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A Field Experiment on the Role of Socioemotional Skills and Gender for Hiring in Turkey

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Abstract

A vast literature shows the importance of socioemotional skills in earnings and employment, but whether they matter in getting hired remains unanswered. This study seeks to address this question and further investigates whether socio-emotional skill signals in job applicants' resumes have the same value for male and female candidates. In a large-scale randomized audit study, an online job portal in Turkey is used to send fictitious resumes to real job openings, collecting a unique data set that enables investigating different stages of candidate screening. The study finds that socio-emotional skills appear to be valued only when an employer specifically asks for such skills in the vacancy ad. When not asked for, however, candidates can face a penalty in the form of lower callback rates. A significant penalty is only observed for women, not for men. The study does not find evidence of other gender differences in the hiring process.

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A Field Experiment on the Role of Socioemotional Skills and Gender for Hiring in Turkey[1]

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1. Introduction

Do socioemotional skill signals in CVs play a role in employers' hiring decisions? A vast literature shows the importance of socioemotional skills in labor market outcomes in the form of earnings or employment, but whether signals of these skills matter in getting hired remains unanswered. Suppose that a young graduate is looking for a job and comes across a vacancy ad with a requirement of, say, teamwork skills, listed alongside other requirements, such as certain levels of education and experience. Should she include a signal demonstrating she has strong teamwork skills, along with her academic degrees and the jobs she worked at? Furthermore, would such a signal have the same effect in terms of advancing the candidate in the recruitment process if that candidate is male? This study seeks to provide answers to these questions.

Economics literature has firmly established that socioemotional skills are valuable in the labor market. Numerous studies demonstrate that possession of socioemotional skills has a positive impact on lifetime earnings (e.g., Cameron and Heckman, 1993; Heckman and Rubinstein, 2001; Bowles et al., 2001a,b; Heckman et al., 2006; Cunha et al., 2006; Cunha and Heckman, 2008). It is also quite common to see socioemotional skills requirements in vacancy ads, and online job search websites recommend job seekers to include some aspect of socioemotional skills in their CVs.

However, little is known about whether including socioemotional skill signals in CVs would help in securing a job interview. Evidence from the literature is scarce and indirect (e.g., the effect of volunteering activities as studied in Baert and Vujijic, 2018 and the effect of sport skills as studied in Rooth, 2011). Piopiunik et al. (2018) is among the first studies to provide evidence that socioemotional skills may matter for employers when they evaluate candidates, although the evidence is collected using an unincentivized survey with hypothetical CVs. Even if employers would consider socioemotional skills during hiring, it remains unclear whether employers can get the relevant information on the candidate's socioemotional skills. While they can rely on educational attainment or technical certifications of prospective workers as signals of cognitive and technical skills, socioemotional skills are more difficult for employers to assess and for job seekers to signal. Furthermore, if socioemotional skill signals are not credible, they might hurt the applicant's chances as they can be perceived by the employer as an attempt to oversell oneself.

The above complications are in part due to the vagueness in the definition of, and the difficulty in measuring, socioemotional skills. There is still no consensus on the definition or even the term: "soft skills", "personality traits", "non-cognitive skills", "non-cognitive abilities", "character", and "socioemotional skills" are all used to identify the personality attributes (Heckman and Kautz, 2012). In practice, the investigation of certain socioemotional skills in the literature depends heavily on data availability (Brunello and Schlotter, 2011). Perhaps the most used measure of socioemotional skills is the Big Five personality traits, and many studies find them important in career success (e.g., Boudreau et al., 2001; Seibert, Scott E. and Kraimer, Maria L., 2001; Gelissen and de Graaf, 2006) and earnings (e.g., Nyhus and Pons, 2005; Mueller and Plug, 2006; Heineck and Anger, 2010). However, the Big Five traits are too general to signal in a CV and some are not clearly applicable to the work context, so employers may not find such signals valuable or credible.

Furthermore, employers may value similar socioemotional skill signals of male and female candidates differently. This may be particularly important considering that women experience higher rates of joblessness or long-term unemployment in most countries. While there is no consensus on the existence of gender discrimination in hiring (see Bertrand and Duflo, 2017 for a review), there is ample evidence on the existence of a gender wage gap (Blau and Kahn 2017, and Ñopo, Daza and Ramos 2012), and that, among other factors, such gender wage gap may, to some degree, be explained by the differences in socioemotional skills between men and women (Palomino and Peyrache, 2010; Cobb-Clark and Tan, 2011). Furthermore, gender differences in preferences and actions are important in labor market outcomes. Research has shown that differences in competitiveness and risk aversion may lead to more unfavorable labor market outcomes for women compared to men, not only because women shy away from asking for more favorable outcomes, but also because employers expect them to have less competitive preferences.[3] Signaling socioemotional skills may thus be a way for women to mitigate employers' potential biases arising from these socially ascribed qualities based on gender.

On the other hand, if the same socioemotional skills are valued differently in the labor market for women and men, there may be more unfavorable labor market outcomes for women who signal the socioemotional skills that are rewarded for men, as noted in research related to the gender double bind (see e.g. Armstrong, 1988). The bind refers to the trade-offs women face due to being perceived differently in relation to certain skills or attributes than men. For example, features associated with leadership, such as assertiveness, can be perceived as a positive attribute for a man but a negative attribute for a woman (Rudman et al 2012, Gipson et al 2017); similarly, for women, being perceived as personable can be associated with an assumption of lower competence, while the same does not hold for men (Phelan et al 2008).[4]

In this paper we conduct a correspondence audit study to assess the effects of an explicit socioemotional skill signal in a CV during the hiring process. We do so by introducing signals of socioemotional skills in fictitious male and female CVs and sending these CVs to real vacancies. We record employer selection behaviors at various stages of the hiring process, including whether the employer selects our candidate for a longlist, whether our candidate's profile is clicked on, and whether the candidate gets a callback (i.e. invitation for an interview). These outcomes enable us to assess (1) the extent to which employers favor men or women in the hiring process, (2) whether employers value socioemotional skills, and (3) whether there is any differential value of such skills for men and women.

To address these questions, we use a two-by-two experimental design, where the first dimension is the existence of socioemotional skill signals in the CV, and the other is gender. By randomly assigning socioemotional skills and gender, we can compare employer selection across otherwise equivalent candidates, isolating the effect of gender and socioemotional skills on hiring. For the socioemotional skills treatment, we carefully define and match socioemotional skills for four different occupational clusters: accounting, marketing, sales, and IT. We use precise skills requirements from the definitions of tasks in

[3] For example, individuals' own perception of "male" traits are linked to entry into male-dominated study fields and occupations (Antecol and Cobb-Clark, 2010), and there is evidence that women negotiate wages less often compared to men (Babcock and Laschever, 2009). Studies also show that women are more risk-averse, less likely to prefer competition, and are less likely to overestimate their qualities, whereas men are more overconfident compared to women (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Dohmen and Falk, 2011; Ludwig et al., 2017).

[4] This also applies to other characteristics, such as being married or having children, which might be positively evaluated for men but not for women (Riach and Rich 2002, Petersen and Togstad 2006).

O*NET, the occupation dictionary widely used in labor market research. By carefully tailoring skills to occupations, we aim to capture the heterogeneity of skills requirements for different jobs in the labor market.

To investigate whether including socioemotional skill signals in CVs might help women's job prospects, we selected a labor market with a traditionally low representation of women. The experiment is run in the two largest cities of Turkey, a country with a labor market characterized by the lowest female labor force participation and among the highest female unemployment rates among the OECD countries.[5] We consider the high-skilled segment of the Turkish labor market, where women with a university degree form almost a quarter of the total unemployed population in Turkey, while representing less than 7 percent in total population.[6]

Altogether we applied for 2,687 real vacancy ads using 10,748 CVs. The vacancy ads were posted on a large online job portal in Turkey. A unique feature of this job portal is that it allows us to track employer behavior at different stages of candidate screening.[7] The first stage is the longlist, formed when the employer filters applicants using hard criteria based on the candidates' profile (age, gender, experience, city and neighborhood, sector, occupation or other keyword search). The second stage, the shortlist, is when the employer clicks on some of the candidates' profiles to view their CVs, and, the third and final stage is when the employer contacts the shortlisted candidates to invite them to an interview, which is the stage evaluated in all other correspondence studies.[8] We are thus able to pinpoint at which screening stage, if any, different CV characteristics, including gender and socioemotional skills, come into play.

Examining selection at various stages of the hiring process, we do not find strong evidence of gender discrimination. There is suggestive evidence of a small bias in favor of women during the longlisting process, but this effect is only marginally significant. Furthermore, we find that employers value socioemotional skill signals positively only when they specifically ask for such skills in the vacancy ad. On the other hand, when socioemotional skill signals are not solicited in the ad, employers do not appear to value them; indeed, in these cases, job seekers may even face a penalty (i.e. lower probability of callback) for including such signals on CVs . This particular penalty for signaling unrequested socioemotional skills is only observed for female candidates, however. The gender-specific penalty for signaling unsolicited socioemotional skills suggests that such signals on CVs may be interpreted differently for men and women.

The following section provides details on the design of the experiment and the collected data, Section 3 presents the results, and Section 4 concludes the paper.

[5] The 2017 national estimate of labor force participation for women aged 15 and above was 34 percent, the lowest female labor force participation rate among the OECD countries. Unemployment levels among working-age women were at 14 percent, almost double the OECD levels (Source: World Bank World Development Indicators).

[6] Source: Calculated using Turkey Household Labor Force Micro Dataset 2016.

[7] To our knowledge, the only other study using a similar data set, albeit with a smaller sample, is Balkan and Cilasun (2018), which investigates whether gender discrimination plays a role in the low female labor force participation in Turkey.

[8] See Neumark (2018) for a survey of audit studies in the labor market.

2. Experimental Design and Data

The experimental design follows the classic design of Bertrand and Mullainathan (2004): we use fictitious CVs and apply for real vacancy ads, varying the CVs in the characteristics of interest.

Our treatments are summarized in Table 1. We have a two-by-two design where the first dimension is the gender of the applicant, and the second is related to whether socioemotional skills are signaled or not. In the latter dimension, we signal socioemotional skills in treatment CVs explicitly through extracurricular activities (e.g., participating in debate tournaments to signal persuasion skills), in the job description (e.g., by indicating that the candidate persuaded current customers to try new products, which enabled meeting targeted sales volume and profit), and in the tagline (i.e. a summary of the individual's profile, reported in the top portion of the CV). For each of the above, the control CVs include neutral text of similar length in the same fields.

Within this design, we first select the aspects of the labor market to focus on, including occupational clusters, location, and the job portal. We then create control and treatment CVs for fictitious male and female candidates. Using these CVs, we apply for a total of 2,687 vacancies between August 2017 and January 2018. The sections below outline each of these procedures.[9]

Table 1: Treatments

	No Socioemotional Skill Signal	Socioemotional Skill Signal
Male	(C , M)	(T , M)
Female	(C , F)	(T , F)

2.1 Labor market

Labor markets

The experiment is conducted in Turkey, where about 32 million people are currently in the labor force. We focus on the two cities with the largest labor markets that make up about 27 percent of the employed population in Turkey: Istanbul (20 percent) and Ankara (7 percent). Furthermore, we separate Istanbul into two regions, Istanbul-Asia and Istanbul-Europe, since they largely represent two different labor markets in terms of hiring decisions.

Occupational clusters

The list of occupational clusters we selected for this experiment is presented in Table 2. The clusters include financial occupations, retail and sales occupations, as well as technical occupations. This varied set of jobs allows us to draw conclusions about the role of gender and socioemotional skills in the broader high-skilled labor market. In addition, we can compare effects across occupations that vary in terms of tasks and hence may require different skills.

The selection of the specific occupational clusters is based on multiple criteria. The first is the gender composition of occupations: we have selected occupations that do not have extreme values of female shares

[9] All procedures used in the experiment are approved by the IRBs of the Middle East Technical University in Ankara, Turkey and the University of Bologna in Bologna, Italy.

in employment, based on data from the 2015 Turkish Household Labor Force Survey.[10] We also collected vacancy information from newspapers and online job portals for a period of 3 months, and we filter out occupations that tend to recruit explicitly one gender (e.g., administrative assistants).

Second, we select occupations that have a large pool of vacancies in the online job portal: the four occupational clusters that we select represent around 65 percent of the total vacancy ads in the online job portal for the selected locations.

Finally, we aim to select clusters that use different socioemotional skills in their daily tasks, based on the classifications in O*NET and the organizational psychology literature. More information on this aspect is given in Section 2.2.

Job vacancies

We collect the vacancy ads and make our applications using the largest online job portal in Turkey, which has around 75,000 registered companies and 24 million CVs.

We use two criteria for selecting vacancies. The first criterion is that the minimum required work experience did not exceed 3 years. We focus on early-career candidates because socioemotional skills, especially in the form of extracurricular activities, are arguably more salient in CVs for early-career candidates. On the other hand, for more mature candidates, aspects of job experience (such as tenure, progression, and gaps in work history) may be strong signs of socioemotional skills that make other signals less salient but that are harder to manipulate in an audit study experiment.

The second criterion in vacancy selection is minimum required level of education. Here, we mostly focus on higher-skilled jobs that require a university degree. However, for vacancies in the sales cluster, we also apply for jobs that would consider candidates with high school degrees.

In addition, we took into account whether we have recently applied to a job with the same employer. If this is the case, in order to avoid detection, we wait at least 4 weeks until we apply to another job with this employer. In addition, we do not apply to more than 5 vacancies with the same employer across the entire study period. Finally, we use occupation classifications of the online platform as filters when we select the vacancies to apply for each occupational cluster. Included occupations are provided in the final column of Table 2.

[10] Extreme values were defined as more than one standard deviation away from the mean female employment share in an occupation.

Table 2: Occupational clusters used in the experiment

Occupational cluster	Share of cluster in total number of vacancy ads	Included occupations (according to online portal's classification)
Accounting	9%	Accounting, Audit, Finance
Marketing	11%	Marketing, Business Development
Sales	19%	Sales
IT	20%	IT, Engineering, R&D

Note: Average shares of cluster in total number of vacancy ads are calculated using the ad counts in the online job portal between January and February 2015.

2.2. Treatments and resume construction

Socioemotional skill signals

A particular challenge associated with this study is the difficulty in defining and measuring socioemotional skills, which also includes personality traits like the Big Five (Heckman and Kautz, 2012). For our purposes, however the Big Five are too general to signal in a CV, and it is not clear whether employers may understand or value a statement that signals, for example, "high conscientiousness." Depending on data availability, some studies use more specific measures, such as misbehavior in childhood (Segal, 2013), leadership positions or behavioral reports in high school (Kuhn and Weinberger, 2005; Protsch and Solga, 2015), and skills such as locus of control, aggression, and withdrawal (Groves, 2005), but most of these studies use information on skills and labor market outcomes for real individuals, which presents a challenge for causal inference.[11] One problem is the potential association between different aspects of an individual's skill set: for example, there is evidence of a significant correlation between an individual's IQ (i.e. cognitive skills) and openness to experience (i.e. socioemotional skills).[12] The other challenge arises because job experience is not orthogonal to socioemotional skills once the individual has started their career: A person with high teamwork skills might be likely to get a job that requires teamwork, but working in a team would improve teamwork skills as well, making it difficult to disentangle the effect of socioemotional skills from that of job experience. Thus, the ideal but unattainable case study would be random assignment of socioemotional skills to two identical individuals and subsequent observation of their performance on the labor market. A more feasible second-best is the audit study methodology, which creates CVs for fictitious similar candidates that significantly differ only on the variables of interest (here, gender and socioemotional skills) and tracks real employers' recruitment decisions for these fictitious candidates.

For this study, the selection process for one of our main variables of interest - occupation-specific socioemotional skills - involved two steps. In the first step, we carefully reviewed the organizational psychology literature and the O*NET occupation descriptors to identify the most relevant socioemotional

[11] Apart from Protsch and Solga (2015), which uses an experimental methodology with fictitious CVs.
[12] E.g. McRae (1987), Ackerman and Heggestad (1997).

skills for each of the selected occupations. O*NET categorizes occupations using one or more of the categories Realistic, Investigative, Artistic, Social, Enterprising, and Conventional (i.e. RIASEC) based on the daily tasks involved in the occupation.[13]

In the second step, which we call the reverse audit study, we collaborated with a private company that allowed us to include solicitation of specific socioemotional skills in two of their vacancy ads, and then provided the research team with anonymized CV information of the received applications. This enabled us to understand the ways in which candidates tend to signal their socioemotional skills (more information on both steps is provided in Appendix B).

Using these two steps, we were able to identify and construct realistic socioemotional skill signals that match the socioemotional skill descriptors in the literature as well as the O*NET. Although a rather long list of socioemotional skills is provided in O*NET for each occupation, we selected three socioemotional skills for each occupational cluster based on their usage in real CVs. These skills are given in Table 3.

Table 3: Selected socioemotional skills for each cluster

Occupational cluster	Socioemotional skill
Accounting	Detail orientation, Organization, Communication
Marketing	Dynamism, Teamwork, Persuasion
Sales	Persuasion, Networking, Teamwork
IT	Detail orientation, Perseverance, Teamwork

We signal all the selected socioemotional skills through activities performed in the context of job-related tasks, through extracurricular activities during undergraduate studies, and in the profile summaries (or "taglines"). We selected to signal socioemotional skills through activities and not as mere collection of adjectives after conducting a discrete choice experiment with senior undergraduate students of psychology and MBA students. This experiment demonstrated that socioemotional skills are salient features in the CV, but that they matter only when signaled through activities and not as mere adjectives (Nas Ozen, 2018).

We include signals of socioemotional skills in three different places in the CV: 1) job descriptions within the listed current job experience, 2) in a section called "Scholarships and projects" including extracurricular activities, and 3) in the CV tagline that is shown at the top of the CV on the online job portal. For the job descriptions, we create sentences of neutral job descriptions for control CVs and alternative sentences for

[13] Definitions for these categories are as follows (from www.onetonline.org): *Realistic* occupations frequently involve work activities that include practical, hands-on problems and solutions. They often deal with plants, animals, and real-world materials like wood, tools, and machinery. Many of the occupations require working outside, and do not involve a lot of paperwork or working closely with others. *Investigative* occupations frequently involve working with ideas and require an extensive amount of thinking. These occupations can involve searching for facts and figuring out problems mentally. *Artistic* occupations frequently involve working with forms, designs and patterns. They often require self-expression and the work can be done without following a clear set of rules. *Social* occupations frequently involve working with, communicating with, and teaching people. These occupations often involve helping or providing service to others. *Enterprising* occupations frequently involve starting up and carrying out projects. These occupations can involve leading people and making many decisions. Sometimes they require risk taking and often deal with business. *Conventional* occupations frequently involve following set procedures and routines. These occupations can include working with data and details more than with ideas. Usually there is a clear line of authority to follow.

treatment CVs that include socioemotional skill signals, both providing information on the same type of task performed at work. For example, for the IT cluster we identified four types of tasks: tasks related to (1) server, (2) internet, (3) software or website, and (4) hardware and maintenance. For each of these tasks, we create alternative bullets for control and treatment CVs. For example, one neutral sentence for a hardware-related task would state "Provided support for technical failures with equipment such as PC, printer or scanner," whereas the alternative sentence that signals teamwork would state "Worked as a team in identifying deficiencies and supplying the necessary hardware." We then randomly allocate four neutral sentences to the control CVs' job description, and one neutral sentence and three sentences that signal each of the three socioemotional skills separately to the treatment CVs' job description.

For generation of realistic, credible, and comparable extracurricular activities, we benefitted from the way candidates signaled their socioemotional skills in the reverse audit study as well as interviews with human resources personnel and a focus group discussion with university placement directors of two prominent universities in Ankara, Turkey. To keep the CV length compatible between control and treatment CVs and to signal high cognitive skills for our candidates, in the same section we also added a sentence in both control and treatment CVs that indicates the candidate was an honors student in their undergraduate university.

Finally, for the taglines, we create comparable statements regarding the current job of the candidate. For the control versions, we include information that is available in the CV characteristics listed below the tagline, for example, of the form "IT specialist who has an experience of 3 years in solving software/hardware issues, internet and servers." For the treatment versions instead, we signal at least one socioemotional skill within the tagline as well: "A determined IT specialist who can coordinate with the team members to provide detailed solutions to server, internet, software or hardware problems." Examples of alternative job descriptions, extracurricular activities, and taglines created in this way are given in Table 18 in Appendix C.

Background characteristics

The goal in the design of the CVs is to generate CVs that are equivalent except for the treatment variables. We therefore assign the other background characteristics either randomly, or we make the characteristic the same for all candidates of the same cluster and/or location.

Age (date of birth): We varied date of birth from September 1989 to December 1991, which implies that our candidates were 25 to 28 at the time of application. We imposed about a 6-month difference in age by gender, with female candidates being, on average, 6 months younger than male candidates. The imposed difference was necessitated by most vacancies requiring men to have completed their compulsory military service at the time of application. Military service in Turkey is compulsory only for men and lasts for about 6 months. Since men and women graduate at the same time of the year (June), our male and female CVs could be equated either on the length of work experience (in months) or on age. We chose the former option. As we know that employers can have age-related preferences, we always control for age in the analysis.

Job experience: Jobs are assigned randomly from a set of available jobs and positions collected from online sources for the selected occupational clusters. We assigned the number of positions held so that 75 percent of the profiles include two jobs (one current and one previous) in the experience section of the CV, and 25 percent have only one (current) job. We assign job duration independently from the number of jobs. In order to equate the average work experience level of CVs created for males and females, while allowing men to have completed their 6-month military service and having men and women graduate at the same time of the year (June), we use different assignment probabilities of work experience for each gender; this produces average work experience of created CVs for both genders of 3.25 years.[14]

Neighborhood: Candidates' residence neighborhoods within cities are selected so that they have similarly large populations (over 100,000, close to 1 million in the case of Çankaya in Ankara), and similar ratios of votes for the conservative-religious or the secular political party. This was done to avoid confounders based on employers' perceptions of candidates' political inclinations.

Education: High schools are assigned based on neighborhood: We selected high schools that have comparable entry scores on the centralized national high school entrance exam. Similarly, for universities, we selected large established public universities that have at least 25,000 students. Our candidates are graduates of Computer Engineering for the IT Cluster, and graduates of Business Administration for the remaining clusters. We make sure that, within occupational clusters, departments have similar minimum entry scores on the centralized national university entrance exam, so that the departments are comparable in terms of quality signals.

Photos and beauty: We also include photos for each candidate, as this is standard practice in Turkey (over 80 percent of all candidates in the online job portal include photos). The photos used in the experiment are artificially generated from publicly available photos or volunteer face shots of Italian and Turkish youth aged 22 to 30. The photos collected in this manner were handed over to a graphic designer, who created sets of fictitious photos in Photoshop using combinations of different facial features from real photos. None of the photos was exactly identical to the rest, and none of them was the original (real) image.

For the resulting photos, two different measures of beauty were collected: objective and subjective beauty scores. The first measure is the attractiveness score based on the face shape, distance between the eyes and lips, mouth size and face symmetry, using the so-called "golden ratio" where appropriate. This type of measurement, which we call the objective beauty score, is on a scale from 0 to 100. The software at www.prettyscale.com was used to obtain these scores.

The objective beauty score depends solely on the placement of facial features without any reference to details such as hair color, color of the eyes, or other features that may affect how beautiful the person in the photo is perceived. Moreover, whereas objective beauty scores do not change according to country context, individuals from different countries may have different conceptions of beauty. This is why we also collected data on a second measure that we call the subjective beauty score. This score is the average of beauty scores obtained from ratings collected through an online survey.[15] We then generated average subjective beauty scores for all photos using the total of 32,676 ratings by 383 participants that we collected

[14] Note that average years of experience increased during the time between CV creation and job applications. See Table 3 for details.

[15] The link to the survey was distributed through Twitter accounts of World Bank Turkey and the Economic Policy Research Foundation of Turkey, so anyone could access the survey. As the tweet and the survey itself were in Turkish language, we expect respondents to be Turkish as well.

through the survey. In selecting the final set of photos, we eliminated those that have extreme scores on either the objective or the subjective beauty measure, and obtained two sets of photos that have no significant difference in mean objective or subjective beauty scores by gender. More details on how we do this are given in Appendix A.

We create two dummy variables to be used in the regressions, one on objective and the other on subjective beauty. The one on objective beauty takes on the value 1 if the rating is above 0.6, the score threshold that the PrettyScale website considers the face to be “pretty”. For the subjective scores, the variable takes on the value 1 if the beauty score is above the median score obtained in the survey.

Other signals: All candidates have an advanced level of English proficiency, but we introduced random variation in the exact levels of listening, speaking, writing, and reading between levels 4 and 5, the two highest levels in the online job portal.

Computer skills are included only for the IT cluster, where we provide the same list of software for all candidates, but in randomized order.

As it is customary in Turkey to include marital status in CVs, we indicate that all our candidates are single.

Final CV construction and application

To ensure comparability across genders, we create duplicate CVs for men and women that have exactly the same information in terms of all background characteristics, except name, photo, contact information, and the date of birth (see the above discussion on the imposed 6-month difference in age by gender due to military service).

For each selected vacancy, we randomly chose four profiles without replacement from our set of 16 profiles in the cluster/location. These four profiles correspond to the four cells in the experiment: male control, female control, male treatment, and female treatment.

2.3. Data

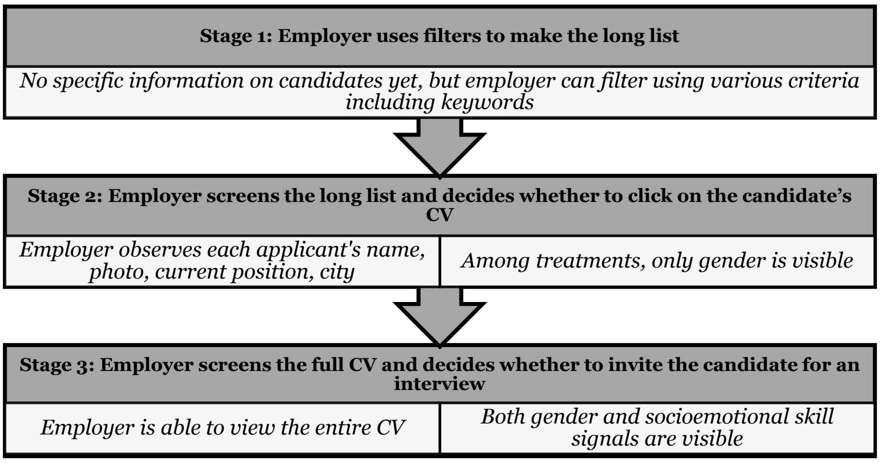
The online job portal used in this experiment allows us to collect information on selection at three different stages of the hiring process. Figure 1 provides the details on these three screening stages. The first stage consists of making the longlist. In screening the applicants, employers can use filtering, whereby they enter search criteria to create a filtered longlist of all applicants. For job seekers, the online portal provides information on whether their application made it to this filtered longlist. In other words, for each application of our fictitious candidates, we observe whether the fictitious candidate made it to the longlist. This indicator is used as a dependent variable for this first recruitment stage.

After creating the longlist, the employer can observe the name, photo, current position, and city of residence for all longlisted applicants. The employer can then click on a candidate from the longlist to obtain more information (i.e. view the candidate’s full CV). Note that clicking on a candidate is costly for the employer as there is a fee associated to clicking on a CV. For jobseekers, the portal provides information on whether the employer from a specific vacancy viewed their full profile. In other words, for each application of all our fictitious candidates, we observe whether the fictitious candidate's CV has been viewed. This indicator is used as a dependent variable for the second recruitment stage.

After clicking on a longlisted candidate and obtaining more information from their full CV, the employer can invite the applicant for an interview. Like previous correspondence audit studies, we collect information on whether our fictitious candidate has received a callback for an interview (either via phone or via email). Upon receiving a callback, we immediately reject the interview offer. We use an indicator for receiving a callback as a dependent variable for the third recruitment stage.

Note that, among our two treatments, gender is visible to the employer at all stages - the employer can filter by gender, they can decide to click only on candidates of a certain gender (using photo and name to identify gender), and they can see the same variables in the full CV. On the other hand, employers can only view socioemotional skills treatment after they click on the longlisted candidate and see their full CV – in other words, employers cannot filter by socioemotional skills (unless they put those skills in a keyword search) in order to create a longlist, and they cannot see those skills in a filtered longlist, as only name, photo, current position, and city of residence are visible at that stage.

Figure 1: Employers' screening process after application

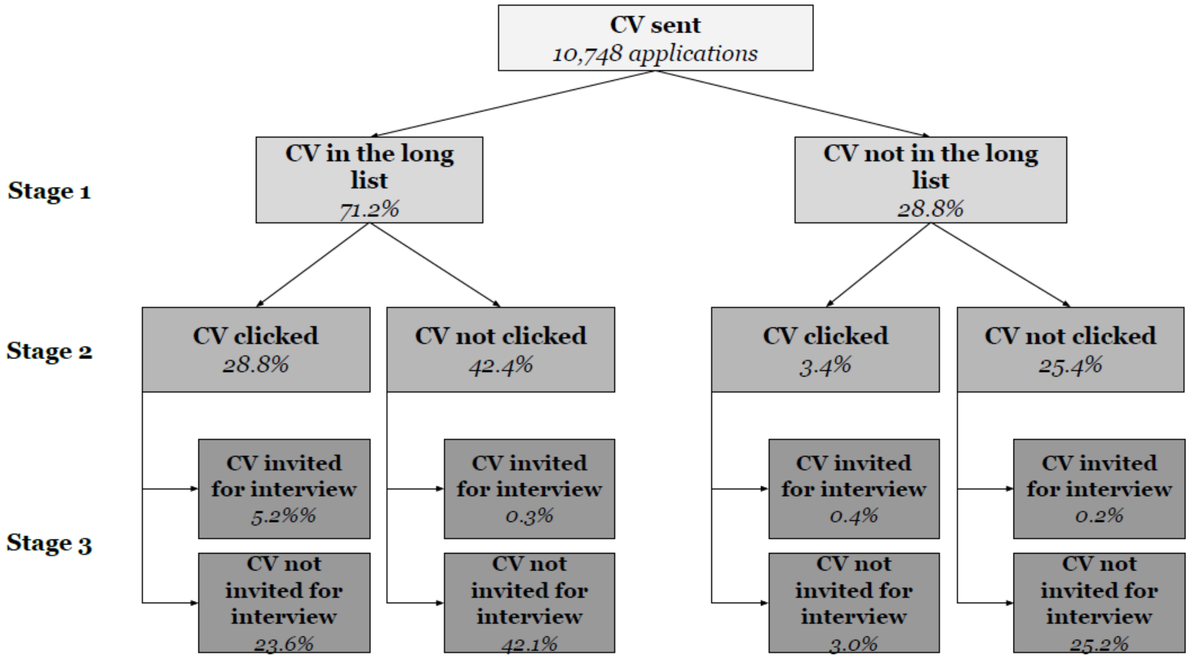


3. Results

The results are organized around two main blocks. First, we consider the aggregate effect of the gender treatment and differentiate the treatment effect for the three recruitment stages. We then move to the socioemotional skills treatment and show the aggregate results, as well as differentiating between genders. Table 4 provides the descriptive statistics for our sample. About 71 percent of our applicants made it to the longlist, 32 percent had their CVs clicked on (i.e. their full CVs viewed) and 6 percent received a callback for an interview.[16] Figure 2 provides the distribution of CVs on the three outcome variables.

[16] Callback rates in the studies using a similar methodology range from around 3 percent (e.g., in Kroft et al., 2013) to 30 percent (e.g., in Booth et al., 2012).

Figure 2: Distribution of CVs on outcome variables



Our applicants are relatively young (around 26 years) and have a university degree. Average work experience is around 49 months, and 26 percent of applicants have obtained all their experience in one job only. In terms of beauty, 94 percent of our fictitious candidates are classified to be pretty according to the PrettyScale website's classification. Finally, applicants have around 4.5 on a scale of 0 to 5 for speaking, reading, and writing proficiency in English.

In terms of vacancy characteristics, vacancies in the IT cluster are more limited compared to other occupational clusters, with 13 percent in IT, 30 percent in sales, 29 percent in accounting, and 28 percent in marketing. Total application size at the time of data collection is 549 on average,[17] but increases to over 30,000 applicants for some vacancies. A requirement for a socioemotional skill is mentioned in 87 percent of vacancies, and 66 percent of vacancies solicit at least one of the socioemotional skills signaled by our treatment candidates' CVs.

Most vacancies come from the Istanbul-Europe region, as expected, since the European side of Istanbul is the largest and most complex labor market in Turkey. Thirty-one percent of vacancies are from the Asian side of Istanbul, and the remaining 18 percent are from Ankara.

[17] The website provides a range for total number of applications for each application that the candidate makes. We collected this information on the final day of data collection along with whether the applicant made it to the long list, and whether her CV was clicked.

Table 4: Descriptive statistics

	N	Mean	Std. dev.	Min	Max
Dependent variables					
Applicant in the longlist	10748	0.71	0.45	0	1
Applicant profile clicked on	10748	0.32	0.47	0	1
Applicant invited for an interview	10748	0.06	0.24	0	1
Experimental variables					
Female	10748	0.50	0.50	0	1
SES treatment	10748	0.50	0.50	0	1
Resume attributes					
Experience (months)	10748	49.17	5.62	37	61
Age at application	10748	26.41	0.65	25	28
Worked in one job only	10748	0.26	0.44	0	1
Objective beauty	10748	0.94	0.23	0	1
Subjective beauty	10748	0.50	0.50	0	1
English proficiency: Speaking	10748	4.52	0.50	4	5
English proficiency: Reading	10748	4.58	0.49	4	5
English proficiency: Writing	10748	4.51	0.50	4	5
Vacancy attributes					
Occupational cluster: Accounting	10748	0.29	0.45	0	1
Occupational cluster: Marketing	10748	0.28	0.45	0	1
Occupational cluster: Sales	10748	0.30	0.46	0	1
Occupational cluster: IT	10748	0.13	0.33	0	1
Total application size (in hundreds)	10748	5.49	9.11	0	302
Signaled SES required in vacancy	10748	0.66	0.47	0	1
Locality: Ankara	10748	0.18	0.38	0	1
Locality: Istanbul Asia	10748	0.31	0.46	0	1
Locality: Istanbul EU	10748	0.51	0.50	0	1

3.1 Gender

Table 5 provides the balance table for the gender treatment of the CVs that were sent out to vacancies. Although for most observed variables, there is no significant difference between the two genders, the male and female CVs are unbalanced on several observables. First, as discussed in Section 2, female applicants are, by design, significantly younger (by about 8 months) due to military service completion for men. To account for any differences in age by construction, we control for this variable in all specifications.

In addition, female applications have a slightly higher level of experience, although the difference is less than two weeks relative to the average job duration of around 50 months. Also, 27 percent of male compared to 24 percent of female candidates spent all their job experience in one job only. Furthermore, female applicants have higher objective and subjective beauty scores, although these differences are quite small. Accordingly, most results for gender comparisons include these five variables as controls whenever it is possible for the employers to use these variables in their decision.[18]

Our first finding suggests that a small share of employers use gender as a filter. Employers are slightly more likely to select female CVs when making their longlists, although this result is only marginally significant. Employers can create their longlist of applicants by entering criteria manually. The criteria can include many variables, including age, gender, experience, city and neighborhood, sector, occupation as well as a keyword search. Note that, when making the longlist, employers cannot filter using beauty, for two reasons. First, photos are not visible at this stage. Second, it is simply not possible to enter beauty as a criterion for filtering. This is why we do not use objective and subjective beauty measures as controls for this stage. Furthermore, whether the candidate has worked in one firm only is also not possible to use as a filter at this stage.

Table 6 provides the results from OLS regressions, using cluster-robust errors at the vacancy level. Models 1 to 6 show that females are 2 to 3 percent more likely to make it to the longlist. Although small in magnitude, this systematic difference indicates that some employers enter gender as a filter when making their longlist and have a preference for longlisting female over male candidates. Model 1 shows the most basic specification, with only a control for age.[19] In Model 2 we add a control for the duration of work experience, and in Model 3 we also add a control for whether the candidate has ever worked in the same sector where the employer operates. Model 4 shows that the observed preference for women result does not change according to clusters.[20] Models 5 and 6 show that employers with vacancies that receive high and low number of applications behave similarly in terms of their gender preferences for longlisting. On the other hand, the tendency to filter males out seems to be somewhat less pronounced in Ankara compared to the European side of Istanbul (Model 7). Finally, the models show occupational clusters (in particular, accounting) and total application size also affect the probability of passing through the filter and making it to the longlist but do not affect gender filtering.

Not all employers use the longlist as the first stage: 11 percent of applicant CVs that are clicked on are CVs that are not in the longlist. This is why we consider both unconditional regressions and regressions conditional on an applicant CV being in the longlist when looking at the determinants of what makes an employer click on a CV. Unconditional regression results are shown in Table 7. A similar result to the case with longlist emerges in this case, where female applicants are significantly more likely to be clicked on compared to their male counterparts. On the other hand, this tendency seems to be more a feature for sales and accounting occupations: Model 4 shows that the effect disappears for marketing and IT clusters. While there seems to be no difference in behavior according to local labor markets, models 3, 5, 6 and 7 show that applicants that are in the same sector with the firm opening the vacancy are more likely to be clicked on by the employers. Finally, as the total application size increases, employers presumably have more CVs

[18] Separate balance tables for each sector are available upon request from the authors. Balance tables look very similar across sectors, with the exception that for cluster B there is no unbalance by gender on experience.
[19] As noted, we include a linear age control in all regressions because by construction male candidates are older than female candidates, due to the mandatory military service for men in Turkey.
[20] Separate regressions for each cluster are in line with these findings and are available upon request from the authors.

to go through and the probability of a particular CV being clicked on gets smaller. In these cases, female CVs are slightly less likely to be clicked on (Models 5 and 6).

Table 8 shows the determinants of applicant CV being clicked on, this time conditional on the applicant making it to the longlist first.[21] Results show that, once they make it to the longlist, females and males are virtually equally likely to be clicked on, and factors other than gender, such as the type of occupation, total application size for the vacancy, and whether the sector of applicant and firm matches affect the probability of employer clicking on the candidate.

Table 5: Balance table for gender treatment

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Istanbul Asia	0.311	0.311	-0.000
	(0.463)	(0.463)	(0.009)
Istanbul EU	0.509	0.509	0.000
	(0.500)	(0.500)	(0.010)
Experience (months)	48.954	49.388	0.434
	(5.578)	(5.651)	(0.108)***
Age	26.767	26.043	-0.725
	(0.561)	(0.509)	(0.010)***
Accounting	0.292	0.292	0.000
	(0.455)	(0.455)	(0.009)
Marketing	0.276	0.276	0.000
	(0.447)	(0.447)	(0.009)
Sales	0.304	0.304	0.000
	(0.460)	(0.460)	(0.009)
IT	0.128	0.128	0.000
	(0.334)	(0.334)	(0.006)
Worked in one job only	0.270	0.247	-0.023
	(0.444)	(0.431)	(0.008)***
Objective beauty	0.926	0.963	0.037
	(0.262)	(0.189)	(0.004)***
Subjective beauty	0.450	0.549	0.100
	(0.498)	(0.498)	(0.010)***
Reading	4.581	4.574	-0.007
	(0.493)	(0.495)	(0.010)
Speaking	4.520	4.522	0.002
	(0.500)	(0.500)	(0.010)
Writing	4.518	4.508	-0.009
	(0.500)	(0.500)	(0.010)
Observations	5,374	5,374	10,748

[21] Conditional balance tables are provided in Appendix D.

Table 6: Determinants of applicant making it to the longlist

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Female	0.0188**	0.0193*	0.0193*	0.0222**	0.0179*	0.0208**	0.0278**
	(0.0082)	(0.0106)	(0.0106)	(0.0105)	(0.0105)	(0.0105)	(0.0115)
Accounting				-0.1028***		-0.0979***	-0.0974***
				(0.0223)		(0.0221)	(0.0222)
Marketing				0.0083		0.0046	0.0051
				(0.0215)		(0.0214)	(0.0214)
IT				0.0450*		0.0137	0.0127
				(0.0266)		(0.0312)	(0.0314)
Istanbul Asia							-0.0015
							(0.0193)
Ankara							0.0147
							(0.0231)
Total application size (100)					-0.0026**	-0.0021**	-0.0020**
					(0.0011)	(0.0009)	(0.0009)
Female * Istanbul Asia							-0.0101
							(0.0070)
Female * Ankara							-0.0156*
							(0.0091)
Female * Acct				0.0049			
				(0.0057)			
Female * Mrkt				-0.0059			
				(0.0052)			
Female * IT				-0.0015			
				(0.0039)			
Female * Total application size					0.0002	0.0002	
					(0.0003)	(0.0003)	
Vacancy and CV sectors match			0.0647***		0.0606***	0.0324	0.0327
			(0.0192)		(0.0192)	(0.0212)	(0.0212)
Experience (in months)		-0.0001	-0.0001	-0.0005	-0.0001	-0.0005	-0.0005
		(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Age	0.0351***	0.0359***	0.0357***	0.0396***	0.0350***	0.0389***	0.0390***
	(0.0106)	(0.0135)	(0.0135)	(0.0134)	(0.0135)	(0.0134)	(0.0135)
Constant	-0.2250	-0.2395	-0.2454	-0.2979	-0.2106	-0.2666	-0.2717
	(0.2837)	(0.3321)	(0.3317)	(0.3307)	(0.3318)	(0.3307)	(0.3323)
N.obs.	10748	10748	10748	10748	10748	10748	10748
R-squared	0.002	0.002	0.004	0.015	0.007	0.017	0.017

Notes: Models 1 to 7 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant makes it through the first screening and into the longlist. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupational clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Determinants of applicant's CV being clicked on

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	0.0286***	0.0230*	0.0234**	0.0259**	0.0285**	0.0309**	0.0313**
	(0.0100)	(0.0118)	(0.0117)	(0.0116)	(0.0122)	(0.0121)	(0.0136)
Accounting				-0.1244***		-0.1216***	-0.1212***
				(0.0189)		(0.0184)	(0.0185)
Marketing				-0.0636***		-0.0742***	-0.0739***
				(0.0202)		(0.0194)	(0.0195)
IT				0.2084***		0.1515***	0.1504***
				(0.0279)		(0.0324)	(0.0325)
Istanbul Asia							0.0096
							(0.0183)
Ankara							0.0108
							(0.0220)
Total application size (100)							
Female * Istanbul Asia							-0.0152
							(0.0155)
Female * Ankara							-0.0078
							(0.0191)
Female * Acct				-0.0015			
				(0.0085)			
Female * Mrkt				-0.0189*			
				(0.0100)			
Female * IT				-0.0250*			
				(0.0149)			
Female * Total application size					-0.0011*	-0.0011*	
					(0.0006)	(0.0007)	
Vacancy and CV sectors match			0.2004***		0.1945***	0.0470**	0.0474**
			(0.0200)		(0.0201)	(0.0225)	(0.0225)
Experience (in months)		0.0008	0.0009	0.0005	0.0008	0.0005	0.0005
		(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Age	-0.0008	-0.0067	-0.0071	-0.0037	-0.0083	-0.0050	-0.0046
	(0.0101)	(0.0130)	(0.0128)	(0.0127)	(0.0128)	(0.0126)	(0.0127)
Objective beauty		0.0310	0.0309	0.0194	0.0324*	0.0218	0.0222
		(0.0193)	(0.0191)	(0.0189)	(0.0191)	(0.0189)	(0.0190)
Subjective beauty		-0.0007	-0.0057	-0.0033	-0.0052	-0.0026	-0.0022
		(0.0087)	(0.0086)	(0.0084)	(0.0085)	(0.0084)	(0.0084)
Total application size (100)					-0.0030***	-0.0024***	-0.0029***
					(0.0010)	(0.0008)	(0.0009)
Constant	0.3290	0.4207	0.3996	0.3985	0.4489	0.4424	0.4302
	(0.2714)	(0.3173)	(0.3127)	(0.3093)	(0.3112)	(0.3080)	(0.3100)
N.obs.	10748	10748	10748	10748	10748	10748	10748
R-squared	0.001	0.001	0.025	0.047	0.030	0.051	0.051

Notes: Models 1 to 7 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant's CV is clicked on. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupational clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8: Determinants of applicant's CV being clicked on, conditional on applicant making it to the longlist

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	0.0245*	0.0156	0.0174	0.0180	0.0218	0.0224	0.0253
	(0.0127)	(0.0149)	(0.0146)	(0.0145)	(0.0152)	(0.0151)	(0.0173)
Accounting				-0.0955***		-0.0923***	-0.0915***
				(0.0238)		(0.0229)	(0.0230)
Marketing				-0.0628***		-0.0714***	-0.0709***
				(0.0238)		(0.0228)	(0.0229)
IT				0.2382***		0.1706***	0.1691***
				(0.0301)		(0.0360)	(0.0361)
Istanbul Asia							0.0115
							(0.0225)
Ankara							0.0116
							(0.0263)
Total application size (100)							
Female * Istanbul Asia							-0.0284
							(0.0206)
Female * Ankara							0.0005
							(0.0252)
Female * Acct				-0.0044			
				(0.0131)			
Female * Mrkt				-0.0173			
				(0.0129)			
Female * IT				-0.0178			
				(0.0175)			
Female * Total application size					-0.0011	-0.0011	
					(0.0008)	(0.0008)	
Vacancy and CV sectors match			0.2272***		0.2211***	0.0664**	0.0664**
			(0.0221)		(0.0221)	(0.0263)	(0.0264)
Experience (in months)		0.0013	0.0015	0.0013	0.0015	0.0013	0.0013
		(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Age	-0.0160	-0.0260*	-0.0257*	-0.0243	-0.0277*	-0.0262*	-0.0263*
	(0.0124)	(0.0157)	(0.0154)	(0.0153)	(0.0154)	(0.0152)	(0.0153)
Objective beauty		0.0325	0.0303	0.0228	0.0316	0.0247	0.0250
		(0.0246)	(0.0244)	(0.0242)	(0.0243)	(0.0242)	(0.0242)
Subjective beauty		-0.0032	-0.0085	-0.0088	-0.0080	-0.0078	-0.0077
		(0.0108)	(0.0106)	(0.0105)	(0.0106)	(0.0104)	(0.0105)
Total application size (100)					-0.0034***	-0.0028***	-0.0034***
					(0.0012)	(0.0010)	(0.0010)
Constant	0.8164**	0.9899**	0.9415**	0.9724***	1.0102***	1.0287***	1.0280***
	(0.3330)	(0.3845)	(0.3778)	(0.3741)	(0.3760)	(0.3724)	(0.3759)
N.obs.	10748	10748	10748	10748	10748	10748	10748
R-squared	0.001	0.001	0.025	0.047	0.030	0.051	0.051

Notes: Models 1 to 7 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant's CV is clicked on. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupational clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

We now move to the final component of our analysis for the gender treatment, callbacks for an interview. Note that among our candidates invited for an interview, 8 percent had CVs that were not clicked on by the employer. For this reason, we present our results in this part both unconditionally and conditional on the applicant's CV being clicked on.

Table 9 provides the correspondence table. Overall, around 7.4 percent of females compared to 4.2 percent of males are invited for an interview, indicating a preference for female over male candidates. However, this result may be affected by the remaining imbalances, which is why we look at the regression results. Tables 10 and 11 provide the regression results, both unconditionally and conditional on applicant's CV being clicked on, respectively.[22] Note that at this stage, applicant's photo is visible to the employer, and therefore we control for subjective and objective beauty measures in Models 2-7. Both tables show that there is no significant gender effect in the probability of being invited for an interview. Model 4 in both tables shows that the insignificance of gender holds for different occupational clusters, apart from a small positive effect of being female for the sales occupations, significant at 10 percent, when the regressions are unconditional (Model 4 in Table 10). This effect disappears when conditioning on whether the CV is clicked on. On the other hand, although the interaction of female with the accounting cluster has a slightly significant coefficient in both tables, joint significance tests show that the effect for the accounting cluster is not significant either.

Table 9: Correspondence table for gender treatment on callbacks for an interview

Equal treatment			Females favored			Males favored		
	Freq.	Percent		Freq.	Percent		Freq.	Percent
0M 0F	2313	86.08	0M 1F	124	4.61	1M 0F	76	2.83
1M 1F	28	1.04	0M 2F	45	1.67	2M 0F	21	0.78
2M 2F	34	1.27	1M 2F	31	1.15	2M 1F	15	0.56
Total	2375	88.39	Total	200	7.44	Total	112	4.17

Local labor markets respond differently to our gender treatment: In Istanbul Asia, females are significantly more likely to be invited for an interview, both unconditionally and conditional on their CV being clicked on. Overall, both of Tables 10 and 11 show that factors other than gender have an effect on the probability of being invited for an interview. Applicants for occupations in accounting and marketing are significantly less likely to be invited for an interview, and the same holds in Istanbul Asia compared to Istanbul Europe.

The findings for the three stages above lead us to the main result on gender:

Result 1. There is no clear indication of gender discrimination in this context. If anything, employers show a minor preference for female applicants when they make their initial longlist for screening, but this is only marginally significant. Once applicants pass through this first stage, employers do not differentiate between the two genders at least until the interview phase.

[22] Conditional balance tables are provided in Appendix D.

Table 10: Determinants of applicant being invited for an interview

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	0.0129**	0.0104	0.0105	0.0108*	0.0104	0.0106	0.0069
	(0.0055)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0077)
Accounting				-0.0447***		-0.0491***	-0.0493***
				(0.0093)		(0.0087)	(0.0087)
Marketing				-0.0418***		-0.0414***	-0.0415***
				(0.0098)		(0.0094)	(0.0094)
IT				0.0020		0.0108	0.0115
				(0.0147)		(0.0174)	(0.0174)
Istanbul Asia							-0.0149*
							(0.0079)
Ankara							-0.0016
							(0.0106)
Total application size (100)							
Female * Istanbul Asia							0.0160*
							(0.0094)
Female * Ankara							-0.0067
							(0.0117)
Female * Acct				-0.0097*			
				(0.0051)			
Female * Mrkt				0.0013			
				(0.0056)			
Female * IT				0.0087			
				(0.0113)			
*Female * Total application size*							
Vacancy and CV sectors match			0.0220**		0.0213**	-0.0064	-0.0066
			(0.0097)		(0.0097)	(0.0119)	(0.0119)
Experience (in months)		0.0004	0.0005	0.0003	0.0004	0.0003	0.0003
		(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)
Age	-0.0109**	-0.0139**	-0.0139**	-0.0133**	-0.0140**	-0.0134**	-0.0135**
	(0.0050)	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0064)
Objective beauty		0.0101	0.0101	0.0080	0.0102	0.0081	0.0064
		(0.0092)	(0.0092)	(0.0091)	(0.0092)	(0.0091)	(0.0091)
Subjective beauty		-0.0007	-0.0013	0.0004	-0.0012	0.0005	0.0003
		(0.0046)	(0.0046)	(0.0045)	(0.0046)	(0.0045)	(0.0045)
Worked in one firm only		0.0050	0.0049	-0.0005	0.0048	-0.0006	-0.0001
		(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Total application size (100)					-0.0004	-0.0003	-0.0003
					(0.0003)	(0.0003)	(0.0003)
Constant	0.3428**	0.3906**	0.3883**	0.4089***	0.3944**	0.4139***	0.4240***
	(0.1346)	(0.1561)	(0.1562)	(0.1552)	(0.1562)	(0.1553)	(0.1554)
N.obs.	10748	10748	10748	10748	10748	10748	10748
R-squared	0.002	0.004	0.004	0.012	0.004	0.012	0.013

Notes: Models 1 to 7 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting*, *Marketing* and *IT* denote the occupational clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 11: Determinants of applicant being invited for an interview, conditional on applicant's CV clicked

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	0.0269*	0.0241	0.0234	0.0225	0.0247	0.0234	0.0085
	(0.0151)	(0.0181)	(0.0181)	(0.0180)	(0.0181)	(0.0180)	(0.0224)
Accounting				-0.0552**		-0.0780***	-0.0763***
				(0.0280)		(0.0252)	(0.0250)
Marketing				-0.0845***		-0.0770***	-0.0763***
				(0.0260)		(0.0246)	(0.0245)
IT				-0.0773***		-0.0259	-0.0238
				(0.0274)		(0.0353)	(0.0352)
Istanbul Asia							-0.0508**
							(0.0225)
Ankara							-0.0082
							(0.0286)
Female * Istanbul Asia							0.0639**
							(0.0267)
Female * Ankara							-0.0268
							(0.0311)
Female * Acct				-0.0384*			
				(0.0203)			
Female * Mrkt				0.0139			
				(0.0196)			
Female * IT				0.0321			
				(0.0204)			
Female * Total application size							
Vacancy and CV sectors match			-0.0292		-0.0274	-0.0413	-0.0410
			(0.0195)		(0.0195)	(0.0275)	(0.0274)
Experience (in months)		0.0003	0.0003	0.0001	0.0002	0.0001	0.0001
		(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0015)	(0.0015)
Age	-0.0278**	-0.0306*	-0.0303*	-0.0299*	-0.0290*	-0.0288	-0.0292*
	(0.0138)	(0.0176)	(0.0176)	(0.0175)	(0.0176)	(0.0175)	(0.0176)
Objective beauty		0.0176	0.0174	0.0163	0.0187	0.0167	0.0125
		(0.0276)	(0.0275)	(0.0275)	(0.0276)	(0.0275)	(0.0275)
Subjective beauty		0.0024	0.0035	0.0077	0.0027	0.0069	0.0073
		(0.0128)	(0.0127)	(0.0126)	(0.0127)	(0.0126)	(0.0126)
Worked in one firm only		0.0000	-0.0001	-0.0041	0.0007	-0.0043	-0.0028
		(0.0140)	(0.0140)	(0.0139)	(0.0140)	(0.0140)	(0.0139)
Total application size (100)					0.0019	0.0022	0.0022
					(0.0016)	(0.0016)	(0.0016)
Constant	0.8957**	0.9354**	0.9392**	0.9757**	0.8963**	0.9407**	0.9716**
	(0.3693)	(0.4280)	(0.4281)	(0.4237)	(0.4292)	(0.4262)	(0.4277)
N.obs.	3469	3469	3469	3469	3469	3469	3469
R-squared	0.005	0.005	0.006	0.014	0.007	0.015	0.018

Notes: Models 1 to 7 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *Female* takes on the value 1 if applicant is female, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Variables *Accounting, Marketing* and *IT* denote the occupational clusters of vacancies (and so of applicants), and the baseline category is sales occupations. Variable *Total application size* denotes the total number of applications for the vacancy. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

3.2. Socioemotional skills

Table 12 provides the balance table for our socioemotional skills treatment. Results indicate that randomization has done a fairly good job in generating subsamples that are similar to each other apart from the treatment. In addition, a joint significance test provides an F-statistic of 0.47, implying that variables do not jointly affect the treatment variable.[23]

Our socioemotional skills treatment is visible only when the applicant's CV is clicked. This is why we only consider the treatment effect on callbacks for an interview and not the earlier stages of screening, and why our preferred specification is that conditional on the CV being clicked.[24] Table 13 shows the results from OLS regressions using cluster-robust standard errors at the vacancy level. Model 1 shows an overall insignificant treatment effect for signaling socioemotional skills. On the other hand, in Model 2 we get a differential result by interacting the treatment variable with a dummy variable that takes on the value 1 if the vacancy asks for the skill we signal in treatment CVs. Models 2 to 4 show that employers evaluate a socioemotional skill signal negatively when not asked for in the vacancy, although this effect becomes insignificant when vacancy characteristics are added (Model 4). Including the signal when it is asked for in the vacancy increases the probability of receiving a callback: the coefficients of socioemotional skills treatment and its interaction with whether the signaled socioemotional skill is required in the vacancy are jointly significant at the 10 percent level.[25] Finally, Model 5 shows that, while the effect sizes may change according to cluster, results are qualitatively similar across all clusters.[26]

Result 2. Signaling a socioemotional skill decreases the probability of being invited for an interview if the skill is not solicited in the vacancy, and it increases the probability of being invited for an interview if the skill is asked for in the vacancy text.

We finally investigate whether the probabilities of callback for our treatment CVs are different according to the applicant's gender. Table 14 provides the results from OLS regressions conditional on the applicant's CV clicked, and with cluster-robust standard errors at the vacancy level. Models 1 to 3 show that female candidates with socioemotional skill signals in their CVs are around 5 percentage points less likely to be invited for an interview when the vacancy text does not solicit the signaled socioemotional skill. On the other hand, Models 4 to 6 show that the same effect is close to zero for the male candidates.

Result 3. Firms that do not ask for the signaled socioemotional skills in the vacancy text evaluate these skill signals negatively only for female applicants.

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[23] Separate balance tables for each sector are available upon request. Balance tables look very similar across sectors.
[24] Unconditional versions of these regressions are available upon request. Results do not vary.
[25] Using Model 4, a joint significance test for SE skills * Signaled SE skill required in vacancy and SE skills gives an F-statistic of 3.60, with a p-value of 0.0579.
[26] Separate regressions for each cluster are in line with these findings and are available upon request from the authors.

Table 12: Balance table for socioemotional skills treatment

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.179	0.179	0.000
	(0.384)	(0.384)	(0.007)
Istanbul Asia	0.311	0.311	0.000
	(0.463)	(0.463)	(0.009)
Istanbul EU	0.509	0.509	0.000
	(0.500)	(0.500)	(0.010)
Experience (months)	49.234	49.109	-0.125
	(5.563)	(5.673)	(0.108)
Age	26.411	26.399	-0.012
	(0.643)	(0.650)	(0.012)
Accounting	0.292	0.292	-0.000
	(0.455)	(0.455)	(0.009)
Marketing	0.276	0.276	0.000
	(0.447)	(0.447)	(0.009)
Sales	0.304	0.304	-0.000
	(0.460)	(0.460)	(0.009)
IT	0.128	0.128	-0.000
	(0.334)	(0.334)	(0.006)
Worked in one firm only	0.253	0.264	0.011
	(0.435)	(0.441)	(0.008)
Objective beauty	0.943	0.945	0.002
	(0.231)	(0.227)	(0.004)
Subjective beauty	0.506	0.493	-0.012
	(0.500)	(0.500)	(0.010)
Reading	4.582	4.573	-0.009
	(0.493)	(0.495)	(0.010)
Speaking	4.517	4.526	0.009
	(0.500)	(0.499)	(0.010)
Writing	4.514	4.512	-0.001
	(0.500)	(0.500)	(0.010)
Total application size (100)	5.491	5.491	0.000
	(9.110)	(9.110)	(0.176)
Observations	5,374	5,374	10,748

Notes: Standard errors are given in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 13: The effect of socioemotional skills, conditional on applicant CV clicked

	Model 1	Model 2	Model 3	Model 4	Model 5
SE skills	0.007	-0.027*	-0.027*	-0.026	-0.051*
	(0.010)	(0.016)	(0.016)	(0.016)	(0.029)
Signaled SE skill required in vacancy		0.004	0.004	0.001	0.001
		(0.022)	(0.022)	(0.022)	(0.043)
SE skills * Signaled SE skill required in vacancy		0.049**	0.050**	0.049**	0.092**
		(0.020)	(0.020)	(0.020)	(0.036)
SE skills * Acct					-0.010
					(0.042)
SE skills * Mrkt					0.036
					(0.044)
SE skills * IT					0.076*
					(0.045)
Signaled SE skill required in vacancy * Acct					0.035
					(0.061)
Signaled SE skill required in vacancy * Mrkt					-0.002
					(0.061)
Signaled SE skill required in vacancy * IT					-0.030
					(0.062)
SE skills * Signaled SE skill required in vacancy * Acct					-0.055
					(0.054)
SE skills * Signaled SE skill required in vacancy * Mrkt					-0.052
					(0.054)
SE skills * Signaled SE skill required in vacancy * IT					-0.080
					(0.056)
Age			-0.0460***	-0.0439***	-0.0433***
			(0.0118)	(0.0116)	(0.0117)
Experience (in months)			0.0015	0.0012	0.0012
			(0.0013)	(0.0013)	(0.0013)
Objective beauty			0.0190	0.0181	0.0180
			(0.0274)	(0.0273)	(0.0275)
Subjective beauty			0.0043	0.0081	0.0072
			(0.0128)	(0.0126)	(0.0126)
Worked in one firm only			-0.0004	-0.0025	-0.0022
			(0.0140)	(0.0139)	(0.0139)
Constant	0.172***	0.169***	1.291***	1.241***	1.280***
	(0.010)	(0.018)	(0.294)	(0.291)	(0.296)
Vacancy char.	No	No	No	Yes	Yes
N.obs.	3469	3469	3469	3469	3469
R-squared	0.000	0.002	0.007	0.017	0.019

Notes: Models 1 to 6 report the results from OLS regressions. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable *SE skills* takes on the value 1 for treatment CVs, 0 otherwise. Variable *Vacancy and CV sectors match* takes on the value 1 if the vacancy is in the same sector with applicant's current or previous sectors. Vacancy characteristics include total number of applications for the vacancy, occupational clusters and location. Symbols ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5% and 10% level, respectively.

Table 14: The effect of socioemotional skills for women and men, conditional on applicant CV clicked

	Women only			Men only		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SE skills	-0.050**	-0.049**	-0.046**	-0.002	-0.001	-0.003
	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
Signaled SE skill required in vacancy	-0.004	-0.004	-0.010	0.014	0.013	0.010
	(0.028)	(0.028)	(0.028)	(0.025)	(0.025)	(0.025)
SE skills * Signaled SE skill required in vacancy	0.071**	0.069**	0.066**	0.027	0.028	0.029
	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)
Experience (in months)		-0.0014	-0.0020		0.0034	0.0033
		(0.0022)	(0.0022)		(0.0022)	(0.0022)
Age		-0.0147	-0.0110		-0.0524**	-0.0534**
		(0.0250)	(0.0247)		(0.0233)	(0.0233)
Objective beauty		-0.0075	-0.0029		0.0373	0.0256
		(0.0517)	(0.0519)		(0.0315)	(0.0311)
Subjective beauty		-0.0231	-0.0092		0.0316*	0.0292
		(0.0188)	(0.0186)		(0.0189)	(0.0191)
Worked in one firm only		-0.0019	-0.0062		-0.0040	-0.0021
		(0.0210)	(0.0212)		(0.0193)	(0.0192)
Constant	0.201***	0.670	0.558	0.134***	1.323**	1.384**
	(0.023)	(0.588)	(0.584)	(0.020)	(0.558)	(0.560)
Vacancy char.	No	No	Yes	No	No	Yes
N.obs.	1813	1813	1813	1656	1656	1656
R-squared	0.003	0.005	0.022	0.002	0.008	0.016

Notes: Models 1 to 6 report the results from OLS regressions. Models 1 to 3 include women only, and models 4 to 6 include men only. Cluster-robust standard errors at the vacancy level are shown in parentheses. Dependent variable in all regressions is a dummy that takes on the value 1 if the applicant is invited for an interview. Variable SE skills takes on the value 1 for treatment CVs, 0 otherwise. Vacancy characteristics include total number of applications for the vacancy, occupational clusters and location. Symbols ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

4 Discussion and Conclusions

Economics literature has clearly demonstrated that socioemotional skills are important in determining earnings, but it is not obvious whether socioemotional skills matter during hiring. Focusing on the hiring stage, this study answers whether and how these skills should be signaled for male and female candidates. Our results suggest that signaling a socioemotional skill increases the probability of receiving a callback only if the skill is specifically solicited in the vacancy text. There is also a penalty for female applicants: if they signal a skill not asked for, their probability of receiving a callback decreases; the same penalty does not apply to men.

Our unique data set allows us to open the black box of candidate screening, and we investigate the importance of gender in all three stages of employer screening: making the longlist, clicking on a candidate's CV, and inviting a candidate for an interview. We find that some employers indicate a preference for women when making the longlist, and that gender discrimination does not exist conditional on candidates making it to the longlist. Interestingly, this result suggests that candidate's beauty does not play a role in gender preference of employers, since employers are simply not able to filter using beauty, and the photos of applicants are not visible at this stage.[27]

Our results imply that for socioemotional skill signals to help in securing job interviews and advance through the hiring process, one must be careful on when and which skills to include in the CVs. A CV tailored only to the candidate's qualifications, at least in terms of socioemotional skill signals, may backfire in the job hunt even though the candidate may in fact have quite strong socioemotional skills that would be useful for the jobs he or she is after. This is especially true for female applicants, whom employers seem to punish for adding unsolicited socioemotional skills. Previous literature suggests that women and men have different traits on risk aversion, competition, negotiation, and aversion to have overestimated themselves (Babcock and Laschever, 2009; Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Dohmen and Falk, 2011; Ludwig et al., 2017). Women are also less likely to be overconfident compared to men (Lundeberg et al., 1994; Barber and Odean, 2001). Employers may then expect female candidates to be less overconfident compared to the male candidates with similar characteristics. Arguably, a candidate who includes a socioemotional skill signal not specifically asked for in the vacancy may be evaluated as overconfident by the employer. If the candidate is female, employers may evaluate the signals negatively because they evaluate her overconfidence negatively, whereas male candidates are expected to show overconfidence in their CVs, pointing to another expression of the double bind women face in the labor market, where women need to tailor their CVs much more than men do.

While our results provide a detailed assessment of whether and how socioemotional skill signals may be useful (or detrimental) in the hiring stage, we can observe what happens only before the interview stage. It is plausible that employers evaluate socioemotional skills of applicants during the interview through specific tests or questions. In this sense, the signaled socioemotional skill signals may be valuable conditional on making it to the interview stage; this would imply that the effects we find are underestimates of the total effects of socioemotional skills in recruitment. It may also be the case that employers value all socioemotional skill signals, but again, conditional on making it to the interview. Unfortunately, these two aspects cannot be investigated using our design and methodology, but they present valuable opportunities for future research.

[27] Hamermesh and Biddle (1994); Barry (2000); Mobius and Rosenblat (2006); Scholz and Sicinski (2015); Doorley and Sierminska (2015) find beauty affects earnings, Deryugina and Shurchkov (2015) find that it does so only when beauty is expected to matter for performance, López Bóo et al. (2013) find that attractiveness increases invitations for interview.

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Appendix A: Objective and subjective beauty scores

Photos are commonly used in the online job portals in Turkey. In order to reflect this aspect in our applications, we followed the following procedure to generate candidates' photos.

Source: The photos used in the experiment are generated using volunteer face shots of Italian and Turkish males and females aged 22 to 30. All collected face shots were taken either by a photographer or the volunteers themselves, and each volunteer signed an informed consent form before sharing his/her photos with us. The photos collected in this manner were handed over to a graphic designer, who created sets of new photos. None of the photos was exactly the same as the real versions, but pieces of several photos were used to create fictitious photos using Photoshop. The photos obtained were then grouped according to their gender, and then two different measures of beauty and attractiveness were collected for each of the photos. The following parts explain the definition and measurement of the two different beauty scores, and the procedure used to eliminate potential biases resulting from differences in attractiveness.

Objective beauty scores: This measure is the attractiveness score based on the face shape, distance between the eyes and lips, mouth size and face symmetry, using the golden ratio where appropriate. It goes in a scale of 0 to 100, and scores were allocated using the software at www.prettyscale.com.

After the scores were collected, photos that had a rating that was too high (above 0.89) or too low (less than 0.45) were removed from the set, resulting in the removal of 7 photos. Then, the sets of male and female photos were compared in terms of the mean and the distribution. In order to make the minimum and maximum values similar for males and females, we deleted the male photos that had an objective beauty score above 0.82, and female photos that had an objective beauty score below 0.58, resulting in the deletion of 25 photos in total.

The objective beauty score depends solely on the placement of facial features without any reference to details such as hair color, color of the eyes and other features that may affect how beautiful the person in the photo is perceived. Moreover, whereas the objective beauty scores do not change according to country, individuals from different countries are known to have different conceptions of beauty.[28] This is why we also collected data on a second measure that we call the subjective beauty score, provided in the next part.

Subjective beauty scores: This measure represents the average beauty scores obtained from the ratings collected through an online survey conducted in Turkey distributed through the Twitter accounts of the World Bank Turkey Office and the Economic Policy Research Foundation of Turkey (TEPAV).

The first page of the online survey included an informed consent form specifying information about the project and the task, and other details including contact details. Participants rated photos from a scale of 1 to 10, 10 being the highest beauty score. On each page, the software showed ten male and female photos in random order. Participants could leave at any moment but were informed that every time they rate a total of 10 photos and click Next or End, their responses would be recorded. The survey was conducted in April 2016 and 384 participants provided a total of 32,676 ratings. On average, a participant rated 85 photos.

Before running the analysis, we eliminated some of the observations: (i) We dropped observations for all respondents under the age of 18, resulting in the deletion of 17 respondents and a total of 1,724

[28] For an example please see the Perceptions of Perfection Across Borders Project conducted by the UK pharmacy Superdrug: https://onlinedoctor.superdrug.com/perceptions-of-perfection/tab.

ratings. (ii) We dropped observations for all respondents that provided the same rating for all photos they viewed, resulting in the deletion of 5 respondents and 91 observations.

Since our aim was to create a set of similar photos for males and females, we removed the photos that had too high or too low average subjective ratings, removing a total of 33 photos and 3,130 observations that had an average subjective rating less than 3 or above 7.[29]

As a result of these stages, the regressions were run using observations from 361 respondents for 237 photos, and a total of 24,392 observations.

The main specification we use throughout the analysis is the following:

$$rating_{ij} = \beta_0 + \beta_1 femalephoto_i + \beta_2 respondent_j + s_1 \qquad (1)$$

To control for objective beauty effects that may account for some of the gender difference in the subjective beauty scores, we also use the following specification where we control for the objective beauty scores:

$$rating_{ij} = \beta_0 + \beta_1 f\ emalephoto_i + \beta_2 respondent_j + \beta_3 beautyscore_i + s_2 \quad (2)$$

where $rating_{ij}$ denotes the subjective beauty rating for photo i from respondent j; $femalephoto_i$ is a dummy that takes the value 1 if photo i is of a female, and 0 otherwise; $respondent_j$ denotes the respondent-specific characteristics, and $beautyscore_i$ denotes the objective beauty score of photo i.

Both equations are estimated using OLS, and the results are shown in the first two columns of Table 1. According to the estimations, both specifications show a significantly higher rating for female photos in the sample. Given this result, we decided to select a subsample of the set so that the distribution of average subjective beauty scores for each gender is similar and use that subsample in our experiment. In order to do that, we first need to find the influential observations, and remove the photos that cause these influential observations.

The measure we use is DFBETA, which measures how much impact a particular observation has in the regression coefficient of an explanatory variable. DFBETA computes the difference in β2 for all observations when that particular observation is and is not included in the data, therefore computing the influence of that particular observation on *femalephoto*. We generate the DFBETAs for each observation that contributes to the significance of *femalephoto*, using Model 2 above. We then get the average DFBETAs for each photo and rank them in terms of the magnitude of the influence and delete the most influential photos from our sample until we obtain an insignificant coefficient for the variable *femalephoto* in the estimation of Model 2.

The final selection includes 99 female and 101 male photos. Models 1 and 2 are run using the observations for these selected photos show an insignificant coefficient for the variable *femalephoto*, as shown in the third and the fourth columns of Table 14.

Finally, we demonstrate that the unconditional means and the distributions of both the objective and the subjective measures of beauty are statistically the same between the male and female samples, using nonparametric tests. Table 15 outlines the results. The results show the tests fail to reject that the female and male objective and subjective beauty measures have the same means. Similarly, the Wilcoxon-Mann-

[29] About two standard deviations around the mean.

Whitney test cannot reject the null that the distributions of the male and the female subjective and objective beauty scores are the same. Figure 3 provides four examples of photos used in the experiment, two each for two genders with low and high subjective and objective beauty scores.

Table 15: Regression results

	All photos		Photos selected for the experiment	
	(1)	(2)	(3)	(4)
femalephoto	0.143***	0.143***	0.031	0.028
	(0.023)	(0.023)	(0.025)	(0.025)
beautyscore		0.025		0.542***
		(0.156)		(0.168)
Constant	5.500***	5.483***	4.000***	3.615***
	(1.069)	(1.074)	0	-0.12
Observations	24,392	24,392	20,573	20,573
R-squared	0.37	0.37	0.377	0.377

Respondent-specific characteristics are included in all regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: Tests for the unconditional means and distributions for the objective and subjective beauty measures

	Two-tailed t-test	Wilcoxon-Mann-Whitney test statistic
Subjective beauty scores	-0.3045 (0.7611)	-0.527 (0.5985)
Objective beauty scores	-0.3984 (0.6908)	0.296 (0.7673)

Note: p-values are given in parenthesis.

Figure 3: Examples of male and female photos

Female lower score   Female - higher score   Male lower score   Male - higher score

Appendix B: Determining the socioemotional skill signals

Step 1: Literature survey

Six occupational themes (i.e. RIASEC -Realistic, Investigative, Artistic, Social, Enterprising, and Conventional occupation themes; Holland, 1959, 1997) form the basis of all occupational classifications. This model specifies what common activities underlie each occupational theme and outlines corresponding personalities and interests that would fit each theme. RIASEC themes are used by vocational counselors and Human Resource specialists to assess person-occupation fit for job matching.

We identified 52 occupational groups and 15 industries that can be described using the six RIASEC themes. Based on the dominant activities and job requirements, each occupation can be summarized with a two-theme of three-theme code. For example, engineering occupations involve dealing with tools and machines and also researching and identifying the most optimum design, thus they typically have a Realistic-Investigative (RI) code. Codes reveal what interest and personality characteristics (including socioemotional skills) are most important to be successful and satisfied in that occupation. We categorize the occupational groups identified by the project team under the RIASEC themes. This was accomplished using the Occupational Information Network (O*NET; www.onetonline.org); an online database compiling years of research and accumulated knowledge on work characteristics and related abilities, personality, and vocational interests based on the Dictionary of Occupational Titles (US Department of Labor, 1991) and the Dictionary of Holland Occupational Codes (Gottfredson & Holland, 1996). Occupations were then matched with the corresponding personality characteristics from the O*NET and also from studies of the 16 Personality Factor model (Conn & Rieke, 1994).

Step 2: The reverse audit study

In this step, we collaborated with a private company in Kocaeli, Turkey, neighboring one of our study provinces (Istanbul). The company was in the process of hiring for two positions, a Customer Relations Manager (CRM) and a Human Resources Specialist (HR). We added the socioemotional skill descriptors we obtained from Step 1 above to these job ads, collected anonymized CV information from the company, and information on which one of the CVs belonged to candidates invited to interviews.

CVs of applicants were analyzed and coded in terms of the socioemotional skills constructs signaled (e.g. leadership), how they were signaled, the type of signal used (adjective, activity or ambiguous), and the section of the CV where it was signaled (e.g. abilities). In coding the type of signal, signals were categorized as "adjective" if the applicant explicitly used adjectives to describe self. Signals were coded as "activity" as long as the applicant provided an experience or an activity that demonstrates the utilization of the signaled skills. The "ambiguous" category was used to refer to completed seminars or certificates related to developing a specific socioemotional skill. In such cases the applicant is not claiming to have developed the skill (unless indicated elsewhere) and there is no experiential indication of such.

The analyses of coded data included how many of the socioemotional skill signals were mentioned, signal type, CV section, and gender. Counts were obtained based on the number of data points including multiple entries by one person, and also based on the number of CVs.

The CRM position ad was soliciting for applicants with the socioemotional skills of strong communication, teamwork orientation, open to continuous self-development and novel approaches, adaptability to dynamic work contexts, strong persuasion skills, and leadership skills (even though the ad only specified leadership skills, managerial skills were also coded as relevant for the job). It received 184 applications. The HR position ad was soliciting for applicants with the socioemotional skills of communication, teamwork, openness to continuous self-development, planning/organization, following through (goal-orientation), detail-oriented, sense of responsibility, and adaptability with a total of 535 applicants. Analyses by Gender and Solicited SE skills for both Positions CVs of 89 men and 95 women applicants were analyzed for the CRM position and 188 men and 347 women applicants were analyzed for the HR position. Table 16 displays the percentage of men and women in terms of providing the solicited signals.

Table 17: Socioemotional signals by candidates

	Ambiguous	Adjective	Activity	Any
Customer Relations				
Women (N = 95)	31.6%	10.5%	9.5%	51.6%
Men (N = 89)	27%	0%	12.4%	39.3%
Total (N = 184)	29.3%	5.4%	10.9%	45.7%
Human Resources				
Women (N = 347)	14.4%	13.5%	6.1%	34%
Men (N = 188)	6.9%	17%	2.1%	26.1%
Total (N = 535)	11.8%	14.8%	4.7%	31.2%

Appendix C: Examples of socioemotional skill signals used

Table 18: Socioemotional skill signals used in the experiment

Occupation cluster	Socio-emotional skill	Taglines		Job descriptions		Additional extracurricular activity (T)
		Control	Treatment	Control	Treatment	
Accounting	Detail orientation, organization, communication	Accountant with more than XX years of experience Have reliable and sufficient knowledge on preparing ac- counting tables and memorandums	Detail-oriented in preparing accounting tables and memos. Accountant who can maintain continuous communication and get the assigned tasks done in an organized and timely manner.	Recording day-to-day financial transactions in the system using the uniform chart of accounts. Prepared the reports on accounting records, profit and loss statement. Presented financial reports and specific budgets. Processing the ledger entries to ensure all business transactions are recorded.	Effectively communicated with clients to determine payment schedules with them that were in line with the company's needs. Preparation of financial sheets and statements ac- cording to the legislation and accounting and financial guidelines. Closing the accounting records in the first five days of the month by organizing the required documents for records. Detailed and careful current account settlements with customers and suppliers.	Worked on accurately recording hundreds of students' contact information during the university's open house.
Marketing	dynamic, teamwork, persuasion	I am a marketing specialist, graduated from the Business Administration Department of XX University, who can effectively determine the market needs and develop strategies accordingly.	I am a specialist who has developed effective marketing strategies by using my dynamism and persuasion skills through my work experience. I have teamwork experience in the tasks I took part in since my undergraduate education.	Identifying new market opportunities based on market analyses. Experienced in working on preparing online marketing materials. Participation in the development of marketing campaigns for a variety of products and services. Experienced in using the reporting and analysis tools.	As an active member of a team of specialists from related departments, preparing new brands, identifying regional marketing activities and campaigns/sales. Took part in the preparation of written and visual materials for media campaigns. Conducting marketing campaigns by having frequent meetings with press organs, organizing all related processes. By carrying out marketing analytics and persuading the team to include new media strategies based on target	Volunteered in a team of 10 at the XX National Youth Work Camp.

Occupation cluster	Socio-emotional skill	Taglines: Control	Taglines: Treatment	Job descriptions: Control	Job descriptions: Treatment	Additional extracurricular activity (T)
					demographics, I contributed to the social media outreach.	
Sales	persuasion, networking, teamwork	I am a sales representative who can successfully transfer the technical knowledge and skills to have the firm meet its sales goals. With an experience of more than XX years.	Able to form networks and use persuasion skills to the extent of improving firm's sales. A good team member who strives to determine the customer needs accurately.	Identifying customer demands and present ways to improve sales volume. Including new customers in the customer portfolio to meet sales targets. Meeting with customers to enable the coordination and cooperation between the company and the customers. Worked on preparing timely sales reports.	Persuaded current customers to try new products, thus enabled surpassing targeted sales volume and profit. I was selected for explaining new staff members on how to effectively communicate with clients during the initial orientation. Making offers to customers for sales by meeting them. I worked in close coordination with the marketing team and provided timely feedback about customer preferences.	Participated in regional debate tournaments.
IT	detail orientation, perseverance teamwork	IT specialist, with the experience and knowledge to improve the success of the firm, who has an experience of XX years with problems in software/ hardware, internet and servers.	A determined IT specialist who can coordinate with the team members and can provide detailed solutions to the problems that may occur in servers, internet, software and hardware.	Maintenance and control of internet servers for secure and reliable performance. Configuration of system network components, installation and monitoring routers and the LAN/WAN network environment. Maintenance and update of company web page and software and applications used. Providing support for technical failures with equipment such as PC, printer or scanners.	Persevered to identify un- known sources of server failures by searching for new technological updates. Installed and configured secured networks. Analysis of company software in detail and identification of errors and providing solutions. Working as a team in coordination and identifying deficiencies and supplying the necessary hardware.	Worked on complete (accurate) entry of university personnel information into the database.

Note: The CVs were constructed in Turkish. The translations included here are for information purposes.

Appendix D: Conditional balance tables

Table 19: Balance table for gender treatment, conditional on applicant being in the longlist

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.185	0.183	-0.002
	(0.388)	(0.387)	(0.009)
Istanbul Asia	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Istanbul EU	0.506	0.509	0.003
	(0.500)	(0.500)	(0.011)
Experience (months)	49.041	49.498	0.457
	(5.588)	(5.664)	(0.129)***
Age	26.786	26.053	-0.733
	(0.561)	(0.506)	(0.012)***
Accounting	0.259	0.261	0.002
	(0.438)	(0.439)	(0.010)
Marketing	0.286	0.286	-0.000
	(0.452)	(0.452)	(0.010)
Sales	0.315	0.313	-0.001
	(0.464)	(0.464)	(0.011)
IT	0.140	0.140	0.000
	(0.347)	(0.347)	(0.008)
Worked in one firm only	0.278	0.247	-0.031
	(0.448)	(0.431)	(0.010)***
Objective beauty	0.928	0.965	0.037
	(0.259)	(0.185)	(0.005)***
Subjective beauty	0.451	0.550	0.099
	(0.498)	(0.498)	(0.011)***
Reading	4.575	4.562	-0.013
	(0.494)	(0.496)	(0.011)
Speaking	4.519	4.525	0.006
	(0.500)	(0.499)	(0.011)
Writing	4.522	4.499	-0.023
	(0.500)	(0.500)	(0.011)**
Total application size (100)	5.170	5.184	0.014
	(8.036)	(8.144)	(0.185)
Signaled SES required in vacancy	0.657	0.654	-0.003
	(0.475)	(0.476)	(0.011)
Besiktas	0.452	0.456	0.003
	(0.498)	(0.498)	(0.011)
Kadikoy	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Kagithane	0.054	0.054	-0.000
	(0.226)	(0.225)	(0.005)
Cankaya	0.185	0.183	-0.002
	(0.388)	(0.387)	(0.009)
Observations	3,845	3,809	7,654

Notes: Standard errors are given in parentheses. Symbols ∗ ∗ ∗, ∗∗, and ∗ indicate significance at the 1%, 5% and 10% level, respectively.

Table 20: Balance table for gender treatment, conditional on applicant's CV clicked

Variable	(1) Males	(2) Females	(3) Difference
Ankara	0.200	0.197	-0.003
	(0.400)	(0.398)	(0.014)
Istanbul Asia	0.316	0.308	-0.008
	(0.465)	(0.462)	(0.016)
Istanbul EU	0.484	0.495	0.011
	(0.500)	(0.500)	(0.017)
Experience (months)	48.816	49.577	0.761
	(5.575)	(5.585)	(0.190)***
Age	26.756	26.052	-0.704
	(0.568)	(0.502)	(0.018)***
Accounting	0.209	0.204	-0.005
	(0.407)	(0.403)	(0.014)
Marketing	0.239	0.243	0.004
	(0.427)	(0.429)	(0.015)
Sales	0.317	0.350	0.033
	(0.465)	(0.477)	(0.016)**
IT	0.235	0.203	-0.032
	(0.424)	(0.402)	(0.014)**
Worked in one firm only	0.275	0.269	-0.006
	(0.447)	(0.444)	(0.015)
Objective beauty	0.938	0.961	0.024
	(0.242)	(0.193)	(0.007)***
Subjective beauty	0.462	0.538	0.076
	(0.499)	(0.499)	(0.017)***
Reading	4.550	4.559	0.010
	(0.498)	(0.497)	(0.017)
Speaking	4.505	4.530	0.025
	(0.500)	(0.499)	(0.017)
Writing	4.520	4.500	-0.020
	(0.500)	(0.500)	(0.017)
Total application size (100)	4.548	4.365	-0.183
	(6.456)	(5.805)	(0.208)
Signaled SES required in vacancy	0.677	0.673	-0.004
	(0.468)	(0.469)	(0.016)
Besiktas	0.389	0.415	0.025
	(0.488)	(0.493)	(0.017)
Kadikoy	0.316	0.308	-0.008
	(0.465)	(0.462)	(0.016)
Kagithane	0.095	0.081	-0.014
	(0.293)	(0.272)	(0.010)
Cankaya	0.200	0.197	-0.003
	(0.400)	(0.398)	(0.014)
Observations	1,656	1,813	3,469

Notes: Standard errors are given in parentheses. Symbols ∗ ∗ ∗, ∗∗, and ∗ indicate significance at the 1%, 5% and 10% level, respectively.

Table 21: Balance table for socioemotional skills treatment, conditional on applicant being in the longlist

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.185	0.183	-0.002
	(0.388)	(0.386)	(0.009)
Istanbul Asia	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Istanbul EU	0.506	0.510	0.004
	(0.500)	(0.500)	(0.011)
Experience (months)	49.296	49.240	-0.056
	(5.548)	(5.711)	(0.129)
Age	26.422	26.420	-0.002
	(0.642)	(0.654)	(0.015)
Accounting	0.259	0.261	0.002
	(0.438)	(0.439)	(0.010)
Marketing	0.287	0.285	-0.002
	(0.452)	(0.452)	(0.010)
Sales	0.314	0.314	-0.001
	(0.464)	(0.464)	(0.011)
IT	0.140	0.140	0.000
	(0.347)	(0.347)	(0.008)
Worked in one firm only	0.255	0.270	0.015
	(0.436)	(0.444)	(0.010)
Objective beauty	0.944	0.948	0.004
	(0.230)	(0.222)	(0.005)
Subjective beauty	0.508	0.493	-0.015
	(0.500)	(0.500)	(0.011)
Reading	4.576	4.561	-0.015
	(0.494)	(0.496)	(0.011)
Speaking	4.510	4.534	0.025
	(0.500)	(0.499)	(0.011)**
Writing	4.515	4.506	-0.008
	(0.500)	(0.500)	(0.011)
Total application size (100)	5.167	5.186	0.019
	(8.084)	(8.095)	(0.185)
Signaled SES required in vacancy	0.654	0.656	0.002
	(0.476)	(0.475)	(0.011)
Besiktas	0.452	0.456	0.004
	(0.498)	(0.498)	(0.011)
Kadikoy	0.309	0.308	-0.001
	(0.462)	(0.462)	(0.011)
Kagithane	0.054	0.054	-0.000
	(0.226)	(0.225)	(0.005)
Cankaya	0.185	0.183	-0.002
	(0.388)	(0.386)	(0.009)
Observations	3,831	3,823	7,654

Notes: Standard errors are given in parentheses. Symbols ∗ ∗ ∗, ∗∗, and ∗ indicate significance at the 1%, 5% and 10% level, respectively.

Table 22: Balance table for socioemotional skills treatment, conditional on applicant's CV clicked

Variable	(1) Control	(2) Treatment	(3) Difference
Ankara	0.194	0.203	0.009
	(0.395)	(0.402)	(0.014)
Istanbul Asia	0.315	0.309	-0.006
	(0.464)	(0.462)	(0.016)
Istanbul EU	0.492	0.488	-0.003
	(0.500)	(0.500)	(0.017)
Experience (months)	49.322	49.101	-0.220
	(5.512)	(5.674)	(0.190)
Age	26.388	26.388	-0.001
	(0.632)	(0.648)	(0.022)
Accounting	0.202	0.211	0.008
	(0.402)	(0.408)	(0.014)
Marketing	0.244	0.238	-0.005
	(0.429)	(0.426)	(0.015)
Sales	0.336	0.333	-0.003
	(0.472)	(0.471)	(0.016)
IT	0.218	0.218	0.000
	(0.413)	(0.413)	(0.014)
Worked in one firm only	0.267	0.278	0.011
	(0.442)	(0.448)	(0.015)
Objective beauty	0.949	0.952	0.003
	(0.221)	(0.215)	(0.007)
Subjective beauty	0.516	0.487	-0.030
	(0.500)	(0.500)	(0.017)*
Reading	4.549	4.560	0.011
	(0.498)	(0.496)	(0.017)
Speaking	4.505	4.531	0.026
	(0.500)	(0.499)	(0.017)
Writing	4.510	4.509	-0.000
	(0.500)	(0.500)	(0.017)
Total application size (100)	4.366	4.542	0.176
	(5.679)	(6.559)	(0.208)
Signaled SES required in vacancy	0.673	0.677	0.004
	(0.469)	(0.468)	(0.016)
Besiktas	0.403	0.402	-0.001
	(0.491)	(0.491)	(0.017)
Kadikoy	0.315	0.309	-0.006
	(0.464)	(0.462)	(0.016)
Kagithane	0.089	0.086	-0.002
	(0.284)	(0.281)	(0.010)
Cankaya	0.194	0.203	0.009
	(0.395)	(0.402)	(0.014)
Observations	1,774	1,695	3,469

Notes: Standard errors are given in parentheses. Symbols ∗ ∗ ∗, ∗∗, and ∗ indicate significance at the 1%, 5% and 10% level, respectively