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Working Paper No. 1373

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Binnur Balkan[1] and Seyit Mumin Cilasun[2]

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Send correspondence to:
Binnur Balkan
Stockholm School of Economics
binnur.balkan@phdstudent.hhs.se

[1] Stockholm School of Economics, Stockholm, Stockholm County, Sweden.

[2] Structural Economic Research Department, Central Bank of the Republic of Turkey, Istiklal Cad. No:10, 06050 Ulus, Ankara, Turkey. Atilim University and ERF. seyit.cilasun@atilim.edu.tr

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Abstract

In this study, we conduct a multiple identity correspondence audit study that we ran in a Muslim majority, developing country. To do that, we bring ethnicity and religiosity into a gender correspondence audit. We also introduce two new measure of discrimination to literature, and show that there is no gender discrimination at the intermediate steps of the hiring process. We find positive discrimination in favor of females at the callback stage but only if they belong to the neutral group. When we interact ethnicity and religiosity with gender, we see that favorable treatment of females disappear for Kurdish and religious females. Hence, we show that it is important to keep multiple identities in mind when conducting correspondence audit studies.

Keywords: Gender discrimination; correspondence audit; field experiment.
JEL Classifications: J71, J21, C93.

1 Introduction

Women still fare worse than men in the labor market in developed and developing countries alike. They face lower labor force participation as well as higher unemployment rates (WorldBank (2018)). A part of these gaps might be attributable to gender discrimination in the labor market. However, it is not straightforward to quantify discrimination via observational data as Bertrand and Duflo (2016) states clearly. However, correspondence audits provide causal estimates of discrimination, where observational data might fail to deliver.

Correspondence audits use fictitious job applicants to apply for real job openings. Fictitious applicants differ systematically only in limited dimensions to match candidates as closely as possible but to reflect group identity. In correspondence audits, the difference in employer communication - mainly callbacks - is attributed to discrimination given there is no reason for the differential treatment of candidates besides their group identity.

In this paper, we investigate the hiring stage discrimination from a multiple identity perspective in a correspondence audit study that we ran in a Muslim majority, developing country. To do that, we first created random fictional resumes with similar qualities and assigned carefully selected neutral, Kurdish, and religious names to those resumes. With these resumes, we applied for vacancies in a commonly used online job portal in Turkey, namely kariyer.net. We sent applicant resumes in quadruplets in two different treatments. In the first treatment, we sent two neutral candidate resumes, one male-one female together with one Kurdish male and one Kurdish female resumes. In the religiosity treatment, we add one religious female resume and one religious male resume to neutral candidates.

We focused on entry-level jobs, which do not require experience or references from the previous employers. Moreover, we only applied for vacancies in İstanbul, which is the biggest market in Turkey.

After the applications, we keep track of three separate hiring outcomes. The first one is the listing of resumes. In this measure, we tracked the automated messages sent out by the online job application portal. We get these messages if the employer filters and lists our fictitious resumes among other candidates. If employers using gender as a filtering tool, we should be able to see it in the listing measure.

The second outcome is the status of our fictitious resumes on the job portal. We tracked whether a potential employer opens our fictitious resumes by another automated message. This is a stronger signal of interest than the aforementioned listing measure since it requires a little more effort from the employer. Moreover, unlike listing, screening is candidate specific. It is important to note that listing or screening a resume is an early step of employer interest in our fictitious candidates and might or might not be followed by an interview request. Finally, the final measure is the standard measure used in the literature, namely callbacks. We keep a record of interview request by the employer via phone and name it the callback.

We show that there is no gender discrimination at listing and screening stages. There is positive discrimination in favor of females at the callback stage but only if they belong to the neutral group. Ethnicity and religiosity interact with gender in our study, and favorable treatment of females in callbacks disappears for Kurdish and religious candidates.

Our contribution to the literature is multifold. First, we are introducing two new metrics of discrimination to the literature. These new measures help us to understand when differential treatment of candidates appears during the hiring process. On top of that, callback rates are generally quite low. But, listing and screening rates in our study go as high as 70 percent, which is a major improvement in terms of number of observations. Additionally, we run a multiple identity correspondence audit. We show that ethnic and religious identities matter for gender discrimination, which is an overlooked feature in correspondence audit literature. Finally, this is one of the few correspondence audit studies carried in a developing market, in a Muslim majority country, and the first one is in Turkey to the best of our knowledge.

The rest of the paper is organized as follows. First, we will lay out the related literature in the following subsection. Then, we briefly familiarize the reader with the labor market conditions of youth in Turkey. In the third chapter, we explain our experimental design in depth and clarify how we keep track of the employer response. In the fourth chapter, we will present our data. Finally, we will go through our findings in the fifth chapter and conclude the paper.

1.1 Literature Review

There is growing literature relying on the correspondence audit methodology, studying gender discrimination at the hiring stage. Baert (2017) provides an excellent overview of correspondence audit studies since 2005 [1]. He reports eleven studies, which focus extensively on gender discrimination from a male-female perspective like our study. Among these studies, there is only one study conducted in a developing country, namely China. The results are mixed among

[1] Rich (2014) also provides a review of studies prior to 2005 for interested readers.

these studies, four studies report positive discrimination in favor of females, five studies report null result, and finally, two studies report discrimination against females.

Our results are in line with both positive discrimination and null result studies. We find positive discrimination in favor of females but only for neutral applicants. For Kurdish and religious applicants, we side with the null result studies and find no gender discrimination. Hence, we bring conflicting results from the literature together and show that multiple identities matter in quantifying discrimination.

Our work talks to three strands of newly growing correspondence audit literature; namely 1) attention discrimination, 2) multiple identity correspondence audits, which are bringing race, ethnicity or religion into gender discrimination, and finally, 3) gender correspondence audits conducted in a developing country context.

The attention discrimination refers to the case where minority and majority applicants get different attention in the hiring process. The difference can be time spent on resumes but also the bits of resumes screened by the prospective employers. For example, employers might spend more time reading the qualifications of majority applicants and end up believing they are more qualified than minority applicants as a result. Bartos et al. (2016) provides theory and field evidence of attention discrimination, both in the labor and the housing markets. They show that information acquisition behavior changes when prospective employers face a minority resume. We add an observation to their finding by showing that employers interact with male and female applicants' resumes similarly. They filter and click resumes at same rates, so they do not discriminate when they are interacting with the applicants from different genders. However, it is important to note that we do not observe which parts of the resumes are getting attention from employers or how much time employers spend on male and female resumes. Hence, similar clicking and screening rates do not eliminate the possibility of attention discrimination as it is defined in Bartos et al. (2016).

Multiple identity discrimination is a phenomenon which is slightly overlooked by the correspondence audit literature so far, and this indifference might be one of the reasons behind the conflicting results in the literature. As Zschirnt and Ruedin (2016) state in their meta-analysis keeping gender in mind while studying ethnicity discrimination matters as discrimination coefficients differ significantly among men and women. Similarly, considering ethnic or religious background might matter when studying gender discrimination. We precisely do that and show ethnicity and religiosity indeed matter for discriminatory outcomes. Discrimination in favor of neutral women does not translate into discrimination in favor of Kurdish women and religious women.

Finally, we are linked to developing country and Muslim majority country audit studies, which are also rare in the literature. We are aware of two developing country correspondence audit studies in the literature. There are also no studies conducted primarily Muslim countries. In a study for China, Zhou et al. (2013) sent resumes to accounting, IT, marketing and secretary positions and find statistically significant discrimination in all the jobs but IT. While the rate of discrimination is 9 percent in favor of men for accounting applications, it is 20 percent and 40.2 percent in favor of women in marketing and secretary applications, respectively. Galarza and Yamada (2014) study focuses on the Peruvian labor market, and the authors find that native people are discriminated in the labor market. Hence, our study is one of the very first gender correspondence audits in a developing country and the first in a Muslim-majority country to the best of our knowledge. We believe studying gender discrimination in developing countries (and Muslim countries) is important given different labor market institutions, norms and regulations govern these markets. For example, anti-discrimination laws in Turkey are weak and not broadly applied. Moreover, conservative groups generally do not welcome females' integration into the labor market in Turkey. Hence, discriminatory outcomes, as well as policy recommendations to fight discrimination, might differ significantly in developing countries and predominantly Muslim countries.

All in all, our study contributes to growing correspondence audit literature by providing evidence from a predominantly Muslim developing country in a multiple identity perspective. More importantly, we do that by generating additional measures of employer response. We show that there is no gender discrimination prior to callbacks during the hiring process. There is positive discrimination in favor of females at the callback stage but only if they belong to the neutral group. Hence, measured gender discrimination might not reflect the population averages if ethnicity and religiosity aspect are not accounted for correctly. In the following section, we will discuss the youth labor market conditions in Turkey and explain how harsh is the labor market conditions, especially for young females.

1.2 Institutional Background

As our fictitious applicants are fresh college graduates who are 22-23 years old, it would be useful to discuss the youth education and labor market conditions for the youth. As of 2016, around thirteen million individuals, 13.6 percent of the population, are aged between 15 and 24. The share of the youth population is still higher than the OECD average albeit there is a decline in recent years.

A schooling reform in 1997 raised compulsory schooling from 5 to 8 years. In turn, education levels of youth increased significantly in Turkey. For instance, the high school graduation rate of 18 to 24 years old people increased from 49 percent to 61 percent between 2009 and 2016. Even more starkly, the college graduation rate is more than doubled and increased from 6 percent to 13 percent for the same age group. It is important to note that this jump is more pronounced for women. As of 2016, the college graduation rate is higher for women than men, 15 percent and 11 percent respectively, for 18-24 years old people in Turkey (Akgunduz et al. (2017)).

An expected outcome of the rise in the education level is the increase in the labor force participation, particularly for women. However, although the female labor force participation increased, the reform did not close the female labor force participation gap in Turkey. Youth labor force participation is 55.3 percent for males and 30.4 percent for females, amounting to 15 percent gender gap in the labor force participation of youth. On the other hand, the share of women who are not in employment, education or training (NEET) decreased from 45 percent to 33 percent between 2009 and 2016, which is a promising development for the future labor market outlook of young women.

Youth employment follows the labor force participation albeit at a slower pace. Youth employment reached 23 percent for females and 45 percent males in 2016. Together with faster increasing participation rates, this also means youth unemployment increased significantly in recent years, exceeding 20 percent for young women as of 2016. The unemployment rate is even higher for college graduate females, which was 35.4 percent in 2016.

All in all, it is clear that young women are disadvantaged in the Turkish labor market compare to young men. Although they have comparable levels of education, they face lower labor market attachment and higher unemployment probabilities. So far, we did not mention anything related to ethnicity or religiosity, and that is no coincidence. It is not possible to observe ethnic origin or the religion of individuals in any official survey in Turkey due to legal prohibition. To overcome this constraint, we utilize a field survey which was held in 2010.[2]. The survey asks the participants their mother tongue, which is a commonly-used proxy for the ethnicity. Using this information, we divide households to Turkish and Kurdish subgroups [3].

Similarly, we use two survey questions to determine religiosity. The first question is the denomination. By this question, we restrict the sample to Sunni people, which is around 72 percent of the respondents. However, reporting Sunni denomination is not necessarily equal to being religious. To overcome this problem, we use another question, which focuses on ideas about religious practices [4]. If the respondent states it is not okay to skip worship, we assign them into religious category. We assign all other respondents into nonreligious category [5].

In Figure 1, we report university graduation rates for different subgroups. It is clear that graduation rates are higher for males than females in all subgroups [6]. The gender gap is especially pronounced

[2]The survey measures social change in Turkey and is conducted under the auspices of Yeditepe University. It covers 1333 households and 5386 respondents. The sample was determined through a multistage stratified cluster sampling technique. At the last step of the sampling process, households were randomly selected by the Turkish Statistical Institute (TURKSTAT). The survey is representative of the Turkish population.

[3]We assign everyone who reports Kurmanci, Sorani, Kelhuri, or Zazaish as their mother tongue Kurdish group. Anyone who reports Turkish as their mother tongue is assigned to Turkish. That classification leaves other ethnicities outside of the classification

[4]The exact question is the following: “Thinking about today’s daily life and working conditions, do you approve not to worship?”

[5]However, we do not define cross groups between ethnicity and religiosity due to sample size concerns

[6]This contradicts with the official figures from 2016 given this survey is from 2010, and graduation rates of women exceeded that of men during this period

for Kurdish and religious sub-populations. We also observe that Turks have higher educational attainment than both Kurds and religious people.

We see a much bigger gender gap in labor force participation and employment as Figure 2 and Figure 3 depict. Labor force participation for women is as high as 32 percent for Turkish females and as low as 22 percent for Kurdish females [7]. Similarly, the employment rate is as high as 22 percent for Turkish females and as low as 12 percent for Kurdish females. It is clear that Kurdish females are the most disadvantaged group in the Turkish labor market. Similarly, nonreligious women have higher labor force participation than religious women in our data [8].

In short, the gender gap is disappearing in higher education but still wide in the Turkish labor market. Moreover, it is a market characterized by low labor force and high unemployment, especially for women. Kurds are faring worse than Turks, and religious people are faring worse than nonreligious people. A part of these gaps might be due to discrimination, and we explore possible labor market discrimination in this study via a correspondence analysis. There are also several studies discussing gender discrimination in the Turkish labor market. We will now mention these studies briefly.

Dayioglu and Kasnakoglu (1997), Yamak and Topbas (2004), Tansel (2005), Kara (2006) and Cudeville and Gurbuzer (2007) all study gender wage gap in the Turkish labor market. They show that education and experience are important determinants of the gender wage gap, but a non-negligible portion of the wage gap stems from

[7] Low labor force participation of females is also studied extensively in the literature. Interested readers can refer to following work Dayioglu and Kirdar (2011), Ilkkaracan (2012), Toksoz (2011), Ilkkaracan (2012), Dildar (2015)

[8] There is an article in the literature examining the labor force participation of conservative women. Dildar (2015) focuses on the role of social conservatism as a constraint of women's labor force participation using Turkey Demographic and Health Surveys. She finds a significant negative association between women's religious practice and labor force participation unlike

discrimination in Turkey. This early work on discrimination relies on decomposition techniques such as Oaxaca (1973) and Blinder (1973) on survey data. We contribute to these findings by providing causal estimates of discrimination from the correspondence audit methodology.

In short, female labor force participation and gender discrimination literature have established that the gender wage gap is prominent and social structures affect female labor force participation negatively in Turkey. However, it is not possible to infer the size and the existence of gender discrimination from the existing studies. In this paper, we provide the first experimental evidence on hiring stage discrimination against women. In the following section, we will explain our methodology.

2 Experimental Design

In this study, we run a gender correspondence audit. In correspondence audits, seemingly similar fictional resumes are sent out to real job openings as pairs. Then, interview requests, in other words, callbacks from these jobs are counted and compared among paired applicants. In these studies, resume characteristics are matched thoroughly beside discrimination related characteristics. In a correspondence audit, it is possible to study gender, beauty, height/weight, religion, ethnicity, race or sexual preference discrimination among others. For example, in a gender discrimination study, the researcher can signal the sex of the applicant by assigning commonly used male and female names to similar resumes.

There are several advantages of running correspondence audits to measure discrimination in a market over observational studies and laboratory experiments. The prime benefit is that the subjects (firms in the current experiment) are not aware that they are taking part in an experiment. Thus, it is not possible for subjects to change their behavior accordingly. That means correspondence audits help to quantify real magnitudes, free from experimenter demand effects. Moreover, by creating fictional resumes, the differences between applicants can be minimized. This concern is especially important in a setting like ours given that pre-labor market differences are stark among our groups. Additionally, sending a small number of resumes prevents distortion in the labor market. Thus, magnitudes observed in the labor market could be matched in audit studies.

There are two alternatives to correspondence audits. First one is estimating causal effects through survey data. Identifying the source of inequality may not be possible in survey data. For example, assuming we find a difference between men and women' employment rates, the difference might depend on inequality of opportunity in education. Conversely, inequality of opportunity in the labor market during hiring, firing or promotion stages might be the cause. However, in a correspondence audit, it is possible to focus on a single channel and quantify the effects correctly.

Another alternative is audit studies where fictitious applicants take interviews with prospective employers. In audit studies, trained individuals take part in interviews and job offers are counted. Besides being costly and slow; direct audits might carry signals more than the assigned traits. The signal might be the personality, beliefs of trained applicants about their quality, etc. On the contrary, correspondence audits block these channels and produce more reliable estimates.

On the other hand, correspondence audits have their limitations. Most important of all, it is not possible to quantify wage and employment discrimination via correspondence audits. Since it is not possible to get a job offer or a wage offer before finalizing the recruitment process, it is also not possible to identify discrimination in those steps.

Very briefly, we can summarize our experiment as follows. We first assign randomly selected names and surnames to fictional resumes and generate similar quality resumes for female and male applicants. With these resumes, we apply for online job openings. After the application, we monitor the online job portal to see how employers interact with our resumes. First interaction step enables us to produce two intermediate discrimination outcomes, namely listing and screening rates. We also monitor and register calls from employers to produce the correspondence audits' standard measure of discrimination, namely callbacks. In the next section, we will explain the experimental design in detail with a focus on our novel discrimination measures.

2.1 Identity Creation of Fictitious Applicants

The name is the main variation among resumes in our study. We define three male and three female name groups to reflect neutral, Kurdish and religious identity. The names in the neutral group can be used and are expected to be used by any sub-population in the society including the ethnic majority, ethnic minority, religious and nonreligious alike. The second group is Kurdish names. We assign only ethnic Kurdish names into this group. These names are not expected to be used by other groups in Turkey, and they are easy to identify as Kurdish. Finally, we created a religious names group, and we assign strong Muslim or Arabic connoted names to this group. In correspondence audits, names should reflect an affiliation to the group of interest but nothing more than that to identify the source of discrimination correctly. Hence, we aim to achieve this end in our name selection process [9].

For surnames, we have chosen some of the most frequently used surnames in Turkey [10]. These surnames do not signal any geographical, ethnic or religious affiliation since they are commonly used by the different groups of society, in diverse geographical areas [11]. Another benefit of using commonly used surnames is that common surnames make searching for candidates online harder, and reduces the probability of getting caught.

Finally, we randomly matched surnames and names to create fictional applicant identities. In that way, we several names and surnames more than once, and we were able to choose the most reliable names in each category regarding their identity signaling power.

2.2 Application Portal and Resume Characteristics

After creating identities, we assigned phone numbers and unique e-mails to our fictitious candidates. We registered e-mails at Hotmail

[9] To ensure this; we designed a survey to choose our names. For this survey, we first go through vastly used names and surnames in Turkey. Additionally, we collect commonly used Kurdish names and religious names online. After putting all names into a list format, we distribute our survey to college seniors and professionals from social science disciplines and ask them to assign as many traits as they like to names in the list. Our respondents have been told that they can assign any trait to names including but not limited to gender, religiosity or ethnicity related characteristics. After collecting the responses back, we eliminate any name which has been assigned both a religious and an ethnic characteristic by any respondent, as well as any name which has been perceived as both as male and female. We first divide the remaining names into male and female names. Then, we assign these names into neutral, Kurdish and religious categories as follow. We assign a name to the neutral category if more than 80 percent of the respondents either fail to assign a category to a name or they assign only Turkish male or Turkish female. We assign a name to Kurdish (religious) category if more than 80 percent of the respondents mention Kurdish (religious) for that name. In the end, we generate six mutually exclusive list of names: Neutral male, neutral female, Kurdish male, Kurdish female, religious male, and religious female names respectively. A full list of names can be found in Appendix B.

[10] The list of these surnames can be found in Appendix A

[11] Surname Law was passed in 1934 in Turkey and people started to get surnames in 1935. No foreign, ethnic, religious or rank implying words are allowed as surnames. In the end, most common surnames are shared by different ethnicities, as well as religious and nonreligious groups

servers with candidate's name and surname [12].

With these e-mails, we opened accounts at kariyer.net website, which is one of the heavily used online job portals in Turkey. One of the critical aspects of kariyer.net is the redundancy of having a resume template. Applicants fill their information into kariyer.net website, and the website generates generic resumes for all applicants. Hence, resume template bias is not a concern in our study given generic and website generated templates are employed by all applicants.

For our applicants, we specify gender, high school and college education, address, birthplace, and birth date information. Additionally, we checked non-smoker and have driving license boxes on the website for all candidates. For male applicants, we checked completed military service box as well to avoid any concerns regarding compulsory military service in Turkey.

Now, we can go over resume characteristics one by one starting from birth to job search period. We assign close birth dates to all our applicants. Our applicants are on average 22.5 years old, some younger and some older. We utilized birthplace as a second instrument to strengthen ethnicity signal for Kurdish applicants. The birthplace is eastern cities for Kurdish applicants and Western cities for religious and neutral applicants.

We randomly assigned average quality high schools from Istanbul to all our applicants. We determined quality by the high school entrance exam cutoffs. Similarly, we assign average quality colleges randomly to all applicants, and we assigned business major to all of them. Again, the quality was determined by the entrance exam cutoff. A list of colleges and college locations can be found in Appendix C.

[12] When it is not possible to register *name_surname@hotmail.com*, we add several random integers to name and surname combination

So far, we matched our applicants in pre-labor market outcomes closely. All applicants are 22-23 years old, attended similar and randomly assigned high schools and colleges. Due to high school location, they spent at least high school years in Istanbul. Finally, we match our applicants during the job search period. To do that, we assigned addresses from similar neighborhoods in Istanbul to all applicants. We differentiate between Anatolian and European sides when assigning addresses because it is an important job search parameter in Istanbul. If the vacancy is on the European side, we apply to that vacancy with a European side address and vice versa [13]. Finally, we did not assign any prior experience to our resumes. Now we have resumes, we are ready to apply for job openings on kariyer.net portal.

2.3 Vacancy Selection and Applying for Vacancies

We used the following algorithm to choose vacancies. First, we limited our interest in Istanbul. Istanbul had roughly half of the vacancies available on the job portal, and it is the largest market in the country. Then, we further limited our interest to entry-level jobs (no experience required), which are suitable for all college graduates (no specific college major requirement). Finally, we chose new advertisements on the website, which were published in the last three days. We applied for all the vacancies that survive the above filtering process.

In the end, we cultivated vacancies mainly from the service sector. Almost half of our vacancies are in sales and marketing departments. Remaining vacancies are distributed to call center positions, secre-

[13] That might seem slightly odd to someone who is not familiar with the city, but it is one of the essential job requirements in Istanbul. It is not rare to see specific address requirements on vacancy postings.

tarial work and other sectors. Wage offers in our selected vacancies are close to minimum wage -mainly up to two times of the official minimum wage- when a wage offer is posted. That is expected and reasonable given that our applicants do not have any experience or special education. Moreover, the total number of applicants at the closing date goes as high as twenty thousand for several vacancies. The lowest number of applicants is around 100 per vacancy. Hence, it is reasonable to say that our chosen vacancies get many applicants even though they post quite lower wages. These observations are in line with the youth labor market facts that we mentioned in the institutional background chapter. Hence, we believe our vacancies match the labor market conditions well albeit they are far from being representative of the labor market for the youth.

Once we have chosen a vacancy, we sent two female and two male resumes in a single day interval with no resumes are closer than 15 minutes to each other. We randomized resume sending order as well as the resumes, i.e., any male name might match any female name from our pool. Since we have two different treatments, namely ethnicity, and religiosity, we sent alternating resume sets to chosen vacancies. In other words, we sent one neutral male, one neutral female, one Kurdish (religious) male, and one Kurdish (religious) female resume to each vacancy.

After completing the application process, we noted the firm and vacancy related information together with the sector, number of employees the firm is aiming to hire, the department in the firm as well as the closing date of the advertisement. At the closing date, we revisit the vacancy advertisement and note the number of applicants for the position. We use this information at the later stage as a proxy to tightness [14].

[14] we gathered all the available information from the vacancy advertisement.Moreover, we could also add additional controls on firm characteristics using web site information of the

2.4 Measuring Responses

kariyer.net portal allows us to track our applications through the hiring process. We get a notification every time a prospective employer filters or reads one of our resumes. This process allows us to create two additional employer response measures in addition to standard callback measure employed in the correspondence audit literature. In short, we generate three discrimination measures in our study, two of them are novel to our study to the best of our knowledge. Now, we will explain our measures in detail.

The first measure is the callback rate, which is the primary metric in correspondence audits. When we got a call from a vacancy, we noted that as a callback for the relevant applicant. Getting no callbacks from vacancies is a fairly common occurrence in correspondence audits, and our study is no exception. When none of four fictitious candidates get a callback, we note that as a no-discrimination outcome.

As we stated, the second and third metrics are unique to our study. kariyer.net portal allows users to keep track of their applications by providing step by step clicking information. We get a notification when the vacancy holder clicks on our resumes and access applicant's information. How much time is spent on each resume is beyond our knowledge, but there is no reason to click one resume and not the other among our applicants besides their name. Hence, we register unequal behavior as screening stage discrimination.

When applications reach the vacancy holders, they first see a limited amount of information about the candidate. If they want to limit the applicant pool to better fitting candidates without opening

firms. But as all the firms may not provide same level of information on their web sites and checking each firm's web site is time costly, we did not collect any other information about the firms.

the resumes one by one, they can use many filters. They can use predetermined filters as well as do keyword search among applicants. For example, if they filter only male applicants, they will not see a female resume at all on their list even though that person has ideal qualifications for the job. The listing measure is the first level clicking information provided by the job application portal. Listing is a weaker interest than the aforementioned ones but allow us to understand if firms use gender as a criterion in the hiring process.

Both of the above pieces of click information suggest interest in the applicant, and we use these pieces of information to create two new measures of discrimination, namely screening rate, and listing rate respectively. A gender difference in screening rate implies female candidates have a hard time to signal their qualifications given potential employers click fewer times on their resumes on average. A gender gap in listing rate implies firms use gender as an active filter in the hiring process. Both of these gaps can directly affect job finding probability and the number of resumes needed to be sent by the applicants. Hence, these are good candidates for being intermediate step discrimination measures.

It is important to note that firms can click on resumes or call applicants without listing them first. They can see name and communication information directly without clicking on resumes as well. Hence, discrimination measures we defined above are not conditional on each other. A candidate gets a call without being listed or screened. For this reason, we differentiate firms that follow a step by step process and that do not and will report our results accordingly. In the following sections, we will summarize our data and report our results.

3 Data

We sent 3728 applications to 932 unique job openings. In the ethnicity treatment, we sent 948 Kurdish resumes (474 for each gender), and 948 neutral candidate resumes. In the religiosity treatment, we sent 916 religious candidate resumes (458 for each gender) together with 916 neutral candidate resumes. In total, we sent 1864 neutral candidate resumes. We draw applicants from a ten name applicant pool for each group and sent four random resumes to each vacancy.

As we stated, we produce three different discrimination measures in our study. Here, we briefly summarize them. Figure 4 presents listing rates by groups. The listing rates are quite high and close to each other for all groups (around 65 percent). Only Kurdish females have a lower listing rate, which is around 60 percent.

Figure 5 depicts screening rates. These rates are significantly lower than listing rates as expected given screening a resume requires higher effort than listing a resume and signals a higher interest in the applicant. Females have slightly higher screening rates at 16 percent compared to males (14 percent) for all groups. Two percent difference seems not negligible but not strong either. Screening rates are the highest for Kurdish candidates, followed by neutral ones. Given neutral candidates are averaged over ethnicity and religiosity treatment this result is quite understandable. Lowest screening rate is observed by religious males at 13 percent and the highest is 17 percent for Kurdish females.

On the other hand, we observe major differences in callback rates among our groups as Figure 6 shows. Neutral females receive callbacks at 7 percent of the time compared to 5 percent callbacks to neutral males. Hence for each callback, a neutral male gets, a neutral female gets 1.4 callbacks. On the contrary, Kurdish males receive 5 percent callbacks in comparison to 3 percent callbacks of Kurdish females. Finally, we do not observe any difference regarding callback rates between religious males and females as both groups get callbacks 3 percent of the resumes they sent.

In addition to raw measures, Table 1 presents the correlations among three measures by pooled sample and subgroups. The strongest correlation for all subgroups is found between callbacks and screening measures. This observation is in line with our expectations of the hiring process since screening a resume is a strong signal of employer interest. The lowest coefficients among these two measures belong to Kurdish females and religious females. The lowest correlations are found between listing and callback metrics, which could be expected as they have the longest distance in the hiring process.

4 Results

Now we familiarized the reader with experimental setup and data, we are ready to present our results. We will present our results in the order they appear in the recruitment process. Respectively, we will present listing rate, screening rate, and callback rate and show that discrimination only appears at the last stage of hiring.

4.1 Listing Rate

We first focus on net discrimination in listings (Table 2). Men favored on average at the listing stage, and it is true for all sub-samples albeit at different rates. Net gender discrimination is smallest for the Kurdish candidates, and greatest for the religious candidates at 4.15 percent, which is still reasonably small compare to the average listing rate of 65 percent. In other words, firms might use gender as a filter at the hiring process, but the number of firms who do that in favor of men is quite negligible.

To get a better understanding of the significance of listing differences, we also employ regression analysis. In all estimations we control for the occupation, application order, application date, assistants that made the application, as well as the college quality [15]. We interact college quality with the applicant type in order to account for a differential effect of college education on the labor market prospects of different groups. For example, if higher quality college education increases the job finding probability of Kurdish women more than Kurdish men, we account for that in our estimation.

As Table 3 displays, We find no statistically significant gender difference in listing rates. This observation is true for all subgroups, neutral, Kurdish, and religious alike. Thus, we conclude that there exists no gender discrimination at the listing stage. Moreover, ethnic and religious identities do not interact with gender in any direction at this stage.

4.2 Screening Rate

When we go one step further and check for the screening rates, we see just the opposite picture than the listing rates. As Table 2 depicts, women are favored on average in screenings, and this observation is valid for all sub-samples. Raw data suggests females resumes are read at a slightly higher rate. Net positive gender discrimination in screening goes as high as 1.7 percentage points for Kurdish females and as low as 0.86 for neutral females. Compare to 14 percent

[15] We use two alternative measures for college quality, entrance exam scores, and the national ranking institute's (URAP's) rankings. Here we report coecients with the URAP rankings, but the results with entrance exam controls are virtually the same

screening rate on average, these numbers are small but possibly not negligible.

We present regression results in Table 4. When we analyze screenings in a regression setup, we find no statistically significant coefficient for any group. As in the listing stage, ethnicity and religiousness do not affect our discrimination findings. Thus, so far firms treat male and female applicants symmetrically in the hiring process.

As correlation coefficients showed, many firms both list and screen applicants. If they follow a logical ordering, we expect them first to list and then screen our applicants. Hence, to see whether firm behavior differs, we also run a regression on a sub-sample based on the conditioned on being listed. According to Table 5, there is no statistically significant gender discrimination at the screening stage for this restricted sample. Firms that are using listing facility interacts with our resumes similar to a firm that do not.

4.3 Callback Rate

As the final stage of the hiring process, we first check for the existence of net discrimination in callbacks. As we show in Table 2, we find small net discrimination on average in favor of females. It is clear that discrimination stems from neutral females. They get noticeably more calls than neutral males. On the contrary, there is a net get discrimination against Kurdish females and religious females. Hence, it looks like multiple identities matter for discriminatory outcomes at the callback stage.

To evaluate the statistical significance of these observations, we run an OLS regression on callback outcome. The results of callback estimations are given in Table 6. In line with net discrimination observation, We find a statistically positive treatment of neutral females at the callback stage compare to neutral males. As Table 7, and Table 8 depict, statistically significant estimates replicate for listed and screened applicants as well. Interestingly, the coefficient gets three times larger for the screened applicants. It looks like firms that go through resumes first treat neutral females even better than rest of the firms. However, they do not show same interest to Kurdish and religious females. Coefficients get stronger for these groups as well but never gets significant.

In short, firms in this study do not discriminate much to start with. They do not use gender as a parameter when filtering applicant pool. Moreover, they read resumes belonging to male and female applicants at the same rate. However, they callback more females than males if the applicants' names are neutral. Kurdish females and religious females are not treated favorably compare to Kurdish males and religious males respectively.

5 Conclusion

In this paper, we present results from a multiple identity correspondence audit study that we ran in a Muslim majority, developing country. In our study, we sent applicant resumes in quadruplets under two different treatments. In the first treatment, we sent two neutral candidate resumes, one male-one female together with one Kurdish male and one Kurdish female resume. In the religiosity treatment, we add one religious female resume and one religious male resume to neutral candidates. We introduce two new measure of discrimination to literature in this study, namely listing and screening rates. We show that there is no gender discrimination at listing and screening stage. There is a positive discrimination in favor of females but only if they belong to the neutral group. Ethnicity and religiosity interact with gender in our study, and positive treatment of females disappear for Kurdish and religious females.

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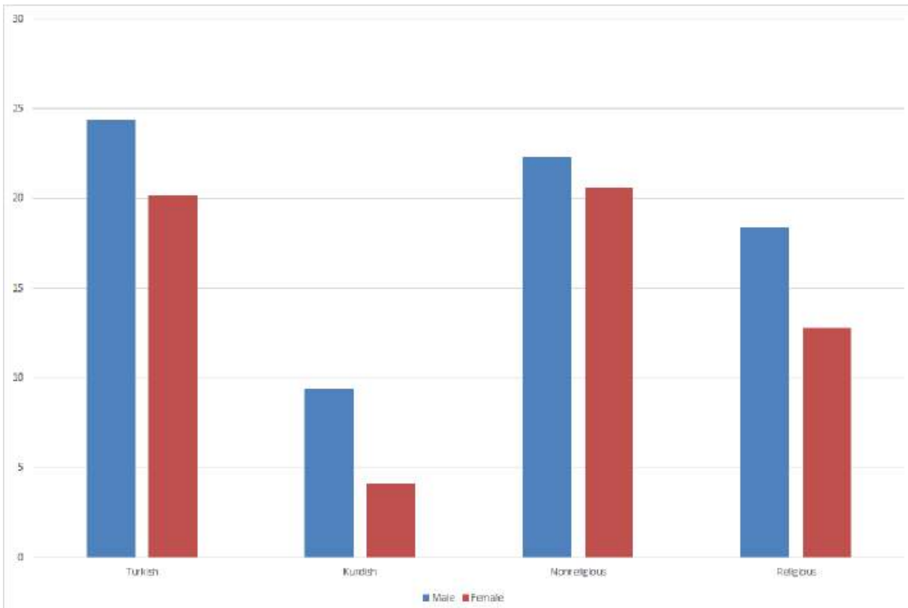

Figure 1: University Graduation Rates

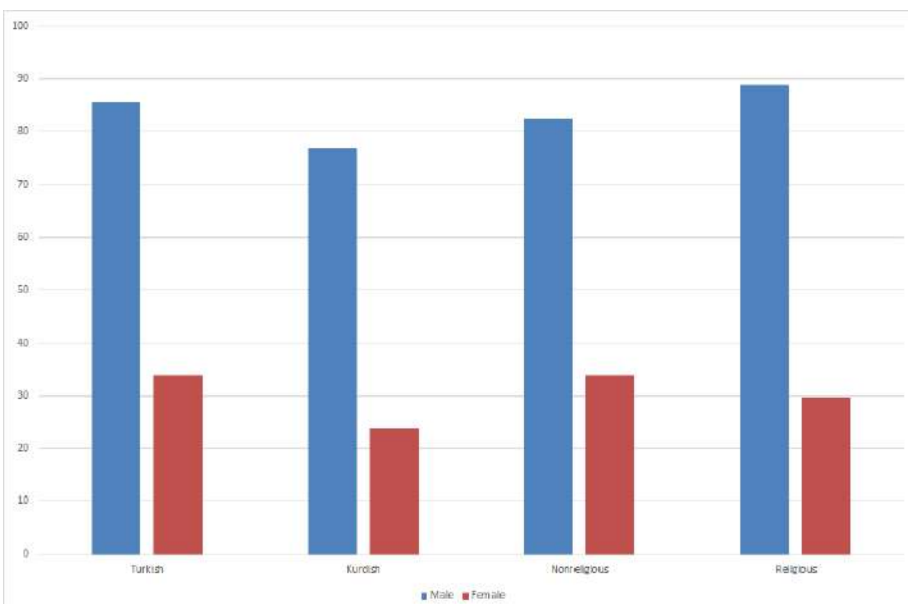

Figure 2: Labor Force Participation Rates

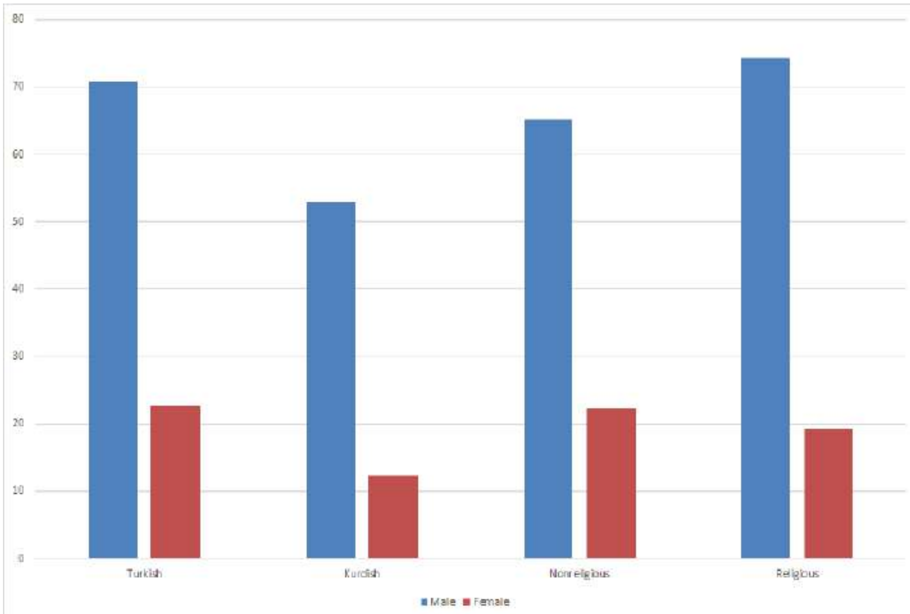

Figure 3: Employment Probabilities

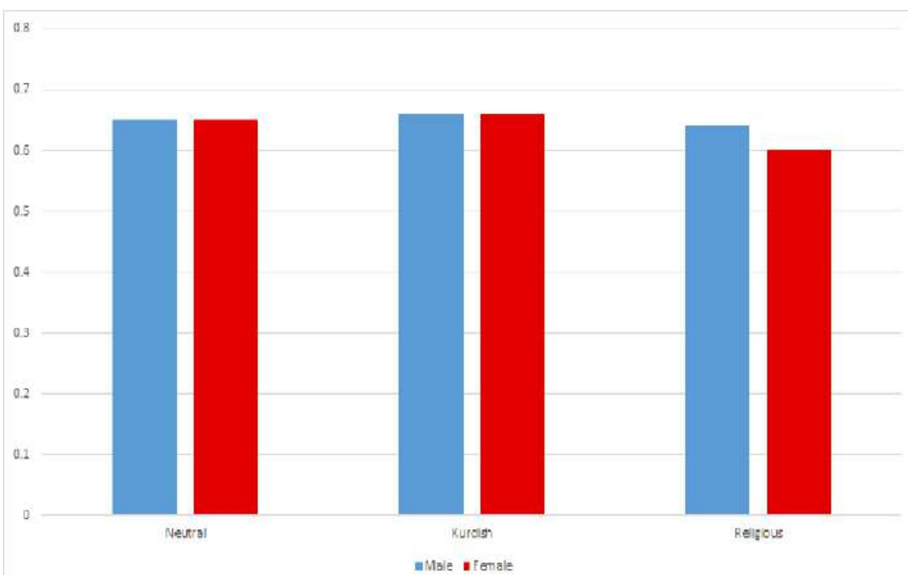

Figure 4: Listing Rates by Groups

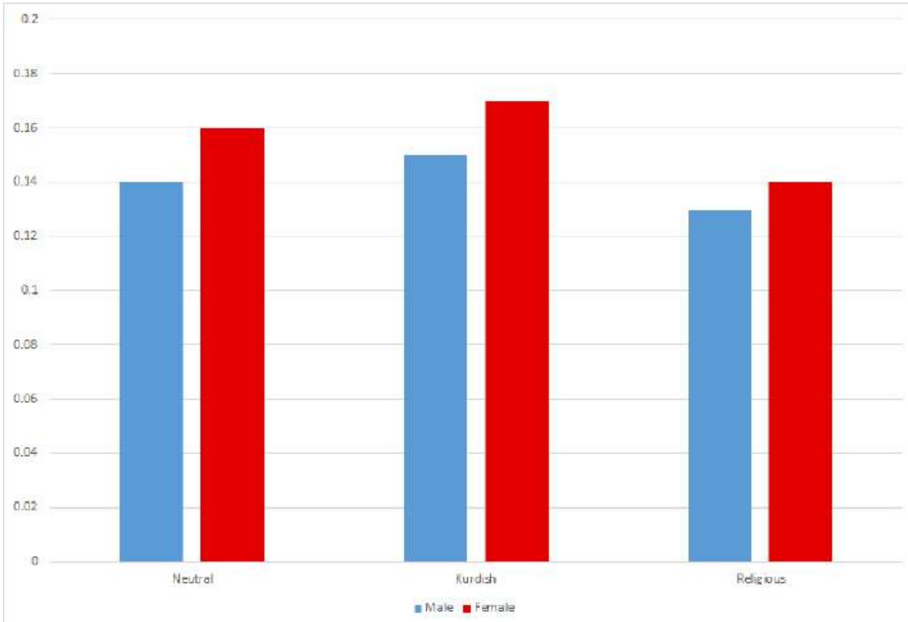

Figure 5: Screening Rates by Groups

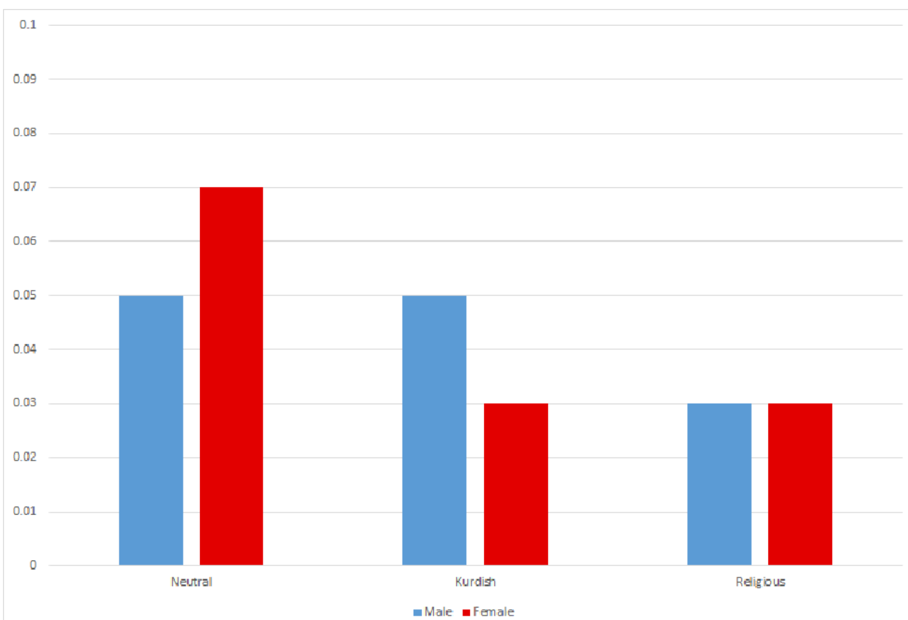

Figure 6: Callback Rates by Groups

	Listings	Screenings	Callbacks
Pooled			
Listings	1.00		
Screenings	0.23	1.00	
Callbacks	0.15	0.46	1.00
Neutral Males			
Listings	1.00		
Screenings	0.23	1.00	
Callbacks	0.15	0.50	1.00
Neutral Females			
Listings	1.00		
Screenings	0.22	1.00	
Callbacks	0.17	0.47	1.00
Kurdish Males			
Listings	1.00		
Screenings	0.22	1.00	
Callbacks	0.14	0.51	1.00
Kurdish Females			
Listings	1.00		
Screenings	0.24	1.00	
Callbacks	0.13	0.36	1.00
Religious Males			
Listings	1.00		
Screenings	0.24	1.00	
Callbacks	0.14	0.49	1.00
Religious Females			
Listings	1.00		
Screenings	0.20	1.00	
Callbacks	0.15	0.40	1.00

Table 1: Correlations between Discrimination Measures

VARIABLES	Listing	Screening	Callback
Pooled Applicants			
Equal Treatment	89.22	89.59	92.65
Men Favored	6.49	4.67	3.38
Women Favored	4.29	5.74	3.97
Net Discrimination	2.20	-1.07	-0.59
Neutral Applicants			
Equal Treatment	89.70	88.84	92.27
Men Favored	6.22	5.15	2.79
Women Favored	4.08	6.01	4.94
Net Discrimination	2.14	-0.86	-2.15
Kurdish Applicants			
Equal Treatment	92.41	89.87	91.77
Men Favored	4.01	4.22	4.85
Women Favored	3.59	5.91	3.38
Net Discrimination	0.42	-1.69	1.47
Religious Applicants			
Equal Treatment	84.93	90.83	94.32
Men Favored	9.61	4.15	3.06
Women Favored	5.46	5.02	2.62
Net Discrimination	4.15	-0.87	0.44

Table 2: Net Discrimination

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	-0.0411	0.0594	-0.0466	0.0625
	(0.0360)	(0.0734)	(0.0614)	(0.111)
Observations	3,716	1,858	942	916
R-squared	0.049	0.049	0.065	0.050
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable is a dummy that takes the value 1 if the individual is listed.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 3: Listing Measure

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	0.00104	0.0212	0.0189	-0.0443
	(0.0263)	(0.0538)	(0.0502)	(0.0740)
Observations	3,716	1,858	942	916
R-squared	0.043	0.052	0.060	0.042
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable is a dummy that takes the value 1 if the individual is screened.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 4: Screening Measure

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	-0.00292	0.0197	0.0458	-0.0615
	(0.0342)	(0.0715)	(0.0658)	(0.0983)
Observations	2,692	1,346	684	662
R-squared	0.056	0.066	0.075	0.064
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** p<0.01, ** p<0.05, * p<0.1
Dependent variable is a dummy that takes the value 1 if the individual is screened.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 5: Screening Measure - Ever Listed Applicants

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	-0.00199	0.0941**	0.00170	0.0423
	(0.0172)	(0.0377)	(0.0336)	(0.0499)
Observations	3,716	1,858	942	916
R-squared	0.022	0.042	0.034	0.029
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** p<0.01, ** p<0.05, * p<0.1
Dependent variable is a dummy that takes the value 1 if the individual received a callback.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 6: Callback Measure

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	-0.00641	0.119**	0.00323	0.0569
	(0.0233)	(0.0506)	(0.0464)	(0.0663)
Observations	2,692	1,346	684	662
R-squared	0.030	0.057	0.047	0.048
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable is a dummy that takes the value 1 if the individual received a callback.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 7: Callback Measure - Ever Listed Applicants

VARIABLES	(1) Pooled	(2) Neutral	(3) Kurdish	(4) Religious
gender	-0.0185	0.305**	0.0441	0.281
	(0.0654)	(0.123)	(0.118)	(0.228)
Observations	948	474	260	214
R-squared	0.062	0.136	0.120	0.139
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable is a dummy that takes the value 1 if the individual received a callback.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 8: Callback Measure - Ever Screened Applicants

VARIABLES	(1) <500 Pooled	(2) >500 Pooled	(3) <500 Neutral	(4) >500 Neutral
gender	0.0126	-0.00889	0.159***	0.0505
	(0.0275)	(0.0226)	(0.0599)	(0.0486)
Observations	1,600	2,116	800	1,058
R-squared	0.050	0.043	0.090	0.069
Application Order	YES	YES	YES	YES
Occupation Groups	YES	YES	YES	YES
Assistant Dummies	YES	YES	YES	YES
Application Date	YES	YES	YES	YES
College Quality Interactions	YES	YES	YES	YES

Standard errors are clustered at the vacancy level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Dependent variable is a dummy that takes the value 1 if the individual received a callback.
Gender is a dummy variable that takes the value 1 if the individual is female.

Table 9: Callback Measure by Applicant Pool Size

A List of Surnames

- Yılmaz
- Demir
- Çetin
- Korkmaz
- Kara
- Aslan
- Yavuz
- Aydın
- Demirci
- Mutlu
- Durmaz
- Kılıç
- Doğan
- Yıldırım
- Uysal
- Koç
- Kurt
- Özkan
- Şimşek
- Keskin
- Yıldız
- Kaya
- Şahin
- Yücel
- Çakır
- Kaplan
- Avcı
- Işık
- Ateş
- Aksoy
- Taş
- Sarı
- Tekin

B List of Names

B.1 Neutral Names

- Males
  - Alican
  - Alper
  - Caner
  - Melih
  - Orkun
  - Tolga
  - Vural
  - Zeki
- Females
  - Berna
  - Buket
  - Cansu
  - Gamze
  - Gözde
  - Melis
  - Sibel

B.2 Kurdish Names

- Males
  - Bahoz
  - Bervan
  - Berzan
  - Botan
  - Hogir
  - Keke
  - Rojen
  - Şervan
  - Şirman
  - Şivan
- Females
  - Avbin
  - Roja
  - Rojbin
  - Rojda
  - Rojder
  - Rojgul
  - Zerşin
  - Zilan
  - Zilda
  - Zozan

B.3 Religious Names

- Males
  - Abdülkerim
  - HacıBayram
  - Halilullah
  - Muhammed
  - Mümin
  - Ubeydullah
  - Şemseddin
- Females
  - Bedrunnisa
  - Esmanur
  - Havva
  - Hayrunnisa
  - Medine
  - Nurinisa
  - Nurunnisa

C List of Universities

- University
  - Uludağ University
  - Çukurova University
  - Dokuz Eylül University
  - Akdeniz University
  - Anadolu University
  - Selçuk University
  - 19 Mayıs University
  - Ege University
  - Gazi University
  - Pamukkale University
- City
  - Bursa
  - Adana
  - Izmir
  - Antalya
  - Eskisehir
  - Konya
  - Samsun
  - Izmir
  - Ankara
  - Denizli

Letter	Number of Applications	Listing Rate	Screening Rate	Callback Rate
A	449	0.65	0.16	0.05
B	575	0.64	0.16	0.03
C	225	0.66	0.14	0.06
E	41	0.66	0.15	0.00
G	338	0.64	0.15	0.07
H	302	0.55	0.11	0.04
K	54	0.72	0.19	0.07
M	368	0.68	0.15	0.06
N	134	0.65	0.15	0.01
O	111	0.60	0.10	0.01
R	273	0.65	0.15	0.05
S	88	0.65	0.14	0.05
T	93	0.71	0.17	0.06
U	91	0.60	0.09	0.03
V	152	0.60	0.18	0.09
Z	270	0.67	0.16	0.00
Ş	164	0.74	0.15	0.07

Table 10: Communication by Applicant Name's First Letter

Letter	Number of Applications	Listing Rate	Screening Rate	Callback Rate
A	858	0.65	0.16	0.05
D	562	0.60	0.10	0.05
I	87	0.66	0.20	0.11
K	819	0.61	0.15	0.05
M	110	0.67	0.16	0.02
S	85	0.69	0.15	0.02
T	94	0.70	0.16	0.17
U	122	0.73	0.10	0.00
Y	565	0.69	0.16	0.04
Ç	255	0.65	0.12	0.02
Ö	101	0.67	0.23	0.02
Ş	70	0.64	0.26	0.00

Table 11: Communication by Applicant Surname's First Letter