Online Appendix for

"Public Attitudes toward Young Immigrant Men"

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Contents

A Details on Survey Design and Implementation

A.1 Randomization of Countries of Origin

The number of immigrants per country of origin were randomized as follows. First, one of three vectors - (60,0,0,0,0,0), (30,20,10,0,0,0), (10,10,10,10,10,10) - was randomly chosen for each profile. Second, the order of the six numbers in the chosen vector was randomized. Finally, the randomly ordered set of six numbers were matched to the six origin countries to represent the number of immigrants per country.

A.2 Attribute Order Randomization and Example Groups

As described in the main text, each immigrant group contained eight attributes: the number of immigrants for each of the six origin countries, the share of young men in the group, and the share of group members with a university education. When presented to respondents, the origin countries were always presented first. The order of the six origin countries was randomly assigned once per respondent and then constant across the four pairs of immigrant groups each respondent evaluated. Below the number of immigrants per countries, the total number of immigrants in the group, which is always fixed at 60, was displayed.

Below the origin country information, the other two attributes, young men and education, were presented under a section titled "Group Traits." The order of these attributes was also randomly assigned for each respondent but then held constant across pairs of immigrant groups. An example of how the groups were presented to respondents is displayed in Table A.1.

A.3 Survey Flow

Before beginning the conjoint tasks, respondents read an informed consent document and answered demographic questions on age, citizenship, gender, education, and state. After these, respondents were informed that they would be asked to compare four pairs of immi-

Table A.1: Example Immigrant Groups

	Group A	Group B
Number of immigrants per country:		
Syria	0	20
Afghanistan	0	0
Albania	0	30
Eritrea	60	0
Serbia	0	10
Nigeria	0	0
Total	60	60
Group Traits:		
Share with university education	0%	30%
Share of male immigrants under age 25	75%	50%

grant groups. In each task, respondents were asked seven items: the single forced choice question, three rating questions about Group A, and three rating questions about Group B. The forced choice item was always asked first, immediately below the group profiles. Whether questions about Group A or Group B appeared second was randomized for each pair of profiles. Within the questions about each group, the order of the three rating scales (*Economic Potential*, *Security Threat* and *Cultural Threat*) were also randomized. Between each of the conjoint tasks, respondents were alerted that they were about to be shown new groups.

A.4 Sample

The survey was conducted online from December 23, 2016 to December 30, 2016. The target population was German citizens aged 18-75. Respondents were provided by the survey firm Respondi AG, who maintain a panel of approximately 100,000 Germans. Respondi primarily recruits their panelists through online channels, although a small fraction of their panel is recruited by computer-assisted telephone interviews (for further details, see Steinbrecher, Roßmann and Bergmann 2013). Respondi's recruitment process requires panelists to complete a questionnaire covering basic socio-demographic information and to pass a series of checks to ensure panelists are not "double-registering" or using false identities before being invited to participate in surveys. To ensure the quality of their panel, Respondi also regularly removes from their panel respondents who do not reply to several successive survey invitations or who provide low-quality responses, by, e.g., speeding through surveys, or regularly providing "straight-line" responses. Respondi compensates respondents depending on the time a survey takes to complete; for this study, respondents were compensated approximately EUR 1.30 for a median interview length of 6 minutes, 13 seconds.

Based on Respondi's pre-collected demographic records, members of Respondi's panel were invited to participate in the survey such that the sample matched population margins on age, gender, state, and education. Hard quotas for these demographics were not used during sampling, however. As shown below, this procedure results in a sample that roughly matched the population margins; to account for remaining imbalances, post-stratification weights were construed. The final sample includes 2,133 respondents.[1]

A.5 Demographic Variables and Descriptive Statistics

Five demographic variables were measured for each respondent: age (years), gender, state, citizenship and highest completed education. All measures are self-reported. Respondents were able to choose from 12 education levels:

1. Still in school
2. Special-needs school leaving certificate
3. Secondary school leaving certificate
4. Degree from polytechnic secondary school in the former German Democratic Republic

[1] Three respondents were inadvertently interviewed twice. The current estimates include both interviews from these respondents, and for the purposes of clustering the standard errors, combine the pairs of interviews into a single cluster. Robustness checks (code to perform these checks is included in the replication materials) show that the results are robust to a) excluding these three respondents from the data, b) including these respondents but treating each interview as a separate "cluster" for the purpose of standard errors, and c) only including the first interview done by each of these respondents.

5. Intermediate school-leaving certificate
6. Entrance qualification for studies at universities of applied sciences
7. High school diploma which allows for university entrance
8. Degree in vocational education
9. Degree from a university of applied science (diploma, bachelor's or master's)
10. University degree (diploma, bachelor's or master's)
11. PhD
12. No completed education programs

These levels were then grouped into four categories: Low (levels 1,2,3, 8 and 12), medium (levels 4 and 5), high-tier high school education (levels 6 and 7), and university education (levels 9, 10, and 11). Table A.2 displays descriptive statistics for age, gender, survey completion time (in seconds), and education for all survey respondents.[2]

Table A.2: Respondent Descriptive Statistics

	Min.	Median	Mean	Max.	Std. Dev.	NA
Age (years)	18	49.5	48.1	100	15.05	0
Male	0	1	0.53	1	0.50	6
Completion Time	59	373	1,175	433,466	12,884	0
Education:	Low	Medium	High	University	NA	
	47.19%	20.65%	14.65%	17.42%	0.09%	

A.6 Sample Weights

As is common in internet panels, my sample deviates from the demographic margins of the population. The first three columns of Table A.3 explores differences between my sample

[2]Statistics for citizenship are not shown as all non-German citizens were screened out of the survey.

and the population in terms of age, gender, state, and education. In general, the sample demographics are quite similar to the population. However, in comparison to the population, middle-aged people, men, residents of North Rhine-Westphalia, and low-education individuals, are overrepresented in my sample, while young people, women, residents of Baden-Württemberg, and medium-education individuals are underrepresented.

To correct for differences, I fit post-stratification weights for my data using the function `rake()` in the `R` package `survey`. Specifically, I construct weights to achieve balance based on the population margins among 18-75 year old Germans on four demographics: age, gender, education, and state. Data on population margins comes from the German Federal Statistical Agency (Statistiches Bundesamt; `destatis.de`) figures for 2016. During the estimation of weights, I drop from the dataset 35 respondents who were outside the target population (i.e. respondents younger than 18 or older than 75) and had missing values on age, education, gender, or state.[3]. Estimated weights above three were trimmed to three. The last two columns of Table A.3 show the sample margins after weighting, and the difference between the population and weighted survey margins. We see that weighting improves the similarity of the sample to the population substantially. These weights are used for all analyses in the main text and the SI unless otherwise noted. Model 2 in Table B.1 shows the robustness of the results of my main analysis to using the unweighted data (and including respondents of all ages); Models 2, 4, and 6 do the same for my analyses of potential mechanisms in Table B.2.

[3]The results are similar if only those respondents with missing data are dropped.

Table A.3: Population and Survey Demographics

	Population	Survey (unweighted)	Difference	Survey (weighted)	Difference
Age					
18-24	9.88%	7.04%	2.84	9.96%	-0.08
25-34	16.21%	16.37%	-0.16	16.40%	- 0.19
35-44	15.32%	16.09%	-0.74	15.49%	-0.17
45-54	22.76%	25.04%	-2.28	23.01%	-0.25
55-64	19.57%	19.09%	0.46	19.73%	-0.16
65+	16.25%	16.37%	-0.12	15.42%	0.83
Mean Absolute Difference:			1.1		0.28
Gender					
Male	49.76%	52.55%	-2.79	49.80%	-0.04
Female	50.24%	47.45%	2.79	50.20%	0.04
Mean Absolute Difference:			2.79		0.04
State					
Baden-Württemberg	12.58%	9.90%	2.68	12.51%	0.07
Bavaria	15.51%	14.33%	1.18	15.43%	0.08
Berlin	4.12%	4.66%	-0.54	4.13%	-0.01
Brandenburg	3.30%	2.09%	1.21	3.33%	-0.03
Bremen	0.78%	1.19%	-0.41	0.79%	-0.01
Hamburg	2.09%	2.71%	-0.62	2.10%	-0.01
Hesse	7.17%	8.19%	-1.02	7.20%	-0.03
Mecklenburg-Vorpommern	2.15%	1.95%	0.20	2.14%	0.01
Lower Saxony	9.90%	10.42%	-0.52	9.89%	0.01
North Rhine-Westphalia	21.31%	24.37%	-3.06	21.27%	0.04
Rhineland-Palatinate	5.00%	5.14%	-0.14	5.00%	0.00
Saarland	1.25%	1.19%	0.06	1.27%	-0.02
Saxony	5.32%	7.33%	-2.01	5.44%	-0.12
Saxony-Anhalt	2.99%	1.95%	1.04	2.99%	0.00
Schleswig-Holstein	3.65%	2.71%	0.94	3.66%	-0.01
Thuringia	2.89%	1.86%	1.03	2.85%	0.04
Mean Absolute Difference:			1.04		0.03
Education					
Low	39.43%	46.83%	-7.40	39.31%	0.12
Medium	29.58%	20.75%	8.83	29.57%	0.01
High	13.78%	14.85%	-1.07	13.90%	-0.12
University	17.20%	17.56%	-0.36	17.24%	-0.04
Mean Absolute Difference:			4.42		0.07

Note: Data on population demographics was retrieved from the Federal Statistical Office of Germany (`http://www.destatis.de`) for 2016. Survey estimates use only respondents aged 18–75 with no missing values on age, education, gender, or state.

B Regression Tables for Figure 1 and 2

The tables in this section report the following results. First, Table B.1 presents the estimates corresponding to Figure 1 in the main text, and also shows the robustness of these estimates to using the unweighted data (which also includes respondents who were older than the target population age range of 18-75 years). Second, Table B.2 presents regression estimates corresponding to Figure 2 in the main text, and additionally, shows the robustness of these results to the exclusion of the survey weights. Worth noting in Table B.2 are the estimated effects of *Education*. Groups with more university educated members are perceived as (1) more likely to contribute economically, (2) less likely to be a security threat, and (3) less likely to be a cultural threat. These results correspond well with earlier studies showing natives have favorable opinions toward educated immigrants (see Bansak, Hainmueller and Hangartner 2016; Hainmueller and Hopkins 2015) and provide reassurance that the three rating variables are measuring their intended concepts.

Table B.1: Regression Results for Figure 1 and Unweighted Results

	Model 1: Weighted	Model 2: Unweighted
Intercept	0.408***	0.407***
	(0.012)	(0.010)
Share of Young Men:		
0%	0.087***	0.093***
	(0.014)	(0.012)
25%	0.063***	0.064***
	(0.013)	(0.012)
75%	−0.092***	−0.081***
	(0.014)	(0.012)
100%	−0.181***	−0.179***
	(0.014)	(0.012)
Share with University Education:		
10%	0.083***	0.080***
	(0.012)	(0.011)
20%	0.162***	0.155***
	(0.012)	(0.011)
30%	0.220***	0.219***
	(0.013)	(0.011)
R^2	0.067	0.066
N	16,528	16,790

Note: The dependent variable in both models is *Settlement Preference*. Estimates are from (weighted) OLS models with standard errors clustered by respondent. Model 1 uses the survey weights described in SI.1.6, Model 2 uses no weights. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table B.2: Regressions Results for Figure 2 and Unweighted Results

	Model 1: Economic Potential Weighted	Model 2: Economic Potential Unweighted	Model 3: Security Threat Weighted	Model 4: Security Threat Unweighted	Model 5: Cultural Threat Weighted	Model 6: Cultural Threat Unweighted
Intercept	0.224***	0.218***	0.433***	0.428***	0.434***	0.427***
	(0.012)	(0.010)	(0.014)	(0.013)	(0.014)	(0.013)
Share of Young Men:						
0%	−0.002	0.002	−0.052***	−0.051***	−0.047***	−0.042***
	(0.012)	(0.010)	(0.013)	(0.012)	(0.013)	(0.012)
25%	0.005	0.003	−0.038**	−0.040***	−0.029*	−0.032**
	(0.011)	(0.010)	(0.013)	(0.012)	(0.013)	(0.012)
75%	0.005	0.006	0.029*	0.027*	0.001	0.002
	(0.012)	(0.010)	(0.013)	(0.012)	(0.013)	(0.012)
100%	−0.008	−0.011	0.065***	0.065***	0.032*	0.038**
	(0.011)	(0.010)	(0.014)	(0.012)	(0.013)	(0.012)
Share with University Education:						
10%	0.023*	0.023*	0.008	0.010	0.005	0.006
	(0.011)	(0.009)	(0.012)	(0.011)	(0.012)	(0.011)
20%	0.009	0.010	−0.030*	−0.019	−0.032**	−0.030**
	(0.010)	(0.009)	(0.012)	(0.011)	(0.012)	(0.011)
30%	0.050***	0.047***	−0.057***	−0.050***	−0.064***	−0.059***
	(0.011)	(0.010)	(0.012)	(0.011)	(0.012)	(0.011)
R^2	0.002	0.002	0.010	0.010	0.006	0.006
N	16,677	16,949	16,659	16,930	16,672	16,943

Note: Estimates are from (weighted) OLS models with standard errors clustered by respondent. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

C Subgroup Effects

Table C.1 shows the results when the data is subset according to gender, age (all respondents above the median age of 49 are coded as old), education (categories "High" and "University" are coded as high; all other categories are coded as low) and region (East and West Germany). These analyses are exploratory, and hence, should not be viewed as a test of any specific hypothesis about how the effect of *Young Men* does or does not vary between subgroups of the sample. Turning to the estimates in Table C.1, the exploratory analysis reveals no evidence that low support for young immigrant men is unique to any specific subgroup: across all eight models, we see estimates similar to those reported for the full sample (i.e. in Figure 1 and Table B.1).

Table C.1: Results for Respondent Subgroups

	Model 1 Men	Model 2 Women	Model 3 Young	Model 4 Old	Model 5 High Education	Model 6 Low Education	Model 7 East Germany	Model 8 West Germany
Intercept	0.399***	0.418***	0.405***	0.412***	0.377***	0.422***	0.439***	0.402***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.018)	(0.015)	(0.033)	(0.012)
Share of Young Men:								
0%	0.096***	0.078***	0.087***	0.088***	0.103***	0.081***	0.060	0.093***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.023)	(0.018)	(0.039)	(0.015)
25%	0.084***	0.042*	0.065**	0.059***	0.071**	0.059***	0.090**	0.056***
	(0.018)	(0.020)	(0.019)	(0.019)	(0.022)	(0.017)	(0.035)	(0.014)
75%	−0.091***	−0.094***	−0.100***	−0.084***	−0.111***	−0.084***	−0.158***	−0.079***
	(0.019)	(0.020)	(0.021)	(0.019)	(0.023)	(0.017)	(0.036)	(0.015)
100%	−0.159***	−0.203***	−0.204***	−0.155***	−0.192***	−0.176***	−0.198***	−0.178***
	(0.019)	(0.019)	(0.020)	(0.018)	(0.022)	(0.017)	(0.036)	(0.015)
Share with University Education:								
10%	0.082***	0.084***	0.097***	0.066***	0.111***	0.070***	0.079*	0.083***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.021)	(0.014)	(0.031)	(0.013)
20%	0.158***	0.166***	0.164***	0.158***	0.213***	0.138***	0.128***	0.168***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.019)	(0.015)	(0.033)	(0.012)
30%	0.216***	0.223***	0.230***	0.206***	0.273***	0.196***	0.186***	0.226***
	(0.018)	(0.018)	(0.019)	(0.017)	(0.020)	(0.016)	(0.032)	(0.014)
R^2	0.064	0.070	0.077	0.057	0.090	0.058	0.071	0.067
N	8,674	7,854	8,436	8,092	5,408	11,120	2,516	14,012

Note: The dependent variable in all models is *Settlement Preference*. Estimates are from weighted OLS models with standard errors clustered by respondent. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

D Labor Market Competition

A central argument to the literature on attitude towards immigrants is that opposition to immigration (or lack thereof) is driven by individuals' fears of labor market competition ("LMC") with new arrivals (see, e.g. Dancygier and Donnelly 2013; Hainmueller and Hiscox 2010; Hainmueller and Hopkins 2014; Malhotra, Margalit and Mo 2013; Scheve and Slaughter 2001). More specifically, the LMC argument predicts that individuals who fear they will lose their job to an immigrant are less likely to support allowing that immigrant into the country. Accordingly, low-skilled natives will view low-skilled immigration less favorably, and high-skilled natives should be less supportive of high-skilled immigration. In the context of my study, the LMC argument would predict that respondents most likely to compete in the labor market with young immigrant men should be less supportive of groups with many young immigrant men than other respondents.

To perform an exploratory analysis of the extent to which labor market competition concerns can explain my results, I re-estimated the effects of *Young Men* including an interaction between *Young Men* and *High LMC Threat*, which is a binary indicator for young male respondents with low education – a set of respondents very likely to be in direct labor market competition with young immigrant men. I consider a number of definitions of both young and low education, to ensure results do not depend heavily on arbitrary coding decisions. For young, I consider respondents less than ages 30, 35, and 40. For low education, I consider respondents with an education in the "Low" category or respondents with an education in either the "Low" or "Medium" group. The estimates for these models are presented in Table D.1.[4]

The estimates in Table D.1 show little difference in attitudes toward the young men between *High LMC Threat* respondents and the rest of the sample. Almost all of the estimated effects are positive, suggesting that *High LMC Threat* respondents both give groups with

[4]I fit interaction models instead of the separate regressions for subgroups (as I do in Table C.1), as interactions make it more straightforward to statistically test they hypothesis that the effect of *Young Men* is no different between the two groups. This comes, however, at the cost of less easily interpretable estimates.

less than 50% young men a larger premium than other respondents and that *High LMC Threat* respondents give groups with fewer than 50% young men a smaller penalty than other respondents. This is only partially consistent with the LMC argument, which would predict both larger premiums and larger penalties for groups with few young immigrant men among respondents with a high LMC threat. However, few of these interaction effects are significant: out of the 24 total estimated interactions, only for 100% in Model 1, 0% and 25% in Model 2, and 0% in Model 5 are the estimates significant at conventional levels.

As a more thorough test of whether effect of *Young Men* is different for the *High LMC Threat* subgroup and all other respondents, I conducted a Wald test of the joint significance of the interaction terms for each model. In other words, I performed a test where the null hypothesis is that none of the four interactions are different from zero. Across all six versions of *High LMC Threat*, I am unable to reject this null hypothesis, as the F statistics and corresponding p-values in Table D.1 show. That the interactions of *Young Men* and *High LMC Threat* are not jointly significant in any model indicates that respondents who are likely to compete with young immigrant men in the labor market did not express different preferences towards these immigrants than other respondents. In sum, this exploratory analysis does not suggest that concerns about LMC explain my findings.

Table D.1: Effect of *Young Men* interacted with *High LMC Threat*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender in High LMC Threat:	Men	Men	Men	Men	Men	Men
Ages in High LMC Threat:	≤ 30	≤ 35	≤ 40	≤ 30	≤ 35	≤ 40
Edu. in High LMC Threat:	"Low"	"Low"	"Low"	'Low", "Medium"	"Low", "Medium"	'Low", "Medium"
Intercept	0.410***	0.411***	0.410***	0.411***	0.412***	0.413***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
High LMC Threat	−0.083*	−0.083*	−0.040	−0.044	−0.049	−0.043
	(0.041)	(0.037)	(0.031)	(0.042)	(0.035)	(0.028)
Share of Young Men:						
0%	0.084***	0.083***	0.084***	0.081***	0.078***	0.079***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)	(0.015)
0% × High LMC Threat	0.127	0.129*	0.069	0.108	0.105*	0.070
	(0.075)	(0.061)	(0.055)	(0.059)	(0.052)	(0.044)
25%	0.060***	0.058***	0.059***	0.062***	0.059***	0.055***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
25% × High LMC Threat	0.093	0.118*	0.060	0.008	0.048	0.061
	(0.062)	(0.055)	(0.046)	(0.064)	(0.049)	(0.041)
75%	−0.094***	−0.095***	−0.094***	−0.093***	−0.095***	−0.097***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)
75% × High LMC Threat	0.058	0.075	0.025	−0.004	0.034	0.042
	(0.073)	(0.055)	(0.047)	(0.075)	(0.057)	(0.046)
100%	−0.184***	−0.184***	−0.183***	−0.184***	−0.183***	−0.182***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
100% × High LMC Threat	0.134*	0.079	0.043	0.051	0.016	0.005
	(0.068)	(0.057)	(0.049)	(0.063)	(0.053)	(0.044)
Share with University Education:						
10%	0.083***	0.083***	0.083***	0.083***	0.083***	0.083***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
20%	0.162***	0.162***	0.162***	0.161***	0.162***	0.162***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
30%	0.220***	0.220***	0.220***	0.220***	0.220***	0.220***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
Test of Joint Significance of Interaction Terms						
F	1.73	1.46	0.63	1.36	1.50	1.25
p-value	0.14	0.21	0.64	0.24	0.20	0.29
R^2	0.067	0.067	0.067	0.067	0.067	0.067
N	16,528	16,528	16,528	16,528	16,528	16,528

Note: The dependent variable in all models is *Settlement Preference*. Estimates are from weighted OLS models with standard errors clustered by respondent. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

E Ecological Validity of Treatments

The share of young men in the experimental immigrant groups varies quite substantially – from 0% to 100% in increments of 25%. One potential concern with this treatment is its ecological validity: how well does it reflect the real world experiences of respondents? Given that approximately 40% of refugees arriving in Germany in 2015 and 2016 were young men, it is possible that few people encountered groups with 100% or 0% young men. The ideal answer to this question would be based on an analysis of the demographics at the various refugee housing centers across Germany. Unfortunately, this data is not publicly available, ruling this option out. As an alternative, I consider whether my results hold when subsetting the data to only immigrant groups with 25% or 50% young men - the two treatments closest to the 40% rate in the population of asylum seekers. This is important to know, as without further knowledge of the asylum seeker distribution system, these are the treatments that we can assign the highest degree of ecological validity, given their closeness to the overall rate of 40%. If the results hold for this subsample, then our confidence will be increased that the results are ecologically valid and not solely due to comparisons to groups with 0% or 100% young men.

Table E.1 shows the results of three models probing the robustness of the results to the use of only observations with 25% or 50% young men. Model 1 begins by simply dropping all observations with 0%, 75%, or 100% young men. Here, the estimated effect of going from 50% to 25% is a premium of 6.3 percentage points, almost identical to the same quantity estimated in the main results. However, Model 1 does not account for the fact that the 25% and 50% groups were often compared to groups with the other three treatments. Model 2 does account for this, by fitting a model which includes only observations from choice tasks in which respondents compared a 25% young men group to a 50% young men group. The estimated effect of 25% young men in this model is again positive and significant, showing that even among these two treatments, respondents showed a clear preference for the 25% young men groups. An even more stringent test is presented in Model 3. Here, the data from

Table E.1: Results for only *Young Men* shares of 25% and 50%

	Model 1	Model 2	Model 3
Comparison within task	Any	25% v. 50%	25% v. 50%
Choice Task	All	All	First
Intercept	0.410***	0.262***	0.120*
	(0.013)	(0.029)	(0.054)
Share of Young Men:			
25%	0.063***	0.282***	0.394***
	(0.012)	(0.037)	(0.069)
Share with University Education:			
10%	0.067***	0.058	0.233**
	(0.017)	(0.038)	(0.075)
20%	0.163***	0.150***	0.231**
	(0.017)	(0.040)	(0.073)
30%	0.215***	0.179***	0.249***
	(0.017)	(0.038)	(0.071)
R^2	0.032	0.099	0.204
N	6,610	1,308	336

Note: The dependent variable in all models is *Settlement Preference*. Estimates are from OLS models with standard errors clustered by respondent. Model 1 uses all observations (i.e. immigrant groups) with 25% or 50% young men, regardless of the percent of young men in the other group a respondent saw in a given choice task. Model 2 restricts the sample to only observations from choice task where respondents compared a 25% young men group to a 50% young men group. Model 3 uses only observations from the subset included in Model 2 which were from the first choice task a respondent completed. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Model 2 is further subset to only include observations from the first of four conjoint tasks that a respondent completed. This ensures that respondent were not even aware that other levels of *Young Men* were in the survey when they were forced to choose between groups with 25% and 50% young men. Again, the estimated effect shows strong preferences in favor of fewer young men: in these 168 choice tasks, the group with 25% young men was almost 40 percentage points more likely to be preferred for settlement.

These results show that between the two levels of *Young Men* that are closest to the population average of young men, respondents had a clear preference in favor of fewer young men. Based on the assumption that the age and gender compositions of groups of asylum seekers that my respondents would encounter are similar to the overall population, that I find results for these two groups speaks in favor of the ecological validity of my results.

Whether this assumption is merited, however, is worth further consideration. It seems unlikely that asylum seekers' assignment to specific housing centers is independent of their characteristics; instead, it is plausible that asylum seekers are clustered based on age, national origin, and gender. This is evidenced by the existence of refugee centers exclusively for women[5] and policies which aim to separate single young men from women and families.[6] Consequently, it is plausible that respondents living next to refugee centers just for women may have actually encountered groups with shares of young men approaching 0%. Similarly, for respondents living near refugee housing centers designated only for unaccompanied men, the 75% and 100% treatments would accurately reflect their experiences.[7] Though a lack of data makes it impossible to know how widespread refugee housing centers exclusively or men or women are, this anecdotal evidence suggests that for at least some segments of the German population, all five of the experimental levels of *Young Men* would be ecologically valid.

A brief word on the ecological validity of the other two attributes randomized in the conjoint study is also merited. As stated in the main text, data on the education level of recent arrivals in Germany is very hard to come by. However, as Rich (2016) indicates, one estimate is that approximately one in five asylum seekers had some amount of higher education. The treatment on the conjoint was share of the group with a university degree, varying from 0% to 30% – amounts that are close to the estimated level of education in the population of asylum seekers. This suggesting a high degree of ecological validity, although because Rich's figures are for any higher education and the treatment is having a degree, to the extent that the treatment deviates from reality, it would be in the direction of too many well-educated immigrants.

Regarding the ecological validity of the origin countries of the immigrants in the conjoint study, it is again difficult to say anything definitive without data on how asylum seekers

[5] "Neue Flüchtlingsunterkunft für Frauen in Tübingen," *Süddeutsche Zeitung* August 10, 2017.
[6] "230 Männer in Gewerbehalle untergebracht," *Stuttgarter Zeitung* October 27, 2015.
[7] For an example of such a center, see: "Einst Promi-Hotel, heute Flüchtlingsunterkunft," *Deutschlandfunk* August 8, 2017.

were assigned to housing centers. It is safe to assume that as with age and gender, there is likely to be some clustering, as asylum seekers from a given country are likely to arrive and be processed together. However, it is also likely that for logistical reasons, e.g. the amount of available lodging, some refugee housing centers contained a variety of different national origins. However, one thing that increases confidence in the ecological validity of this treatment is that all six of the countries included in the conjoint were the origin for a large number of asylum applicants in Germany in 2015. Specifically, based on data from the Bundesamt für Migration und Flüchtlinge (2015), the numbers of asylum applicants originating from the six countries included in the conjoint were: 158,657 (Syria), 53,805 (Albania), 31,382 (Afghanistan), 10,876 (Eritrea), and between 5,000 and 8,199 (Nigeria and Serbia). Hence, while it is more likely for a group of 60 to be comprised entirely of Syrians than entirely of Nigerians, if we assume some degree of clustering on national origin in the settlement of asylum seekers, it is plausible that a group of 60 could be comprised entirely of asylum seekers from any one of these six countries.

F Details about Mechanical Turk Pilot Study

For the purpose of refining the survey instrument, I conducted a pilot study of my conjoint experiment on a sample of 200 American respondents from Amazon's Mechanical Turk in September 2016. In the pilot study, each respondent evaluated six pairs of immigrant groups. Prior to completing the conjoint tasks, respondents answered a battery of demographic questions. Respondents were paid \$0.25 for completing the survey, and on average, the survey took respondents six minutes to complete.

The conjoint used in this pilot study differed from the conjoint in the main study in the following ways. First, the six origin countries reflect immigration to the United States instead of Germany, as were: the Dominican Republic, India, Mexico, Nigeria, the Philippines, and Syria. Second, the possible distributions of the 60 immigrants across the 6 origin countries were: (60, 0, 0, 0, 0, 0,). (40, 20, 0, 0, 0, 0), (30, 20, 10, 0, 0, 0), (20, 20, 20, 0, 0, 0), (15, 15, 15, 10, 5, 0), and (10, 10, 10, 10, 10, 10). Third, two additional attributes were presented for each group, their work experience (<1 year, 1 year, 3 years, and 5 years), and the share with basic English skills (0%, 10%, 20%, and 30%).

The main outcome from the pilot study - *Settlement Preference* - is similar to the outcome from the main study. For each pair of immigrant groups, respondents were asked "Which of these groups of immigrants would you prefer settle in your community?" Groups preferred for settlement were coded as 1, while groups not preferred were coded as 0. To analyze the responses to the pilot, I fit an OLS model with standard errors clustered by respondent. The attributes included in this model are *Young Men*, *Education*, *Work Experience* and *English Skills*. The results of this model are shown in Table F.1.

In Table F.1, the estimates for the levels of *Young Men* are of primary interest. As in the main study, groups with many young men are preferred for settlement at lower rates. Specifically, groups with 75% and 100% young men suffer penalties of approximately 6 and 10 percentage points, respectively, in comparison to the baseline group with 50% young men. The Mechanical Turk respondents appear less opposed to groups with small numbers

Table F.1: Results from Mechanical Turk Pilot Study

	Model 1
Intercept	0.249^{***}
	(0.037)
Share of Young Men:	
0%	0.006
	(0.033)
25%	0.036
	(0.031)
75%	-0.062^{*}
	(0.031)
100%	-0.103^{**}
	(0.032)
Share with University Education:	
10%	0.037
	(0.028)
20%	0.117^{***}
	(0.029)
30%	0.182^{***}
	(0.029)
Amount of Work Experience:	
1 year	0.068^{*}
	(0.028)
3 years	0.124^{***}
	(0.029)
5 years	0.173^{***}
	(0.032)
Share with English Skills:	
10%	0.072^{*}
	(0.029)
20%	0.142^{***}
	(0.033)
30%	0.194^{***}
	(0.034)
R^2	0.069
N	2,352

Note: Estimates are from a weighted OLS model with standard errors clustered by respondent.The omitted categories are 0% (Young Men, Education, and English Skills) and < 1 year (Work Experience). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

of young men than the German respondents, however: groups with 25% and 00% young men are not selected at rates significantly different than groups with 50% young men. These results suggest that opposition to young men is (1) not exclusive to the German context but also (2) potentially less strong outside of Germany.

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