Does Gender Discrimination Contribute to Low Labor Force Participation of Women in Turkey? Evidence from Survey and Field Data

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Abstract

Low female labor force participation continues to be an important problem in the Turkish labor market. Labor market participation of women might be worsened by the cultural and traditional factors such as the division of labor at the household or economics factors, such as discrimination against females. In this paper, we try to identify hiring stage differences among men and women via a correspondence audit methodology. In doing so, we produce two new measures of employer response in addition to the standard callback measure used in the literature. We show that employers interact with female and male applications and resumes similarly when evaulating the job applications. However, there is a positive discrimination against female applicants in the Turkish labor market.

JEL codes: J71, J21, C93.

Keywords: gender discrimination; correspondence audit; female labor force participation.

1 Introduction

Although labor force participation rates both for men and women in Turkey are lower than the OECD averages, the participation rate for women is exceptionally low. The female labor force participation (FLFP) rate was 23.3 percent in 2004 in Turkey [1]. It only increased to 23.6 percent in 2007, which is almost one third of OECD and EU-19 averages. The most recent figures suggest that the FLFP rate is still around 30 percent. The main reasons behind this low female labor force participation could be grouped into educational and social reasons. On the education side, lower educational attainments of women compared men force them into informal sector with low wages and low to nonexistent benefits. As a result, women might not be able to find jobs exceeding their reservation wages. Among the social reasons, we can count social norms aroud family, mainly the patriarchal family structure. Child and elderly care is mainly considered as female's job in the family, tying them strongly to homes.

In addition to these, women could prefer not to enter the labor market due to the presence of discrimination i.e. if a woman believes she will not be able to find a job or she would be paid a lower wage compared to men due to discrimination, she could prefer to stay out of the labor force.

However, disentangling mechanisms that create lower labor force participation of women is not trivial. On the discrimination side, it is also hard to argue whether observed differences between women and men are due to discrimination. To this end, correspondence audit methodology became a popular tool in discrimination research

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in the recent years. In correspondence audits, same quality resumes belonging to fictitious applicants are sent to the real job vacancies. Then, callbacks to each applicant is recorded and compared with the other applicants. In these studies, the applicants differ only in a single trait e.g. gender, age or race, which is the source of discrimination.

In this study, we conduct an online correspondence audit in Turkey. Since we are interested in the gender discrimination, we first prepared almost identical resumes, which vary only in the gender aspect. We signal the gender of the applicant via female and male names in our study. After cultivating the resumes, we applied to 960 online job openings available in a popular job search site.

After sending out the applications, we collect three different employer response to our applications. Those responses are

- Application access: Employers can filter and list our fictitious application together with other applications and saw some brief information about the candidate, including the name and contact information of the candidate. We will call this measure as listing through out the paper.
- Resume access: With our without listing the applications, employer can click and access the detailed resume of the applicant. We will call this measure as screening in our study.
- Callback: Employer can call the applicant and request an interview for the vacancy. When this happens, we note the interview request and the company name. In line with the existing literature, we call this measure callback.

The last measure, namely callback is the traditional measure in correspondence audit studies. To the best of our knowledge, we are the first ones introducing the other two measures into the literature. We will discuss the drawbacks and strengths of these measures in the experimental setting chapter.

We also employed survey data to summarize labor market outcomes of women compared to men. It is important to remember correspondence audits target hiring stage discrimination but are not salient about whether the hiring is completed and possible wage discrimination once the hiring is completed. Hence, survey data on labor market outcomes could potentially fill this gap in the analysis.

In line with the existing literature, we find that survey data indicates deep differences between males and females in Turkish labor market. On the other hand, we did not detect any discrimination against females in the correspondence audit study. The listing and screenings measures indicate neutrality of the employers in gender dimension. Moreover, we find a weak but positive discrimination for women via the callback measure in the Turkish labor market.

Rest of the paper is structured as follows. We first summarize the related literature in the following section. Then, we will explain our experimental design in detail. The fourth chapter will briefly summarize survey data, which will be followed by findings of the paper. Finally, we conclude with the sixth chapter.

2 Literature Review

Our work is closely related to two strands of the literature. The first one is the gender correspondence studies. However, to the best of our knowledge, there is no correspondence study carried out in a predominantly Muslim and developing country, where female labor force participation is also quite low. The second one is the female labor market participation and gender wage gap studies conducted in Turkey. However, there is not much discrimination flavor to Turkish studies, given they mostly focus on explaining participation difference and wage gap between women and men via observed characteristic. Therefore, our study is one of the very first papers studying gender discrimination in Turkey as well as one of the very few audit studies conducted in a developing country.

Although women took a big step in labor markets in the recent decades, we still observe gender gap in terms of employment level and earnings. Early work on discrimination mainly used regression analysis and decomposition techniques such as Oaxaca (1973) and Blinder (1973) on observational data. However, limitations of this approach as explained in Bertrand and Duflo (2016) shifted the emphasis on field experiments such as audit and correspondence studies.

There is a growing literature relying on the correspondence audit methodology, studying the gender discrimination at the hiring stage. Riach and Rich (2006) used a matched pair of applicants and applied to vacancies for engineers, computer analyst programmers, secretaries and accounting positions in UK labor market. They found net discrimination in favor of women in vacancies for computer analyst programmers, secretaries and accounting positions and in favor of men in engineering jobs. They attribute this discrimination to taste-based factors.

In a study that investigates the effect of hiring discrimination on gender segregation in the Swedish labor market Carlsson and Rooth (2007) sent matched paired applications for positions of construction workers, sales assistants, IT professionals, high school teachers, restaurant workers, drivers, accountants, nurses, pre-school teachers and cleaners. While female applicants have slightly higher probability to receive a call back compared to men for the pooled sample for all occupations, in male dominated professions male applicants have a slight (insignificant) advantage.

More recently, Booth and Leigh (2010) focused on female-dominated professions (wait staff, data-entry, customer service, and sales jobs) in Austrian labor market and found an excess call-back of 1.28 in favor of women.

In a study for China, Zhou et al. (2013) sent CVs to accounting, IT, marketing and secretary positions and find statistically significant discrimination in all the jobs but the IT. While the level 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.

All the aforementioned correspondence studies that measures gender discrimination are carried out in developed countries. Only exception is the one for China, but due to its different labor market regulations, it is hard to generalize its results to other developing countries. In this respect, our study also contributes to the literature by providing evidence from a developing country.

There exist only a limited number of studies on labor market discrimination (ethnic, religion and gender) in Turkey. Gender discrimination analysis mostly oriented to wage gap analysis which in general focus on a single year and use Oaxaca-Blinder decomposition. Second research area for the gender base analysis aims to understand main features and problems of the female labor force participation in Turkey.

Dayioglu and Kasnakoglu (1997), using 1987 Household Income and Expenditure Survey data set, estimate wage regressions made up mostly of human capital variables. The most important determinant of the wage differentials is work experience. Another finding of the study is that the positive effect of education on female wages is quite remarkable and lowers the degree of wage gap. Yamak and Topbas (2004) analyze the extent of male-female wage gap, using 1994 Household Consumption Expenditures Survey using same decomposition method and their results show that wage discrimination accounts for 78 and 80 percents of the gender wage gap according to Oaxaca-Blinder and Cotton methodologies, respectively.

Tansel (2005) investigates the sectoral differences male-female earnings gap using 1996 Household Consumption Expenditure Survey. Their results also indicate significant wage gap, particularly in the private sector. The main reason underlying the gender wage gap in for men in the private sector is the higher returns to wage-determining characteristics for male workers. Hisarciklilar and Ercan (2005) using 1988 Household Labor Force Survey find that human capital characteristics of women significantly reduce the wage differential. Kara (2006) using Turkish Household Expenditure and Income Survey analyze the gender wage gap, and he also concludes that gender wage gap decreases with education. The analyses of Cudeville and Gurbuzer (2007) using 2003 Household Budget Survey report a gender wage gap in favor of men at on average 25.2 percent and reveal that 60 percent of the gap stems from wage discrimination. Comparing the results with that of European countries, the authors claim that the gender-based wage discrimination in Turkey is similar to that of some south European countries. However, they also emphasize that wage discrimination is only an insufficient indicator of discrimination against women and that the main distressing concern is, in fact, the underrepresentation of women in the labor market.

Using 2002 Household Budget Survey data set, Gurler and Ucdogruk (2007) investigate the factors underlying the differences in the male-female labor force participation and wage rates in Turkey. The Oaxaca decomposition analyses reveal the presence of significant gender wage discrimination. The extended wage regression decomposition estimations depict that only 14.96 percent of gender wage differentials stem from differences in endowments, and 85.8 percent is indeed due to discrimination. In their analysis of gender-based wage differentials in the Turkish labor market. Ilkkaracan and Selim (2007) use 1995 Employment and Wage Structure Survey and Oaxaca decomposition method based on Mincerian wage regression models. The reduced wage model comprising only the conventional human capital variables displays that 43 percent of the male-female earnings gap is attributable to discrimination. When the model is extended to incorporate occupation, sector and firm characteristics variables, the share due to wage discrimination falls to 22 percent.

Dayioglu and Kirdar (2011) examine the labor supply behavior of women using cohort analysis, and they show that younger cohorts of women are participating more than older cohorts in urban areas. But after controlling for education, they find that women participation rates do not change between cohorts. Ilkkaracan (2012) and Toksoz (2011) indicates that during the import-substituting phase of Turkey's development trajectory, the articulation between patriarchy and capitalism was realized through the exclusion of women from the labor market. Within the export-oriented firms, female participation rate intend to increase, but it was relatively weak in comparison to the similar countries. Ilkkaracan (2012) and Dildar (2015) argued that the import-substitution industrialization period reinforced conservative family-oriented care regime and the dual career model supported by institutional care provision are seen only among the university graduate.

Ilkkaracan (2012) shows that the cultural constraint doesn't have a significant effect on women's labor market outcomes in Turkey. But because of the patriarchal era, women can not be entered into the public sphere and this situation, strengthens the traditional approach that defines women as "good wives and mothers". The patriarchal era is the main argument that can be capable of explicating the significant difference of the participation between married and single women with identical education level. Tasci (2009) and Eryar and Tekguc (2013), indicates that mobility patterns differentiate regarding gender; and the probability of women's transition from a job to inactivity increase with marriage.

Guner and Uysal (2014) analyze the causal relationship between culture and female labor force participation and they find that female employment rates in the province of origin around the time the migrants were born, has a positive impact on labor supply behavior of female migrants.Dildar (2015) in her article focuses on the role of social conservatism as a constraint of women's labor force participation using Turkey Demographic and Health Surveys. One of the most important findings of her research is "significant negative association between women's religious practice and labor force participation. The social transformation that Turkey has undergone during the last 15 years (especially on the education system) increase the importance of this result with the possible and continuing future effects. The second important finding is the negative association between patriarchal values and labor force participation. İt is known, and very clear result for the rural area but Dildar's findings indicate that urbanization does not weaken the effect of the conservatism and women's labor force participation still continue to be weak in the urban areas.

Oztop and Finkel (2015), based on their research women's awareness and perception about the civil rights realized focus groups interviews.

When they asked questions about their most important actual social problems, the majority of women noted domestic violence and lack of employment opportunities respectively as top two concerns Turkish women face at the moment.

In this paper, we are aiming to contribute the female labor force participation literature in Turkey by providing the first experimental evidence on the lack of hiring stage discrimination against women via a correspondence audit study.

3 Experimental Design

In this study, we are employing a correspondence audit methodology. In a correspondence audit, seemingly similar fictional resumes are sent out to real job openings as a pair and interview requests or callbacks from those job openings are compared among these paired fictitious applications. In these studies, applicants generally differ only in one trait, which is the studied source of discrimination. 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, researcher can signal the sex of the applicant by assigning commonly used male and female names to identical resumes. It is important to note that, discrimination in general is defined with respect to a reference group in all discrimination studies and correspondence audits are no exception. For example, people with normal body mass index are taken as the reference group when working on discrimination against overweight people. In a similar fashion, males belonging to the major ethnic group constitute the reference group in a gender study.

The prime benefit of audit studies is the subjects (firms in this set up) are not aware that they are taking part in a study. Thus, it is not possible for subjects to change behavior accordingly. Hence, correspondence audits help to quantify the real magnitudes. Moreover, by creating fictional resumes, the qualification differences between reference and investigated applicants could be minimized. Finally, sending a small number of resumes prevent distorting 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 analyzing the magnitudes through survey data. Yet, identifying the source of inequality may not be possible in survey data. For example, assuming we find a difference between men and women's employment rates, the difference might depend on inequality of opportunity in education. Also, 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 magnitudes correctly.

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

On the other hand, correspondence audits have their own limitations. Most important of all is that it is not possible to quantify wage and employment discrimination via correspondence audits. Since it is not possible get a job offer or a wage offer before finalizing the recruitment process, it is also not possible to quantify discrimination at those steps. Moreover, it is almost impossible to apply to managerial positions in correspondence audits especially if the market for that profession is small and existing people are well-known. Any fictional resume will be detected immediately in such positions and markets hence there would be no point in carrying out correspondence audits.

All in all, although they are not perfect, correspondence audits are good tools for quantifying labor market discrimination. Hiring stage discrimination is an important source of labor market discrimination and correspondence audits can help us understand how hiring process discrimination works against different groups in the labor market.

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 to online job openings and count the number of listings, screenings and callbacks from the prospective employers for each pair of applicants. Via this study, we aim to identify differences in the hiring stage and expect understand whether the inequality of opportunity influences labor market outcomes of females. In the next section, we will explain the experimental design in detail and try to explain what we did to mimic some of the drawbacks of correspondence audits.

3.1 Identity Creation of Fictitious Applicants

The name and the gender of the applicant is the main variation among resumes in our study. In order to identify the source of the discrimination correctly, names should reflect an affiliation to the group of interest but nothing more than that to potential recruiters. At this point, we designed a survey in the name selection stage to ensure that we are signaling only a gender difference with our selected names but not any other affiliation.

Before the survey stage, we gathered most common female and male names in Turkey. We did this for neutral sounding names. Neutral names should not signal any ethnic or religious affiliation to anyone in Turkey. In other words, those names could be used by the majority of the population without a reference group in mind. Some examples to those names could be Mehmet or Ayşe, which are quite popular names and used by many major ethnic and religious groups in Turkey.

When we conducted the survey, we let survey takers to assign any characteristics they want to a name including but not limited to religious, ethnic or socioeconomic background. When we collected the responses back, we only kept the names which no affiliation or affiliation of majority is attached by our respondents. That is, our respondents should fail to assign our "neutral" names into a religious or ethnic group. We desire this feature in order to signal a clear gender signal with the chosen names but nothing else.

For the surnames, we have chosen some of the heavily used surnames in Turkey. These surnames do not signal any geographical, ethnic or religious affiliation since they are commonly used by the different groups of society, in a diverse geographical area. Another benefit of using commonly used surnames is that it makes harder for recruiters to search candidates online if they have such intentions. The list of these surnames could be found in the appendix.

Finally, we randomly matched surnames and names to create fictional applicant identities. In that way, we could use any name and surname more than once, and we were able to choose the strongest names in each category in terms of their identity signaling power.

3.2 Resume Characteristics

We included the following characteristics in each resume. The characteristics are chosen in order to match job application portal's required information and clarify the gender signal that we want to send the prospective employers.

- Gender
- Birth place
- Age
- Educational Attainment
- Address
- Work experience

As we explained above, we have female and male applications with neutral sounding and common Turkish names. We also choose the gender of the candidate in the application portal in line with the name given to them. Then, we assigned cities from Western Turkey for all applicants in order to minimize possible cultural or ethnic background signal. All of our resumes are also assigned a reasonable quality college name together with similarly rated high schools from Istanbul[2]. That means, our fictitious candidates are not only comparable in terms of educational attainment but also where they spent their school lives. List of colleges could be found in the appendix.

Similar to birth place and educational institution selection, we assigned addresses from similar neighborhoods in terms of socioeconomic characteristics to our resumes. We have selected addresses

[2]We controlled the high school quality by the required threshold points in the high school entrance exam for enrollment.

from Istanbul and we matched the Anatolian side vacancies to Anatolian side addresses and European side vacancies to European side addresses. That might seem slightly odd to someone who has not been familiar with the city but it is one of the most important job requirements for most job openings[3].

Finally, we did not assign any prior experience to any of our resumes and creates the resumes for fresh graduates who are 22 - 23 years of age at the time of the application.

3.3 Applying to Vacancies

When choosing vacancies to apply, we first limited our interest to Istanbul. Istanbul had roughly the half of the vacancies available in the job portal website and it is the biggest labor market in the country. Then, we limited our interest into entry level jobs (with no experience requirement) and eligible for all college graduates (with no specific college major requirement). Finally, we also chose new advertisements in the website, which were published in the last three days.

During the application stage, we sent one female and one male resume to each job opening. We randomized which resume to send first for each vacancy and we also randomized among our female and male applicant pools, i.e. any male name might match any female name from our pool. We sent our resumes within 15 minutes to one hour intervals in line with the general practice in the literature.

After completing the application, we noted firm information together with sector, number of employees the firm is aiming to hire, the department in the firm as well as the closing date of the advertisement.

[3] It is not rare to see specific address requirements in the vacancy advertisements.

3.4 Measuring Responses

We measured three different type of employer responses in our study. The first one is the traditional callback rates, which is heavily used in correspondence audits. We noted all the interview requests we got from the potential employers. Callbacks could end up in four different combinations in our setting. The first one is when the male candidate gets a callback and the female does not. The second is when female gets a callback but not the male candidate. Finally, either both or none of them get interview requests, which is fairly common in audit studies. When none of the candidates get a callback, we consider that observation as no discrimination observation. But when only one of the candidates gets a phone call, we consider that as discrimination given candidates are almost identical except their gender. After calculating the difference between calls to females and males, we generate our callback measure of discrimination in line with the literature.

The second and third measures are unique to our study and to the best of our knowledge, we are the first paper employing such an approach to quantifying discrimination in the literature. The web portal we are using for application lets users to keep track of their applications by providing the following "click" information. You get a notification when the employer lists your resume together with other applications. Employers could use several filters while listing the applications and they can only see a limited amount of information about the applicant when they list the applications, including but not limited to the name of applicant. For example, if they list only the male applicants they will not see a female application at all in their list even that person has the perfect qualifications for the job. This is the first click information provided by the job application portal. Then, if the employer chooses to open a resume, the web portal sends you another notification suggesting that application has not only been listed but also has been screened by the potential employer. That is the second click information provided. Both of these click information suggests interest in the application and we used that information to create two new measures of discrimination.

We believe the first measure - which we call as "listing rate" - signals whether employers use gender as a filter when they list the resumes. Hence, it corresponds to probability of application being actually heard by the firm. Hence, a difference in this probability could directly affect job finding probability and the number of resumes needed to be sent by the applicants.

The second measure of "screening rate" signals how employers react to basic characteristic of applicants when they list the applications. Even if a recruiter does not filter resumes when listing them, s/he could still click only the resumes coming from a single gender pool. That means lack of difference in application listing rate might not translate into the lack of difference in resumes' screening rate. Moreover, discriminated agents might fail to signal their skills to prospective employers when their resumes are not read. Hence, both of these access rates measure whether females can signal their abilities as well as male counterparts in the hiring stage and these ratios are good candidates for being a hiring stage discrimination measurement.

4 Data

4.1 Household Labor Force Survey

We utilize micro data from Turkish Labor force Survey (LFS) in this study. LFS is cross sectional, nationally representative dataset, collected and published annually by Turkish Statistical Institute (TURKSTAT). Official labor market statistics such as unemployment rate and labor market participation are calculated monthly from LFS.

LFS captures non-institutionalized resident population of Turkey. In addition to individual and household characteristics such as education, age and household formation, LFS also provides detailed information on the labor market status of the individuals. Employment status, unemployment duration, sector and occupation information could be found in LFS for individuals above 15 years old. LFS has around 500,000 observations per wave and it is also representative at the regional (NUTS-2) level. For our analysis, we focus on the working age population, namely individuals between 15 years of age to 64 years of age.

5 Results

In this section, we present results from both survey and experimental data. Survey evidence suggests that there are differences between women and men in Turkish labor market and differences start with education and carry out to the labor market outcomes. Then, we point out discrimination at the hiring stage is probably not one of the channels causing gender differences in the Turkish labor market.

5.1 Survey Results

We first look at the educational attainments by gender (Figure 1) as the labor market outcomes are partly determined by education. The first thing to mention about the graph is that, females are significantly less educated compared to males. While around 20 percent of the females have no degree, this ratio is only 5.5 percent for males. Beginning from secondary school for all higher educational attainment levels, the share of males is higher.

In order to analyze the share of working population for both genders, we create a dummy variable that takes the value 1 if individual is working and 0 otherwise and graph it in Figure 2. One of the main problems of Turkish labor market is the low labor force participation rates of the females. Figure 2 confirms this fact. The share of working individuals is significantly higher among males compared to females (71.9 percent vs 28 percent).

For further investigation of labor market status by gender, we next plot the share of public-private sector workers for both groups (Figure 3). As can be seen from the figure, the share of female public sector workers and male public sector workers are very close. Even the share of females (14.58 percent) is higher than that of males (14.36 percent). This result might reflect the fact that, there exists no hiring discrimination against women in public sector or females have stronger preferences for public sector over the private sector.

We also investigate the sectoral distribution of the two working females and males (Figure 4). According to the figure, females have higher share compared to men only in agricultural sector. As the education levels of the females are lower than men, their concentration on the low-skilled sector is expected. High share of females in service sector could also be interpreted as a reflection of low education. On the other hand, construction sector is male dominated as expected.

Low education level of females is also evident in Figure 5. 30.85 percent of the females are working as unpaid family workers. For the males this ratio is only 4.39 percent. As expected for both groups wage earners have the biggest share but the share is higher for males. On the other hand, working as employer is very rare among females. Only 1.26 percent of the women are employer in the sample.

We also investigate the unemployment among females and males. Although the labor force participation rate is low for women, their unemployment rate (11.77 percent) is higher that male unemployment rate (8.47 percent). Overall unemployment rate is 9.93 percent which is close to official rate of 10.1 percent. The higher unemployment rate for women could indicate a discrimination against women but it could also arise from the above mentioned differences in education as well. To control for the education effect, we create two groups. The first group consists of individuals with the degree below high school levels, the second group consists of individuals with the degree high school and above levels. We calculate the unemployment rates of males and females for these education groups. For the first education group, the unemployment rate of the males is 9.12 percent and the unemployment rate of females is 8.35 percent. For the second education group the rates are as follows; males 7.48 percent and females 16.78 percent. Compared to the whole sample unemployment rates for both groups (8.47 percent and 11.77 percent), more educated females and less educated males have higher unemployment rates. Even the unemployment rate of less educated women is lower than that of less educated men. This seems a natural outcome of women working in the low-skilled job, in the informal sector and working as unpaid family worker, in other words segregation. On the other hand, for the higher educated individuals, unemployment rate of females (16.68 percent) is more than two times of unemployment rate of males (7.48 percent). This could be interpreted as an indicator of discrimination against educated females. Also, this is the group we focus in our correspondence audit.

The survey asks to the unemployed individuals "for how long they have been looking for a job" and the results are reported as months. We see that not only the female unemployment rates are higher but also their unemployment spells are longer (Figure 6). When we focus on the two above mentioned education groups, we see that for both gender, duration is longer for higher educated groups. Moreover, unemployment spells of females are longer than unemployment spells of males for both education groups.

Finally, we employ regression analyses to investigate the effects of socio-economic and demographic characteristics on the employment probability of both genders. We run a probit model with a dependent variable that takes the value 1 if the individual is employed and 0 otherwise. The independent variables used in the model are the educational attainment, age, marital status and urban-rural settlement of the individuals. We also control for the region fixed effects. We first run this model by adding a gender dummy that takes the value 1 for females and 0 for males, and try to get a clue for an existence of discrimination between genders. Then, we run the same model for females and males separately to see how the possible effects of the variables on the probability of the employment of the individuals differ among genders. Table 1 presents the estimation results.

According to the results, the probability of being employed is lower for females compared to males. For both genders, having a high school and university diploma increases the probability of being employed. However, the effect of university degree on employment probability is higher for males than females. Probability of being employed exhibits a hump-shape for both groups but it peaks later for females. While being married has a positive effect on probability of being employed for males, it has a negative effect for females. For household size variable the results are just the opposite. We find a negative effect for males and positive effect for females. Finally, those who are living in the rural areas have higher probability to be employed, independent of the gender.

5.2 Correspondence Audit Results

The listing and screening measures can be found in Table 2 and 3 respectively. In Table 2, average application resumes listing rate for males is 65 percent and 62 percent for females. Although female access rate is a 3 percent lower, there is no statistically significant difference between these numbers.

In Table 3, resume screening rates show a slightly different pattern, with higher resume access rates for females than males. As expected, resume access rates are much lower than the application access rates given resume access requires an additional effort on the employer side. However, the difference between genders is not statistically significant again.

The callbacks by name of the applicant are reported in Table 4. Although there is a bit variation of callbacks among the applicants in both genders, the aggregate difference of callbacks is about 1.5 percent, which is in favor of females. The average callback rate to male applicants is 4.6 percent whereas average callback rate of female applicants is 6.3 percent. Hence, we observe a positive treatment in callbacks in favor of women. From the aggregate measures, we can say that men need to send 4 resumes to get equal number of callbacks for every 3 resumes sent by the female applicants. Again, callbacks ratios are even lower than the resume access rates given it is probably occurring after the resume access and only the applicants which are planned to be invited to an interview are called.

Calculations for net discrimination are given in Table 5. To calculate net discrimination, we first find applications in which male and female applicants are treated equally. Equal treatment can occur either from positive callbacks, listing or screening for both applicants or no callbacks, listing or screening for both. It is seen that more than 90 percent of the time our fictitious applicants are treated equally. While only the males get a callback from the employer is 2.5 percent of the time, 3.2 percent of the time only the female gets a callback. That means, in opposed to expectations, there exists net discrimination against men but it is very small in magnitude.

These results are somehow different from what we observe in the survey data, which is characterized by higher unemployment rate and longer unemployment spells for females, especially the higher educated ones. This discrepancy can have two different explanations. The first and most obvious one is related to our applicant pool and job pool. In correspondence audit, all our applicants have university degree, suggesting that they are highly educated individuals. However, the entry level jobs that we were applying mostly do not require high human capital and offer minimum wage. That might explain why we do not observe a difference between males and females at the callback rates[4].

The second explanation comes from the stark difference between female and male labor force participation rates in Turkey. Even if employers have slight distaste for women, they need to seek female employees disproportionally if they want to have at least some female employees. Given labor force participation for women is low and highly educated females are even harder to find, employers might be discriminating in favor of women at the hiring stage to bring some women into the workplace.

[4]Remember, unemployment among lower educated females was also lower in our survey data and results from the correspondence study seem to be inline with that observation.

In Table 6, we run regressions on our discrimination measures to make inference on the statistical significance of our results. We find that, probability of getting a callback is 1.7 percent higher for female applicants on average. However, probability of being listed is 2.4 percent lower for females, albeit the significance of listing is sensitive to error structure we choose for the estimations. In other words, firms favors males while listing the applicants although the margin is quite small. The probability of resume listing goes up from 62 percent to 65 percent if the applicant is male. Given the listing rate is quite high in our sample, that is only around 5 percent overall improvement for male applicants. On the contrary, probability of callback is 1.7 percent higher for the female applicants compared to males. Given the callback rate is quite low, that difference implies a 37 percent improvement in callbacks when the applicant is female. This is both economically and statistically significant difference in callback rates in favor of females [5].

We have the chance to see how many applicants were applying to each vacancy. To use this observation, we followed the jobs we applied till the closing date of the vacancy and observe the number of total applicants. The applicant number went as high as 50,000 and as low as 100. To make sense of these data, we divide the sample into two by defining 500 applications as the cutoff value.

As can be see from Table 7, the differential treatment of female applicants in terms of listings are due to vacancies with less than 500 applicants. The probability of being listed is 4.3 percent lower for a female applicant compare to male applicant if the vacancy has less than 500 applications but the significance is sensitive the error structure selection again. However, the differential treatment

[5] Since our dependent variable is binary, we also carried probit estimations. Neither the coefficients nor the inference are different when we run probit estimates. Therefore, we choose to present linear probability estimations for ease of interpretation.

disappears if the number of applicants are higher than 500 cutoff.

When we look at the callbacks by applicant pool size, we see that females are favored in terms of callback by the vacancies with less than 500 applicants. Particularly, the probability of getting a callback is 3.4 percent higher for female applicants if the vacancy has less than 500 applications (Table 9). That observation is especially important given the number of callbacks overall are higher when the number of total applicants are lower. Although around 40 percent of all vacancies have less than 500 applications in our data set, around 60 percent of all callbacks are due to those vacancies. That means, the discrimination against males is higher when we focus on the vacancies which are producing most of the callbacks.

When we investigate the gender discrimination by the sectors, we find an unexpected result as Table 10 presents. Although the significance is specification sensitive, the probability of getting a callback is higher for females that are applying to vacancies in manufacturing and other production sectors compared to services. Given the services is female intensive and manufacturing is male intensive in Turkey as we stated in survey results, the positive treatment of women in manufacturing is confusing at the face value. However, this observation is also inline with our previous prediction on employer tastes and employee preferences. Even if employers have distaste against women - which we have no evidence for - it cannot be as strong as the lack of women who is interested in working in the manufacturing sector. That discrepancy might result in positive discrimination in favor of women especially in the manufacturing sector.

Finally, we would like to conclude our findings by looking into correlations among our discrimination measures. Table 11 summarizes the correlations of listing, screening and callbacks measures for males and females. According to correlations between listing and callbacks, females are more likely to have a callback if they are listed by the firm. On the contrary, males are more likely to have a callback if their application is screened by the firm. Moreover, listings and screening are more correlated for women than men. That observation is weakly inline with our predictions on employer preferences. Employers are more inclined to call women without screening their resumes indicates that they might be trying to recruit more women given the labor force characteristics of the country.

As a result, we find evidence of positive discrimination towards women in Turkish labor market at the hiring process defined by the callback measure in our correspondence audit. However, given the lack of women in the labor market, it is hard to understand whether this treatment is due to employer preferences, i.e. discrimination against men or some other reason, such as trying to gender balance work space environment slightly.

6 Conclusion

In this study, we try to shed a light on a possible mechanism, namely gender discrimination at the hiring stage which might correlates with the low labor force participation of women in Turkey. We first showed that female labor force participation in Turkey is quite low, unemployment rate is higher and unemployment spells are longer for females. Then, we conducted a correspondence audit study in Istanbul and measure the callbacks, resumes screening and application listing responses by employers to produce hiring stage discrimination measures. With those measures at hand, we show that the hiring stage discrimination is probably not a source of those gender differences in the labor market. There is no difference between males and females for listing rate and screening rate measures, which reflect the hiring process prior to a callback. Moreover, we show that females are positively treated at the hiring stage. We calculate that for every 3 resumes sent by a female applicant, male applicants need to send 4 resumes to get the same number of callbacks in our study. Given employer responses to similar quality resumes are not different among genders in listing and screening measures and in favor of females in callbacks, we conclude that gender discrimination might not be a good medium in explaining labor market differences of genders in Turkey.

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VARIABLES	All Employment	Female Employment	Male Employment
female	-1.12111***		
	(0.00500)		
primary education	-0.00304	0.00323	0.00662
	(0.00808)	(0.00990)	(0.01576)
secondary education	0.05423***	0.01707	0.01365
	(0.00967)	(0.01352)	(0.01641)
high school	0.15933***	0.20569***	0.08353***
	(0.00940)	(0.01266)	(0.01646)
college and above	0.77663***	1.09302***	0.43169***
	(0.01050)	(0.01373)	(0.01772)
age	0.13741***	0.11279***	0.12855***
	(0.00121)	(0.00171)	(0.00171)
agesq	-0.00176***	-0.00142***	-0.00179***
	(0.00001)	(0.00002)	(0.00002)
married	0.18051***	-0.14090***	0.75336***
	(0.00680)	(0.00873)	(0.01120)
household size	0.00715***	0.01284***	-0.00509***
	(0.00132)	(0.00187)	(0.00190)
rural	0.55238***	0.70639***	0.40472***
	(0.00584)	(0.00792)	(0.00856)
Constant	-2.22343***	-2.86673***	-2.02090***
	(0.02508)	(0.03590)	(0.03595)
Observations	379,742	196,822	182,920
Region FE	Yes	Yes	Yes

The dependent variable is the employment status, =1 if employed
Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$ are corresponding significance levels.
Reference group: Turk, male, no graduation, single, living in urban area.

Table 1: Determinants of Employment by Gender

Male	Number of Applications	Number of Listings	Listing Rate
Tolga Aydın	95	67	0.71
Melih Aslan	85	59	0.69
Zeki Keskin	75	52	0.69
Alican Korkmaz	97	63	0.65
Alper Mutlu	115	75	0.65
Alican Doğan	106	68	0.64
Caner Yavuz	119	76	0.64
Vural Kaplan	75	46	0.61
Orkun Koç	113	68	0.60
Vural Korkmaz	78	46	0.59
Average	**95.8**	**62**	**0.65**
Female			
Berna Sarı	85	59	0.69
Cansu Ateş	112	75	0.67
Berna Avcı	119	79	0.66
Gözde Tekin	102	67	0.66
Melis Işık	87	57	0.66
Sibel Çakır	89	58	0.65
Gamze Şahin	70	45	0.64
Gamze Durmaz	100	62	0.62
Buket Ateş	116	70	0.6
Gözde Koç	78	25	0.32
Average	**95.8**	**59.7**	**0.62**

Table 2: Listings by Applicant Name

Male	Number of Applications	Number of Screenings	Screening Rate
Vural Kaplan	75	14	0.19
Vural Korkmaz	78	14	0.18
Alican Doğan	106	18	0.17
Alper Mutlu	115	19	0.17
Tolga Aydın	95	16	0.17
Alican Korkmaz	97	15	0.15
Zeki Keskin	75	11	0.15
Melih Aslan	85	10	0.12
Caner Yavuz	119	13	0.11
Orkun Koç	113	11	0.10
Average	**95.8**	**14.1**	**0.15**
Female			
Gamze Şahin	70	18	0.26
Buket Ateş	116	24	0.21
Melis Işık	87	17	0.20
Cansu Ateş	112	19	0.17
Gözde Tekin	102	16	0.16
Berna Sarı	85	13	0.15
Berna Avcı	119	16	0.13
Sibel Çakır	89	12	0.13
Gözde Koç	78	6	0.08
Gamze Durmaz	100	6	0.06
Average	**95.8**	**14.7**	**0.16**

Table 3: Screenings by Applicant Name

Male	Number of Applications	Number of Callbacks	Callback Rate
Alican Korkmaz	97	13	0.13
Vural Kaplan	75	10	0.13
Alican Doğan	106	9	0.08
Tolga Aydın	95	6	0.06
Vural Korkmaz	78	4	0.05
Alper Mutlu	115	2	0.02
Caner Yavuz	119	1	0.01
Orkun Koç	113	1	0.01
Melih Aslan	85	0	0.00
Zeki Keskin	75	0	0.00
Average	95.8	4.6	0.05
Average	**95.8**	**4.6**	**0.05**
Female			
Gözde Tekin	102	17	0.17
Cansu Ateş	112	13	0.12
Melis Işık	87	10	0.11
Gamze Durmaz	100	7	0.07
Berna Avcı	119	5	0.04
Sibel Çakır	89	4	0.04
Buket Ateş	116	3	0.03
Gözde Koç	78	2	0.03
Berna Sarı	85	2	0.02
Gamze Şahin	70	0	0.00
Average	95.8	6.3	0.06
Average	**95.8**	**6.3**	**0.06**

Table 4: Callbacks by Applicant Name

VARIABLES	Listing	Screening	Callback
Equal Treatment	93.00	91.02	91.52
Turkish Men Favored	3.55	4.07	2.51
Turkish Women Favored	3.45	4.90	3.24
Net Discrimination	0.10	-0.83	-0.73

Table 5: Net Discrimination

Discrimination Measures - Male vs Female Applicants

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	list	list	screen	screen	call	call
Female	-0.0240	-0.0240**	0.00626	0.00626	0.0177*	0.0177**
	(0.0220)	(0.0105)	(0.0163)	(0.0109)	(0.0106)	(0.00903)
Constant	0.647***	0.647***	0.147***	0.147***	0.0480***	0.0480***
	(0.0154)	(0.0155)	(0.0115)	(0.0115)	(0.00691)	(0.00691)
Observations	1,916	1,916	1,916	1,916	1,916	1,916
R-squared	0.001	0.001	0.000	0.000	0.001	0.001

Robust standard errors are reported in parentheses for columns 1, 3, 5.
Standard errors are clustered by vacancy for columns 2, 4, 6. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Discrimination Measures

VARIABLES	(1) <500 Applicants	(2) <500 Applicants	(3) >500 Applicants	(4) >500 Applicants
Female	-0.0416	-0.0416**	-0.0118	-0.0118
	(0.0333)	(0.0163)	(0.0305)	(0.0140)
Constant	0.672***	0.672***	0.629***	0.629***
	(0.0232)	(0.0233)	(0.0215)	(0.0215)
Observations	818	818	1,014	1,014
R-squared	0.002	0.002	0.000	0.000

Robust standard errors are reported in parentheses for columns 1, 3.
Standard errors are clustered by vacancy for columns 2, 4. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Listings by the Applicant Pool Size

VARIABLES	(1) <500 Applicants	(2) <500 Applicants	(3) >500 Applicants	(4) >500 Applicants
Female	0.00733	0.00733	-0.00001	-0.00001
	(0.0286)	(0.0194)	(0.0187)	(0.0125)
Constant	0.208***	0.208***	0.0986***	0.0986***
	(0.0201)	(0.0201)	(0.0133)	(0.0133)
Observations	818	818	1,014	1,014
R-squared	0.000	0.000	0.000	0.000

Robust standard errors are reported in parentheses for columns 1, 3.
Standard errors are clustered by vacancy for columns 2, 4. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Screenings by the Applicant Pool Size

VARIABLES	(1) <500 Applicants	(2) <500 Applicants	(3) >500 Applicants	(4) >500 Applicants
Female	0.0342*	0.0342**	0.00394	0.00394
	(0.0176)	(0.0158)	(0.0125)	(0.0105)
Constant	0.0513***	0.0513***	0.0394***	0.0394***
	(0.0109)	(0.0109)	(0.00865)	(0.00866)
Observations	818	818	1,014	1,014
R-squared	0.005	0.005	0.000	0.000

Robust standard errors are reported in parentheses for columns 1, 3.
Standard errors are clustered by vacancy for columns 2, 4. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Callbacks by the Applicant Pool Size

VARIABLES	(1) Manufacturing	(2) Manufacturing	(3) Services	(4) Services
Female	0.0280	0.0280*	0.0113	0.0113
	(0.0189)	(0.0161)	(0.0130)	(0.0110)
Constant	0.0467***	0.0467***	0.0498***	0.0498***
	(0.0118)	(0.0118)	(0.00873)	(0.00874)
Observations	642	642	1,244	1,244
R-squared	0.003	0.003	0.001	0.001

Robust standard errors are reported in parentheses for columns 1, 3.
Standard errors are clustered by vacancy for columns 2, 4. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Callbacks by Sectors

	Listings	Screenings	Callbacks
Males			
Listings	1.00		
Screenings	0.23	1.00	
Callbacks	0.16	0.51	1.00
Females			
Listings	1.00		
Screenings	0.27	1.00	
Callbacks	0.18	0.48	1.00

Table 11: Correlations between Discrimination Measures

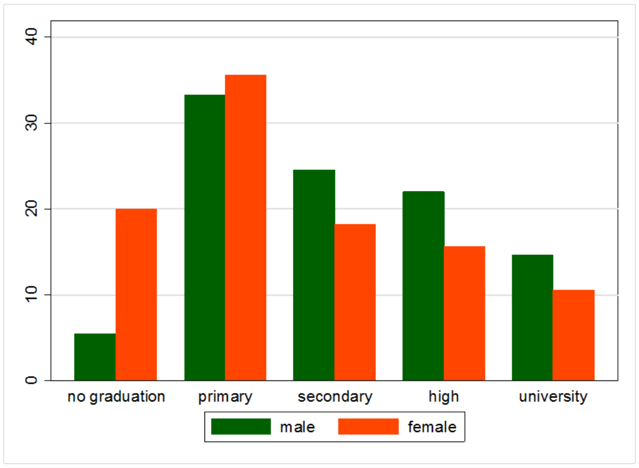


Figure 1: Educational Attainments by Gender

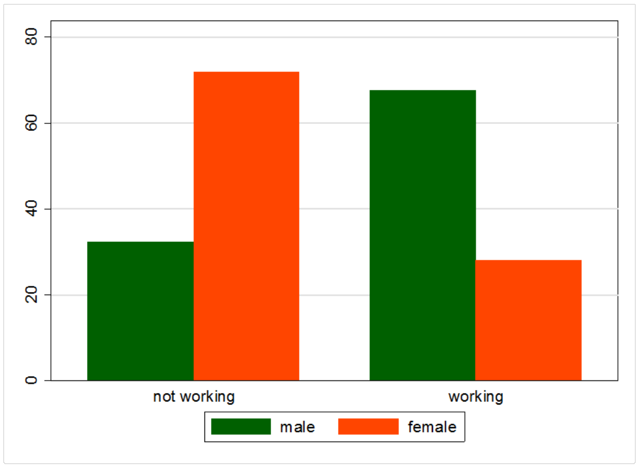


Figure 2: Employment by Gender

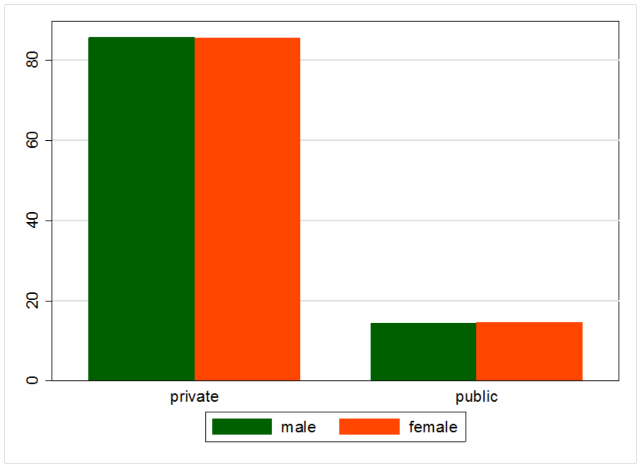


Figure 3: Share of Private vs. Public Workers by Gender

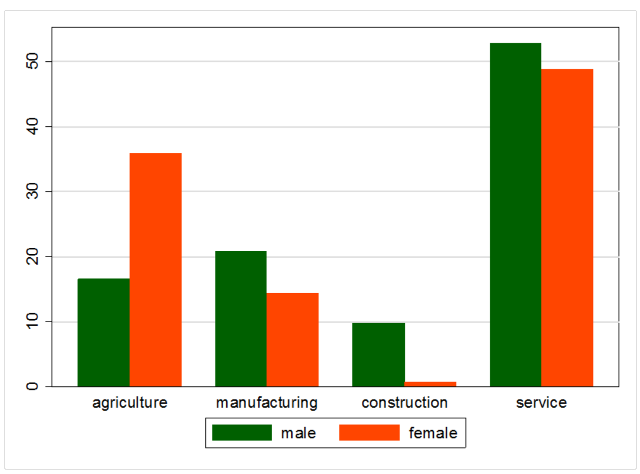


Figure 4: Sectoral Distribution by Gender

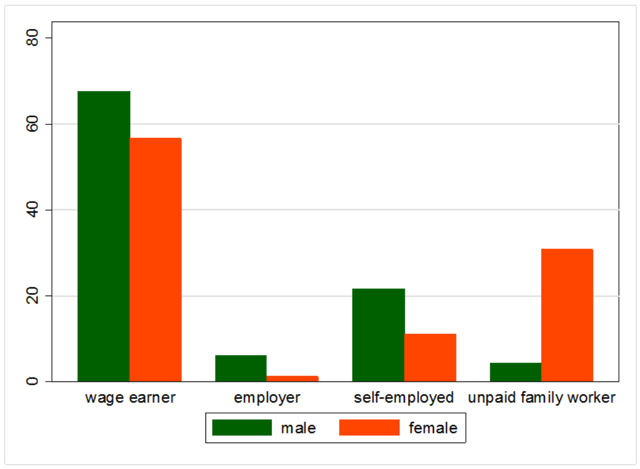
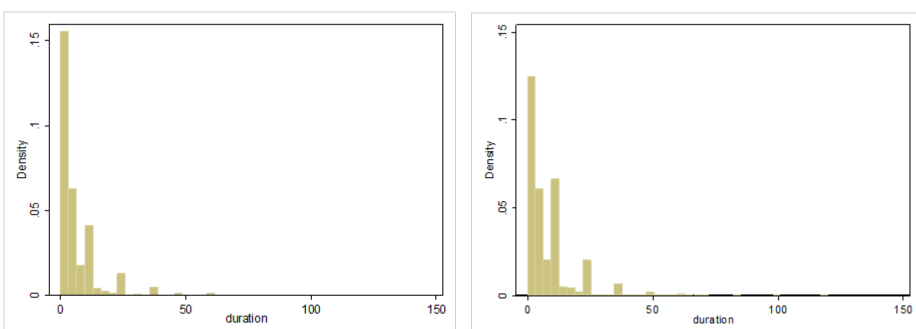


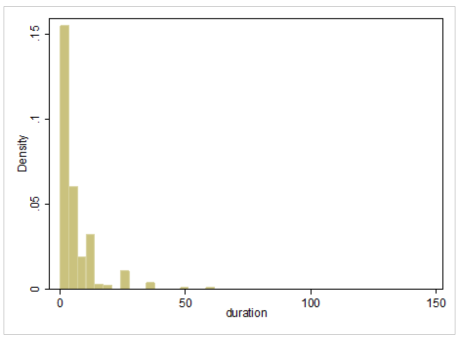
Figure 5: Employment Status by Gender



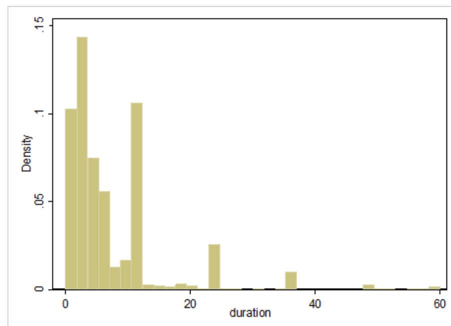
(a) Males

(b) Females

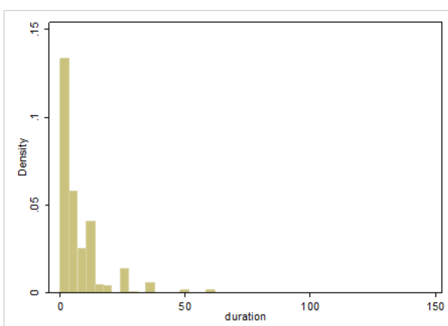
Figure 6: Duration of Unemployment by Gender



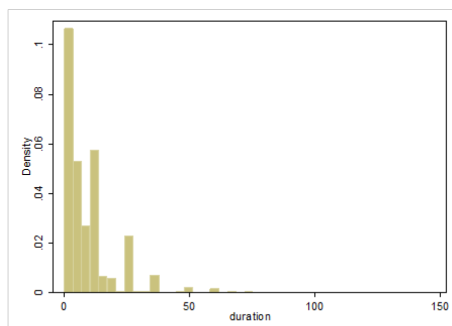
(a) Below High School Males



(b) Below High School Females



(c) Above High School Males



(d) Above High School Females

Figure 7: Duration of Unemployment by Gender and Education

A List of Neutral 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 Universities

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