Online Appendix: The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes Toward Immigrants

Jens Hainmueller – Massachusetts Institute of Technology
Daniel J. Hopkins – Georgetown University

August 2012

Abstract

This appendix provides additional analysis referenced in the main paper.

Jens Hainmueller, Department of Political Science, 77 Massachusetts Avenue, Cambridge, MA 02139. E-mail: jhainm@mit.edu. Daniel J. Hopkins, Department of Government, Intercultural Center 681, Georgetown University, Washington, DC, 20057. E-mail: dh335@georgetown.edu.

Appendix A: Data Description

Survey Questions

- *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." Groups, in randomized order are: Latinos or Hispanics 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 .69.

- *Attitudes Towards 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.

Appendix B: Other Moderators

The following presents results when we replicate the baseline model for different subgroups of respondents including subgroups differentiated by the percent of immigrant workers in the respondent's industry (Figure B.1), household income (Figure B.2), fiscal exposure to immigration (Figure B.3), demographics of the ZIP code (Figure B.4), ideology (Figure B.5), immigration attitudes (Figure B.6), gender (Figure B.7), and age (Figure B.8). 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 effect estimates are similar regardless of whether we consider rich or poor respondents, old or young respondents, or many other subgroups.

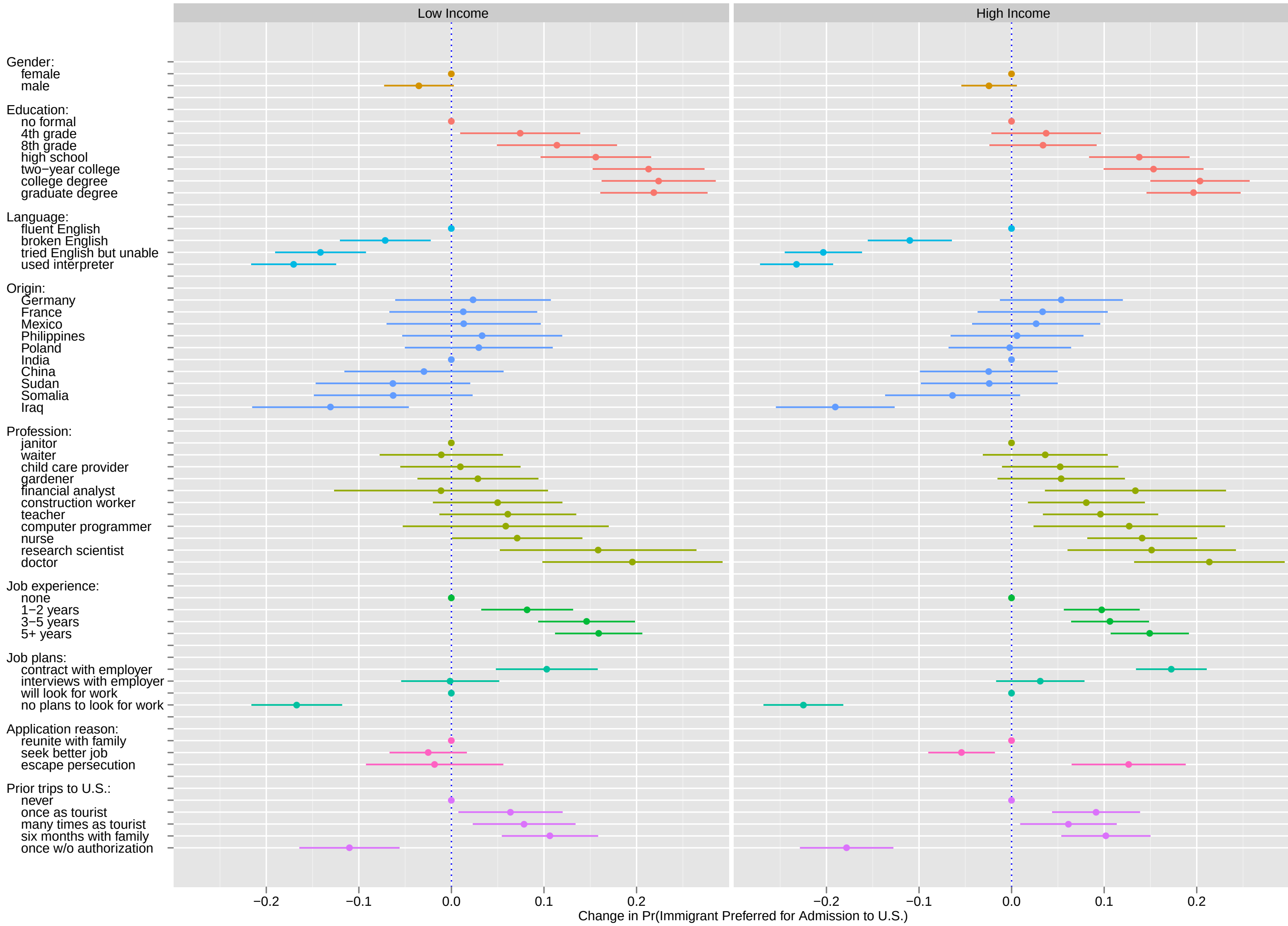
Our handling of the demographics of the ZIP code requires additional explanation. Local demographics are another moderator consistent with the claim that immigration attitudes are to an important extent attitudes toward racial or ethnic out-groups. It is plausible that how our respondents evaluate these 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 less negative toward Iraqi immigrants (-9.4) than are those living near other immigrant groups (-26.8), but the associated 95% confidence intervals span from -21.0 to 2.0 and from -38.1 to -15.6, respectively.

As Figure B.5 illustrates, the same pattern of stable responses holds true for self-reported political ideology. While conservative respondents penalize immigrants with no plans to work (-19.7), liberal respondents do as well (-18.7). One difference is the penalty for entering without authorization, which is larger for conservatives (-20.9, SE=3.3) than for liberals (-12.1, SE=3.3). 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 conditional logit 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

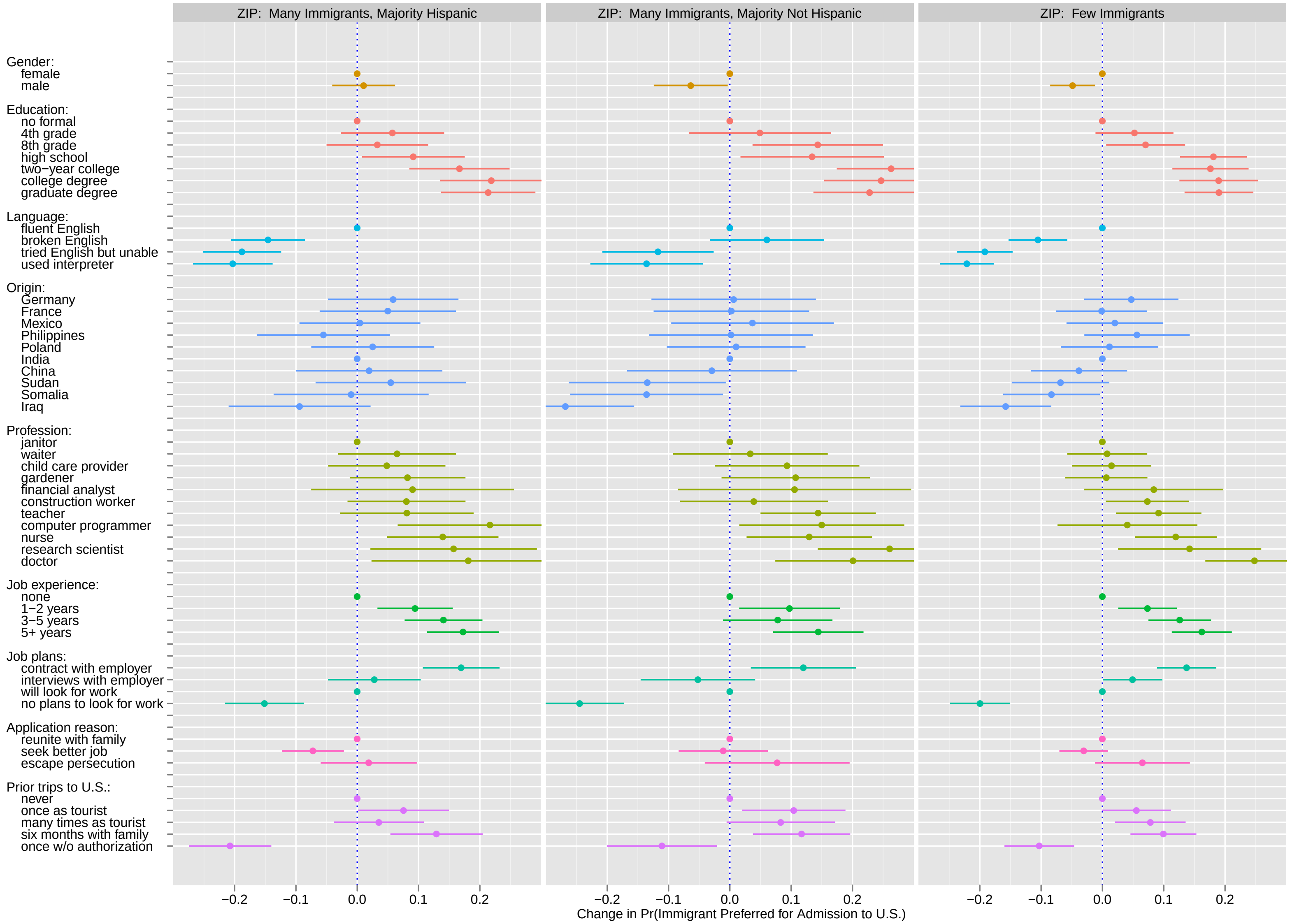


Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on conditional logit models with clustered standard errors estimated for the group of respondents with house incomes below (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 conditional logit 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

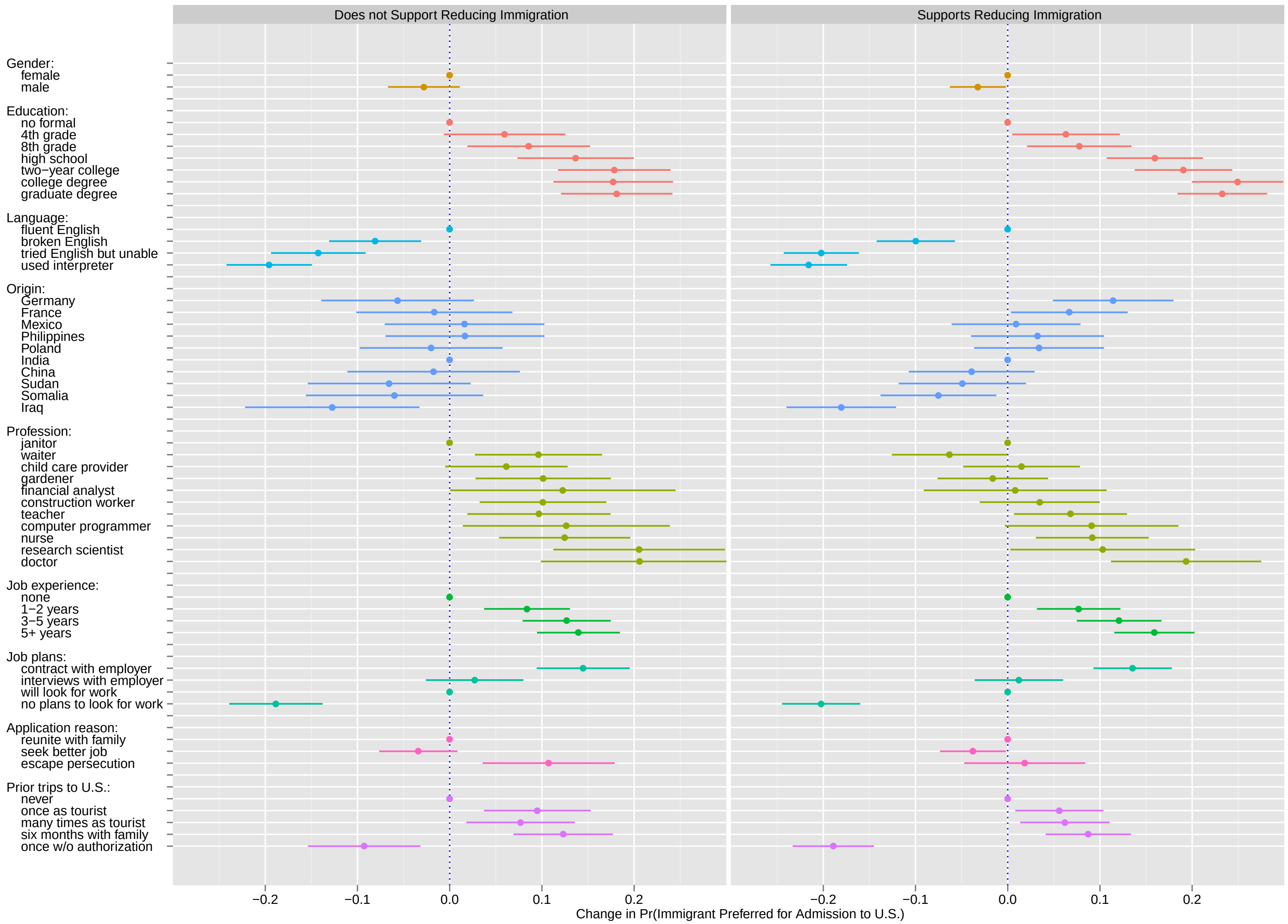


Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on conditional logit models with clustered standard errors estimated for respondents residing in a ZIP code with: many immigrants, 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 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 conditional logit models with clustered standard errors estimated for the group of respondents who self-identify as liberal (n=457) or conservative (n=628), 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 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 conditional logit models with clustered standard errors estimated for the group of respondents who do not support reducing immigration (n=742) or do (n=953), 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 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 conditional logit models with clustered standard errors estimated for the group of male (n=854) and female (n=860) 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.8: 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 conditional logit 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.

Appendix C: Robustness Checks

A. Panel and Spillover Effects

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.1 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.[1] 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.2. It plots the results separately for profiles that were seen first, second, third, fourth, or fifth. Yet again, the core results hold across each of the subsets, with no clear effects of the repeated pairings. Consistent with this, Wald tests for each of the attribute value sets suggest that the effect of the values does not vary significantly across a respondent's five pairings.[2] The pattern of results is very similar across each of the five

[1] For instance, in our panel, attitudes about overall levels of immigration were slightly less restrictionist at the end of the second wave. On a five-point scale from one (immigration should be decreased a lot) to five (immigration should be increased a lot), attitudes measured at the end of the second wave increased by a small but significant 0.084 ($p < 0.001$). Certainly, this change could have been induced by any event between the administration of the two waves.

[2] In particular, we fit our benchmark model using the data from all pairings but interact each attribute value with indicator variables for the pairing numbers (1, 2,...,5). We then test whether the interaction terms for the attribute values are jointly insignificant. The p-values are for these joint tests are: Gender .14, Education .17, Language .39, Origin .22, Profession .43, Job Experience .07, Job Plans .81, Application reason .45, and Prior trips to U.S. .69. Except for Job Experience, we therefore cannot reject the null that the effects of the attribute values are the same across all five pairings. For Job Experience, the significant rejections occur when comparing the 1st and 2nd pairing mostly, but this finding is only marginally significant and would not pass

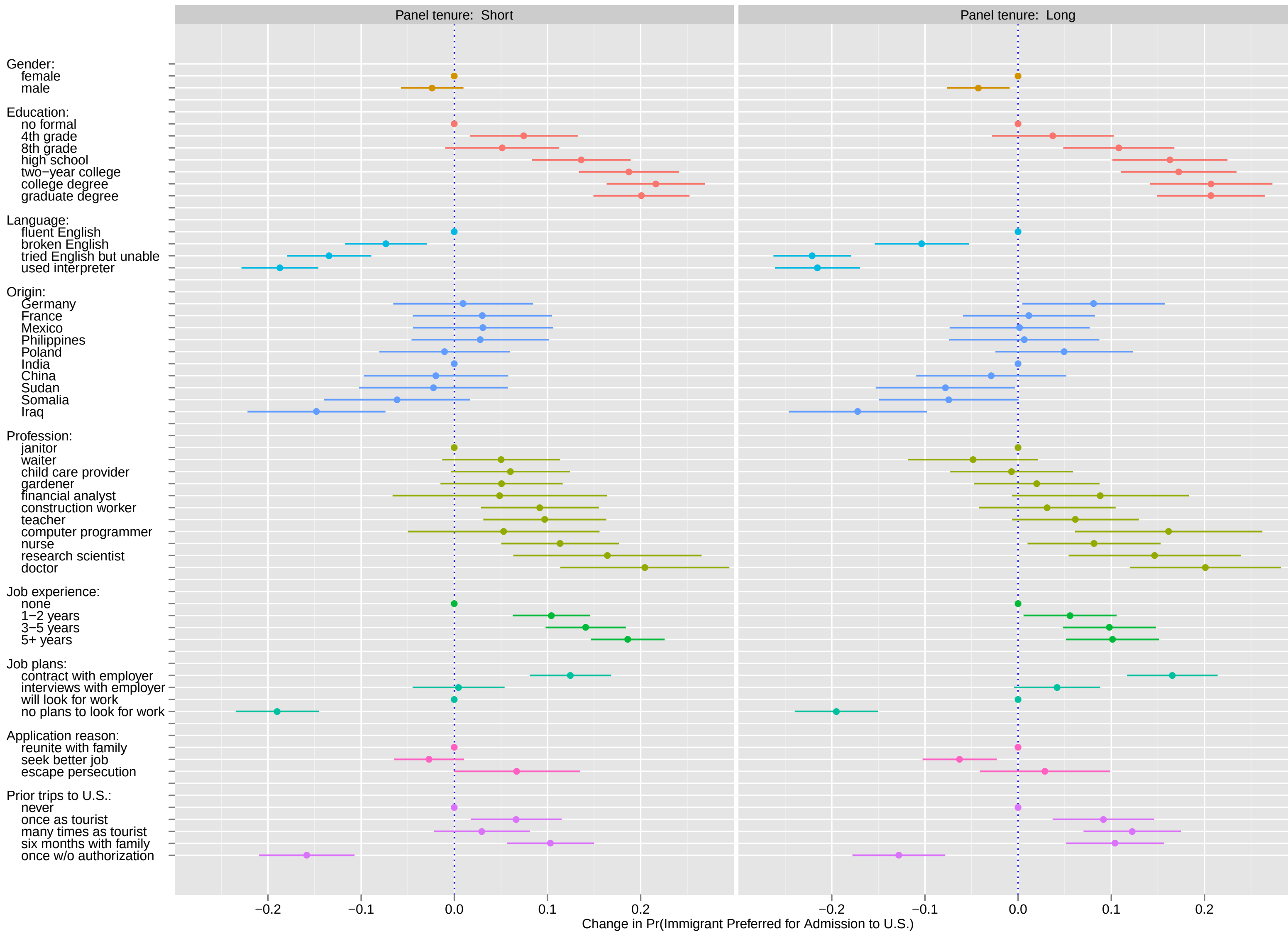
pairings, with no clear evidence of increased satificing or other adaptations by the respondents.

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.[3] We then broke down the respondents into three roughly equal sized groups including respondents that were exposed to a low (0-3), medium (4-5), or high (6-9) number of atypical profiles and replicated the baseline model for each group. The results are displayed in Figure C.4. Again, the pattern of results is fairly similar across all three groups indicating that respondents are not easily distracted by seeing atypical profiles.

adjustments for multiple testing. Consistent with this, the interactions for all attribute values are insignificant when we replicate the test with *Support Admission* as the outcome variable. The p-values from the joint tests are: Gender .64, Education .71, Language .22, Origin .57, Profession .52, Job Experience .10, Job Plans .77, Application reason .87, and Prior trips to U.S. .21.

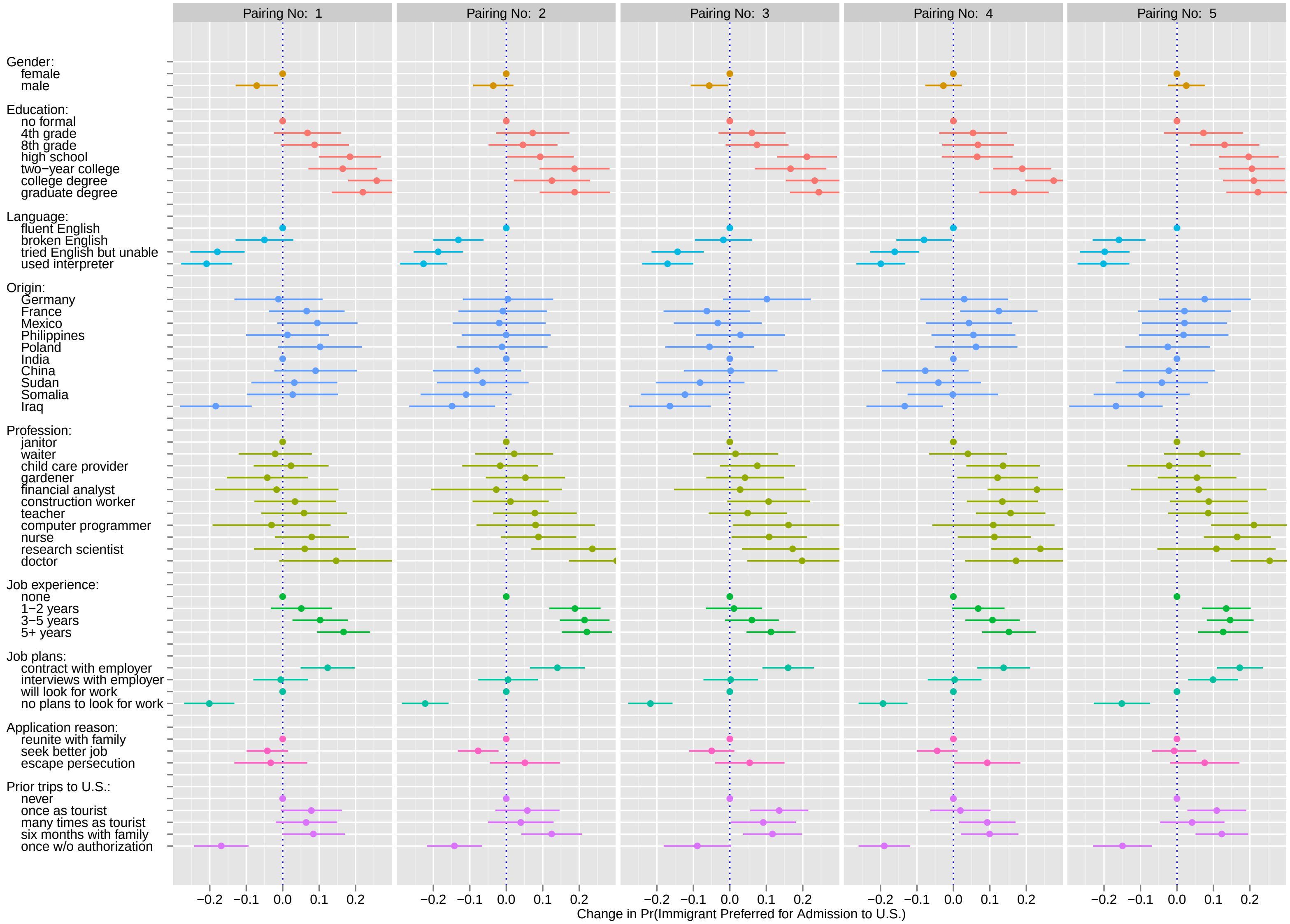
[3]The full list of atypical profiles is as follows: Mexico and some college or college degree or graduate degree; Mexico and doctor or research scientist or computer programmer or financial analyst; Somalia and some college or college degree or graduate degree; Somalia and doctor or research scientist 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; Indian and no formal education or 4th grade education or 8th grade education; Indian and janitor or waiter or child care provider or gardener; Indian 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.1: 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 conditional logit 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.2: Effects of Immigrant Attributes on Probability of Being Preferred for Admission by Pairing

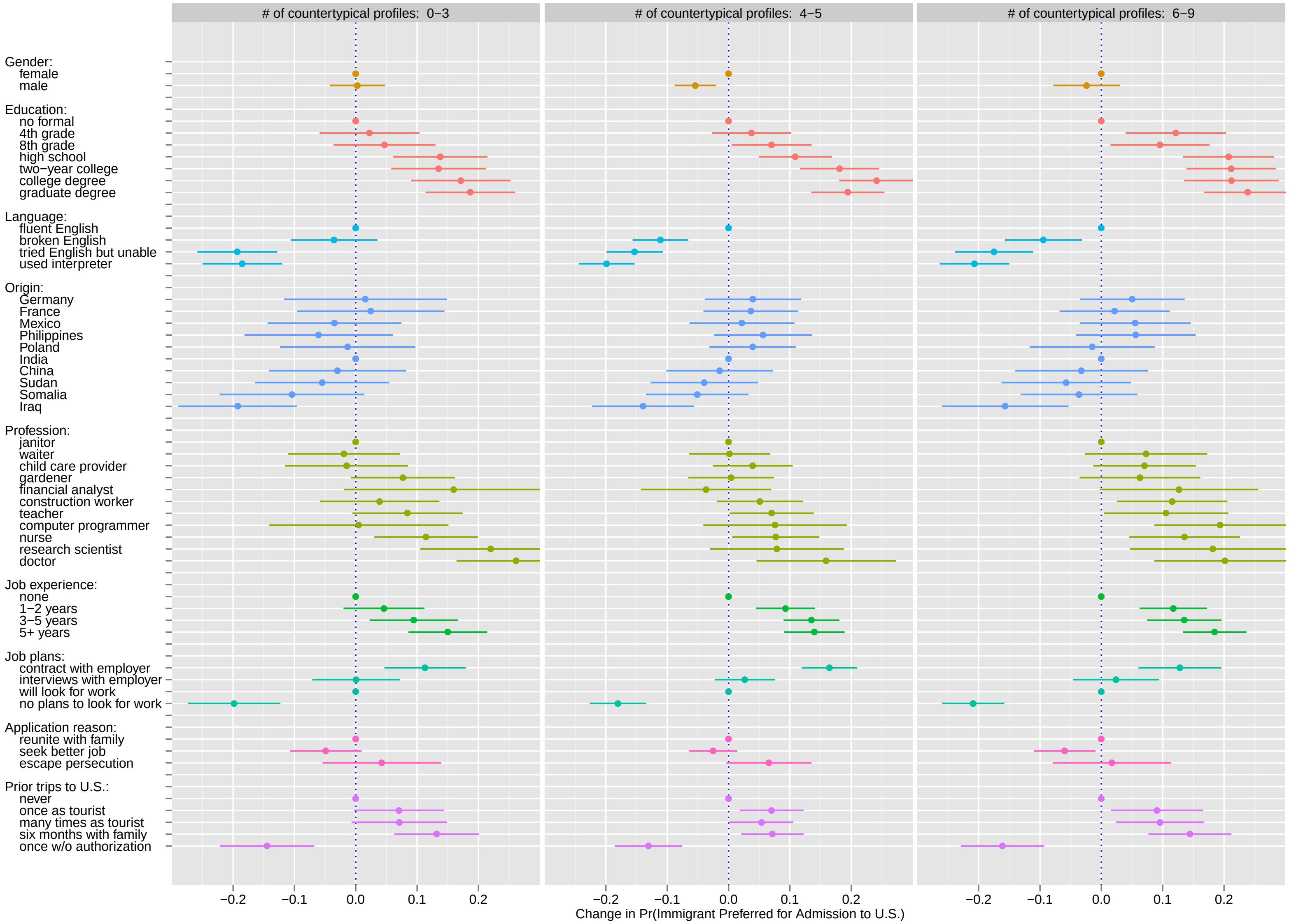


Note: These plots show estimates of the effects of the randomly assigned immigrant attributes on the probability of being preferred for admission to the U.S. Estimates are based on conditional logit models with clustered standard errors estimated for respondents' first, second, third, fourth, and fifth 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.3: 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 conditional logit 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.

Figure C.4: 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 conditional logit models with clustered standard errors estimated for the group of respondents exposed to a small, medium, or high number of countertypical 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.

Appendix D: Additional Tables

	Number	% of 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 D.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.

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

Model No:	(1)	(2)	(3)
Model	Cond. Logit	Logit	OLS
Outcome Variable:	Immigrant Preferred	Support Admission	Immigrant Rating
Match (1/0)	0.003	-0.007	0.029
	(0.049)	(0.045)	(0.175)
Observations	12,064	12,100	12,100

Note: This table reports the first difference when we augment our primary models to estimate the effect of 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 dummy variables for all immigrant attributes and also dummy variable for the respondent profession (marginal effects not shown here). The unit of observation is the immigrant profile; standard errors are clustered by respondent.

Appendix E: Automated Content Analysis

Both the sociotropic and norms-based hypotheses can find considerable support in the evidence presented above. 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 above 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 E.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 immigrant's 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 E.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 E.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.

References

Berinsky, A. J., Huber, G. A. and Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com's mechanical turk, *Political Analysis* **Forthcoming**.

Berinsky, A. J. and Lavine, H. (2011). Self-monitoring and political attitudes, *in* J. H. Aldrich and K. M. McGraw (eds), *Improving Public Opinion Surveys: Interdisciplinary Innovation and the American National Election Studies*, Princeton University Press.

Blei, D. M., Ng, A. Y. and Jordan, M. I. (2003). Latent dirichlet allocation, *Journal of Machine Learning Research* **3**: 993–1022.

Chang, J. (2010). Package "lda". Version 1.2.3. Available online at: http://cran.r-project.org.

Hainmueller, J. and Hiscox, M. J. (2010). Attitudes toward Highly Skilled and Low-Skilled Immigration: Evidence from a Survey Experiment, *American Political Science Review* **104**(01): 61–84.

Hanson, G. H., Scheve, K. and Slaughter, M. J. (2007). Public Finance and Individual Preferences Over Globalization Strategies, *Economics and Politics* **19**(1): 1–33.

Krosnick, J. A. (1999). Survey research, *Annual Review of Psychology* **50**(1): 537–567.

Ostfeld, M. C. and Mutz, D. (2011). Revisiting the effects of personalization: American attitudes towards immigration policy. Paper Presented at the 2011 Meeting of the Midwest Political Science Association, Chicago, IL.

Paolacci, G., Chandler, J. and Ipeirotis, P. G. (2010). Running experiments on amazon mechanical turk, *Judgment and Decision Making* **5**(5): 411–419.

Snyder, M. (1974). Self-monitoring of expressive behavior., *Journal of personality and social psychology* **30**(4): 526.