Will Ugly Betty ever find a job in Italy?*

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Abstract

This paper evaluates the impact of beauty, gender, and nationality on employability on Italian labor market. We propose a field experiment that consists in sending 9680 curricula vitae to firms looking for employees. We use binary probit to investigate the influence of discrimination on the probability of a candidate to be called for a job interview; considering firms' responses, we estimated our model using a sample of 7184 observations. Comparing differences between the response rates to unattractive candidates and to foreign candidates, we show that the discrimination in the Italian labor market is based on both attractiveness and country of origin.

1 Introduction

In 2006, ABC channel started a new TV series called "Ugly Betty", which ironically explored the impact of concepts such as beauty, class, race, and sex on employability of job searchers. The series won several awards because it represents a possible way to shed the light on several kinds of discriminations in everyday life. Betty Suarez is an unattractive 22-year-old Mexican American women. She lands a job at Mode, a trendy, high fashion magazine in Manhattan. The series thereby examines all the possible discrimination concerning gender, attractiveness, and race in the labor market. The success of the series reflects the attention paid to discrimination issues in the USA.

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Italy represents another country in which, historically, beauty and attractiveness has always played a relevant role. Gundle (1997) wrote "Feminine beauty has been more discussed, appreciated, represented in art and associated with national, cultural identity in Italy than in any other country". The author examined the role played by beauty, finding that "although the public discussion of feminine beauty was largely a male affair, the women were caught up in it, and who were seen, on account of their beauty, to embody the nation, were never passive objects. Indeed, they often used or manipulated the tradition of beauty for their own ends".

Moreover, Gundle (2000) underlined that "after 1945 the Italian tradition of feminine beauty was redefined in a democratic context in which women, for the first time, became full citizens. Faced with a far-reaching challenge from Hollywood, traditional criteria of beauty were first strenuously defended and then modified and commercialized. Beauty contests proved to be a vital vehicle in this transition, since they acted both as a forum for the reassertion of Italian beauty and as a vehicle for the displacement of old ideas centered on the face with a new concept based on the eroticized body. This transition became bound up with the ongoing political conflict between Catholics and the left for the moral and political leadership of the country. While both, with different emphases, championed 'natural' at the expense of American-style 'manufactured' beauty, competition led them to engage with, and in some way adopt, the sexualized beauty that was the hallmark of the role of the United States in furnishing new models for the consumer society that would develop rapidly in the later 1950s."

In the light of these considerations our research question is the following: could Ugly Betty find a job in Italy? In other words, is discrimination, based on gender and/or attractiveness still a major problem on the Italian labor market? In this paper, we aim to investigate the profile of discrimination in Italy, using a unique database created by sending fictitious CVs to real job openings. Furthermore, as Italy is a growing immigration market, we decided to analyze contextually why the foreign-born, individuals are not doing as well as the home-born. To do so, it seems necessary to study not only the individuals who are or are not employed, but also the decisions of those who recruit for jobs. Consequently, the focus of this paper is on employers. Can employer discriminate between natives and immigrants, between attractive and unattractive men and women? How does discrimination based on gender interact with that based on attractiveness and nationality in different kinds of jobs?

In order to analyze the impact of gender, race and attractiveness, we sent several times the same resume with the same skills to all job postings displayed online in the period between August 2011 and September 2012, changing the photo attached or attaching no photo at all. Indeed, the Italian labor market represents a perfect context for our research: as the use of photographs in job applications is not so common, its absence does not penalize applications. Most of the websites start to suggest including photos in the CV, given that a professional dress code is used. Therefore, also including a picture in the resume does not entail any kind of penalization. At the same time not including a photo it is not necessarily a signal of a bad looking person, since between no photo resumes and the ones with unattractive photos differences are significant. The resumes are based on the European format and structure, and are using fictitious names and addresses. We sent 9680 curricula vitae (hereafter CVs) to 1210 advertised job openings, receiving 2711 callbacks that correspond approximately to the rate of 28% of the CVs sent (see Table 3). The analysis consists of a binary probit to investigate the influence of discrimination on the probability of a candidate to be called for a job interview.

On respect to previous papers based on field experiments (see Rich, 2014, for a complete review), we build a unique database, as we mentioned earlier. Moreover, we design our experiment in order to have complete control and observability over candidate backgrounds: our applicants are identical in every respect (including their education, work experience, language and computer skills, and completely fulfilling employer requirements regarding such respects) for each kind of job offer. Indeed, in our experiment, candidates CVs change only in name, nationality, gender, race and pictures (or lack thereof). Such strategy might have amplified the effects of these variables, but allows us to focus on the profile of discrimination in Italy, since all candidates who apply to the same firm are equivalent, and differences in callbacks does not depend on the matching between jobs and worker characteristics. Moreover, in our paper we use a large number of observations that permits us to shed new light on the question of discrimination based on gender, physical appearance and nationality. We consider such aspects simultaneously, while previous works consider them separately. For instance, Bertrand and Mullainathan (2004, 1300 job ads and 5000 CVs) and Oreopoulos (2011, 3225 job ads and 12910 CVs) investigate racial discrimination. Ruffle and Shtudiner (2010, 2656 job ads and 5312 CVs), Rooth (2009, 985 job ads and 1970 CVs), and Lopez Bóo, Rossi and Urzua (2013, 2540 CVs) used the same methodology to investigate the impact of attractiveness and, as in Rooth's case, also its interaction with obesity.

On respect to other papers, which basically analyze only job's main characteristics (*e.g.* hard work or front office), we collect data on job types so that we are able to calculate the impact of discriminatory variables (gender, physical appearance and nationality) on each type of job (executive, technicians, sales,...), while other papers .

We also noted that this kind of investigation is uncommon in Italy. The only audit studies we are aware of dealing with the impact of beauty in Italian labor market are Ponzo and Scoppa (2013) and Busetta, Fiorillo and Visalli (2013). The first analysis concerned, in particular, the impact of professors' beauty on teaching evaluation, finding strong evidence of its influence. The second, like the present one, analyzed the first stage of the hiring process using only a decomposition variance analysis[1].

Comparing differences in response rates to both unattractive and to foreign candid-

[1]In particular, considering various characteristics of the candidates, the study shows that, in order to classify callback rates, the most important characteristic is the one based on attractiveness.

ates, we show that the discrimination in the Italian labor market is based on attractiveness and the country of origin.

The paper is organized as follows: in section 2 we describe the data used in the empirical analysis, while section 3 focusses on the statistical methodology we apply. In section 4 we present the main empirical results and section 5 concludes.

2 Experimental design

The field experiment we propose consists in sending 9680 CVs, based on the European format[2] and structure, to 1210 firms looking for employees. All of the CVs were sent in the period between September 2011 and August 2012. During this period, we regularly scrutinized job postings on all the main online job service websites[3] offering positions in Italy. We chose only the websites that require no registration in order to prevent firms to detect that CVs in question were fictitious. The same[4] CV was sent to the same company eight times: four CVs with different applicants photos, and four without photos[5]. The photos in the CVs were representig attractive and unattractive Italian women, and attractive and unattractive Italian men respectively. A CV containing no photo of an Italian and an African (in terms of name and origin) was sent to each firm for both genders.

Thus, each employer received 8 CVs from 4 females and 4 males, of 28 years old each one, living in Rome, and with exactly the characteristics required for the job. We randomly matched first name, surname and photos. In choosing the pictures to be included in the resumes, we selected 20 male and 20 female photographs from the internet, modified in order to make them unrecognizable. All faces used in the photos were caucasian

[2]European format or "Europass" is an European Union (Directorate General for Education and Culture) initiative to increase transparency of qualification and mobility of citizens in Europe (Decision 2241/2004/EC, Article 1). It aims to make a person's skills and qualifications clearly understood throughout Europe (including the European Union, European Economic Area and EU candidate countries).

[3]Namely lavoratorio.it, Lavoro&Stage, Miojob, Lavorare.net, Page Personnel, Trovalavoro, Kijiji, Inique Agenzia, Archimede agenzia per il lavoro, Manpower divisione Horeca, Combinazioni s.r.l, Quanta agenzia per il lavoro, Humangest, Alma, Orienta agenzia per il lavoro, Varese centro per l'impiego, Adecco, Obiettivo lavoro, Temporary agenzia per il lavoro, Free work, Maw, Euro Interim, Mr Comunication, and Open Job.

[4]As a precautionary measure, in order not to let employers realize that they were receiving identical CVs, we staggered the dispatch of the CVs to the same firms over a few days. As each firm receives thousands of CVs, we are convinced that receiving eight CVs over few days should not make them suspicious. For the same reason, we used different names and addresses. All the addresses belongs to the city of Rome in order not to make the scrutinizers perceive the candidates as different because of where they lived. Finally, we randomly chose the order of CVs sent to the same firm.

[5]In this respect, the best experimental design would be to send to the same employer applications with identical information, except for the photo. As pointed out by Oreopoulos (2011), such a strategy would be impossible to implement without employers becoming suspicious. Therefore, we decided to associate a different name and address to each different photo (or no photo included).

smiling individuals; thus we eliminate the racial preferences. One hundred students (50 women and 50 men) from the University of Messina were asked to score CVs photos on a scale from 1 to 10. We summed the score obtained by each photo, and identified unattractive/attractive males and females as those obtaining the lowest/highest scores. In order to test the robustness of the ranking, we calculated how many students assigned the maximum to the most attractive male and female photos. The inverse procedure was followed for the less attractive photos.

Overall, 85% of the students agreed on the most attractive man and 93% on the least attractive, 90% agreed on the most attractive woman and 95% on the least attractive. We are therefore confident that subjectivity can be excluded from the choice. Moreover, on a scale from 1 to 1000, most attractive candidates obtained over 850 points, while less attractive ones less than 250 (see Table 1 in the Appendix).

[Table 1 about here]

Unlike the procedure applied by Rooth (2009), once we made the association between names, surnames, address and photos, we did not change it for all the experiment. In other words, once we associated these attributes, we maintained consistency in the application, since we could not exclude the same vacancy to be present in several of the web search engines posting job offers. Moreover, whatever is the distortion produced, it will affect each job offer in the same way[6].

In order to minimize the effects of differences in names influencing our results, we chose the most common first names and surnames in Rome, home to the eight fictitious applicants[7]. As regards names, surnames and addresses of the fictitious foreign candidates, we applied the same procedure. Since we wanted to evaluate the impact of race and nationality on the probability of obtaining a job interview, we chose the most common non-white nationality of immigrants in Italy, which is Moroccan. As in Morocco the most common names (one male and one female) are Mohammed and Fatima and surnames are Elalawe and Benkeran, we chose them for our fictitious foreign candidates. We created

[6]Search engines do not make any selection of the candidates, acting just a repository for the CVs. Moreover, in several of the job postings analyzed, there is no information on the single firm offering vacancies because the web search engine hide this information.

[7]We chose the six most popular surnames in Rome: Rossi (2644 families), Mancini (1676), Proietti (1399), Ricci (1369), Russo (1116), and Bianchi (887). We excluded De Angelis (1437), De Santis (1294) and Conti (982) since their surnames could be perceived as noble. In terms of first names we adopted the same procedure both for females and males. The most common first names in Rome for males are Andrea, Luca, Marco and Francesco and for females they are Giulia, Chiara and Francesca. We excluded Andrea because this name in Italy can be used either for males or females and we did not wish to generate any kind of confusion. All applicants are from Parioli, the most affluent district in Rome. We did so in order to minimize the differences due to the distance from the workplace and applicants' residence, and to make the distortion driven by family income as homogeneous as possible.

eight *Gmail-Google* accounts, one for each fictitious individual, to collect employer responses and we included this email address in the CV as contact information[8].

[Table 2 about here]

Thus, our design strategy allows us to examine whether there is a preference for attractive and/or Italian candidates, and whether this preference interacts with the applicant's gender.

In all, 11008 CVs were prepared to be sent in response to 1542 advertised job postings. In order to make an accurate analysis regarding gender discrimination, we dropped the CVs sent to job opened exclusively to female or male workers[9]. Applications from female (male) workers were invited by 127 (205) firms, and 508 (820) CVs were sent to them, each firm receiving only four CVs per vacancy. Thus, 9680 CVs sent to 1210 firms remained for the analysis and they form the entire sample. Finally, to avoid matching problems and to be competitive with respect to other applicants, for each different job offered we add, to each association already made (name, surname, address and photo), the characteristics (*i.e.* education, work experience, language and computer skills) which completely fulfill the skills required by the firms. Basically, we customized the CVs sent for responding to each job posting. Using this procedure, we thus sent eight CVs, identical in every respect except name, surname, nationality and photo (or lack thereof). In this way, we intended to polarize the results focussing on the effect of attractiveness and gender, regardless to other differences in candidate's profile.

The only other difference in the CVs sent are font and font size as in Rooth (2009). Thus, all applicants for the same vacancy had the same characteristics in terms of age (28 years old), education[10], and amount of work experience. The design of our experiment, as previously illustrated by Ruffle and Shtudiner (2010) and Lopez Bóo, Rossi and Urzua (2013), gave us complete control over candidates' backgrounds. Indeed, our applicants were very similar in every respect for each kind of job offer. This methodology ensures that perceived productivity characteristics on the supply side are held constant. Gender, nationality and pictures (or lack thereof) were the only items which changed among different CVs sent in response to the same job offer. Photos are differentiated with respect to a constant rank of attractiveness[11].

[8]Almost all the job postings required the inclusion of an email address and/or telephone number in the application form. We decided to include only the email address in the applications in order to make the collection of callbacks easier.

[9]In Italy is not illegal to ask only for men or only for women depending on the typology of the job ad.

[10]To prevent the scrutinizers being influenced by the prestige of the school or the university in which the applicant had studied, we used institutions considered comparable. For the CVs with university degree, we used "La Sapienza" University, the largest university in Italy and located in Rome.

[11]A different strategy would be to send to each firm a multiple of six CVs. This strategy would have the advantage of increasing the sample size, but it has a great disadvantage: a larger number of photos

Therefore, differences between candidates only concern gender, nationality, photo and attractiveness. The degree of differential treatment can be noticed from the different number of callbacks for a job interview.

Responses were classified as callbacks if the employer requested an applicant to contact them, not just for clarification. To minimize inconvenience to the employer, we promptly declined via email the invitations for interview, telling to employers that the applicant had accepted another position and was no longer looking for employment.

Table 3 summarizes the characteristics of job openings in our dataset. The abbreviations in brackets are those that will be used in the analysis below. The sample was equally divided into CVs which include photos of an attractive (variable `A`) and an unattractive (`U`) person, CVs including no photo of an Italian and a foreigner (`F`), and CVs for men (`M`) and for women (`W`).

[Table 3 about here]

The data collected with this method gave us the opportunity to explore the effect of a picture and its attractiveness (or lack thereof) on the likelihood of being invited for a job interview. Moreover, sending CVs with no photos allowed us to consider as a benchmark the Italian individuals with no information on their attractiveness and to control for racial discrimination. Finally, our design strategy of sending fictitious CVs which exactly meet the firms' requirements allowed us to eliminate matching problems as a possible explanation for the difference in the rate of response.

Being aware that beauty might be relevant and contribute to worker productivity in some of the fields involved in the advertised job postings, we decided to divide job positions into front- and back-office tasks. Thus, we classified all job openings according to whether the position involves face-to-face (`FO`) contact with the public. In particular, we classified as front office jobs those which either explicitly stated that the job required face-to-face contact with people, or where such contact could be unequivocally inferred from the job advertisement. Otherwise, the job is classified as back office. We then included in the first category, for instance, jobs belonging to fields like sales and customer service. By contrast, we decided to include in the back-office category jobs like accounts management, budgeting, industrial engineering, and computer programming.

While 39.59% of the job openings in our sample are positions that involve face-to-face contact, the remaining are job positions which do not require any kind of direct contact in person with the customer. Another distinction that we made was between jobs for which physical strength is required (13.47% of our observations), and jobs for which it is not required. As for front and back office jobs, we classified as hard work either jobs for which physical strength is explicitly required, or those for which it may be unequivocally inferred. Otherwise, they are classified as jobs which do not imply hard work.

would have generated a subjective beauty ranking among each employer's responses without having the possibility to control for it.

The last characteristics that we considered in the analysis are the qualifications required and the functions offered. As regards the former, 27.52% of our sample of job offers required no qualification, 44.30% required a high school diploma (`High`), and the remaining a university degree (`Grad`). In terms of functions offered, managers accounted for 5.62% of job offers, professionals posts for 9.09%, technical jobs 40.17%, clerical jobs 13.88%, commercial posts 14.88%, skilled workers 5.79% and elementary occupation 4.05% (Based on International Standard Classification of Occupations - ISCO).

In Table 3 the distribution of call back rates is presented. In respect to attractiveness, it emerges that attractive Italian people have much higher call back rates (almost 50%) than unattractive ones (13.51%) and Italians with no photo (37.98%). Also racial discrimination appears to be significant. Furthermore, markedly lower callback rates are associated to foreign candidates (10.62%). According to gender classification, men get 28.93% of callbacks, while women 27.09%.

Regarding front and back office classification, we obtained 28.90% for those entailing back office work and 26.64% for those involving front office work. With respect to hard and "soft" jobs, 26.38% is the callback rate for jobs involving hard work, and 38.42% for those not entailing hard work.

In terms of qualifications required, we obtained the highest callback rates for jobs which do not require any qualification (33.60%), while jobs for graduate candidates obtained 27.71% and jobs for high school diploma candidates obtained about 23% (see Table 3).

In terms of the ISCO classification of jobs, we have about 37% for elementary occupations, 26.49% for wire workers, 45.71% for craftsmen and skilled workers, and definitely lower callback rates for managers (about 16%), and scientific and intellectual professions (about 26%).

The correlation between job characteristics and classification is shown in Table 4. The matrix shows that, while graduate jobs are strongly positively correlated to executive and specialized jobs, they are negatively correlated to sales, front office and hard work. On the other hand, high school jobs are strongly positively correlated to technical and front office jobs and negatively correlated to unskilled and hard work. Obviously, vacancies requiring high school qualifications are strongly negatively correlated to those requiring university degrees. Front office jobs are highly positively correlated to sales staff, and finally hard work is strongly positively correlated to service work, workmen and to unskilled work and negatively correlated to technical jobs.

[Table 4 about here]

3 Data and methodology

In order to inquire which are the principal components influencing the probability of obtaining a job interview, we performed a probit analysis. As our goal was to obtain as many responses as possible from employers, we included in the CVs all the characteristics required by the advertised job postings. Moreover, we add to the CVs the qualifications required so that the applicants would not be perceived as over-qualified. As we sent identical CVs to each advertised job posting, differences in response rates between candidates can only be due to different pictures or lack thereof.

Throughout our analysis, the dependent variable is the dichotomic variable $\texttt{RESP}$, that represents the employers responses; it is equal to 1 if the employer emailed the applicant to invite him/her for an interview and 0 if the email was not initiated. Since 312 firms does not replay at any CV, we exclude these firms from the sample and we use for estimation $N = 7184$ observations. Therefore, we perform four linear probit models where the probability of receiving an email with the invitation for an interview is estimated via the equation

$$Pr(\texttt{RESP}_i = 1) = \Phi(z_i'\gamma), \tag{1}$$

where $i = 1, 2, \ldots, N$ and $\Phi(\cdot)$ is the cumulative density function of a normal distribution; in the more general setup, the vector containing the covariates is partitioned as follows

$$z_i' = [\ 1 \quad r_i' \quad d_i' \quad c_i' \quad e_i' \quad \texttt{A}_i \quad \texttt{U}_i \quad \texttt{F}_i \quad x_i'\ ],$$

and the related parameters vector is

$$\gamma = [\ \gamma_0 \quad \gamma_r \quad \gamma_d \quad \gamma_c \quad \gamma_e \quad \gamma_A \quad \gamma_U \quad \gamma_F \quad \gamma_x \quad]'.$$

Focussing on the regressors included in the row vector z_i, the partition r_i is a set of regional dummies in which each variable takes the value 1 if the job vacancy comes from a given Italian region and 0 otherwise. The sub vectors d_i and c_i include the job classification dummies and the job characteristic dummies respectively; the variables included in former group account for seven job sectors ($\texttt{Managers}_i$, $\texttt{Professionals}_i$, $\texttt{Clerical}_i$, $\texttt{Sales}_i$, $\texttt{Skilled}_i$, $\texttt{Elementary}_i$ and $\texttt{Technicians}_i$), while the latter group concerns the job type (variable $\texttt{FO}_i$ for front office and variable $\texttt{HW}_i$ for hard work) and the education level (variable $\texttt{High}_i$ for high school diploma and variable $\texttt{Grad}_i$ for graduation). Among the set of control, the partition e_i represents the job advertisement effects (see, for instance, Riach and Rich, 2002). Obviously the scalar variables $\texttt{A}_i$, $\texttt{U}_i$ and $\texttt{F}_i$ are dummy variables for the attributes already defined in section 2. In this context, the parameters γ_A, γ_U and γ_F are crucial because they measure the difference between the applicant's feature of being attractive, unattractive or foreign (with no photo) and the benchmark applicant. In our model the benchmark individual is Italian and applies for a technical job offer in Lazio (whose capital is Rome), sending a CV with no photo attached and using the web service Open Job. No other special characteristics are required by companies from him/her. Consequently, in our estimation we dropped variables $\texttt{Technicians}_i$ and $\texttt{OpenJob}_i$ from the partitions d_i and e_i respectively. All the estimated parameters measure the differences from such representative individual.

Finally, x_i is the interaction vector between the beauty attributes $\mathtt{A}_i$, $\mathtt{U}_i$ and $\mathtt{F}_i$ and the job characteristics (d_i) and/or the job classification (c_i).

The model in equation (1) does not take into account potential gender discriminations, thus we also genderify the regressors by defining $w_i = \mathtt{W}_i z_i$ and $m_i = \mathtt{M}_i z_i$, where $\mathtt{W}_i$ is a scalar dummy variable for women and $\mathtt{M}_i$ is a scalar dummy variable for men. The genderified model is

$$Pr(\mathtt{RESP}_i = 1) = \Phi(w_i'\gamma^w + m_i'\gamma^m). \tag{2}$$

This specification is useful to carry out a battery of Wald tests on the null hypothesis of no gender discrimination given by the equality

$$H_0 : \gamma_j^w = \gamma_j^m \tag{3}$$

for each $j = 1, 2, \ldots, k$, where k is the size of γ^w and γ^m. It is worth noting that "genderification" has the same parameters of two separate estimations for women and for men, therefore we can consider the complete covariance matrix to perform the test.

4 Empirical results

The analysis we performed consists of four linear probability models for the dependent variable `RESP`. Following equations (1) and (2), for each Model 1, 2, 3 and 4 we estimate the probit twice, before and after the genderification. The genderified version is accompanied by the Wald tests on the hypothesis (3), which have been conducted parameter by parameter.

All the estimation results are summarized in Table 5 in the Appendix, together with some measures to evaluate the goodness of each model specification. In particular, we provide the condition number, in order to control the degree of collinearity among a large number of regressors, the Akaike, Bayesian and Hannan-Quinn information criteria (IC) in order to determine which specification best fits the data, the McFadden R^2 and the correct prediction percentages in order to evaluate the models' goodness of fit. Moreover, we carried out a normality test on the model residuals and a likelihood ratio tests (LR) for the null hypothesis of no job advertisement effects.

In the Model 1 we do not consider any interaction (hence $x_i = 0$). In the Model 2 we interact beauty attributes (`A`, `U`, `F`) with job characteristics (`FO`, `HW`, `Grad`, `High`), with no consideration of job classification (hence $d_i = 0$), while in Model 3 beauty is interacted with job classification (`Managers`, `Professionals`, `Clerical`, `Sales`, `Skilled`, `Elementary`), without considering job characteristics ($c_i = 0$). Finally, in Model 4 we consider all the regressors used in the previous three specifications. In Models 3 and 4 we found that $Pr(\mathtt{RESP} = 0|\mathtt{Managers\_F\_M} = 1) = 1$ and $Pr(\mathtt{RESP} = 0|\mathtt{Managers\_U\_W} = 1) = 1$, therefore the variables calculated as the cross product between the managerial job position with foreign man and ugly woman have been dropped from estimation.

The results seem robust since they do not change substantially among models. As we expect, all the regression statistics at the end of Table 5 indicate that Model 4, in which the number of regressors is the largest, provides the best prediction and performance, while Model 1 seems to be the worse specification. The condition number always indicates that the explanatory variables are not collinear; the only exception is the genderized Model 4 that contains 132 paremeters, but the value of 30.5568 is close to the critical value 30.

All the estimated models do not account for the job advertisement effects since all the related variables have been dropped; this model specification seems better because the values of all information criteria diminish and, at the same time, the McFadden R^2 has small positive and often negative increments. Moreover, the parameters associated to the various online job service websites are not statistically significant, with the only exception of Adecco and Kijiji, which are the most used in Italy. That is why the exclusion of these variables does not produce any relavant effect on the final results. Conversely, the exclusion of the job advertisement effects has a negative impact on the number of correct predictions, especially for the genderized models[12], but the loss is always less than 1% of the sample size. Furthermore, the LR test strongly rejects the null hypothesis of no job adverstisement effects for the genderized models, while the p-values related to the non genderized models lie between 1.3% and 2.62%. In this context, the non genderized Model 1 represents the exception because the null is not rejected, while in the genderized model the p-value of 3.36% is the maximum available. Finally, the normality test for residuals does not reject the null only for Models 2 and 3.

The estimation results highlight that firms have different callback rates in each region, but the majority of the coefficients associated to regions are not statistically significant. Callback rates differ by gender only in four regions. In particular, observing the Wald tests, the probability of being called back is always higher for men in Aosta Valley, Trentino Alto Adige, Tuscany and Calabria. This situation is confirmed for Umbria in Models 3 and 4. The regional distribution of callbacks does not reveal any relevant dualism between North and South of Italy in terms of gender discrimination.

The gender discrimination emerges for job classification and job characteristics. On the one hand, there is a strong evidence that the probability of being called back is higher for women for managerial, clerical, sale and service job positions, while men are preferred for professional and skilled activities. On the other hand, gender discrimination acts in favour of women for front office jobs, while we observe a significant positive impact on the probability of callback for hard works in Model 1 (the one without the interaction variables) when the applicant is a male. Surprisingly, in our estimates the graduation does

[12]Specifically, for non genderized models, there is a loss of 36 (0.5%) cases correctly predicted in Model 1, 20 (0.28%) cases in Model 2, 34 (0.47%) cases in Model 3 and 24 (0.33%) cases in Model 4. For genderized models these reductions are 35 (0.49%), 57 (0.79%), 47 (0.65%) and 29 (0.4%) respectively. All the estimates of the models which use the job advertisement effects as a set of controls are available upon request from the authors.

not play any role and there is no gender discrimination between graduated people, while the possession of a high school diploma produces a discrimination in favour of women.

Observing the beauty premium provided by the parameters γ_A, attractive people seem to have a higher chance of being contacted by the firms. In other words, being good looking seems to be a prerequisite for obtaining a job in Italy. These results are in line with those obtained by Garner-Moyer (2010) in France. In this respect, the author showed a major difference in callback rates to job interview between attractive (42%) and unattractive (16%) candidates during the first stages of the hiring process. Unsurprisingly, the beauty premium seems to be definitely more relevant to women than to men. Since $\gamma_U < 0$, there is a cost of unattractiveness: the callback rate is lower for unattractive people, and such a cost is higher for women. In Model 4, variables attractiveness and ugliness have an impact on the dependent variable only when they interact with the job types and job characteristics. Furthermore, the estimated negative values of γ_F highlight that foreigners experience a lower callback rate than that of Italian people. In this case, foreign women are contacted more than foreign men.

As regards the interactions, we found that variables `A`, `U` and `F` play a relevant role. Comparing the effects of interaction of beauty with job classifications, in both Models 3 and 4 the results are similar. In particular, attractiveness gives aspiring executives, clerical and sales staff an advantage, while it seems to have opposite effects in the other types of jobs. All the Wald tests highlight that there are no gender discriminations in presence of beauty in this context. Being ugly or stranger is a penalty especially for clerical jobs, and has a positive impact on `RESP` when the associated job is elementary. All the statistically relevant gender discriminations are in favour of men, with the exception of sales for which employability is higher for foreign women than for foreign men.

As expected, attractiveness provides a beauty premium for front office work and reduces the callback rate for hard work. Such a cost is higher for women. On the other hand, for graduates and high school leavers, the beauy premium is higher for women, but it is not relevant in general when the differences in gender are not considered. This suggests that women and men have different job opportunities that depend on beauty. Symmetrically, unattractiveness is a cost in terms of job-seeking, and this cost is higher for front office tasks and for women, while it seems to be an advantage for hard work, in particular for men. For foreign candidates, the more important result is that the probability of receiving a callback is higher when a male candidate applies for hard works.

Table 6 contains the estimated probabilities of receiving a callback obtained by using our genderized models. In this case, the benchmark individual is an applicant living in Rome, who sent a CV with no photo, with no particular level of education explicitly required, applying for a back office job or a job not entailing hard work. The table shows that the four models provide the same information; sometimes such information can be remarkably different for Model 4, because the regressors contain all the cross products. In general, the probability of being called back for an interview is higher for men applicants, except some peculiar cases, and this is a clear signal that some gender discrimination affects the job market in Italy. Women are preferred especially for clerical jobs and services. Beauty is a very important attribute because it augments the estimated percentages of being called back for both females and males. Only in Models 3 and 4 attractiveness seems to be a penalty for women when they apply for elementary jobs or services, but it always represents a premium for men. The impact of attractiveness is high for female graduates, where a callback probability increases by 20% (Models 1 and 4) if the CV includes the photo of an attractive woman. On the contrary, if the photo is of an unattractive woman, the probability for graduates dramatically diminish. It is worth noting that a female foreign graduate has more chance of receiving a callback. For graduated men, the impact of attractiveness exists but it is less pronounced. Obviously, opposite results are associated to ugliness and foreign people. In this context, our estimates clearly suggest that being a stranger does not help one to obtain a job in Italy. In fact the percentages of callbacks are often very small. This is true especially for men, with the only exceptions of elementary or hard jobs.

Our results are consistent with the findings of Lopez Bóo, Rossi and Urzua (2013), who performed an empirical strategy based on a similar experimental approach: they sent fictitious resumes with pictures of attractive and unattractive faces for real job openings in Buenos Aires, Argentina. The results of our estimation suggest that attractive candidates should attach a photograph to their resumes when have the opportunity to do so, since including it increases the probability to be called for interview by about 30%. Unattractive candidates, on the other hand, should not attach a photograph to their resumes since an unattractive picture decreases the probability of receiving a callback by about 5%. Our evidence is even more striking because the difference between responses to applications with no photo and unattractive applicants is even higher. Thus, we can conclude that, when attractiveness is a feature required by the job, women have an advantage over men. However, in this case an unattractive woman is more discriminated than an unattractive man. Indeed, an unattractive woman has no chance of being called back to interview for an executive task.

5 Concluding remarks

In our analysis we used a field experiment based on real job on-line openings in Italy to test the existence of either a beauty, gender or/and racial premium at the early stage of job search. The sample we analyze consists of observations collected in response to advertised job postings after sending 9680 CVs to firms looking for workers.

Comparing the response rates for different categories, we obtained the following results: attractive subjects are those who receive the highest number of positive answers; both unattractive and foreign candidates obtained lower callback rates. Attractiveness is quantitatively more important for women than for men: attractive Italian women have higher callback rates than unattractive or foreign women. This discrepancy is greater than in the case of men. Moreover, generally an unattractive woman receives fewer offers than an unattractive man, but this is not true for all the examined kinds of jobs. Most responses to unattractive subjects involve low-skilled jobs. Beauty appears to be essential for front office and executive jobs, while unattractiveness appears to strongly reduce chances also for clerical jobs. This effect is more pronounced for women.

Racial discrimination also appears to be substantial. For women it is less prominent than discrimination based on physical features. Instead, the racial discrimination applies for men because the estimated percentages of callbacks are generally very low, especially for "soft" or highly qualified jobs. Conversely, unattractive or foreign men have a higher probability of receiving a callback if they apply for a hard and poorly qualified activity.

In conclusion, attractiveness is relevant to almost all kinds of jobs, also to those that require high qualifications (managerial and specialized). In these cases, women have an advantage over men. By contrast, unattractive candidates receive a sizable number of callbacks only when they apply for low-skilled jobs that require no contact with people. In other words, it seems that a woman wishing to find a good job in Italy has to be attractive, while an unattractive woman, even if she is highly qualified, has little chance of getting a highly-skilled job, at least if she applies on-line and attaches a photo.

For foreigners, the probability to find a job in Italy is greater for women, with the exception of several job categories such as services, elementary and hard work for which men are preferred. Foreign men are taken into consideration only in the cases of hard or low skilled works.

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Appendix

Table 1: Ranking of candidate's photos

Photos	F	M	Photos	F	M
1	858	926	11	452	600
2	767	842	12	432	576
3	752	820	13	421	534
4	695	772	14	382	515
5	651	751	15	364	472
6	632	712	16	332	437
7	598	702	17	310	382
8	572	651	18	296	320
9	543	632	19	274	285
10	489	618	20	223	247

Table 2: Names, surnames and photos chosen for the profiles

	Name	**Surname**	**Gender**	**Photo**	**Nationality**
1	Giulia	Rossi	Female	Attractive	Italian
2	Chiara	Mancini	Female	Unattractive	Italian
3	Francesca	Ricci	Female	No Photo	Italian
4	Luca	Proietti	Male	Attractive	Italian
5	Francesco	Bianchi	Male	Unattractive	Italian
6	Marco	Russo	Male	No Photo	Italian
7	Mohammed	Elalawe	Male	No Photo	Moroccan
8	Fatima	Benkeran	Female	No Photo	Moroccan

Table 3: Summary statistics

		CVs sent		Callbacks	
sample		9680	-	2711	28.01%
Candidate characteristics					
picture	Attractive Italian	2420	25.00%	1208	49.92%
	Unattractive Italian	2420	25.00%	327	13.51%
	Foreigner	2420	25.00%	257	10.62%
	No photo Italian	2420	25.00%	919	37.98%
gender	Women	4840	50.00%	1311	27.09%
	Men	4840	50.00%	1400	28.93%
Job characteristics					
public	Front office	3832	39.59%	1021	26.64%
	Back office	5848	60.41%	1690	28.90%
strenght	Hard work	1304	13.47%	501	38.42%
	Soft work	8376	86.53%	2210	26.38%
qualification	Graduation	2728	28.18%	628	23.02%
	High school	4288	44.30%	1188	27.71%
	No qualification	2664	27.52%	895	33.60%
function offered	Managers	544	5.62%	87	15.99%
	Professionals	880	9.09%	229	26.02%
	Technicians	3888	40.17%	1030	26.49%
	Clerical jobs	1344	13.88%	426	31.70%
	Sales workers	1440	14.88%	360	25.00%
	Services workers	440	4.55%	207	47.05%
	Skilled and craft workers machine and plant operators	560	5.79%	256	45.71%
	Elementary occupation	392	4.05%	145	36.99%

Table 4: Sample correlation between job characteristics and classification ($N = 9680$ Obs.)

	Professionals	Technicians	Clerical	Sales	Services	Skilled	Elementary	FO	HW	Grad	High
Managers	-0.0772	-0.1999	-0.0980	-0.1020	-0.0532	-0.0605	-0.0501	-0.1902	-0.0963	0.3895	-0.2176
Professionals		-0.2591	-0.1270	-0.1322	-0.0690	-0.0784	-0.0650	-0.1090	-0.1248	0.5048	-0.2820
Technicians			-0.3290	-0.3425	-0.1788	-0.2030	-0.1683	0.0159	-0.2986	-0.0261	0.2943
Clerical				-0.1679	-0.0876	-0.0995	-0.0825	-0.1100	-0.1584	-0.0815	0.0894
Sales					-0.0912	-0.1036	-0.0859	0.5164	-0.0017	-0.2619	0.1415
Services						0.8806	-0.0448	-0.1766	0.4252	-0.1279	-0.1627
Skilled							-0.0509	-0.1933	0.4207	-0.1474	-0.1925
Elementary								-0.0548	0.4961	-0.1287	-0.1832
FO									-0.0818	-0.3343	0.2069
HW										-0.2472	-0.3519
Grad											-0.5586

Table 5: Estimated Probit models

	Model 1				Model 2				Model 3				Model 4			
	All	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**
const	0.0670 (0.0668)	−0.0594 (0.0984)	0.2101** (0.0941)	3.9171 [0.0478]	0.0896 (0.0971)	−0.0629 (0.1367)	0.2468* (0.1396)	2.5116 [0.1130]	−0.0091 (0.0572)	0.0245 (0.0818)	−0.0114 (0.0804)	0.0982 [0.7540]	−0.0180 (0.1072)	−0.1793 (0.1527)	0.1769 (0.1547)	2.6859 [0.1012]
Regions (r_i)																
Piedmont	−0.1876 (0.1392)	−0.0719 (0.1816)	−0.3254 (0.2128)	0.8209 [0.3649]	−0.2149 (0.1373)	−0.0928 (0.1825)	−0.3709* (0.2102)	0.9980 [0.3178]	−0.1616 (0.1422)	−0.1235 (0.1951)	−0.2178 (0.2105)	0.1079 [0.7426]	−0.2165 (0.1416)	−0.0982 (0.1979)	−0.3947* (0.2083)	1.0649 [0.3021]
AostaValley	0.1019 (0.0767)	−0.0435 (0.1136)	0.2455** (0.1083)	3.3900 [0.0656]	0.1151 (0.0838)	−0.0583 (0.1259)	0.2928*** (0.1198)	4.0823 [0.0433]	0.1384* (0.0818)	−0.0134 (0.1245)	0.2819*** (0.1123)	3.1009 [0.0782]	0.1340 (0.0842)	−0.0464 (0.1263)	0.3061*** (0.1201)	4.0862 [0.0432]
Lombardy	0.0095 (0.0578)	−0.0111 (0.0832)	0.0265 (0.0829)	0.1027 [0.7486]	0.0125 (0.0615)	−0.0146 (0.0894)	0.0387 (0.0885)	0.1790 [0.6723]	0.0410 (0.0597)	0.0017 (0.0871)	0.0739 (0.0849)	0.3524 [0.5527]	0.0190 (0.0616)	−0.0140 (0.0896)	0.0468 (0.0889)	0.2319 [0.6301]
TrentinoAA	−0.0096 (0.1061)	−0.3784** (0.1632)	0.3168** (0.1455)	10.1119 [0.0015]	−0.0274 (0.1055)	−0.4450*** (0.1617)	0.3612*** (0.1408)	14.1407 [0.0002]	0.0308 (0.1060)	−0.4064*** (0.1682)	0.4040*** (0.1415)	13.5940 [0.0002]	−0.0242 (0.1079)	−0.4724*** (0.1730)	0.3694*** (0.1440)	13.9906 [0.0002]
Veneto	0.0557 (0.0643)	−0.0092 (0.0955)	0.1199 (0.0909)	0.9589 [0.3275]	0.0547 (0.0669)	−0.0203 (0.0992)	0.1284 (0.0968)	1.1503 [0.2835]	0.0718 (0.0658)	−0.0423 (0.0998)	0.1710* (0.0916)	2.4790 [0.1154]	0.0552 (0.0679)	−0.0296 (0.1027)	0.1286 (0.0981)	1.2397 [0.2655]
FriuliVG	−0.0181 (0.1154)	0.1129 (0.1679)	−0.1427 (0.1608)	1.2093 [0.2715]	−0.0099 (0.1237)	0.1326 (0.1802)	−0.1400 (0.1761)	1.1713 [0.2791]	0.0135 (0.1213)	0.1378 (0.1695)	−0.0954 (0.1766)	0.9082 [0.3406]	−0.0142 (0.1228)	0.1375 (0.1743)	−0.1471 (0.1760)	1.3201 [0.2506]
Liguria	−0.2007 (0.1253)	−0.3299* (0.1775)	−0.1195 (0.1841)	0.6770 [0.4106]	−0.1978 (0.1252)	−0.3539** (0.1723)	−0.0973 (0.1917)	0.9914 [0.3194]	−0.1838 (0.1233)	−0.3518** (0.1755)	−0.0749 (0.1762)	1.2393 [0.2656]	−0.1972 (0.1310)	−0.3651* (0.1872)	−0.1092 (0.1940)	0.9005 [0.3427]
Emilia-Romagna	0.1602* (0.0886)	0.1140 (0.1287)	0.2185* (0.1267)	0.3354 [0.5625]	0.1724* (0.0914)	0.1102 (0.1316)	0.2545* (0.1330)	0.5947 [0.4406]	0.1983** (0.0898)	0.1057 (0.1305)	0.2933** (0.1277)	1.0545 [0.3045]	0.1748* (0.0921)	0.1125 (0.1339)	0.2591* (0.1338)	0.6005 [0.4384]
Tuscany	−0.0610 (0.0656)	−0.1646* (0.0946)	0.0235 (0.0942)	1.9860 [0.1588]	−0.0815 (0.0689)	−0.2041** (0.1010)	0.0220 (0.0995)	2.5454 [0.1106]	−0.0477 (0.0680)	−0.1880* (0.1006)	0.0648 (0.0963)	3.2955 [0.0695]	−0.0783 (0.0702)	−0.2147** (0.1037)	0.0245 (0.1018)	2.7089 [0.0998]
Umbria	0.0071 (0.1056)	−0.1335 (0.1575)	0.1491 (0.1504)	1.6849 [0.1943]	−0.0021 (0.1109)	−0.1642 (0.1643)	0.1678 (0.1633)	2.0545 [0.1518]	0.0652 (0.1125)	−0.1730 (0.1702)	0.2739* (0.1654)	3.5456 [0.0597]	0.0070 (0.1122)	−0.2062 (0.1682)	0.1981 (0.1686)	2.8826 [0.0895]
Marche	−0.1850 (0.1217)	−0.0688 (0.1641)	−0.3460* (0.1828)	1.2734 [0.2591]	−0.2262* (0.1286)	−0.0742 (0.1721)	−0.4126** (0.1876)	1.7664 [0.1838]	−0.2073* (0.1250)	−0.0219 (0.1684)	−0.4044** (0.1781)	2.4355 [0.1186]	−0.2627* (0.1365)	−0.0829 (0.1835)	−0.4597*** (0.1906)	2.0284 [0.1544]
Abruzzo	−0.1314 (0.1872)	−0.1898 (0.2771)	−0.0972 (0.2453)	0.0626 [0.8024]	−0.1274 (0.1974)	−0.2157 (0.2933)	−0.0710 (0.2755)	0.1294 [0.7190]	−0.1975 (0.1925)	−0.2340 (0.2781)	−0.2170 (0.2763)	0.0019 [0.9655]	−0.1228 (0.2042)	−0.2364 (0.3225)	−0.0521 (0.2882)	0.1817 [0.6700]
Molise	−0.2462 (0.1772)	−0.4417* (0.2544)	−0.0737 (0.2338)	1.1347 [0.2868]	−0.3031 (0.1981)	−0.5293** (0.2495)	−0.1058 (0.2894)	1.2285 [0.2677]	−0.3062 (0.1870)	−0.5067** (0.2410)	−0.1582 (0.2658)	0.9432 [0.3314]	−0.3311 (0.2063)	−0.5776** (0.2517)	−0.1391 (0.2983)	1.2624 [0.2612]
Campania	−0.1703* (0.0916)	−0.2552* (0.1356)	−0.1235 (0.1319)	0.4845 [0.4864]	−0.1862* (0.0956)	−0.2836** (0.1433)	−0.1465 (0.1393)	0.4705 [0.4927]	−0.1703* (0.0942)	−0.2652* (0.1408)	−0.1108 (0.1331)	0.6347 [0.4256]	−0.1778* (0.0969)	−0.2941** (0.1464)	−0.1460 (0.1404)	0.5339 [0.4650]
Apulia	0.0967 (0.1043)	0.0187 (0.1515)	0.1670 (0.1458)	0.4976 [0.4806]	0.0865 (0.1087)	−0.0189 (0.1629)	0.1804 (0.1476)	0.8223 [0.3645]	0.0935 (0.1039)	0.0090 (0.1524)	0.1542 (0.1456)	0.4750 [0.4907]	0.1071 (0.1107)	−0.0262 (0.1692)	0.1932 (0.1497)	0.9427 [0.3316]
Basilicata	−0.1574 (0.1771)	−0.4752** (0.2347)	0.0720 (0.2547)	2.4953 [0.1142]	−0.1796 (0.1784)	−0.5080** (0.2331)	0.0771 (0.2619)	2.7856 [0.0951]	−0.1093 (0.1796)	−0.5498** (0.2418)	0.2020 (0.2554)	4.5688 [0.0326]	−0.1773 (0.1801)	−0.5277** (0.2414)	0.0705 (0.2667)	2.7666 [0.0962]
Calabria	0.0422 (0.0752)	−0.0935 (0.1114)	0.1712 (0.1059)	2.9638 [0.0851]	0.0548 (0.0789)	−0.1164 (0.1161)	0.2143* (0.1134)	4.1499 [0.0416]	0.0512 (0.0770)	−0.1162 (0.1145)	0.1954* (0.1077)	3.9294 [0.0474]	0.0683 (0.0801)	−0.1174 (0.1178)	0.2258* (0.1163)	4.2962 [0.0382]
Sicily	0.1962*** (0.0815)	0.1499 (0.1227)	0.2558** (0.1110)	0.4093 [0.5223]	0.2212*** (0.0892)	0.1656 (0.1328)	0.2924*** (0.1253)	0.4825 [0.4873]	0.2031*** (0.0867)	0.1767 (0.1317)	0.2365** (0.1191)	0.1132 [0.7365]	0.2415*** (0.0909)	0.1855 (0.1363)	0.3170*** (0.1279)	0.4952 [0.4816]
Sardinia	0.0188 (0.1447)	0.0932 (0.2040)	−0.0839 (0.2104)	0.3652 [0.5456]	0.0140 (0.1702)	0.1121 (0.2621)	−0.1436 (0.2313)	0.5348 [0.4646]	−0.0424 (0.1514)	0.1166 (0.2274)	−0.2412 (0.2122)	1.3235 [0.2500]	0.0336 (0.1763)	0.1002 (0.2767)	−0.1430 (0.2481)	0.4281 [0.5129]
Job Classif. (d_i)																
Managers	−0.3011*** (0.0933)	−0.0698 (0.1284)	−0.5196*** (0.1355)	5.8054 [0.0160]	−0.2986*** (0.0931)	−0.0530 (0.1339)	−0.5275*** (0.1342)	6.2665 [0.0123]	−0.5835*** (0.1572)	−0.6077*** (0.1979)	−0.7767*** (0.1890)	0.3816 [0.5368]	−0.5872*** (0.1766)	−0.4847** (0.2226)	−0.9368*** (0.2098)	2.1852 [0.1393]
Professionals	0.0565 (0.0764)	−0.2520** (0.1153)	0.3056*** (0.1061)	12.6684 [0.0004]	0.0559 (0.0771)	−0.2797** (0.1256)	0.3167*** (0.1054)	13.2373 [0.0003]	0.1468 (0.1105)	−0.3694** (0.1590)	0.7241*** (0.1719)	21.8105 [0.0000]	0.2330* (0.1350)	−0.2252 (0.1923)	0.7438*** (0.1988)	12.2723 [0.0005]
Clerical	0.1477*** (0.0465)	0.4598*** (0.0654)	−0.1395** (0.0672)	40.8361 [0.0000]	0.1514*** (0.0507)	0.5101*** (0.0716)	−0.1704** (0.0738)	43.8166 [0.0000]	0.4714*** (0.0929)	0.8794*** (0.1420)	0.1004 (0.1268)	16.7495 [0.0000]	0.4714*** (0.0949)	0.9237*** (0.1473)	0.0474 (0.1287)	20.0786 [0.0000]
Sales	−0.1033** (0.0520)	0.0397 (0.0739)	−0.2497*** (0.0750)	7.5518 [0.0060]	−0.1376** (0.0608)	0.0192 (0.0875)	−0.3319*** (0.0898)	7.8397 [0.0051]	−0.4981*** (0.0883)	−0.2947*** (0.1225)	−0.7350*** (0.1286)	6.1450 [0.0132]	−0.3453*** (0.0989)	−0.2356* (0.1391)	−0.4712*** (0.1442)	1.3824 [0.2397]
Services	0.1391 (0.1814)	0.7761*** (0.2745)	−0.4088 (0.2746)	9.3154 [0.0023]	0.1098 (0.1749)	0.5877*** (0.2484)	−0.4977* (0.2967)	7.8686 [0.0050]	0.4790 (0.3130)	1.0433*** (0.4304)	−0.4300 (0.5674)	4.2797 [0.0386]	0.1823 (0.3257)	0.8260* (0.4405)	−0.7413 (0.6493)	3.9904 [0.0458]
Skilled	0.3942*** (0.1577)	0.0622 (0.2371)	0.7560*** (0.2382)	4.2613 [0.0390]	0.3507** (0.1570)	0.1149 (0.2210)	0.7535*** (0.2655)	3.4174 [0.0645]	0.4768* (0.2723)	−0.0487 (0.3717)	1.3566*** (0.5227)	4.8005 [0.0285]	0.4435 (0.2818)	0.0911 (0.3737)	1.0626* (0.5764)	2.0002 [0.1573]
Elementary	0.0250 (0.1169)	0.1794 (0.1728)	−0.0537 (0.1678)	0.9367 [0.3331]	−0.0234 (0.0965)	0.0630 (0.1387)	−0.1061 (0.1424)	0.7236 [0.3950]	−0.0031 (0.1459)	−0.2726 (0.2113)	0.2574 (0.2113)	3.1469 [0.0761]	−0.2777 (0.1887)	−0.3387 (0.2673)	−0.2407 (0.2788)	0.0644 [0.7996]
Job Charact. (c_i)																
FO	−0.2497*** (0.0413)	−0.1176** (0.0597)	−0.3887*** (0.0585)	10.5273 [0.0012]	−0.4312*** (0.0704)	−0.2430*** (0.0994)	−0.6229*** (0.1006)	7.2207 [0.0072]	-	-	-	-	−0.3249*** (0.0773)	−0.1072 (0.1105)	−0.5719*** (0.1102)	8.8659 [0.0029]

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Table 5 — continued from previous page

	Model 1				Model 2				Model 3				Model 4			
	All	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**	**All**	**Woman**	**Man**	**diff**
HW	0.2647*** (0.0849)	−0.0154 (0.1237)	0.4983*** (0.1221)	8.7341 [0.0031]	0.2385* (0.1232)	0.1107 (0.1712)	0.3929** (0.1813)	1.2804 [0.2578]	-	-	-	-	0.3849*** (0.1479)	0.3130 (0.2063)	0.4920** (0.2203)	0.3514 [0.5533]
Grad	−0.0656 (0.0678)	−0.0673 (0.0989)	−0.0798 (0.0955)	0.0083 [0.9274]	−0.0116 (0.1099)	−0.0136 (0.1566)	0.0234 (0.1566)	0.0278 [0.8675]	-	-	-	-	0.0257 (0.1265)	0.0978 (0.1791)	−0.0030 (0.1776)	0.1595 [0.6896]
High	0.0534 (0.0489)	0.2103*** (0.0734)	−0.0927 (0.0683)	9.1325 [0.0025]	0.1850** (0.0889)	0.3221*** (0.1252)	0.0530 (0.1273)	2.2713 [0.1318]	-	-	-	-	0.2196*** (0.0934)	0.3654*** (0.1342)	0.0811 (0.1341)	2.2464 [0.1339]
Attributes (a_i)																
A	0.4146*** (0.0437)	0.5348*** (0.0611)	0.3149*** (0.0638)	6.2006 [0.0128]	0.2497** (0.1268)	0.0381 (0.1742)	0.4422*** (0.1886)	2.4770 [0.1155]	0.4355*** (0.0630)	0.5557*** (0.0891)	0.3060*** (0.0882)	3.9667 [0.0464]	0.1197 (0.1496)	−0.2609 (0.2292)	0.2601 (0.2153)	2.7446 [0.0976]
U	−0.9894*** (0.0447)	−1.3275*** (0.0705)	−0.7875*** (0.0606)	33.7453 [0.0000]	−0.7988*** (0.1445)	−0.8846*** (0.2260)	−0.7188*** (0.1967)	0.3062 [0.5800]	−1.0595*** (0.0692)	−1.4205*** (0.1071)	−0.8582*** (0.0923)	15.8075 [0.0001]	−0.2642 (0.1740)	−0.0877 (0.2834)	−0.2572 (0.2568)	0.1963 [0.6577]
F	−1.1439*** (0.0473)	−1.0212*** (0.0672)	−1.3529*** (0.0689)	11.8774 [0.0006]	−1.1540*** (0.1415)	−0.8498*** (0.1920)	−1.7622*** (0.2449)	8.5975 [0.0034]	−1.1238*** (0.0703)	−1.0540*** (0.0983)	−1.2387*** (0.0978)	1.7738 [0.1829]	−0.7857*** (0.1656)	−0.4659** (0.2226)	−1.2505*** (0.2775)	4.8641 [0.0274]
Interactions (x_i)																
FO_A	-	-	-	-	0.7599*** (0.0961)	0.7609*** (0.1390)	0.8603*** (0.1361)	0.2609 [0.6095]	-	-	-	-	0.7233*** (0.1153)	0.8074*** (0.1755)	0.8702*** (0.1598)	0.0699 [0.7914]
HW_A	-	-	-	-	−1.1996*** (0.1620)	−0.9792*** (0.2257)	−1.4808*** (0.2395)	2.3241 [0.1274]	-	-	-	-	−1.2209*** (0.2059)	−0.6610** (0.3012)	−1.7542*** (0.3096)	6.4069 [0.0114]
G_A	-	-	-	-	−0.0516 (0.1473)	0.4846*** (0.2042)	−0.5737*** (0.2169)	12.6196 [0.0004]	-	-	-	-	0.1112 (0.1805)	0.6833*** (0.2693)	−0.3175 (0.2563)	7.2458 [0.0071]
Hi_A	-	-	-	-	0.0932 (0.1293)	0.5573*** (0.1822)	−0.2896 (0.1894)	10.3850 [0.0013]	-	-	-	-	0.1314 (0.1373)	0.7388*** (0.2169)	−0.2439 (0.1962)	11.2895 [0.0008]
FO_U	-	-	-	-	−0.6223*** (0.1206)	−1.0704*** (0.2290)	−0.5136*** (0.1647)	3.8949 [0.0484]	-	-	-	-	−1.0215*** (0.1570)	−1.7804*** (0.4523)	−0.8894*** (0.2046)	3.2207 [0.0727]
HW_U	-	-	-	-	0.9075*** (0.1786)	0.6431*** (0.2668)	1.3363*** (0.2646)	3.4037 [0.0651]	-	-	-	-	0.3864* (0.2243)	−0.5682 (0.3788)	1.2316*** (0.3585)	11.9082 [0.0006]
G_U	-	-	-	-	−0.0434 (0.1667)	−0.5324* (0.2834)	0.0678 (0.2236)	2.7641 [0.0964]	-	-	-	-	−0.4970*** (0.2135)	−1.3663*** (0.3497)	−0.2675 (0.2979)	5.7205 [0.0168]
Hi_U	-	-	-	-	−0.5837*** (0.1567)	−0.6422*** (0.2482)	−0.5257*** (0.2152)	0.1257 [0.7229]	-	-	-	-	−0.8816*** (0.1693)	−1.1386*** (0.2777)	−0.7999*** (0.2531)	0.8125 [0.3674]
FO_F	-	-	-	-	0.1809* (0.1067)	0.2035 (0.1477)	0.0256 (0.1706)	0.6216 [0.4304]	-	-	-	-	−0.0754 (0.1322)	−0.1278 (0.1790)	−0.0709 (0.2019)	0.0445 [0.8329]
HW_F	-	-	-	-	0.6324*** (0.1733)	0.3669 (0.2374)	1.2048*** (0.2881)	5.0378 [0.0248]	-	-	-	-	0.2813 (0.2209)	−0.1026 (0.2998)	0.9770*** (0.3739)	5.0742 [0.0243]
G_F	-	-	-	-	−0.2471 (0.1681)	−0.3913* (0.2366)	0.1323 (0.2764)	2.0713 [0.1501]	-	-	-	-	−0.3476* (0.2051)	−0.6548** (0.2861)	−0.0322 (0.3142)	2.1461 [0.1429]
Hi_F	-	-	-	-	−0.3528*** (0.1469)	−0.5748*** (0.1941)	0.0744 (0.2634)	3.9374 [0.0472]	-	-	-	-	−0.4924*** (0.1534)	−0.6734*** (0.2004)	−0.2655 (0.2817)	1.3923 [0.2380]
Managers_A	-	-	-	-	-	-	-	-	0.7258*** (0.2224)	1.1347*** (0.3217)	0.6294** (0.2839)	1.3871 [0.2389]	0.9301*** (0.2506)	1.2630*** (0.3598)	0.9833*** (0.3194)	0.3379 [0.5610]
Professionals_A	-	-	-	-	-	-	-	-	−0.5816*** (0.1557)	−0.2871 (0.2224)	−0.9461*** (0.2326)	4.1925 [0.0406]	−0.5614*** (0.1912)	−0.3589 (0.2760)	−0.8377*** (0.2758)	1.5059 [0.2198]
Clerical_A	-	-	-	-	-	-	-	-	0.1953 (0.1425)	0.6321** (0.2863)	0.2167 (0.1865)	1.4776 [0.2242]	0.2031 (0.1536)	0.9030*** (0.3714)	0.2137 (0.1945)	2.7037 [0.1001]
Sales_A	-	-	-	-	-	-	-	-	0.7051*** (0.1272)	0.6268*** (0.1827)	0.8394*** (0.1804)	0.6857 [0.4076]	0.4173*** (0.1477)	0.3904* (0.2231)	0.4326** (0.2079)	2.3654 [0.1241]
Services_A	-	-	-	-	-	-	-	-	−0.7943* (0.4307)	−1.2504** (0.5903)	−0.1165 (0.7381)	1.4395 [0.2302]	0.0721 (0.4656)	−0.7926 (0.6313)	0.9866 (0.8397)	0.3220 [0.5704]
Skilled_A	-	-	-	-	-	-	-	-	−0.4356 (0.3805)	−0.3417 (0.5179)	−0.7495 (0.6774)	0.2288 [0.6324]	0.1241 (0.4135)	0.5920 (0.5482)	−0.1847 (0.7639)	0.4179 [0.5180]
Elementary_A	-	-	-	-	-	-	-	-	−1.3272*** (0.2230)	−1.9097*** (0.3971)	−1.0889*** (0.3049)	2.6871 [0.1012]	−0.0417 (0.2746)	−0.7001 (0.4904)	0.4119 (0.3951)	0.0819 [0.7748]
Managers_U	-	-	-	-	-	-	-	-	0.2893 (0.2595)	-	0.6301** (0.3085)	-	−0.0084 (0.2888)	-	0.2899 (0.3452)	-
Professionals_U	-	-	-	-	-	-	-	-	0.3233** (0.1624)	0.3909 (0.2781)	0.0246 (0.2336)	1.1254 [0.2888]	0.1681 (0.2070)	0.5675 (0.3531)	−0.1724 (0.2849)	3.6350 [0.0566]
Clerical_U	-	-	-	-	-	-	-	-	−0.9862*** (0.1649)	−1.0956*** (0.2543)	−0.7986*** (0.2215)	0.7490 [0.3868]	−1.2611*** (0.1746)	−1.6269*** (0.2635)	−1.0428*** (0.2446)	1.2401 [0.2655]
Sales_U	-	-	-	-	-	-	-	-	0.0116 (0.1532)	−0.1992 (0.2621)	0.2250 (0.2022)	0.6752 [0.4113]	0.4612** (0.2048)	0.9016* (0.4640)	0.3655 (0.3038)	83.4142 [0.0000]
Services_U	-	-	-	-	-	-	-	-	0.5097 (0.4320)	5.5886*** (0.4749)	0.5563 (0.7508)	35.7838 [0.0000]	0.2721 (0.4699)	6.1801*** (0.5595)	−0.3504 (0.9789)	26.5268 [0.0000]
Skilled_U	-	-	-	-	-	-	-	-	0.4153 (0.3772)	−4.4923*** (0.3795)	0.4054 (0.6806)	43.1855 [0.0000]	−0.4500 (0.4162)	−5.8700*** (0.4363)	−0.2773 (0.8442)	1.7790 [0.1823]

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Table 5 — continued from previous page

	Model 1				Model 2			
	All	Woman	Man	diff	All	Woman	Man	diff
Elementary_U	-	-	-	-	-	-	-	-
Managers_F	-	-	-	-	-	-	-	-
Professionals_F	-	-	-	-	-	-	-	-
Clerical_F	-	-	-	-	-	-	-	-
Sales_F	-	-	-	-	-	-	-	-
Services_F	-	-	-	-	-	-	-	-
Skilled_F	-	-	-	-	-	-	-	-
Elementary_F	-	-	-	-	-	-	-	-

	Model 3				Model 4			
	All	Woman	Man	diff	All	Woman	Man	diff
Elementary_U	1.1870 *** (0.2085)	1.4869 *** (0.3037)	1.0678 *** (0.3046)	0.6879 [0.4069]	0.2495 (0.2782)	0.9768 *** (0.4139)	−0.4181 (0.4274)	0.8805 [0.3481]
Managers_F	−0.2612 (0.3414)	0.0941 (0.4031)	-	-	−0.2498 (0.3668)	0.1607 (0.4448)	-	-
Professionals_F	−0.3614 * (0.1853)	0.0193 (0.2740)	−0.8029 *** (0.2646)	4.6599 [0.0309]	−0.3567 (0.2262)	0.1127 (0.3309)	−0.8295 *** (0.3084)	4.3391 [0.0372]
Clerical_F	−0.8938 *** (0.1632)	−1.0180 *** (0.2188)	−1.1097 *** (0.3160)	0.0570 [0.8113]	−0.9220 *** (0.1725)	−1.1157 *** (0.2292)	−1.0354 *** (0.3256)	0.0407 [0.8402]
Sales_F	0.3076 ** (0.1442)	0.4428 *** (0.1887)	−0.1861 (0.2793)	3.4818 [0.0620]	0.2164 (0.1651)	0.3597 * (0.2107)	−0.6099 * (0.3650)	5.2932 [0.0214]
Services_F	−0.2470 (0.4349)	−1.1376 * (0.5990)	0.9720 (0.7195)	5.0782 [0.0242]	−0.3943 (0.4579)	−1.0656 * (0.6197)	0.3310 (0.8573)	1.7430 [0.1868]
Skilled_F	0.1403 (0.3857)	0.8273 (0.5263)	−0.8619 (0.6613)	3.9947 [0.0456]	−0.3034 (0.4033)	0.2728 (0.5352)	−1.1235 (0.7687)	2.2221 [0.1360]
Elementary_F	1.3162 *** (0.2089)	1.5047 *** (0.3013)	1.1727 *** (0.2993)	0.6113 [0.4343]	0.7295 *** (0.2663)	1.0539 *** (0.3758)	0.2482 (0.4061)	2.1206 [0.1453]

	Model 1 Genderization		Model 2 Genderization		Model 3 Genderization		Model 4 Genderization	
	NO	YES	NO	YES	NO	YES	NO	YES
Sample size	7184	7184	7184	7184	7184	7184	7184	7184
Condition Number	6.1252	10.6307	11.9239	25.9048	15.4735	16.5340	19.1501	30.5568
McFadden R^2	0.1953	0.2278	0.2694	0.3105	0.2467	0.2811	0.2905	0.3399
Akaike IC	7730.8290	7488.9321	7049.1114	6750.0810	7275.2141	7045.5602	6889.8441	6549.5869
Bayesian IC	7964.7358	7956.7457	7365.5735	7383.0053	7626.0743	7733.5214	7350.7781	7457.6956
Hannan-Quinn IC	7811.3245	7649.9232	7158.0171	6967.8925	7395.9574	7282.3118	7048.4677	6862.0989
correct predictions	5289 (73.62%)	5385 (74.96%)	5445 (75.79%)	5572 (77.56%)	5437 (75.68%)	5493 (76.46%)	5527 (76.93%)	5669 (78.91%)
actual 0-predicted 0	3523 (49.04%)	3631 (50.54%)	3603 (50.15%)	3702 (51.53%)	3496 (48.66%)	3583 (49.87%)	3630 (50.53%)	3718 (51.75%)
actual 1-predicted 1	1766 (24.58%)	1754 (24.42%)	1842 (25.64%)	1870 (26.03%)	1941 (27.02%)	1910 (26.59%)	1897 (26.41%)	1951 (27.16%)
actual 0-predicted 1	950 (13.22%)	842 (11.72%)	870 (12.11%)	771 (10.73%)	977 (13.60%)	890 (12.39%)	843 (11.73%)	755 (10.51%)
actual 1-predicted 0	945 (13.15%)	957 (13.32%)	869 (12.10%)	841 (11.71%)	770 (10.72%)	801 (11.15%)	814 (11.33%)	760 (10.58%)
normality test	161.454	121.15	3.6335	7.3543	0.6571	10.3767	31.6519	18.1378
p-value	0.0000	0.0000	0.1625	0.0253	0.7200	0.0056	0.0000	0.0001
LR test	33.2283	65.0421	37.8863	75.0369	40.6443	75.4221	38.3444	74.6536
p-value	0.0772	0.0336	0.0262	0.0044	0.0130	0.0040	0.0234	0.0048

Table 6: Estimated probabilities of receiving a callback

				Attractive		Ugly		Foreign	
	Model	Woman	Man	Woman	Man	Woman	Man	Woman	Man
Benchmark	1	47.63%	58.32%	68.27%	70.02%	8.27%	28.18%	13.99%	12.66%
	2	47.49%	59.75%	49.01%	75.46%	17.17%	31.84%	18.07%	6.48%
	3	50,98%	49,54%	71,91%	61,58%	8,14%	19,23%	15,16%	10,56%
	4	42.89%	57.02%	32.99%	66.90%	39.47%	46.80%	25.94%	14.15%
Managers	1	44.86%	37.85%	65.75%	50.22%	7.12%	3.39%	12.29%	0.84%
	2	45.39%	38.95%	46.90%	56.41%	16.09%	3.80%	16.96%	0.24%
	3	27,99%	21,53%	86,59%	55,85%	2,26%	15,48%	6,14%	2,13%
	4	25.34%	22.37%	63.24%	68.56%	22.61%	23.36%	16.62%	2.22%
Professionals	1	37.78%	69.70%	58.84%	79.69%	4.95%	15.83%	8.96%	5.86%
	2	36.60%	71.35%	38.04%	84.27%	11.17%	17.63%	11.85%	2.42%
	3	36,51%	76,20%	46,96%	52,89%	8,46%	45,19%	8,39%	9,19%
	4	34.29%	82.14%	15.28%	63.43%	53.00%	68.83%	22.43%	12.32%
Clerical	1	65.56%	52.82%	82.51%	65.01%	17.42%	7.40%	26.39%	2.21%
	2	67.26%	53.04%	68.63%	69.80%	33.45%	7.83%	34.73%	0.69%
	3	81,70%	53,54%	98,18%	72,96%	5,34%	5,85%	12,14%	1,19%
	4	77.17%	58.88%	91.72%	75.75%	16.60%	14.11%	20.12%	1.96%
Sales	1	49.21%	48.42%	69.67%	60.85%	8.73%	5.98%	14.65%	1.69%
	2	48.26%	46.61%	49.78%	63.95%	17.92%	5.73%	18.84%	0.44%
	3	39,35%	22,77%	81,92%	65,51%	2,94%	8,39%	18,91%	1,50%
	4	33.91%	38.43%	38.77%	65.48%	65.50%	42.62%	30.12%	1.56%
Services	1	76.32%	42.12%	89.46%	54.63%	26.72%	4.31%	37.64%	1.13%
	2	70.02%	40.09%	71.33%	57.58%	36.32%	4.06%	37.63%	0.27%
	3	85,72%	32,95%	64,54%	40,06%	100,0%	22,86%	13,05%	23,94%
	4	74.11%	28.62%	34.21%	75.25%	100.0%	12.06%	18.82%	6.89%
Skilled	1	50.11%	83.30%	70.45%	89.99%	9.09%	29.08%	15.18%	13.21%
	2	52.07%	84.14%	53.59%	92.54%	20.53%	31.11%	21.54%	6.22%
	3	49,03%	91,07%	57,53%	81,64%	0,00%	81,39%	40,10%	22,50%
	4	46.48%	89.24%	59.60%	90.57%	0.00%	75.96%	38.93%	12.83%
Elementary	1	54.78%	56.21%	74.37%	68.13%	11.16%	8.68%	18.10%	2.70%
	2	50.00%	55.59%	51.52%	72.00%	19.09%	8.81%	20.05%	0.83%
	3	40,20%	59,71%	5,46%	29,56%	42,79%	67,57%	58,03%	57,14%
	4	30.22%	47.46%	6.96%	72.85%	64.47%	22.99%	52.79%	14.32%
Front Office	1	42.97%	42.91%	63.97%	55.42%	6.49%	4.50%	11.34%	1.19%
	2	37.99%	35.34%	39.44%	52.63%	11.89%	3.08%	12.59%	0.18%
	4	38.72%	34.64%	60.26%	76.89%	1.56%	6.16%	18.94%	4.30%
Hard work	1	47.02%	76.06%	67.72%	84.69%	7.89%	20.93%	13.43%	8.47%
	2	51.91%	73.88%	53.42%	86.03%	20.41%	19.67%	21.42%	2.89%
	4	55.32%	74.82%	21.53%	20.46%	30.08%	94.98%	33.19%	65.37%
Graduation	1	44.96%	55.18%	65.84%	67.19%	7.15%	8.27%	12.34%	2.54%
	2	46.95%	60.65%	48.47%	76.19%	17.08%	11.07%	17.97%	1.17%
	4	46.75%	56.91%	63.34%	54.64%	6.23%	36.29%	11.47%	13.38%
High school	1	55.99%	54.67%	75.35%	66.72%	11.76%	8.08%	18.92%	2.47%
	2	60.23%	61.78%	61.69%	77.09%	26.91%	11.64%	28.07%	1.27%
	4	57.38%	60.18%	74.67%	60.80%	14.91%	21.21%	17.03%	10.42%