List of Appendices

A.1 Results of Applicant Attractiveness Survey

To rank the experiment participants according to their attractiveness, I conducted a survey. The survey included pictures of the participants and asked subjects to assign them to a category - above average looking (compared to the same age/gender group), average looking and below average looking. The survey was sent to volunteer students of different nationalities studying in various universities in Prague, the Czech Republic. In total 35 subjects responded to the survey. There was a total of 10 applicant pictures in the survey, 4 female and 6 males. After the survey, I chose a picture of one female and male participant from each category. As Table A.7 shows, there is a consensus about participants' attractiveness among the students surveyed.

Table A.7: Attractiveness evaluation of experiment participants

Participant #	**Attractiveness category**		
	Above average looking	*Average looking*	*Below average looking*
1	0	40	60
2	85.8	8.6	5.6
3	31.4	48.6	20
4	20	62.9	17.1
5	20	31.4	48.6
6	80	14.1	5.9

Notes: Numbers are percentages of votes in the survey

I wanted to make sure that applicants are not rejected because of characteristics other than a visible tattoo, for ethnicity, for example, so I wanted candidates to have a "German look". Ideally one could use pictures of German people, although in my case it was not feasible, as only one participant is from Germany. For this reason, I needed to make sure that participants' perceived nationality was similar in the treatment and control group. In the first survey described above, in addition to perceived attractiveness, I asked respondents to state (their perceived) nationality of the person depicted on the pictures.[1] Alongside this survey I created another survey, this time using photos with tattoos, and asked another set of participants to state the perceived nationality of the person in the picture. 26 volunteers completed the survey. Table A.8 shows the top three nationalities indicated by volunteers (with respective percentages). As the table shows, there is no

[1] In that survey participants did not have tattoo.

difference in the perceived nationality of applicants with and without tattoos. This ensures that applications in the treatment and control group will not be treated as different nationals, which may complicate the results.

Table A.8: Perceived nationality of experiment participants

Without Tattoo	**Participant #**	**With Tattoo**
Top 3 nationalities		Top 3 nationalities
German - 31%; Czech - 26%; British - 22%	1	Czech - 42%; German - 27%; British - 15%
German - 29%; American - 29%; British - 17%	2	German - 35%; Czech - 23%; British - 23%
British - 67%; American - 17%; German - 6%	3	British - 46%; German - 27%; American - 23%
Czech - 26%; American - 17%; German - 9%	4	American - 31%; Czech - 23%; German - 8%
Czech - 31%; American - 29%; German - 20%	5	American - 31%; British - 31%; Czech - 15%
American - 29%; Czech - 26%; German - 23%	6	American - 35%; British - 31%; Czech - 23%

A.2 Randomization Check

As I sent only one application to one employer, I needed to ensure that firms and jobs were similar in the treatment and control group in terms of all controllable characteristics. In the paper I presented evidence that in terms of a firm's characteristics the sample is balanced. Here I do the same exercise for regions. I test whether regions of the country are similarly represented in the treatment and control group. Table A.9 shows balanced check results for regions. None of the differences are statistically significant, meaning that the randomization ensures the treatment and the control groups are similar in terms of controllable characteristics. Thus, I can rule out that any differential treatment of tattooed applicants is related to firm characteristics and/or to region- specific factors. Therefore, I argue that any difference in callback rates between the treatment and the control group should be due to the treatment itself.

Table A.9: Randomization check – regions

Region	*Non-Tattooed*	*Tattooed*	*P-value*
Baden-Württemberg	0.09 (0.29)	0.09 (0.29)	0.89
Bavaria	0.19 (0.39)	0.19 (0.39)	0.84
Berlin	0.10 (0.31)	0.10 (0.30)	0.98
Brandenburg	0.00 (0.05)	0.01 (0.07)	0.58
Bremen	0.02 (0.14)	0.03 (0.16)	0.68
Hamburg	0.08 (0.27)	0.08 (0.28)	0.89
Hesse	0.14 (0.35)	0.14 (0.35)	0.94
Lower Saxony	0.03 (0.18)	0.04 (0.19)	0.63
Mecklenburg-Vorpommern	0.00 (0.05)	0.01 (0.07)	0.58
North Rhine-Westphalia	0.22 (0.41)	0.22 (0.41)	0.90
Rhineland-Palatinate	0.01 (0.10)	0.01 (0.09)	0.67
Saarland	0.00 (0.05)	0.00 (0.05)	0.98
Saxony	0.05 (0.01)	0.04 (0.01)	0.34
Saxony-Anhalt	0.01 (0.07)	0.01 (0.09)	0.43
Schleswig-Holstein	0.03 (0.17)	0.02 (0.15)	0.60
Thuringia	0.01 (0.09)	0.01 (0.09)	0.74
N	385	397	

Notes: The table shows mean comparison of regions across treatment (tattooed) and the control (non-tattooed) groups. Standard deviations are in parenthesis. Column 3 shows p-values of the hypothesis of equal means.

A.3 Pictures Used in the Experiment

A.4 Robustness Check – Probit Model Estimates

To perform the robustness of the Linear Probability Model (LPM) used in the main text I performed the same analysis using Probit model. Tables below confirm that the Probit model produces results that are qualitatively same the LPM model results.

Table A.10: Estimates of the Probit Model – Firm Characteristics

Dependent variable: Callback	(1)	(2)	(3)	(4)	(5)	(6)
Visible Tattoo	-0.13***††† (0.03)	-0.13***††† (0.03)	-0.13** (0.05)	-0.11***† (0.04)	-0.17** (0.08)	-0.15* (0.08)
Male			-0.12** (0.06)			
Visible Tattoo * Male			-0.01 (0.07)			
International firm				-0.06 (0.05)		
Visible Tattoo * International firm				-0.07 (0.07)		
West Germany					-0.07 (0.06)	
Visible Tattoo * west Germany					0.05 (0.09)	
Urban area						-0.03 (0.07)
Visible Tattoo * Urban area						0.02 (0.09)
Constant	0.30***††† (0.02)	0.29***††† (0.02)	0.28***††† (0.02)	0.28***††† (0.02)	0.28***††† (0.02)	0.28***††† (0.02)
Monthly and regional dummies	*N*	*Y*	*Y*	*Y*	*Y*	*Y*
Control variables	*N*	*N*	*Y*	*Y*	*Y*	*Y*
R^2	0.02	0.06	0.09	0.09	0.09	0.08
N	782	782	782	782	782	782

Notes: The table shows marginal effects at means of the Probit model. Robust standard errors in parentheses. Columns 2-6 include monthly and regional dummies. In columns 3-6, I control for firm characteristics including age, size, number of job advertisements and whether the location of the job is in an urban area. * p<0.1, ** p<0.05, *** p<0.01. † - significance level with multiple hypothesis testing adjusted.

Table A.11: Estimates of the Probit Model – Job requirements

Dependent variable: Callback	(1)	(2)	(3)	(4)
Visible Tattoo	-0.13***††† (0.03)	-0.14***†† (0.04)	-0.16***††† (0.04)	-0.14*** (0.05)
Front office		0.05 (0.05)		
Visible Tattoo * Front office		0.02 (0.07)		
Appearance requirement			-0.04 (0.05)	
Visible Tattoo * Appearance requirement			0.09 (0.08)	
Teamwork requirement				-0.08 (0.05)
Visible Tattoo * Teamwork requirement				0.05 (0.07)
Constant	0.29***††† (0.02)	0.28***††† (0.02)	0.28***††† (0.02)	0.25***††† (0.02)
Monthly and regional dummies	*Y*	*Y*	*Y*	*Y*
Control variables	*N*	*Y*	*Y*	*Y*
R^2	0.06	0.09	0. 09	0.11
N	782	782	782	782

Notes: The table shows marginal effects at means of the Probit model. Robust standard errors in parentheses. Columns 2-4 include monthly and regional dummies. In columns 2-4, I control for firm characteristics including age, size, number of job advertisements and whether the location of the job is in an urban area. * p<0.1, ** p<0.05, *** p<0.01. † - significance level with multiple hypothesis testing adjusted.

Table A.12: Estimates of the Probit Model – Channels of statistical discrimination

Dependent variable: Callback	(1)	(2)	(3)
Visible Tattoo	-0.13***††† (0.03)	-0.13***†† (0.04)	-0.17***††† (0.04)
Reference signal		-0.03 (0.05)	
Visible Tattoo * Reference signal		-0.02 (0.07)	
Group membership			-0.00 (0.05)
Visible Tattoo * Group membership			0.09 (0.07)
Constant	0.29***††† (0.02)	0.28***††† (0.02)	0.28***††† (0.02)
Monthly and regional dummies	*Y*	*Y*	*Y*
Control variables	*N*	*Y*	*Y*
R^2	0. 06	0.08	0.11
N	782	782	782

Notes: Estimates of the linear probability model. Robust standard errors in parentheses. All specifications control for monthly and regional dummies and firm characteristics including age, size, number of job advertisements and whether the location of the job is in an urban area. * p<0.1, ** p<0.05, *** p<0.01. † - significance level with multiple hypothesis testing adjusted.

B.1 Robustness Check – Probit Model Estimates

Table B.4: Estimates of the Probit model

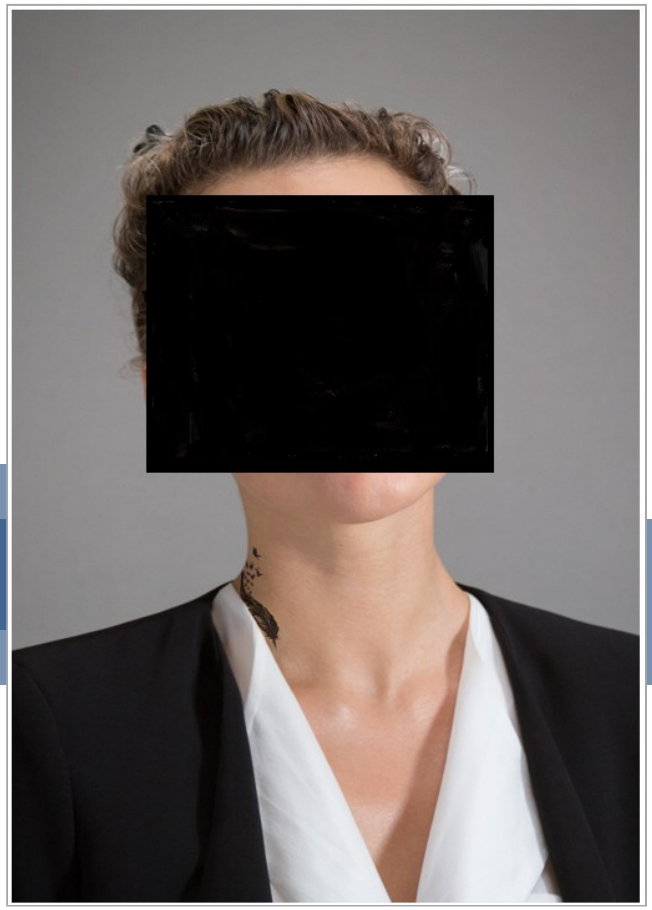
Dependent variable: Callback	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Visible Tattoo	-0.09***	-0.08**	-0.09*	-0.06	-0.01	-0.12	-0.03
	(0.03)	(0.03)	(0.05)	(0.05)	(0.09)	(0.07)	(0.07)
Male			-0.08*				
			(0.05)				
Visible Tattoo * Male			0.03				
			(0.07)				
High skill				0.05			
				(0.05)			
Visible Tattoo * High skill				-0.03			
				(0.07)			
West Germany					0.03		
					(0.20)		
Visible Tattoo * west Germany					-0.07		
					(0.09)		
Urban area						-0.03	
						(0.06)	
Visible Tattoo * Urban area						0.05	
						(0.08)	
Small firm							0.09
							(0.09)
Visible Tattoo * Small firm							-0.13
							(0.09)
Medium firm							-0.02
							(0.07)
Visible Tattoo * Medium firm							-0.01
							(0.08)
Constant	0.31***	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Monthly and regional dummies	*N*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Control variables	*N*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
R^2	0.007	0.061	0.064	0.061	0.061	0.061	0.065
N	800	799	799	799	799	799	799

Notes: The table shows marginal effects at means of the Probit model. Robust standard errors in parentheses. Columns 2-7 include monthly and regional dummies. In columns 2-7, I control for firm characteristics including age, size, \# of job advertisements, \# of required programs, gender of HR contact, whether the position includes "senior" in the title or requires teamwork, whether the location of the job is in an urban area and whether the firm is international. * p<0.1, ** p<0.05, *** p<0.01.

B.2 Sample Application of High Skilled Female Applicant

Name Surname

Software Engineer



Attachments:
Cover Letter
Resume

Street name ##| Postcode City
xxxxxx@xxxmail.xxxx | +49 XX XXXXXXX

Company name
Address
XXXXX City

Name Surname
Street name XX
Postcode Coty

Date of applying

Application for the position of *POSITION NAME*

Dear *Mrs/Mr Surname*,

The creation of dimensioning and design software for XXXXXX, XXXXX XXXXX XXXXX are very promising areas of responsibility for me. On the position I will benefit from the experience I was able to gain in the context of my current work as a software developer in the area XXXX XXXXX for XXXX in *CITY*. In the course of this activity I have acquired profound know-how in software development, especially in XXXXX XXXXX XXXXX & XXXXX XXXXX XXXXX and the conception of database solutions. In doing so, I demonstrated my profound knowledge as XXXXX XXXXX XXXXX at *UNIVERSITY NAME*, *CITY* and my pronounced analytical and conceptual skills. In XXXXX XXXXX XXXXX XXXXX XXXXX XXXXX and XXXXX XXXXX XXXXX I also use my independent and goal-oriented way of working optimally.

During this activity I built on my knowledge of XXXXX XXXXX XXXXX, which I worked XXXXX XXXXX XXXXX for the *COMPANY NAME*. On this position, I brought in my experienced IT knowledge in the field of software development and participated actively and competently in a variety of IT projects. The focus was on the implementation and optimization of sophisticated IT applications for banks and financial service providers based on Java and C #.

You can expect from me an extensive knowledge of the programming language such as C # / VB.NET and XXXXX XXXXX XXXXX, which is particularly relevant for the position I am applying.

Since your position offers me a very diverse XXXXX XXXXX XXXXX, I would like to take the opportunity with you and convince you as soon as possible with my high IT expertise, taking into account my notice period of 2 weeks. My annual salary expectation for this position is *AMOUNT* Euro p.a.

I would like to start working with you as soon as possible and, of course, I am also willing to change my place of residence for this exciting job.

I look forward to supporting your team in *CITY* as soon as possible with my high level of commitment and I am looking forward to your feedback.

Kind regards

RESUME

NAME SURNAME

Street name, ## · Postcode City · xxxx@xxxmail.xxxx | +49 XXXX XXXXXXX

PERSONAL DATA

Nationality: German
Date of birth: DD MMMMM YYYY

PROFESSIONAL EXPERIENCE

MM/YYYY – today
COMPANY NAME – CITY
POSITION TITLE

- Transformation of existin XXXXX XXXXX XXXXX
- XXXXX XXXXX XXXXX MS SQL Server & Web-applications
- Development and XXXXX XXXXX XXXXX
- XXXXX XXXXX XXXXX of proposed solutions and responsibility for timely implementation

MM/YYYY – MM/YYYY
COMPANY NAME – CITY
POSITION TITLE

- Participation in XXXXX XXXXX XXXXX
- Realization and optimization of demanding IT applications XXXXX XXXXX XXXXX Java or C#
- XXXXX XXXXX XXXXX, desing and implementation before testing
- XXXXX XXXXX XXXXX of database solutions

APPRENTICESHIP

MM/YYYY – MM/YYYY
COMPANY NAME – CITY
IT internship POSITION TITLE

- XXXXX XXXXX XXXXX applications with .NET and C#
- XXXXX XXXXX XXXXX with WPF and ASP.NET MVC
- XXXXX XXXXX XXXXX of business logic with C#, Webservices and MS-SQL

MM/YYYY – MM/YYYY
COMPANY NAME – CITY
Voluntary internship during the semester break, IT

- Active participation in IT projects and XXXXX XXXXX XXXXX
- Creation, XXXXX XXXXX XXXXX in Java and JavaScript
- XXXXX XXXXX XXXXX in business processes and services as well as the implementation of new and modification of existing applications

EDUCATION

MM/YYYY – MM/YYYY
UNIVERSITY NAME, CITY

Diploma: Master of Science in IT
GPA: 1.7

MM/YYYY – MM/YYYY
UNIVERSITY NAME, CITY
Diploma: Bachelor of Science in IT
GPA: 1.3

HIGH SCHOOL EDUCATION

MM/YYYY – MM/YYYY
HIGH SCHOOL NAME, CITY
Diploma: General University Entrance Qualification
GPA: 1.3

IT- KNOWLEDGE

Programming languages: Java, J2EE, C++, XXXXX, Delphi, PHP, XXXXX, MS SQL XML, HTML, VB.NET

Experiences in SPSS, Matlab with XXXXX, WinCC, Step7/Simatic,

Very good knowledge of MSOffice, XXXXX, Unix/Linux

LANGUAGES

German (native)
English (advanced)

SIGNATURE

_____
CITY, DD.MM.YYYY

C.1 Discrete Choice Model

The mathematical equations for the discrete choice model are as follows.[2] Decision makers observe utility of option *i* as $Utility\_i = Value\_i + \varepsilon_i$, where ε_i is the error term. They then maximize their own utility by choosing the option with the highest utility (or if there is a tie, randomly choosing between items with the highest utility). If errors are Type I Extreme Value distributed[3], then the probability that an option will be chosen is calculated as follows:

$$P(\text{option i chosen}) = \frac{e^{Value_i}}{\sum_{j=1}^{N} e^{Value_j}}$$

In other words, the probability that an option is chosen is its exponentiated value, divided by the sum of exponentiated values of all options. This particular form of a discrete choice model is known as a conditional logit model.

C.2 Randomization Check

The two tables below replicate Tables 3.2 and 3.3 respectively, but with the outliers dropped. A participant is defined as an outlier if they answered too slowly/fast given the number of workers they had to choose from (more than 2.5 standard deviations below or above the mean for the number of workers they had to choose from), and/or if they failed attention checks. Specifically, 4 subjects were dropped in the 2-worker condition since they spent more than 144 seconds (more than 2.5 standard deviations above the mean). For the same reason, 3 subjects were dropped in the 8-worker condition as it took them more than 127 seconds to complete the survey. No subject was dropped in 4 worker conditions or because they completed the survey too fast. As an attention check, we asked participants what type of questions potential employees answered. 22 subjects answered either "Liberal Arts" or "Other", while the correct answer was "Math"/"Science". Therefore, we dropped those 22 subjects who failed the attention check question. After dropping the outliers, 157 subjects remain and are used as the subject pool in the robustness checks.

[2] Value is computed as described in the main text.

[3] This is the standard assumption made by the literatures in various disciplines that use discrete choice modelling, arbitrary as it may be. See the references we cited in the main text.

Table C.6 confirms that the qualitative results remain unchanged when we drop outlier observations: All explanatory variables that were statistically significant in Table 2 remain statistically significant and have the same sign. The estimates are also largely similar in magnitude, with only a few exceptions. For example, the estimate of *Female* is reduced to 0.20 after dropping outliers (it was 0.36 in Table 3.2), and the estimate of *Black* and subgroup information treatment interaction is also lower compared to Table 3.2 values (-0.58 vs -0.41) (leftmost column of Table C.6). Similarly, the qualitative results remain the same as in Table 3.3 when outliers are dropped from analysis (Table C.7).

Table C.6: Replication of Table 3.2 models with outliers dropped

Dependent variable: *Choice*	Full sample	Prior performance shown			
		none	*individual*	*subgroup*	*All*
Attractiveness	0.14*** (0.04)	0.25*** (0.06)	0.02 (0.06)	0.17*** (0.06)	0.25*** (0.06)
Attractiveness * Individual info treatment					-0.23*** (0.09)
Attractiveness * Subgroup info treatment					-0.09 (0.09)
Female prop	0.38*** (0.06)	0.20** (0.10)	0.55*** (0.10)	0.40*** (0.11)	0.20** (0.10)
Female prop * Individual info treatment					0.35** (0.15)
Female prop * Subgroup info treatment					0.20 (0.15)
Asian prop	0.28** (0.09)	0.34** (0.16)	-0.01 (0.17)	0.44*** (0.15)	0.34** (0.16)
Asian prop * Individual info treatment					-0.35 (0.24)
Asian prop * Subgroup info treatment					0.10 (0.22)
Black prop	-0.14* (0.08)	0.12 (0.13)	-0.10 (0.14)	-0.46*** (0.14)	0.12 (0.13)
Black prop * Individual info treatment					-0.22 (0.19)
Black prop * Subgroup info treatment					-0.58*** (0.19)
Latino prop	-0.07 (0.14)	0.18 (0.22)	0.01 (0.25)	-0.44* (0.25)	0.18 (0.22)
Latino prop * Individual info treatment					-0.17 (0.33)
Latino prop * Subgroup info treatment					-0.62* (0.33)
N	7726	2770	2296	2660	7726
Number of clusters	1871	677	572	622	1871
Pseudo R^2	0.020	0.019	0.022	0.031	0.026

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

Table C.7: Replication of Table 3.3 models with outliers dropped

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.13**	0.13***	0.17***	0.13**
	(0.07)	(0.06)	(0.06)	(0.07)
Attractiveness * 4 worker treatment				-0.00
				(0.09)
Attractiveness * 8 worker treatment				0.04
				(0.09)
Female prop	0.45***	0.25***	0.47***	0.45***
	(0.11)	(0.10)	(0.10)	(0.11)
Female prop * 4 worker treatment				-0.20
				(0.15)
Female prop * 8 worker treatment				0.03
				(0.15)
Asian prop	0.13	0.33**	0.34**	0.13
	(0.16)	(0.15)	(0.16)	(0.16)
Asian prop * 4 worker treatment				0.20
				(0.22)
Asian prop * 8 worker treatment				0.21
				(0.23)
Black prop	-0.03	-0.16	-0.22	-0.03
	(0.14)	(0.13)	(0.14)	(0.14)
Black prop * 4 worker treatment				-0.13
				(0.19)
Black prop * 8 worker treatment				-0.19
				(0.20)
Latino prop	0.00	-0.01	-0.20	0.00
	(0.24)	(0.23)	(0.25)	(0.24)
Latino prop * 4 worker treatment				-0.01
				(0.33)
Latino prop * 8 worker treatment				-0.20
				(0.35)
N	1630	2352	3744	7726
Number of clusters	815	588	468	1871
Pseudo R^2	0.025	0.014	0.026	0.022

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.3 Odds Ratio

Below are tables showing the odds ratios for each table presented in the main text. That is, if a coefficient in a table was estimated as X, the coefficient in the corresponding table shows e^X. These tables can be used to compute effect sizes by subtracting 1 from the relevant odds ratio.

Table C.8: Odds Ratios of the estimates from Table 3.2

Dependent variable: *Choice*	Full sample	Prior performance shown			
		none	*individual*	*subgroup*	*All*
Attractiveness	1.15*** (0.04)	1.28*** (0.07)	1.03 (0.06)	1.15*** (0.04)	1.27*** (0.07)
Attractiveness * Individual info treatment					0.81*** (0.07)
Attractiveness * Subgroup info treatment					0.92 (0.07)
Female prop	1.60*** (0.09)	1.38*** (0.13)	1.98*** (0.19)	1.52*** (0.15)	1.43*** (0.13)
Female prop * Individual info treatment					1.37** (0.18)
Female prop * Subgroup info treatment					1.06 (0.15)
Asian prop	1.23** (0.10)	1.33* (0.19)	0.95 (0.15)	1.43** (0.21)	1.35** (0.20)
Asian prop * Individual info treatment					0.69* (0.15)
Asian prop * Subgroup info treatment					1.07 (0.22)
Black prop	0.85** (0.06)	1.02 (0.13)	0.85 (0.11)	0.68*** (0.09)	1.03 (0.13)
Black prop * Individual info treatment					0.81 (0.14)
Black prop * Subgroup info treatment					0.66** (0.12)
Latino prop	0.91 (0.11)	1.28 (0.25)	0.82 (0.18)	0.69 (0.16)	1.23 (0.24)
Latino prop * Individual info treatment					0.66 (0.20)
Latino prop * Subgroup info treatment					0.56* (0.17)
N	9256	3320	2846	3090	9256
Number of clusters	2216	796	703	717	2216
Pseudo R^2	0.024	0.025	0.032	0.031	0.030

Notes: Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table C.9: Odds Ratios of the estimates from Table 3.3

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	1.15*** (0.07)	1.14** (0.06)	1.16*** (0.07)	1.15** (0.07)
Attractiveness * 4 worker treatment				0.99 (0.08)
Attractiveness * 8 worker treatment				1.01 (0.08)
Female prop	1.73*** (0.18)	1.34*** (0.12)	1.86*** (0.18)	1.73*** (0.18)
Female prop * 4 worker treatment				0.77* (0.11)
Female prop * 8 worker treatment				1.07 (0.15)
Asian prop	1.10 (0.17)	1.42** (0.20)	1.16 (0.17)	1.10 (0.17)
Asian prop * 4 worker treatment				1.29 (0.27)
Asian prop * 8 worker treatment				1.06 (0.22)
Black prop	0.92 (0.12)	0.87 (0.11)	0.74** (0.09)	0.92 (0.12)
Black prop * 4 worker treatment				0.95 (0.17)
Black prop * 8 worker treatment				0.81 (0.14)
Latino prop	0.93 (0.21)	0.98 (0.19)	0.79 (0.17)	0.93 (0.21)
Latino prop * 4 worker treatment				1.06 (0.32)
Latino prop * 8 worker treatment				0.85 (0.27)
N	1912	2736	4608	9256
Number of clusters	956	684	576	2216
Pseudo R^2	0.035	0.017	0.031	0.027

Notes: Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table C.10: Odds Ratios of the estimates from Table 3.4

Dependent variable: *Choice*	(1)	(2)
Attractiveness	1.08* (0.05)	1.08** (0.04)
Female prop	1.62*** (0.09)	1.71*** (0.11)
Female * Attractiveness	1.05 (0.06)	
Asian prop	1.22** (0.10)	1.09 (0.10)
Black prop	0.84** (0.06)	0.93 (0.08)
Latino prop	0.89 (0.11)	0.92 (0.13)
Prediction		2.91*** (0.13)
N	9256	9256
Number of clusters	2216	2216
Pseudo R^2	0.025	0.024

Notes: Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

C.4 Details of Experimental Trials

The order of trials was randomized across participants. The order of candidates (i.e., workers) within each trial was also randomized. Also, whether information about past performance was displayed was randomized across participants (i.e., between subjects' experimental manipulation).

C.4.1 Two Workers Condition

Tables below show examples of experimental conditions in two, four and eight workers conditions with the past performance displayed at the individual level. In these tables, for example Male 5 means a Male who got 5 questions correct; Female 4 - a Female who got 4 questions correct. For example, in the second trial in Table C.11, participants had to choose between a male who got 2 questions correct, and a female that got 2 questions correct.

Table C.11: Example of past performance at individual level - two worker condition

Trial #	Candidate 1	Candidate 2
1	Male 0	Female 0
2	Male 2	Female 2
3	Male 4	Female 4
4	Male 5	Female 5
5	Male 1	Female 2
6	Male 2	Female 3
7	Male 1	Female 4
8	Male 2	Female 5
9	Male 2	Female 1
10	Male 3	Female 2
11	Male 4	Female 1
12	Male 5	Female 2

C.4.2 Four Workers Condition

Table C.12: Example of past performance at individual level - four worker condition

Trial #	Candidate 1	Candidate 2	Candidate 3	Candidate 4
1	Male 0	Female 0	Male 0	Female 0
2	Male 2	Female 2	Male 2	Female 2
3	Male 1	Female 4	Male 4	Female 1
4	Male 2	Female 2	Male 4	Female 4
5	Male 4	Female 4	Male 1	Female 1
6	Male 3	Female 1	Male 1	Female 3
7	Male 4	Female 5	Male 1	Female 1
8	Male 5	Female 4	Male 1	Female 1
9	Male 4	Female 1	Male 1	Female 4
10	Male 3	Female 4	Male 1	Female 1
11	Male 4	Female 3	Male 1	Female 1
12	Male 4	Female 2	Male 2	Female 4

C.4.3 Eight Workers Condition

Table C.13: Example of past performance at individual level - eight worker condition

Trial #	Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5	Candidate 6	Candidate 7	Candidate 8
1	Male 3	Female 3	Male 3	Female 3	Male 3	Female 3	Male 3	Female 3
2	Male 4	Female 1	Male 0	Female 4	Male 1	Female 1	Male 1	Female 0
3	Male 0	Female 4	Male 1	Female 1	Male 4	Female 2	Male 1	Female 0
4	Male 5	Female 2	Male 2	Female 2	Male 1	Female 5	Male 2	Female 1
5	Male 0	Female 0	Male 5	Female 4	Male 1	Female 2	Male 2	Female 1
6	Male 0	Female 0	Male 4	Female 5	Male 1	Female 2	Male 2	Female 1
7	Male 1	Female 3	Male 0	Female 1	Male 5	Female 1	Male 0	Female 1
8	Male 0	Female 4	Male 0	Female 1	Male 3	Female 0	Male 1	Female 0
9	Male 0	Female 0	Male 3	Female 1	Male 0	Female 3	Male 1	Female 0
10	Male 1	Female 4	Male 0	Female 0	Male 4	Female 1	Male 1	Female 0
11	Male 5	Female 0	Male 0	Female 5	Male 1	Female 1	Male 2	Female 2
12	Male 1	Female 1	Male 4	Female 0	Male 1	Female 4	Male 1	Female 1

C.4.4 Information Provision Treatment

The tables in the condition where no information about the prior performance was displayed are identical to the above tables, except that prior performance at the individual level was not displayed.

The tables in the condition where only subgroup performance by gender was displayed are identical to the above tables, except that prior performance at the individual level was not displayed, and additionally, Figure 3.2 in the main text was displayed to participants at the start of the study, and they could click on a link to see the figure again at any point in the experiment if they wanted.

C.5 Recruiter Gender

This section replicates Tables 3.2, 3.3 and 3.4 disaggregated by gender of the recruiter. 57% of our recruiter subjects were male and remaining 43% were female.

C.5.1 Female Recruiter

Table C.14: Replication of Table 3.2 – Female recruiter

Dependent variable: *Choice*	Full sample	Prior performance shown			
		none	*individual*	*subgroup*	*All*
Attractiveness	0.07 (0.05)	0.16* (0.08)	-0.03 (0.11)	0.07 (0.09)	0.16* (0.08)
Attractiveness * Individual info treatment					-0.19 (0.13)
Attractiveness * Subgroup info treatment					-0.09 (0.12)
Female prop	0.44*** (0.09)	0.40*** (0.13)	1.07*** (0.18)	0.04 (0.15)	0.40*** (0.13)
Female prop * Individual info treatment					0.67** (0.22)
Female prop * Subgroup info treatment					-0.36* (0.20)
Asian prop	0.20 (0.13)	0.28 (0.20)	-0.11 (0.28)	0.34 (0.22)	0.28 (0.20)
Asian prop * Individual info treatment					-0.39 (0.35)
Asian prop * Subgroup info treatment					0.06 (0.30)
Black prop	-0.13 (0.11)	0.08 (0.18)	-0.15 (0.23)	-0.34* (0.19)	0.08 (0.18)
Black prop * Individual info treatment					-0.23 (0.29)
Black prop * Subgroup info treatment					-0.42 (0.26)
Latino prop	-0.00 (0.19)	0.25 (0.30)	-0.08 (0.39)	-0.10 (0.31)	0.25 (0.30)
Latino prop * Individual info treatment					-0.33 (0.49)
Latino prop * Subgroup info treatment					-0.36 (0.43)
N	3848	1550	932	1366	3848
Number of clusters	952	403	238	311	952
Pseudo R^2	0.018	0.023	0.071	0.012	0.031

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

Table C.15: Replication of Table 3.3 – Female recruiter

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.17* (0.09)	-0.11 (0.09)	0.13 (0.09)	0.17* (0.09)
Attractiveness * 4 worker treatment				-0.28** (0.13)
Attractiveness * 8 worker treatment				-0.04 (0.13)
Female prop	0.70*** (0.15)	0.28* (0.15)	0.36** (0.14)	0.70*** (0.15)
Female prop * 4 worker treatment				-0.42* (0.22)
Female prop * 8 worker treatment				-0.34* (0.21)
Asian prop	0.08 (0.23)	0.38 (0.23)	0.15 (0.22)	0.08 (0.23)
Asian prop * 4 worker treatment				0.30 (0.32)
Asian prop * 8 worker treatment				0.07 (0.32)
Black prop	-0.16 (0.19)	0.08 (0.21)	-0.34* (0.20)	-0.16 (0.19)
Black prop * 4 worker treatment				0.24 (0.28)
Black prop * 8 worker treatment				-0.19 (0.27)
Latino prop	-0.09 (0.32)	0.32 (0.33)	-0.15 (0.34)	-0.09 (0.32)
Latino prop * 4 worker treatment				0.40 (0.46)
Latino prop * 8 worker treatment				-0.05 (0.47)
N	920	1008	1920	3848
Number of clusters	460	252	240	952
Pseudo R^2	0.054	0.011	0.015	0.024

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

Table C.16: Replication of Table 3.4 – Female recruiter

Dependent variable: *Choice*	(1)	(2)
Attractiveness	0.05 (0.07)	0.01 (0.06)
Female prop	0.45*** (0.09)	0.48*** (0.10)
Female * Attractiveness	0.01 (0.09)	
Asian prop	0.19 (0.13)	0.09 (0.15)
Black prop	-0.13 (0.11)	0.09 (0.13)
Latino prop	-0.00 (0.19)	0.21 (0.23)
Prediction		1.31*** (0.08)
N	3848	3848
Number of clusters	952	952
Pseudo R^2	0.018	0.298

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.5.2 Male Recruiter

Table C.17: Replication of Table 3.2 – Male recruiter

Dependent variable: *Choice*	Full sample	Prior performance shown			
		none	*individual*	*subgroup*	*All*
Attractiveness	0.20***	0.32***	0.08	0.21***	0.32***
	(0.04)	(0.08)	(0.07)	(0.08)	(0.08)
Attractiveness * Individual info treatment					-0.24**
					(0.10)
Attractiveness * Subgroup info treatment					-0.10
					(0.11)
Female prop	0.52***	0.32**	0.52***	0.73***	0.32**
	(0.07)	(0.13)	(0.12)	(0.14)	(0.13)
Female prop * Individual info treatment					0.20
					(0.13)
Female prop * Subgroup info treatment					0.41**
					(0.19)
Asian prop	0.21*	0.32	-0.07	0.37*	0.32
	(0.11)	(0.21)	(0.19)	(0.19)	(0.21)
Asian prop * Individual info treatment					-0.39
					(0.28)
Asian prop * Subgroup info treatment					0.05
					(0.28)
Black prop	-0.22**	0.00	-0.24	-0.39***	0.00
	(0.10)	(0.18)	(0.15)	(0.18)	(0.18)
Black prop * Individual info treatment					-0.24
					(0.23)
Black prop * Subgroup info treatment					-0.39
					(0.25)
Latino prop	-0.19	0.16	-0.21	-0.63*	0.16
	(0.17)	(0.27)	(0.27)	(0.34)	(0.27)
Latino prop * Individual info treatment					-0.38
					(0.38)
Latino prop * Subgroup info treatment					-0.79*
					(0.43)
N	5384	1770	1890	1724	5384
Number of clusters	1252	393	453	406	1252
Pseudo R^2	0.033	0.032	0.021	0.064	0.038

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

Table C.18: Replication of Table 3.3 – Male recruiter

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.12 (0.09)	0.26*** (0.07)	0.17** (0.07)	0.12 (0.09)
Attractiveness * 4 worker treatment				0.14 (0.11)
Attractiveness * 8 worker treatment				0.04 (0.11)
Female prop	0.45*** (0.14)	0.29** (0.12)	0.82*** (0.13)	0.45*** (0.14)
Female prop * 4 worker treatment				-0.16 (0.18)
Female prop * 8 worker treatment				0.37* (0.19)
Asian prop	0.07 (0.21)	0.34* (0.18)	0.16 (0.19)	0.07 (0.21)
Asian prop * 4 worker treatment				0.27 (0.28)
Asian prop * 8 worker treatment				0.09 (0.28)
Black prop	-0.10 (0.18)	-0.26* (0.16)	-0.26 (0.16)	-0.10 (0.18)
Black prop * 4 worker treatment				-0.16 (0.24)
Black prop * 8 worker treatment				-0.16 (0.24)
Latino prop	-0.02 (0.32)	-0.21 (0.26)	-0.28 (0.28)	-0.02 (0.32)
Latino prop * 4 worker treatment				0.19 (0.41)
Latino prop * 8 worker treatment				-0.27 (0.43)
N	968	1728	2688	5384
Number of clusters	484	432	336	1252
Pseudo R^2	0.024	0.031	0.048	0.037

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

Table C.19: Replication of Table 3.4 – Male recruiter

Dependent variable: *Choice*	(1)	(2)
Attractiveness	0.10* (0.06)	0.12*** (0.05)
Female prop	0.52*** (0.07)	0.57*** (0.08)
Female * Attractiveness	0.07 (0.08)	
Asian prop	0.19* (0.11)	0.09 (0129)
Black prop	-0.22** (0.10)	-0.17 (0.11)
Latino prop	-0.20 (0.17)	-0.25 (0.18)
Prediction		0.92*** (0.05)
N	5384	5384
Number of clusters	1252	1252
Pseudo R^2	0.033	0.208

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.6 Information Provided to Employer Subjects

C.6.1 No Prior Performance Info Provided

Table C.20: Replication of Table 3.3 - No prior performance info provided

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.21**	0.14	0.35***	0.21**
	(0.11)	(0.09)	(0.10)	(0.11)
Attractiveness * 4 worker treatment				-0.07
				(0.14)
Attractiveness * 8 worker treatment				0.14
				(0.14)
Female prop	0.52***	-0.23	0.94***	0.52***
	(0.17)	(0.15)	(0.17)	(0.17)
Female prop * 4 worker treatment				-0.75***
				(0.23)
Female prop * 8 worker treatment				0.42*
				(0.24)
Asian prop	0.35	0.48**	0.09	0.35
	(0.27)	(0.24)	(0.25)	(0.27)
Asian prop * 4 worker treatment				0.13
				(0.36)
Asian prop * 8 worker treatment				-0.26
				(0.37)
Black prop	0.23	0.07	-0.18	0.23
	(0.22)	(0.21)	(0.22)	(0.22)
Black prop * 4 worker treatment				-0.16
				(0.30)
Black prop * 8 worker treatment				-0.40
				(0.31)
Latino prop	0.46	0.06	0.24	0.46
	(0.35)	(0.32)	(0.36)	(0.35)
Latino prop * 4 worker treatment				-0.39
				(0.47)
Latino prop * 8 worker treatment				-0.21
				(0.51)
N	680	1008	1632	3320
Number of clusters	340	252	204	796
Pseudo R^2	0.048	0.012	0.078	0.048

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.6.2 Individual Performance Info Provided

Table C.21: Replication of Table 3.3 - Individual performance info provided

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.03 (0.12)	0.13 (0.09)	-0.09 (0.11)	0.03 (0.12)
Attractiveness * 4 worker treatment				0.10 (0.15)
Attractiveness * 8 worker treatment				-0.12 (0.16)
Female prop	0.81*** (0.19)	-0.63*** (0.14)	0.64*** (0.19)	0.81*** (0.19)
Female prop * 4 worker treatment				-0.17 (0.24)
Female prop * 8 worker treatment				0.17 (0.27)
Asian prop	-0.11 (0.30)	0.32 (0.23)	-0.66* (0.19)	-0.11 (0.30)
Asian prop * 4 worker treatment				0.43 (0.38)
Asian prop * 8 worker treatment				0.56 (0.42)
Black prop	0.02 (0.25)	-0.17 (0.18)	-0.40* (0.24)	0.02 (0.25)
Black prop * 4 worker treatment				-0.19 (0.31)
Black prop * 8 worker treatment				-0.42 (0.35)
Latino prop	-0.25 (0.46)	-0.06 (0.33)	-0.45 (0.41)	-0.25 (0.46)
Latino prop * 4 worker treatment				0.20 (0.56)
Latino prop * 8 worker treatment				-0.20 (0.61)
N	542	1152	1152	2846
Number of clusters	271	288	144	703
Pseudo R^2	0.056	0.039	0.028	0.039

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.6.3 Subgroup Performance Info Provided

Table C.22: Replication of Table 3.3 - Subgroup performance info provided

Dependent variable: *Choice*	Number of displayed candidates			Full sample
	2	*4*	*8*	
Attractiveness	0.18* (0.10)	0.14 (0.12)	0.16* (0.09)	0.18* (0.10)
Attractiveness * 4 worker treatment				-0.04 (0.16)
Attractiveness * 8 worker treatment				-0.02 (0.14)
Female prop	0.38** (0.17)	0.59** (0.22)	0.35** (0.15)	0.38** (0.17)
Female prop * 4 worker treatment				0.21 (0.28)
Female prop * 8 worker treatment				-0.03 (0.23)
Asian prop	0.03 (0.24)	0.26 (0.29)	0.67*** (0.22)	0.03 (0.24)
Asian prop * 4 worker treatment				0.23 (0.38)
Asian prop * 8 worker treatment				0.63* (0.32)
Black prop	-0.47** (0.21)	-0.41 (0.28)	-0.29 (0.20)	-0.47** (0.21)
Black prop * 4 worker treatment				0.07 (0.35)
Black prop * 8 worker treatment				0.18 (0.30)
Latino prop	-0.44 (0.38)	-0.05 (0.47)	-0.48 (0.37)	-0.44 (0.38)
Latino prop * 4 worker treatment				0.39 (0.61)
Latino prop * 8 worker treatment				-0.04 (0.54)
N	690	576	1824	3090
Number of clusters	345	144	228	717
Pseudo R^2	0.033	0.040	0.033	0.035

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01.

C.7 Other Characteristics by Gender

This section reviews the results of "other characteristics" by gender of applicants. As the results in the two tables below indicate, the impact of *Attractiveness* relates to female applicants, with beauty irrelevant for male applicants. Similarly, *Masculine* and *Feminine* impact is also driven by female applicants. On the other hand, *Asian* and *Dominant* effects are mainly driven by male applicants. The impact of the rest of the characteristics (*Black*, *Latino*, *Angry*, *Happy*, *Trustworthy* and *Threatening*) are not driven by any particular gender.

Table C.23: Estimates of Discrete Choice Model – Other characteristics: Female applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attractiveness	0.21***	0.22***	0.13**	0.07	0.22***	0.17***	0.20***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)
Asian prop	0.21	0.22	0.17	0.20	0.18	0.17	0.18
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Black prop	-0.18*	-0.18	-0.18	-0.18	-0.16	-0.20*	-0.18*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Latino prop	-0.09	-0.09	-0.17	-0.11	-0.06	-0.07	-0.09
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Angry	-0.04						
	(0.07)						
Happy		-0.04					
		(0.04)					
Masculine			-0.13**				
			(0.06)				
Feminine				0.18**			
				(0.07)			
Dominant					-0.13***		
					(0.05)		
Trustworthy						-0.13	
						(0.09)	
Threatening							-0.14***
							(0.05)
N	2896	2896	2896	2896	2896	2896	2896
Number of clusters	977	977	977	977	977	977	977
Pseudo R^2	0.018	0.018	0.021	0.022	0.019	0.022	0.018

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.

Table C.24: Estimates of Discrete Choice Model – Other characteristics: Male applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attractiveness	0.05	0.09	0.11	0.08	0.11	0.05	0.05
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)
Asian prop	0.28*	0.30*	0.27*	0.31*	0.23	0.25	0.23
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)
Black prop	-0.15	-0.15	-0.11	-0.14	-0.09	-0.18	-0.15
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Latino prop	0.00	-0.00	0.03	-0.00	-0.10	0.02	0.01
	(0.25)	(0.25)	(0.25)	(0.25)	(0.26)	(0.25)	(0.25)
Angry	-0.13						
	(0.09)						
Happy		0.00					
		(0.09)					
Masculine			-0.10				
			(0.07)				
Feminine				0.09			
				(0.07)			
Dominant					-0.19***		
					(0.09)		
Trustworthy						-0.14	
						(0.18)	
Threatening							-0.16
							(0.10)
N	1787	1787	1787	1787	1787	1787	1787
Number of clusters	643	643	643	643	643	643	643
Pseudo R^2	0.008	0.006	0.008	0.007	0.009	0.006	0.008

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.

C.8 Other Characteristics by Race

In this section, we review the results of "other characteristics" by the race of applicants. The tables below show that the strong positive impact of *Attractiveness* is driven by *White* applicants, with beauty not a significant factor for other races. We also see that the impact of *Female* is largely homogeneous by the race of applicants: for all races, *Females* have a large positive (and in most cases significant) impact on hiring probability. As for "other characteristics", *White* applicants are the main driver of the impact of *Masculine* and *Feminine*, while *Asians* drive a negative impact for *Angry* faces. The *Dominant* impact is driven by *Asian* and *Black* applicants, with the rest of the

characteristics (*Happy*, *Trustworthy* and *Threatening*) are not driven by any particular race.

Table C.25: Estimates of Discrete Choice Model – Other characteristics: Asian applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attractiveness	-0.00 (0.14)	0.04 (0.16)	0.10 (0.14)	-0.11 (0.18)	0.08 (0.13)	0.03 (0.16)	0.05 (0.14)
Female prop	0.77*** (0.21)	0.74*** (0.21)	0.79 (0.68)	-0.45 (0.74)	0.59*** (0.21)	0.71*** (0.21)	0.70*** (0.21)
Angry	-0.27* (0.15)						
Happy		0.08 (0.15)					
Masculine			0.04 (0.27)				
Feminine				0.42 (0.26)			
Dominant					-0.44** (0.19)		
Trustworthy						0.18 (0.28)	
Threatening							-0.17 (0.19)
N	622	622	622	622	622	622	622
Number of clusters	253	253	253	253	253	253	253
Pseudo R^2	0.061	0.054	0.053	0.059	0.065	0.054	0.055

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.

Table C.26: Estimates of Discrete Choice Model – Other characteristics: Black applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attractiveness	0.09	0.13	0.13	-0.01	0.14	0.23*	0.11
	(0.12)	(0.12)	(0.14)	(0.22)	(0.10)	(0.12)	(0.12)
Female prop	0.71***	0.70***	0.43	-0.04	0.49***	0.70***	0.66***
	(0.16)	(0.16)	(0.70)	(0.81)	(0.18)	(0.16)	(0.16)
Angry	-0.17						
	(0.14)						
Happy		0.09					
		(0.13)					
Masculine			-0.10				
			(0.24)				
Feminine				0.27			
				(0.28)			
Dominant					-0.37**		
					(0.16)		
Trustworthy						-0.20	
						(0.27)	
Threatening							-0.17
							(0.19)
N	829	829	829	829	829	829	829
Number of clusters	322	322	322	322	322	322	322
Pseudo R^2	0.051	0.049	0.049	0.050	0.056	0.049	0.050

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.

Table C.27: Estimates of Discrete Choice Model – Other characteristics: Latino applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Attractiveness	-0.16 (0.17)	-0.09 (0.19)	-0.17 (0.17)	-0.07 (0.18)	-0.15 (0.17)	-0.15 (0.19)	-0.17 (0.17)
Female prop	0.49*** (0.22)	0.41* (0.23)	0.72 (0.54)	1.32 (0.82)	0.47** (0.22)	0.48** (0.21)	0.47** (0.21)
Angry	-0.03 (0.19)						
Happy		-0.15 (0.18)					
Masculine			0.08 (0.17)				
Feminine				-0.30 (0.28)			
Dominant					-0.01 (0.17)		
Trustworthy						-0.01 (0.37)	
Threatening							-0.14 (0.20)
N	457	457	457	457	457	457	457
Number of clusters	191	191	191	191	191	191	191
Pseudo R^2	0.017	0.019	0.018	0.021	0.017	0.017	0.019

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.

Table C.28: Estimates of Discrete Choice Model – Other characteristics: White applicants

Dependent variable: *Choice*	(1)	(2)	(3)	(4)	5	6	7
Attractiveness	-0.24***	-0.23**	-0.17**	-0.07	-0.23**	-0.28***	-0.22***
	(0.08)	(0.09)	(0.08)	(0.11)	(0.08)	(0.09)	(0.08)
Female prop	0.42***	0.42***	-0.34	-0.49	0.42***	0.45***	0.42***
	(0.13)	(0.13)	(0.37)	(0.45)	(0.14)	(0.13)	(0.13)
Angry	0.04						
	(0.10)						
Happy		0.00					
		(0.12)					
Masculine			-0.31**				
			(0.14)				
Feminine				0.34**			
				(0.16)			
Dominant					-0.00		
					(0.11)		
Trustworthy						-0.21	
						(0.22)	
Threatening							-0.04
							(0.12)
N	1133	1133	1133	1133	1133	1133	1133
Number of clusters	421	421	421	421	421	421	421
Pseudo R^2	0.033	0.033	0.040	0.039	0.033	0.034	0.033

Notes: Standard errors are clustered at the subject level. * p<0.1, ** p<0.05, *** p<0.01. Various characteristics from the Chicago Face Database are added to the main specification in this table.