred for Admission with Respondent Fixed Effects



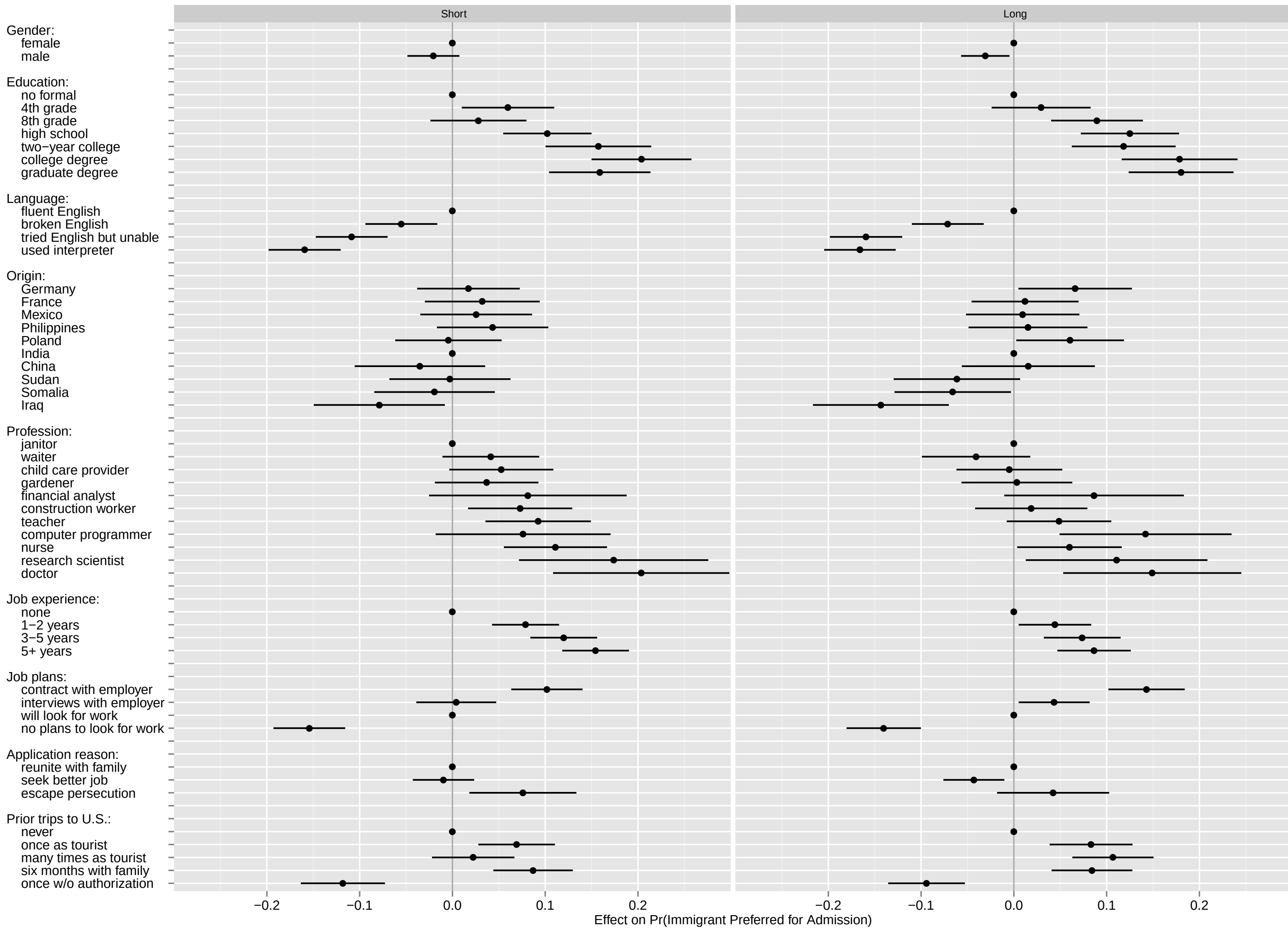
Note: This plot shows estimates of the effects of the randomly assigned immigrant attribute values on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS model with respondent fixed effects and clustered standard errors; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure C.3: Effects of Immigrant Attributes on Probability of Being Preferred for Admission with Respondent Random Effects



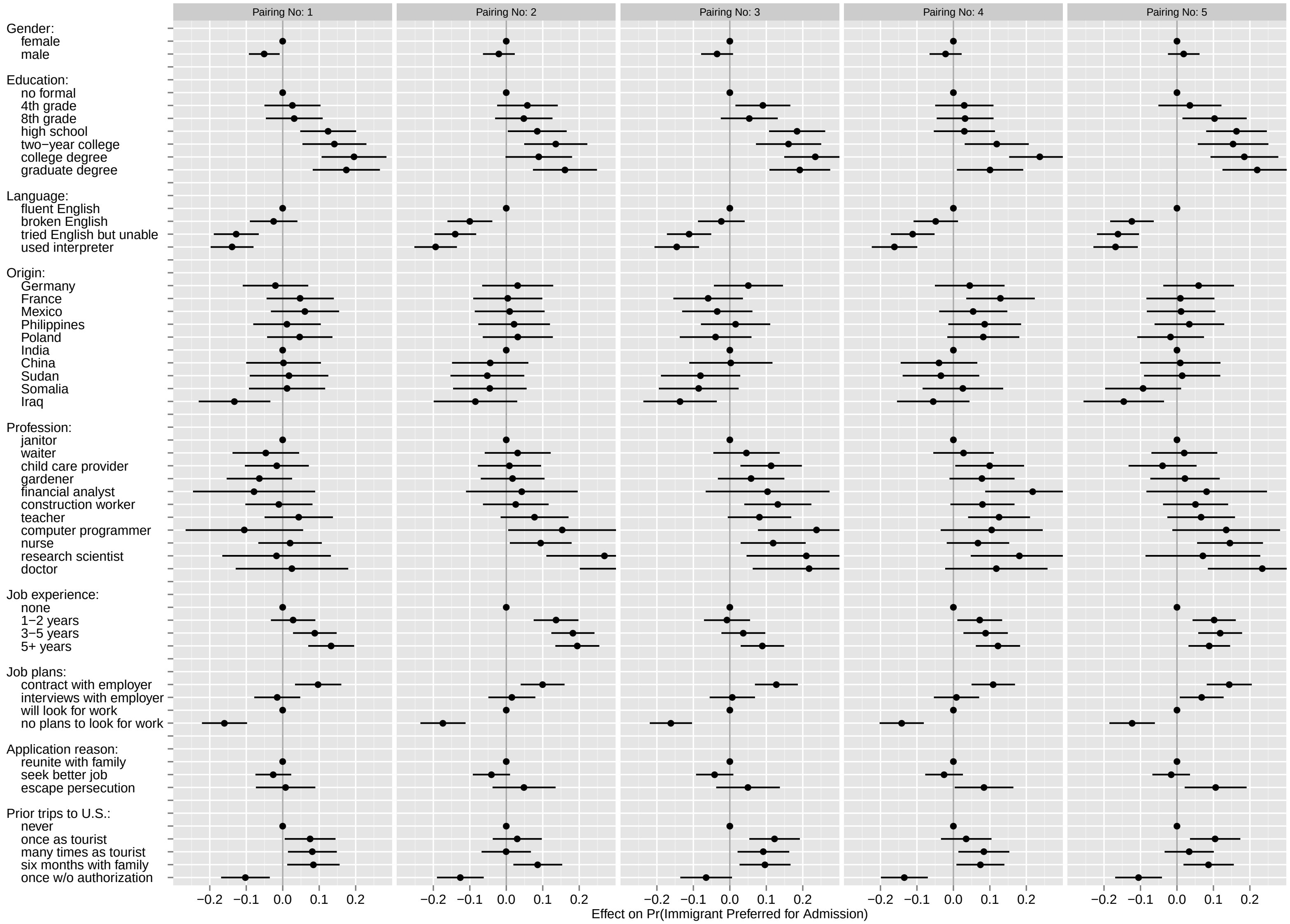
Note: This plot shows estimates of the effects of the randomly assigned immigrant attribute values on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS model with respondent random effects and clustered standard errors; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure C.4: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Panel Tenure



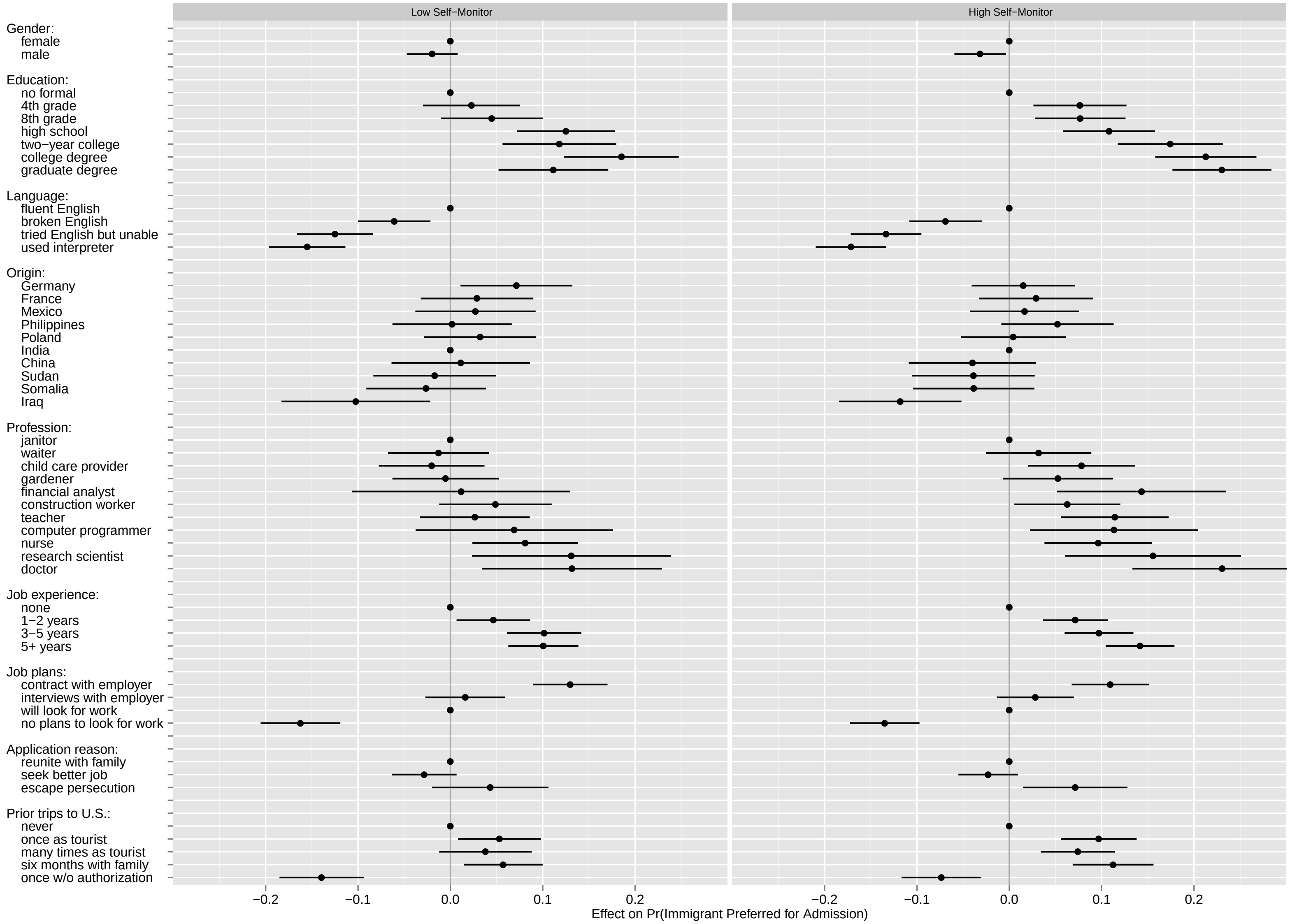
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents with short and long panel tenures, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. Median tenure is 11 months in the short group and 71 months in the long group.

Figure C.5: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Pairing



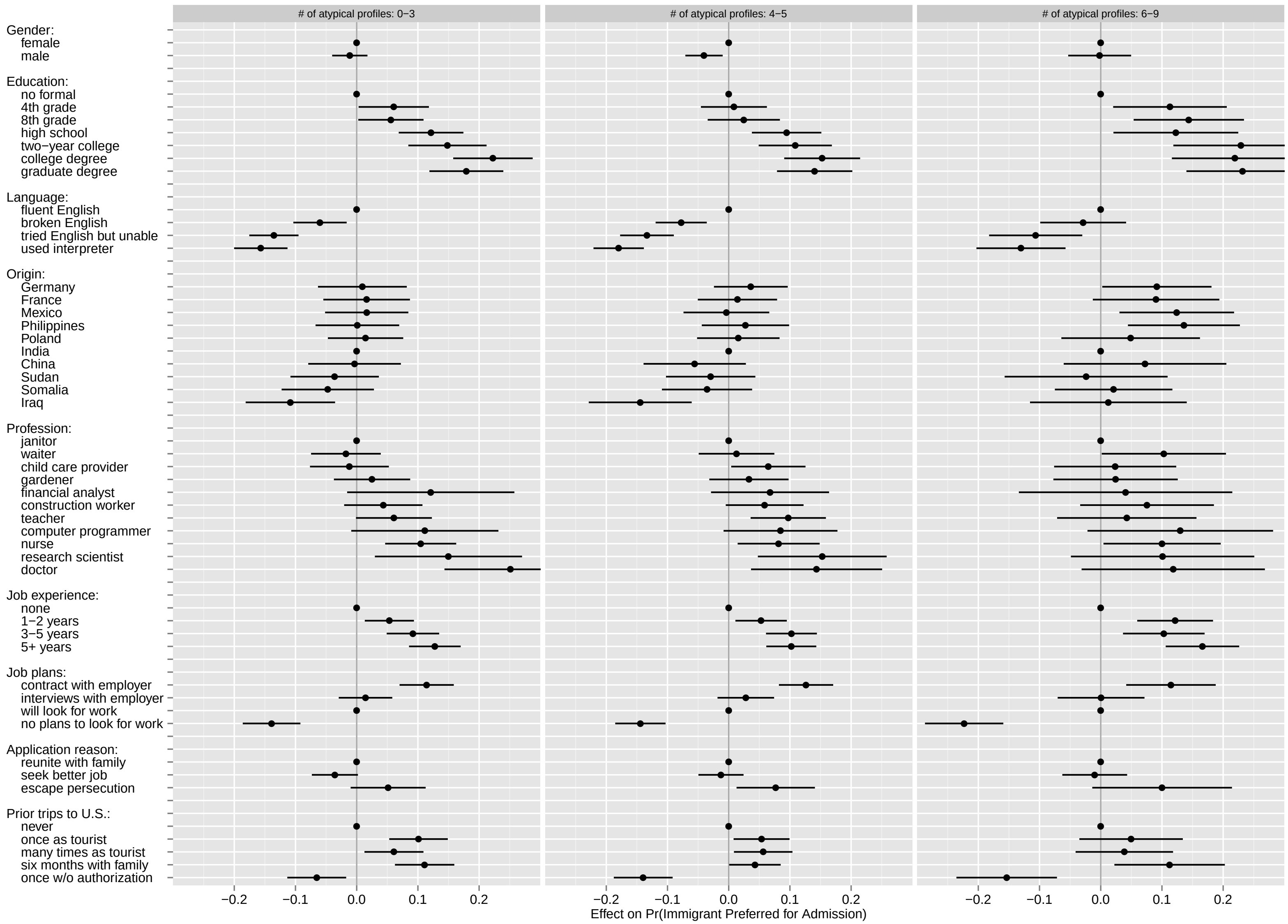
Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for respondents' first, second, third, fourth, and fifth binary responses, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

Figure C.6: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Self-Monitoring Level



Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents with low and high levels of self monitoring, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute. We divide the sample at the median of the self-monitoring scale, which is an additive index of the three self-monitoring questions.

Figure C.7: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Number of Atypical Profiles



Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents exposed to a small, medium, or high number of atypical immigrant profiles, respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

D. Automated Content Analysis

Both the sociotropic and norms-based hypotheses find considerable support in the evidence presented in the manuscript. To some degree, it shouldn't surprise us that conjoint analysis returns evidence in favor of multiple perspectives, as the technique encourages researchers to move away from binary hypothesis tests in favor of more continuous assessments of relative effect size. Still, as another robustness check, and as an alternate attempt to test the relative explanatory power of these two approaches, we turn to the tools of automated content analysis—and specifically, to Latent Dirichlet Allocation (Blei et al.; 2003).

Using a sample of 400 respondents on Amazon's Mechanical Turk (Paolacci et al.; 2010; Berinsky et al.; 2012), we repeated the conjoint experiment described in the manuscript on June 14th, 2012. However, after identifying the preferred immigrant in each of the five pairings, the respondents were also asked to explain their choice in their own words. These 1,996 open-ended responses enable us to see the extent to which the preferences identified by conjoint analysis match those voiced by the respondents themselves. In Table C.2 below, we present the results of an eight-cluster implementation of Latent Dirichlet Allocation fit using the R package "LDA" (Chang; 2010). Each column lists a cluster of words that tend to co-occur, with the single most common word in that cluster listed first. Even eliciting attitudes through a very different method, the conclusions are largely similar to those uncovered using conjoint analysis. For example, the first, fifth, sixth, and seventh clusters all support the sociotropic approach, as they demonstrate that the respondents preferred immigrants who had plans to work, education, and job experience. In the first cluster, words including "contribute," "society," "profession," "educational," and "skills" are among the most distinctive, signaling a connection between immigrants' professions and their ability to contribute to American society. Still, the norms-based approach finds support as well, with the second cluster emphasizing legal entry and the eighth cluster emphasizing English. While it is clear that Americans assess would-be immigrants in terms of their likely economic impact, their adherence to norms about language and entry matter as well. By varying immigrant profiles with respect to their adherence to norms while explicitly holding economic contributions constant, future research could productively test these hypotheses in another way.

Table C.1: Results of eight-cluster implementation of Latent Dirichlet Allocation

	1	2	3	4	5	6	7	8
1	immigrant	illegally	family	persecution	experience	look	contract	english
2	society	enter	reunite	escape	education	plans	employer	speaks
3	chose	country	education	escaping	job	educated	degree	fluent
4	able	entered	looking	seeking	training	experience	college	speak
5	contribute	tried	person	experience	lined	time	graduate	broken
6	profession	educated	united	society	level	job	immigrant	spoke
7	educational	authorization	support	trying	formal	speaking	applicant	teacher
8	skills	reason	shes	person	schooling	field	equivalent	fluently
9	people	legal	system	political	teacher	legally	lined	applicant
10	chance	doctor	research	religious	useful	planning	job	care
11	language	law	probably	politicalreligious	looking	qualified	doesnt	child
12	seek	didnt	desire	help	society	choice	time	makes
13	education	immigrant	reunited	education	slightly	nurses	experience	able
14	background	breaking	urgent	profession	hes	seek	live	skill
15	employment	previously	asylum	religiouspolitical	valuable	easier	looking	reuniting
16	america	teacher	looks	lined	willing	shes	illegal	communicate
17	level	hasnt	demand	priority	programmer	finding	employment	field
18	worker	valid	simply	nurses	highly	highly	learn	set
19	skilled	past	somalia	people	professional	applicant	nurse	little
20	doctor	rules	smarter	skilled	looks	jobs	family	language

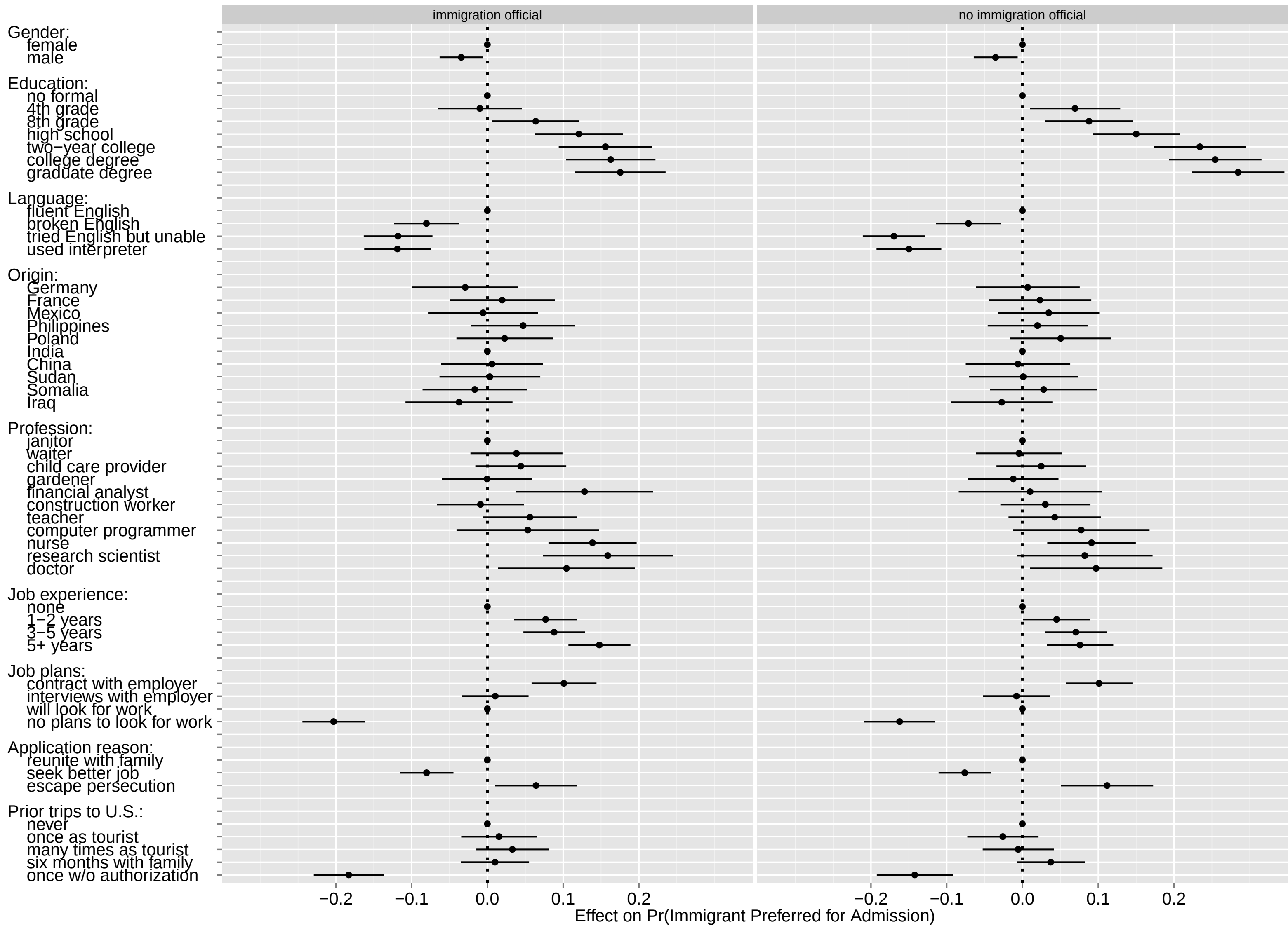
Table C.2: This table presents the results of Latent Dirichlet Allocation applied to the open-ended responses of survey respondents on Amazon Mechanical Turk. Each column identifies a separate cluster of words that tend to occur together, while each row identifies the ranking of specific words within that cluster.

E. Introductory Framing Experiment

Using a sample of 750 respondents from Amazon's Mechanical Turk, we replicated the conjoint experiment described in the manuscript on January 20th, 2012. For this robustness check, we randomly assigned the respondents to two different conditions. In the first, the respondents completed the same conjoint experiment described in the manuscript. In the second, we changed only the wording of the introduction by removing the sentence, "we are going to ask you to act as if you were an immigration official." The modified introduction instead read: "This study considers immigration and who is permitted to come to the United States to live. For the next few minutes, we will provide you with several pieces of information about people who might apply to move to the United States. For each pair of people, please indicate which of the two immigrants you would personally prefer to see admitted to the United States. This exercise is purely hypothetical. Please remember that the United States receives many more applications for admission than it can accept. Even if you aren't entirely sure, please indicate which of the two you prefer."

Figure C.8 show the results for both groups of respondents. We find that the results are very similar across groups, indicating that the results are robust to these different framings of the task. Interestingly, the results are also very similar to the results from the KN sample used in the main study.

Figure C.8: Effects of Immigrant Attributes on Probability of Being Preferred for Admission (different introductory text)



Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on the benchmark OLS models with clustered standard errors estimated for the group of respondents that saw the introduction with and without the language about acting "as if you were an immigration official", respectively; bars represent 95% confidence intervals. The points without horizontal bars denote the attribute value that is the reference category for each attribute.

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