Are job applicants in Germany discriminated by their appearance or religious practice? - A lab experiment*

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Abstract

This paper investigates effects of appearance and religious practice of job applicants on the hiring decision. We asked participants in our laboratory experiment to select fictitious candidates for an interview from a pool of CVs with comparable characteristics but different photos. One of our main contributions is to demonstrate effects of appearance, ethnicity and religious practice simultaneously. We attempt to uncover relationships between the chance of being selected for an interview and a certain religious practice (veiling) by taking photos of the same Turkish-looking women with and without veil and inserting these photos randomly into comparable CVs. We find heterogeneous effects of appearance, ethnicity and religious practice on selection rates based on characteristics of raters and the time participants spend to look at the photo. Our results indicate a significant discrimination against veiling, particularly among occupations in high skilled sector and jobs with customer contact. Such findings illustrate how characteristics and behaviours of human resources staffs might induce discrimination during the hiring process at firm-level.

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1 Introduction

The topic of discrimination based on, for example, ethnic origin and gender in the labour market came under scrutiny of the economics discipline after the influential doctoral dissertation entitled "The Economics of Discrimination" by the Nobel laureate, Gary Becker in 1957. Becker proposed the concept of taste discrimination that prejudiced persons receive disutility from their interaction with certain groups of people. Hence, they monetise their prejudice by applying a mark-up to the transaction. This leads to difference in compensation between demographic groups despite having identical productive characteristics. In the labour market, taste discrimination can be classified by the source of the prejudice into employer, employee and customer discrimination.

To circumvent endogeneity problems, researchers would ideally like to observe labour market performances of two groups which are the same in every aspect except for the characteristic of interest (e.g. gender, ethnic origin). Bertrand and Mullainathan (2004) attempted to consistently estimate the discrimination effect by investigating the racial discrimination at the very first stage of getting into the labour market, i.e. the chance of being called back for the job interview. They adopted the technique called "correspondence testing" by creating fake CVs and allocating black-sounding names like Lakisha or Jamal and white-sounding names such as Emily or Greg at random to each CV. On average, the CVs of these two groups should be comparable in every observed characteristic except for their ethnicity. Then they sent replies to job adverts and recorded callback rates of each applicant. They found that white names receive 50 percent more callbacks for interviews, hence, a piece of evidence for differential treatment by ethnicity in the U.S. labour market.

There are studies replicating this technique in other countries as well. For example, in Sweden, Carlsson and Rooth (2007) found that applicants with a Swedish name received 50 percent more callbacks for an interview than applicants with an Arabic sounding name. In Germany, Kaas and Manger (2012) used correspondence testing to compare the chance of callbacks for student internship jobs between applicants with German and Turkish names. They reported that a German name increases the chance of getting into an interview by 14 percent. However, the difference disappears when they included reference letters with favourable information about the applicants' personality. They interpreted this finding as evidence for statistical discrimination[1].

Other than ethnicity, is there any discrimination against your appearance? Using a nationally representative data set in the 1970s, containing information on earnings and rating of the respondents beauty, Hamermesh and Biddle (1994) were the first to estimate the effect of beauty on earnings in the US. Their findings suggest that women who were rated as below-average, received 4 percent lower pays than average-looking women while those rated as above-average received 8 percent higher pays than the average-looking. For men, the beauty premium is 4 percent whereas the penalty of being below-average is 13 percent. In other words, moving from being a below-average looking men to the above-average is comparable to having one and a half year more education.

Yet a fraction of the beauty premium could result from productive characteristics of beauty itself. There is evidence of sorting by looks and beauty premium from some occupations where the workers have to appear in public or confront the buyers directly such as salespersons, lawyers and prostitutes. For instance, using data of graduates from one law school, Biddle and Hamermesh (1998) showed that better-looking attorneys earned more and the effect increased with experience. Furthermore, private attorneys (who tend to interact more with clients, judges and juries) are better-looking than those in the public sector due to sorting and customer behaviour. Nevertheless, some studies demonstrate a significant beauty premium in occupations where beauty should not play an important role in their

[1] Statistical discrimination happens when the recruiters face incomplete information about some unobservable characteristics of the applicants. Therefore, they have to form some beliefs about such characteristics of that applicant based on the "perceived" average of the groups (ethnicity, gender, or appearance) which the applicant belongs to (Altonji and Blank, 1999).

productivity such as American footballers or economics professors (see Hamermesh (2011) for an extensive review).

Researchers already used the correspondence testing technique in the domain of appearance. Rooth (2009) assessed the effect of obesity in the hiring process in Sweden. He used a computer program to transform photos of non-obese persons into being obese. He then randomly inserted these photos into the otherwise similar CVs. The result showed that an obese applicant received 20 percent fewer callbacks for an interview. Therefore, he concluded that customer discrimination and/or statistical discrimination based on the correlation between job performance and being obese could be the explanation.

In terms of beauty, an unpublished thesis by Kraft (2012) employed the same strategy and sent out applications for student internship positions to 990 German firms. He found that attractive candidates are on average 14% more likely to get an invitation for an interview, while unattractive applicants have to wait a couple of days longer for the callbacks. Yet he did not find differential effects between high and low customer contact positions. Hence, his result does not provide supporting argument that beauty is more valuable in some occupations than others.

Recently, some studies employ correspondence testing to uncover possible discrimination against certain religious practices. In France, Valfort (2015) distinguished effects of applicants' religion from their country of origin by comparing the callback rates among fictitious candidates whose religion is Catholic, Judaism or Islam; all of them came from Lebanon, completed their high school, then received a certificate in Paris and became naturalised French citizens. She found that practicing Catholics raises a callback rate by 30% and 100% higher than practicing Jews and practicing Muslims respectively. However, these disadvantages could be alleviated if the applicants signalled through extra-curricular activities in their CVs that they were secular rather than serious practitioners of these religions.

In terms of religious practice signalled by attire, Weichselbaumer (2016) sent out the same CV of a female candidate with different combination of names and photos to job openings for secretaries, accountants and chief accountants in Germany. Particularly, she took photos of the same person with and without headscarf and assigned either German or Turkish sounding names to the CV. Her results showed that a photo with German name was significantly more likely to get a callback than the same photo with Turkish name. In addition, the same person with Turkish name and headscarf suffered additional discrimination than the same Turkish woman without headscarf.

This paper aims to fill the gap by assessing the effects of beauty, ethnicity and religious practice simultaneously. Our approach combines a randomised CV approach with a laboratory experiment. We recruit students from local universities to participate in an experiment where they will be asked to select applicants for an interview of fictitious positions from the pool of candidates whose CVs are randomised in every other aspects except for appearance. While exploiting the ability to draw causal inference from the randomisation technique, an additional advantage of conducting such a lab experiment is to be able to control for personal characteristics of the participants (acting as HR recruiters) involved in the selection process[2]. Furthermore, we track the time each participant uses to evaluate each part of the presented CVs. Therefore, we can control for the relative weight each participant puts on each component of a particular CV, especially the photo page, with respect to his or her own average. Despite some applications in business and psychology, to the best of our knowledge, this paper is the first to use such time-tracking technique together with the correspondence testing.

Exploiting a sizeable proportion of Turkish descendants in Germany, we randomly insert photos of the same Turkish looking women with and without headscarf into comparable

[2]There are very few studies based on the correspondence testing technique that can acquire information of HR personnel involving in the selection process. Rooth (2010) in Sweden is one of the paper that conducted follow-up surveys with the HR responsible for the recruitment of the positions, to whom the fake CVs were sent to.

quality of CVs in the experiment. Apart from providing consistent estimates of the differences in the probability of being selected for an interview owing to beauty, ethnicity and headscarf, we attempt to identify the source of such discrimination based on job positions, characteristics of the CVs and the participants. Specifically, we classify our job openings into high and low skilled occupations as well as jobs with and without (or minimal) customer contact. We hypothesize that occupations with more interaction with customers would prefer better-looking persons and avoid minorities or females with headscarf due to anticipated customer discrimination and, hence, potentially higher productivity such as higher sales. Conversely, any discrimination observed in low customer contact jobs such as back-office operations could mainly arise from either within firm (employer/employee) discrimination or statistical discrimination.

Our results suggest that the beauty premium prevails in all types of occupations and is quite large in high skilled occupations. So, the beauty premium could be driven by both taste discrimination and potential productive attributes of beauty. Nevertheless, a slightly larger premium in high skilled jobs supports the argument for employee discrimination because this is a sector where our participants could relate the candidates as their future co-workers. Interestingly, better-looking candidates with the same gender as the recruiter are less likely to be chosen for the interview in the high skilled positions. Although a simple difference in the probability of being chosen between Turkish and German applicants shows a significant discrimination against Turks, such an effect disappears after controlling for beauty and interactions between some applicants' characteristics and headscarf. This finding provides an alternative explanation to the previous studies that racial discrimination in Germany might be partly explained by the fact that Turkish applicants (in our sample) are perceived as less beautiful than German looking counterparts.

Lastly, similar to Valfort (2015) and Weichselbaumer (2016), we find negative impacts of a religious practice, i.e. headscarf and mitigating effects of positive characteristics of the applicants. However, such discrimination is more prominent in case of high skilled occupations and jobs with customer contact. More importantly, we do not find evidence that such discrimination is driven by gender of the recruiters. However, older participants are those who discriminate against headscarf but at the same time additionally rewarding good characteristics of such applicants. Our results imply that the characteristics and behaviours of the human resources staffs could be the main driver of observed discrimination during the hiring process. Yet such practices might not reflect the best interest of their employers in terms of firms' productivity or profit.

The paper is organized as follows. Section 2 explains the experimental design. Section 3 presents our methodology, whereas Section 4 discusses the results. Section 5 concludes; Figures and Tables are included in the appendix.

2 Experimental design

The presented experiment is divided into two parts; all participants are students of the local universities. The first part was carried out in December 2015 where 120 students had to act as HR-stuff and choose candidates for a call back based on CVs. This part took one hour and the students were paid 20 Euro for participation. Descriptive statistics for the participants are summarized in Table 1. In order to detect whether beauty is a significant determinant for the probability of being chosen we conducted a second part, where the only task was to rate the photos. This rating was performed in March 2016, with 40 students in total. The second part took around 20 minutes and the students were paid 7 Euro. The experiment took place in the computer lab of the Leibniz University Hannover in several sessions, each of them with 10 to 17 participants. We did not acquire the photos in Hannover, so that possibility of the participants seeing the persons they choose in real life is negligible.

As the objective of the first part was to simulate the recruiting process, participants were asked to select applicants for an interview of fictitious positions. For each position they selected applicants based on seven characteristics, application photos[3] and the names of the applicant. The seven characteristics were (in the presented order):

- working experience (ranging from zero to three years)
- asked wage (average wage, 10% higher/lower than average, 20% higher/lower than average)
- Grade university/school (average, higher/lower than average)
- Quality of education (reputation of the college for high skilled jobs and amount of absence days for low skilled jobs[4])
- Current unemployment (currently not unemployed, 1-6 Month unemployed 7-12 month unemployed, 13-18 month unemployed)
- Computer skills (sufficient, good, very good)
- English skills (basic, advanced, fluently)

The characteristics were randomly assigned, the photos appeared in a random order, and the names were randomly assigned (corresponding to gender and ethnical background of the photo). In order to figure out whether the amount of time participants look at the photo is correlated with discrimination based on appearance we presented the photos and the characteristics separately (see Figure 1 and Figure 2). In order to investigate a possible discrimination against persons with a headscarf we asked a professional photographer to take application photos of three Turkish-looking women with and without the headscarf. Keeping everything else the same, but changing only the headscarf (see Figure 3).

We framed the task such that all presented candidates satisfy the formal requirements for the respective position, and differ only by the presented characteristics. The participants of

[3]It is common in Germany to send an application photo in a CV

[4]The amount of absence days is reported on the school certificate and is an important criteria when hiring low skilled job entrants

the experiment have to carry out a pre-selection, and choose their first and second preference out of four candidates for each position.

Each participant had to review 32-40 applications for 8-10 positions. These positions were organized in blocks of four positions. After reviewing 16 applications the participants were asked to take a break and answer a questionnaire (paper-and-pencil questionnaire about socio-demographic characteristics, and a questionnaire for another project).

In order to investigate the potential productive characteristics of beauty Biddle and Hamermesh (1998), the jobs in each block can be classified into four groups by level of skill (high or low skilled) and interaction with customers (high or low levels of contact). Concerning the rating of characteristics of each photo, we ran part two of the experiments, where we asked another group of students to rate persons on the photos by five characteristics, which are beauty, trustworthy, friendliness, intelligence and physical resilience. We then applied a "double standardization" method (within both raters and photos) to these ratings before using them as our explanatory variables.

3 Methodology

We adopt the Linear Probability Model (LPM)[5] to estimate the impacts of beauty, ethnicity and veiling on the chance of being selected for the interview by the participants in our experiment.

$$y_{ij} = \beta_0 + X'_{ij}\beta + Z'_{ij}\gamma + B'_k\delta + Int_{ik}\theta + time_{ij} + D_i + \varepsilon_{ij}$$

where y_{ij} be a dummy variable equal to 1 if CV i is chosen by participant j. X'_{ij} is a vector of the CV's seven characteristics discussed previously while Z'_{ij} is a vector of participant j characteristics from participants responses in a questionnaire. B'_k is a vector for our main explanatory variables (based on the photo k connected with each CV), which are a female

[5]The results are qualitatively similar when we use the Conditional Logit Model instead.

dummy if the applicant is a female, a composite beauty rating score of photo k, a dummy variable for ethnic Turkish and a dummy if the applicant wears a headscarf.

Then Int_{ik} are vectors of interaction terms between the photos specific characteristics such as beauty rating, dummy variables for ethnic Turkish or headscarf and selected CV's characteristics. Due to our moderate sample size of photos and participants, we decide not to include interactions between all characteristics of photos and CVs at the same time. Hence, we run three separated sets of regressions with one photo's characteristic interacting with all CV's characteristics. In addition, we assess an effect of beauty rating when the candidate is the same gender as the recruiter (student participant) by adding an interaction term between beauty score and a dummy equal to one if the recruiter and the candidate have the same gender.

Since our variables of interest are drawn from the photo accompanying each CV, we control for proportion of time each participant j looked at the photo page of CV i ($time_{ij}$). Meanwhile, D_i are dummies for the order of CV i, i.e. applicant number 2, 3 or 4 in each job-position (with the first applicant as the reference group). These dummies are included to control for the tendency of some participants who might systematically choose first, second, third or fourth applicant more often than other choices. Lastly β, γ and θ are vectors of parameters and ε_{ij} are the error terms which are clustered by photo. As for robustness checks, we also cluster standard errors by participant and use two-way clustered robust standard errors by both photo and participant (Cameron and Miller, 2015).

Moreover, in order to ascertain if the results are driven by characteristics of job openings or participants, we estimate the model for several sub-samples based on classifications, comprising four types of jobs (high skilled, low skilled, with and without customer contact), gender of participants and age of participants (either older or younger than 23 years).

4 Results

Following the model of Section 3 we focus mainly on the results of the linear probability model with OLS, results for fixed effects logit estimation are very similar to our OLS results and are available upon request. Table 2 shows that our randomisation process worked well and there are no significant differences in relevant characteristics between different sub-groups. Table 3 shows simple regressions with dummy variables for gender, Turkish ethnical background and headscarf. We do not observe significant discriminations for headscarf in such a setting, only discrimination for Turkish background, especially for high skilled jobs, and jobs with no customer interaction. This result remains quite robust after including controls (see Table 4) for characteristics and the position of the candidate in each job opening (from one to four).

However, Table 5 shows that these negative and significant coefficients for Turkish looking applicants disappear after controlling for beauty, i.e. we observe this lower labour market chances because females with Turkish origin are perceived less beautiful in our sample compared to German looking applicants. This result is quite surprising because most studies on correspondence testing in different countries tend to find significant lower callback rates for minorities on average. Yet there are some exceptions; for example, recent study by Edo et al. (2016) in France shows no significant discrimination against female foreigners who signal good language skills. Owing to our focus on young professionals, all Turkish applicants are female in their 20s. Hence, it corresponds to second or third generation migrants, who in general speak German as their mother tongue.

Table 4 and Table 5 show also quite intuitive and robust results about the significance of characteristics. So we observe that especially labour market experience, the final grade and the quality of education increase the chances for a call back. Computer skills are also significant and positive, but intuitively the importance is lower for jobs with customer contact and low skilled jobs. Also English skills are only important in certain kind of occupations (customer interaction and high skilled jobs). Surprisingly, previous unemployment and asked wage is not important for our decision makers across occupations.

Table 5 also shows a very significant and robust effect of appearance on the chance to be selected. We do not observe a clear difference in the effect of beauty between jobs with and without customer interaction. The effect of beauty differs slightly between low skilled and high skilled occupations. This means that in our experiment the decision makers do not judge according to productive characteristics of beauty in jobs with customer interaction, but discriminate more for high skilled occupations, perhaps because these types of occupations are perceived as their peer group. This difference between high skilled and low skilled occupation becomes more pronounced, when we include an interaction term for same gender and the beauty rating in Table 6. The advantage of a laboratory experiment compared to a fake CV approach is to control for characteristics of the rater and the time used for each part of the application. So we are able to detect that the beauty premium is only positive and significant for applicants of a different gender. The interaction term significantly reduces this beauty premium for same gender applicants in Column (1) for the whole sample, and for the Column (4) as the subsample of high skilled.

Our laboratory design allows us also to divide the sample by different groups. Table 7 shows that decision makers who take more time for our experiment discriminate less towards headscarf and appearance. Although the magnitude of the headscarf-dummy is very high for fast participants, this result is insignificant. This might come from the heterogeneity of this group, which should comprise those who do not take the experiment seriously and just randomly choose a candidate, so should not discriminate, and those who do not carefully look at the characteristics, but are guided by their intuition and therefore discriminate more than the average. On the other hand, those who take more time for the experiment are more judicious and try not to judge by appearance. Although the effect of beauty rating shrinks for the subsample of slow decision makers it still remains very robust and significant at 1%-level for all subgroups.

Table 8 decomposes the source of discrimination further. Our results indicate that there is no significant difference between the genders in discrimination against headscarf and by appearance. Female decision makers favour Turkish applicants. When dividing the sample by the age of participant we observe the same level of discrimination by appearance, but the magnitude of discrimination against females and headscarf is increased.

5 Conclusion

Exploiting a German practice to include photos in a CV allows us to measure how differences in appearance can influence career paths. Our laboratory experiment contributes to the sizable literature on correspondence testing (fake CVs) in many aspects. First, our research design enable us to measure how long a person looks at the photo of each applicant. Additionally, we have information on socioeconomic background of our participants. Since the participants were asked to fill fictitious positions, the sources of discrimination might come from the decision makers themselves, statistical discrimination and the productive characteristics of appearance. Therefore, we are able to exclude discrimination which might come from the composition of the team, whereas in correspondence testing experiments the result might also come from the endeavour to hire someone who fits into the existing team. We also show that discrimination against headscarf is driven by older participants but not by how long a decision maker looks at the photo. Furthermore, due to a large number of decisions and variations in characteristics, we can partly illustrate the mechanism behind the decisions through interaction effects.

Unfortunately, the choice between correspondence testing and laboratory experiment comes with a trade-off. On the one hand, we are able to observe more variables of interest. On the other hand, our results might underestimate the true discrimination in the labour market. There are several reasons for this underestimation. Firstly, the participants were instructed by the experimenter and knew that they were observed. Therefore, the "true" effect might be underestimated as a result of experimenter demand effects Zizzo (2010), where people tend to act socially desirable even if it would contradict their true believes. This might be the reason why our experiment shows a much lower effect for discrimination against the headscarf comparing to field experiment by e.g. Weichselbaumer (2016). Secondly, the discrimination against the headscarf might be underestimated because our experimental design gives four applications for each position, and always asks the participants to choose two of them. Results from Becker (1957) indicate that discrimination is prevailing in industries with highly competitive labour markets because it is cheaper for firms to discriminate; our setting, however, does not consider such a competition. Finally, different discrimination outcomes between a laboratory experiment and field experiments with correspondence testing could result from differences in age structure of the participants. Although the field of studies of students in our experiment match quite well to the actual HR-population, they are of course younger and hence might be less prejudiced compared to the "real" decision makers. Table 8 shows that decision makers who are 22 and younger discriminate less against headscarf than those who are 23 years old and older. Such a difference is quite remarkable, considering that our participants are quite young, i.e. 95% of our participants are 28 years old or younger.

In sum, our findings suggest significant beauty effects on the hiring decision in every type of jobs and such effects do not depend on gender or age of the recruiters. Interestingly, we do not find any discrimination against Turkish after controlling for beauty rating. Though our results indicate a significant discrimination toward Turkish looking women with headscarf, desirable characteristics of these applicants do help to reduce their disadvantages. Such results give us optimism to narrow down the job opportunity gaps of minorities through some education, internship or apprenticeship programme. We hope that our results will spur more discussion and encourage future research to consider appearance as a package of, for instance, beauty, ethnicity and observable religious practice simultaneously.

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6 Appendix

Figure 1: Example of the experiment screen 1

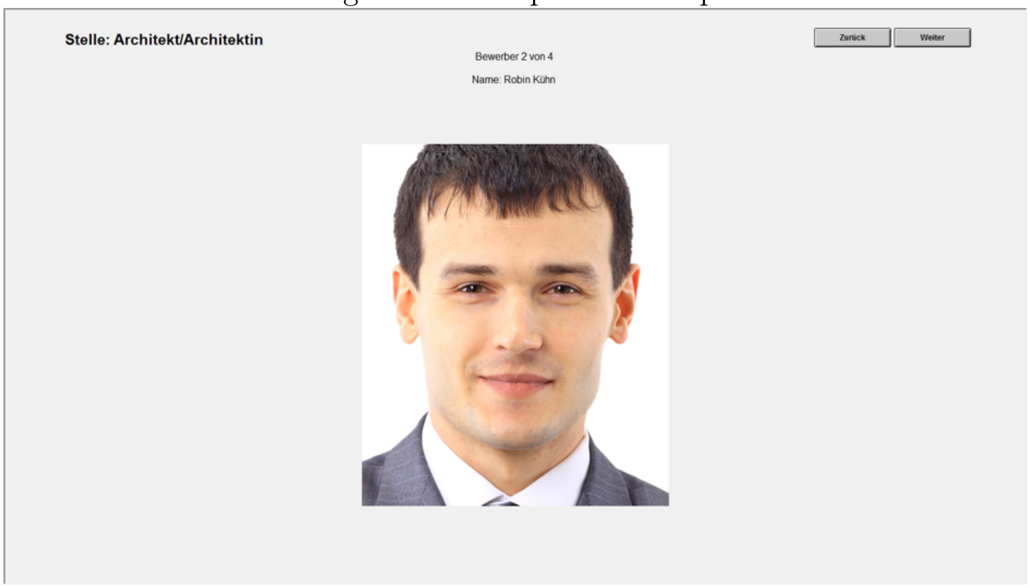
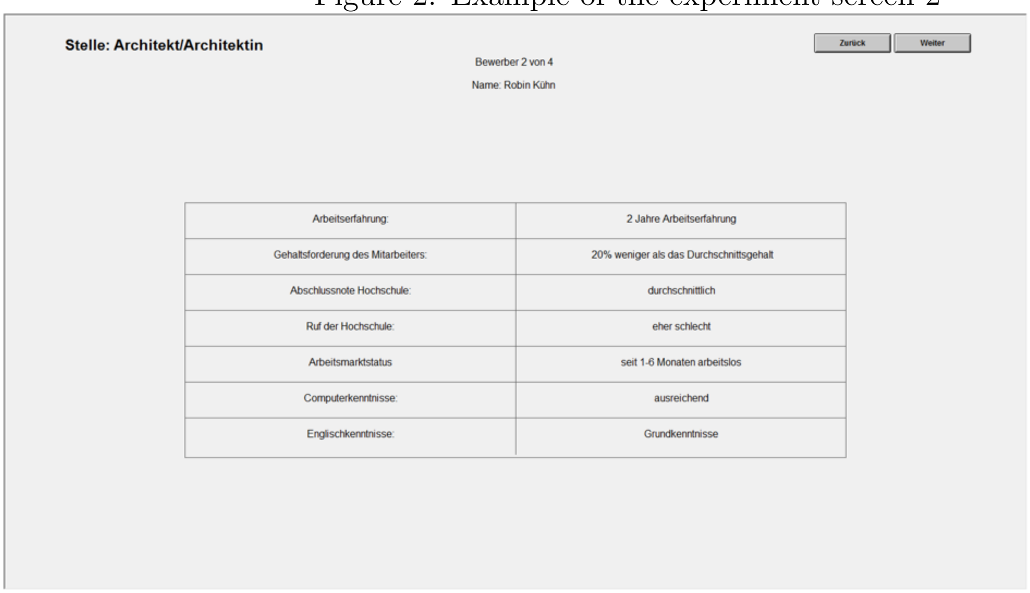


Figure 2: Example of the experiment screen 2



Arbeitserfahrung:	2 Jahre Arbeitserfahrung
Gehaltsforderung des Mitarbeiters:	20% weniger als das Durchschnittsgehalt
Abschlussnote Hochschule:	durchschnittlich
Ruf der Hochschule:	eher schlecht
Arbeitsmarktstatus	seit 1-6 Monaten arbeitslos
Computerkenntnisse:	ausreichend
Englischkenntnisse:	Grundkenntnisse

Figure 3: :An example of photos of the same person with and without veil (the photos are anonymized here for privacy reasons)

Table 1: Descriptives

	mean	**sd**	**min**	**max**
Main experiment				
female	0.46	0.50	0.00	1.00
age	23.28	3.23	18.00	45.00
siblings	1.35	0.98	0.00	4.00
study semester	3.97	2.64	1.00	15.00
study prog (bachelor)	0.60	0.49	0.00	1.00
study prog (master)	0.29	0.45	0.00	1.00
born in Germany	0.94	0.24	0.00	1.00
migration backgr	0.19	0.40	0.00	1.00
N	118	-	-	-
Beauty-panel				
female	0.53	0.51	0.00	1.00
age	23.70	3.29	18.00	33.00
siblings	1.60	0.96	0.00	4.00
study semester	4.90	3.23	1.00	15.00
study prog (bachelor)	0.57	0.50	0.00	1.00
study prog (master)	0.20	0.41	0.00	1.00
born in Germany	0.90	0.30	0.00	1.00
migration backgr	0.17	0.38	0.00	1.00
N	40	-	-	-

Table 2: Characteristics by headscarf dummy

variable	without headscarf	headscarf	p_value
exp	1.456	1.410	0.261
wage	2.132	1.999	0.00590
educ	0.988	0.994	0.843
quality	0.960	0.968	0.790
unemployed	1.557	1.660	0.0106
computer	0.755	0.791	0.233
english	0.748	0.799	0.0875

Table 3: no controls, no interaction

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected	(5) Selected
turkish origin = 1	-0.0439*	-0.0780***	-0.0134	0.0324	-0.1221***
	(0.0257)	(0.0270)	(0.0366)	(0.0309)	(0.0285)
headscarf = 1	0.0168	0.0953	-0.0563	-0.0301	0.0665
	(0.0419)	(0.0593)	(0.0376)	(0.0406)	(0.0532)
female	0.0137	-0.0234	0.0512**	-0.0027	0.0298
	(0.0198)	(0.0264)	(0.0237)	(0.0230)	(0.0247)
Observations	4,384	2,188	2,196	2,176	2,208
R^2	0.0007	0.0033	0.0028	0.0003	0.0047
Characteristics	No	No	No	No	No
Type of Occupation	All	no contact	contact	low skill	high skill
Decision-Maker	All	All	All	All	All

Robust clustered(by Photo) standard errors in parentheses

Table 4: controls, no interaction

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected	(5) Selected
turkish origin = 1	-0.0424	-0.0686**	-0.0130	0.0356	-0.1226***
	(0.0281)	(0.0322)	(0.0347)	(0.0371)	(0.0254)
headscarf = 1	0.0131	0.0779	-0.0533	-0.0367	0.0754
	(0.0466)	(0.0613)	(0.0398)	(0.0452)	(0.0497)
female	0.0113	-0.0227	0.0432*	-0.0070	0.0253
	(0.0176)	(0.0238)	(0.0239)	(0.0209)	(0.0220)
Experience in years	0.0455***	0.0288***	0.0602***	0.0492***	0.0508***
	(0.0102)	(0.0102)	(0.0162)	(0.0130)	(0.0131)
Asked wage	0.0037	0.0054	0.0015	0.0172	-0.0023
	(0.0089)	(0.0091)	(0.0177)	(0.0121)	(0.0125)
Final grade	0.1618***	0.1496***	0.1721***	0.1307***	0.1988***
	(0.0111)	(0.0130)	(0.0189)	(0.0174)	(0.0139)
Quality of Education	0.1152***	0.1118***	0.1201***	0.1721***	0.0641***
	(0.0133)	(0.0127)	(0.0195)	(0.0145)	(0.0152)
Previous unemployment	-0.0022	-0.0215*	0.0164	0.0066	-0.0044
	(0.0091)	(0.0125)	(0.0143)	(0.0142)	(0.0123)
Computer skills	0.0422***	0.0549***	0.0312*	0.0271**	0.0649***
	(0.0104)	(0.0131)	(0.0153)	(0.0132)	(0.0137)
English skills	0.0214**	-0.0109	0.0539***	0.0141	0.0356**
	(0.0100)	(0.0117)	(0.0174)	(0.0130)	(0.0151)
Time rel. (photo)	0.1965	0.1398	0.2699	0.1511	0.2351
	(0.1270)	(0.1700)	(0.1666)	(0.1764)	(0.1561)
Observations	4,384	2,188	2,196	2,176	2,208
R^2	0.0773	0.0872	0.0841	0.0797	0.1083
Characteristics	Linear	Linear	Linear	Linear	Linear
Type of Occupation	All	no contact	contact	low skill	high skill
Decision-Maker	All	All	All	All	All

Robust clustered(by Photo) standard errors in parentheses

Table 5: controls and beauty, no interaction

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected	(5) Selected
turkish origin = 1	0.0504	0.0158	0.0895*	0.1021*	-0.0114
	(0.0331)	(0.0396)	(0.0466)	(0.0507)	(0.0308)
headscarf = 1	0.0135	0.0798	-0.0543*	-0.0360	0.0736*
	(0.0390)	(0.0559)	(0.0314)	(0.0402)	(0.0421)
Beauty-rating (double std)	0.0640***	0.0623***	0.0656***	0.0429**	0.0811***
	(0.0135)	(0.0155)	(0.0207)	(0.0193)	(0.0161)
female	-0.0526***	-0.0818***	-0.0265	-0.0551*	-0.0474**
	(0.0155)	(0.0212)	(0.0298)	(0.0313)	(0.0207)
Experience in years	0.0448***	0.0281***	0.0594***	0.0491***	0.0495***
	(0.0101)	(0.0101)	(0.0163)	(0.0130)	(0.0130)
Asked wage	0.0038	0.0058	0.0009	0.0173	-0.0023
	(0.0087)	(0.0089)	(0.0176)	(0.0123)	(0.0122)
Final grade	0.1615***	0.1492***	0.1718***	0.1316***	0.1968***
	(0.0109)	(0.0126)	(0.0188)	(0.0172)	(0.0135)
Quality of Education	0.1152***	0.1118***	0.1202***	0.1721***	0.0642***
	(0.0131)	(0.0122)	(0.0195)	(0.0145)	(0.0150)
Previous unemployment	-0.0016	-0.0205	0.0163	0.0075	-0.0045
	(0.0091)	(0.0125)	(0.0143)	(0.0143)	(0.0120)
Computer skills	0.0417***	0.0545***	0.0304*	0.0264*	0.0653***
	(0.0104)	(0.0131)	(0.0152)	(0.0132)	(0.0136)
English skills	0.0211**	-0.0110	0.0537***	0.0145	0.0332**
	(0.0100)	(0.0120)	(0.0173)	(0.0131)	(0.0145)
samegender	0.0145	0.0161	0.0142	-0.0077	0.0348
	(0.0181)	(0.0241)	(0.0191)	(0.0243)	(0.0234)
Beauty-rating*samegender	-0.0405*	-0.0430	-0.0360	-0.0248	-0.0555*
	(0.0205)	(0.0262)	(0.0229)	(0.0231)	(0.0273)
Time rel. (photo)	0.1977	0.1467	0.2673	0.1571	0.2228
	(0.1261)	(0.1681)	(0.1646)	(0.1755)	(0.1560)
Observations	4,384	2,188	2,196	2,176	2,208
R^2	0.0816	0.0913	0.0885	0.0815	0.1160
Characteristics	Linear	Linear	Linear	Linear	Linear
Type of Occupation	All	no contact	contact	low skill	high skill
Decision-Maker	All	All	All	All	All

Robust clustered(by Photo) standard errors in parentheses. Controls for position included

Table 6: controls and beauty, interaction

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected	(5) Selected
turkish origin = 1	0.0509	0.0165	0.0897*	0.1010*	-0.0117
	(0.0331)	(0.0397)	(0.0465)	(0.0508)	(0.0309)
headscarf = 1	-0.1829**	-0.2153*	-0.1676**	-0.1127*	-0.2228**
	(0.0743)	(0.1149)	(0.0735)	(0.0658)	(0.0978)
Quality of Education	0.1098***	0.1022***	0.1197***	0.1696***	0.0555***
	(0.0137)	(0.0131)	(0.0207)	(0.0157)	(0.0153)
c.scarfall#c.quality	0.0596	0.1178***	0.0028	0.0292	0.0997*
	(0.0375)	(0.0373)	(0.0381)	(0.0233)	(0.0581)
Experience in years	0.0405***	0.0240**	0.0556***	0.0451***	0.0457***
	(0.0102)	(0.0109)	(0.0164)	(0.0134)	(0.0136)
c.scarfall#c.exp	0.0466***	0.0568**	0.0365*	0.0463***	0.0370*
	(0.0115)	(0.0235)	(0.0190)	(0.0156)	(0.0189)
Final grade	0.1573***	0.1443***	0.1684***	0.1325***	0.1891***
	(0.0108)	(0.0136)	(0.0190)	(0.0181)	(0.0135)
c.scarfall#c.educ	0.0423**	0.0762***	0.0196	-0.0090	0.0808**
	(0.0206)	(0.0248)	(0.0199)	(0.0247)	(0.0355)
English skills	0.0175	-0.0131	0.0484**	0.0159	0.0245
	(0.0103)	(0.0132)	(0.0177)	(0.0146)	(0.0144)
c.scarfall#c.english	0.0385**	0.0243	0.0503	-0.0079	0.0918*
	(0.0183)	(0.0187)	(0.0337)	(0.0209)	(0.0454)
Beauty-rating (double std)	0.0642***	0.0625***	0.0656***	0.0428**	0.0808***
	(0.0134)	(0.0156)	(0.0206)	(0.0193)	(0.0159)
female	-0.0530***	-0.0828***	-0.0267	-0.0544*	-0.0478**
	(0.0156)	(0.0212)	(0.0298)	(0.0314)	(0.0207)
Beauty-rating*samegender	-0.0403*	-0.0419	-0.0354	-0.0249	-0.0544*
	(0.0203)	(0.0261)	(0.0229)	(0.0230)	(0.0267)
Time rel. (photo)	0.1973	0.1396	0.2715	0.1686	0.2315
	(0.1263)	(0.1681)	(0.1643)	(0.1770)	(0.1530)
Observations	4,384	2,188	2,196	2,176	2,208
R^2	0.0829	0.0943	0.0894	0.0825	0.1196
Characteristics	Linear	Linear	Linear	Linear	Linear
Type of Occupation	All	no contact	contact	low skill	high skill
Decision-Maker	All	All	All	All	All

Robust clustered(by Photo) standard errors in parentheses. Controls for position included

Table 7: controls and beauty, interaction, by time

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected
turkish origin = 1	0.0509	0.0582	0.0556	0.0561*
	(0.0331)	(0.0758)	(0.0431)	(0.0292)
headscarf = 1	-0.1829**	-0.2760	-0.1603*	-0.0930
	(0.0743)	(0.2381)	(0.0855)	(0.1621)
Quality of Education	0.1098***	0.1117***	0.1079***	0.1089***
	(0.0137)	(0.0249)	(0.0207)	(0.0250)
c.scarfall#c.quality	0.0596	0.0595	0.1223	-0.0029
	(0.0375)	(0.0596)	(0.0743)	(0.0591)
Experience in years	0.0405***	0.0184	0.0395**	0.0617***
	(0.0102)	(0.0195)	(0.0154)	(0.0176)
c.scarfall#c.exp	0.0466***	0.0725*	0.0119	0.0567
	(0.0115)	(0.0376)	(0.0234)	(0.0403)
Final grade	0.1573***	0.1690***	0.1310***	0.1687***
	(0.0108)	(0.0226)	(0.0182)	(0.0142)
c.scarfall#c.educ	0.0423**	0.1130**	0.0079	0.0142
	(0.0206)	(0.0441)	(0.0235)	(0.0266)
English skills	0.0175	0.0163	0.0107	0.0227
	(0.0103)	(0.0202)	(0.0192)	(0.0150)
c.scarfall#c.english	0.0385**	0.0065	0.0510	0.0244
	(0.0183)	(0.0906)	(0.0554)	(0.0513)
Beauty-rating (double std)	0.0642***	0.0806***	0.0736***	0.0409***
	(0.0134)	(0.0259)	(0.0266)	(0.0142)
female	-0.0530***	-0.0718**	-0.0370	-0.0469*
	(0.0156)	(0.0335)	(0.0326)	(0.0266)
Beauty-rating*samegender	-0.0403*	-0.0654**	-0.0363	-0.0209
	(0.0203)	(0.0308)	(0.0414)	(0.0203)
Time rel. (photo)	0.1973	-0.0602	0.1051	0.4595**
	(0.1263)	(0.1871)	(0.2138)	(0.2158)
Observations	4,384	1,456	1,432	1,496
R^2	0.0829	0.1085	0.0742	0.0876
Characteristics	Linear	Linear	Linear	Linear
Type of Occupation	All	All	All	All
Decision-Maker	All	Fast	Middle	Slow

Robust clustered(by Photo) standard errors in parentheses. Controls for position included

Table 8: controls and beauty, interaction (by subgroups)

VARIABLES	(1) Selected	(2) Selected	(3) Selected	(4) Selected	(5) Selected
turkish origin = 1	0.0509	-0.0100	0.1297*	0.0212	0.0742*
	(0.0331)	(0.0411)	(0.0700)	(0.0548)	(0.0378)
headscarf = 1	-0.1829**	-0.2009*	-0.1569**	-0.0839	-0.2653***
	(0.0743)	(0.0984)	(0.0759)	(0.1646)	(0.0618)
Quality of Education	0.1098***	0.1146***	0.1025***	0.1055***	0.1118***
	(0.0137)	(0.0168)	(0.0221)	(0.0196)	(0.0182)
c.scarfall#c.quality	0.0596	0.0712	0.0465	0.0593	0.0587***
	(0.0375)	(0.0507)	(0.0338)	(0.0894)	(0.0208)
Experience in years	0.0405***	0.0307**	0.0504***	0.0462**	0.0356***
	(0.0102)	(0.0133)	(0.0166)	(0.0175)	(0.0120)
c.scarfall#c.exp	0.0466***	0.0443*	0.0456**	0.0159	0.0711***
	(0.0115)	(0.0217)	(0.0181)	(0.0185)	(0.0149)
Final grade	0.1573***	0.1696***	0.1434***	0.1650***	0.1504***
	(0.0108)	(0.0133)	(0.0184)	(0.0151)	(0.0133)
c.scarfall#c.educ	0.0423**	0.0735***	0.0109	0.0565	0.0353
	(0.0206)	(0.0149)	(0.0431)	(0.0582)	(0.0302)
English skills	0.0175	0.0158	0.0207	0.0336**	0.0045
	(0.0103)	(0.0139)	(0.0174)	(0.0147)	(0.0158)
c.scarfall#c.english	0.0385**	0.0051	0.0573	0.0071	0.0640***
	(0.0183)	(0.0283)	(0.0442)	(0.0409)	(0.0162)
Beauty-rating (double std)	0.0642***	0.0467**	0.0448***	0.0618**	0.0642***
	(0.0134)	(0.0228)	(0.0159)	(0.0261)	(0.0209)
female	-0.0530***	-0.0430*	-0.0676**	-0.0264	-0.0779**
	(0.0156)	(0.0251)	(0.0289)	(0.0392)	(0.0282)
Beauty-rating*samegender	-0.0403*	-0.0056	-0.0005	-0.0426	-0.0358
	(0.0203)	(0.0299)	(0.0347)	(0.0288)	(0.0299)
Time rel. (photo)	0.1973	0.1359	0.2493	0.1182	0.2801*
	(0.1263)	(0.1777)	(0.1822)	(0.2351)	(0.1377)
Observations	4,384	2,360	2,024	1,928	2,456
R^2	0.0829	0.1007	0.0732	0.0748	0.0956
Characteristics	Linear	Linear	Linear	Linear	Linear
Type of Occupation	All	All	All	All	All
Decision-Maker	All	Male	Female	Age under 23	Age 23 and older

Robust clustered(by Photo) standard errors in parentheses. Controls for position included