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Working Paper No. 1205

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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 in the household, or economic 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 treat male and female applicants' resumes similarly prior to the callback stage. However, there is weak but positive discrimination against female applicants in the Turkish labor market. Hence, hiring stage discrimination does not contribute to the low female labor force participation in Turkey.

JEL Classifications: J71, J21, C93

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

ملخص

لا تزال مشاركة النساء المنخفضة في القوى العاملة مشكلة مهمة في سوق العمل التركي. بل قد تتفاقم المشكلة في سوق العمل نتيجة لعوامل الثقافية والتقليدية، مثل تقسيم العمل في الأسرة المعيشية، أو العوامل الاقتصادية، مثل التمييز ضد الإناث. في هذا المقال، نحاول تحديد الاختلافات في مراحل التوظيف بين الرجال والنساء من خلال منهجية مراجعة المراسلات. بالقيام بذلك، فإننا ننتج قياسين جديدين لاستجابة أصحاب العمل، بالإضافة إلى قياس الاتصال النمطي المستخدم في الأدبيات. كما نبين أن أصحاب العمل يعاملون المتقدمين من الذكور والإناث على قدم السواء وبنفس الطريقة قبل مرحلة الاتصال بهم ولكن هناك تمييز إيجابي ضد المتقدمات في سوق العمل التركي. ومن ثم، فإن التمييز في مراحل التوظيف لا يسهم في انخفاض مشاركة النساء في القوى العاملة في تركيا.

1. Introduction

Although the labor force participation rates for both men and women are lower than the OECD averages, the participation rate for women is exceptionally low in Turkey. The female labor force participation (FLFP) rate was 23.3 percent in 2004, barely increasing to 23.6 percent in 2007. The most recent figures suggest that the FLFP rate is still around 30 percent in Turkey, which is slightly higher than the half of the OECD average. Social gender norms and the low educational attainment of the women are two principal concerns regarding the female labor force participation in the country. On the education side, lower educational attainment of women compared to men forces them into the informal sector with low wages and nonexistent benefits. As a result, it is hard for women to find jobs exceeding their reservation wages. In addition to low educational attainment, the patriarchal family structure burdens females with child and elderly care, as well as other home production activities.

However, an additional channel affecting the female labor force participation negatively might be the gender discrimination in the labor market. Gender discrimination can potentially affect the FLFP through lower wages and longer unemployment duration, both of which might deter females from entering the labor market. This channel is rarely studied in the Turkish context.

However, disentangling mechanisms that create the low labor force participation of women is not a trivial task. It is particularly hard to ascertain whether the observed differences in labor force participation between women and men are due to discrimination. To this end, correspondence audit methodology became a popular tool in discrimination research in the recent years. In correspondence audits, equally qualified resumes belonging to fictitious applicants are sent to the real job vacancies. Then, callbacks to each applicant are recorded and compared with the other applicants' callbacks. In these studies, the applicants differ only in a single trait, e.g. gender, age or race, which is the source of discrimination studied by the researcher.

In this study, we first conduct an online correspondence audit in Turkey in line with the existing literature. Since we are interested in gender discrimination, we first prepare almost identical resumes, which differ in the gender. We signal the gender of the applicant via distinctively female and male names in our study. After cultivating the resumes, we applied for 960 online job openings in a popular job search site in Turkey.

After sending out the applications, we collect three different employer response to our applications. These responses, from the least informative to the most informative, are:

- *Resume listing*: Employers can filter and list our fictitious application together with other applications and see some brief information about the candidate, including the name and contact information. We call this measure as "resume listing" or listing throughout the paper.
- *Resume screening*: An employer can click and access the detailed resume of the applicant. They do not need to list the resume to access it so some resumes can be opened before they are listed. We call this measure as "resume screening" or 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 as "callback".

There is an implied increase in effort and interest from the employer between the listing and screening measures. Mainly because the employers do not actively communicate with the applicants in listing and screening measures. The last measure callback, is the traditional measure in correspondence audit studies. To the best of our knowledge, this is the first study that introduces the other two measures into the literature. We will discuss the drawbacks and strengths of these measures in the experimental setting chapter, but we can easily say that they provide more comprehensive information about the hiring stage discrimination by shedding light on the different stages of the hiring process.

We also employ 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 the completion of the hiring and possible wage discrimination. Hence, the survey data on labor market outcomes could potentially fill this gap that we observe in correspondence audits.

In line with the existing literature, we find that survey data indicates deep differences between males and females in the Turkish labor market. Particularly, women in Turkey have lower labor force participation rates, higher unemployment rates, and longer unemployment spells relative to men. In contrast, we do 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 weak but positive discrimination for women via the callback measure in the Turkish labor market.

The rest of the paper is structured as follows: We first summarize the related literature in the following section. Then, we explain our experimental design in the third chapter. The fourth chapter briefly summarizes the survey data, which is followed by findings of the paper. Finally, the sixth chapter concludes.

2. Literature Review

Our work is closely related to two strands of the literature. The first strand is that of the gender correspondence studies. To the best of our knowledge, no correspondence studies to date have been conducted in a predominantly Muslim and developing country, where female labor force participation is quite low. The second area is the female labor market participation and gender wage gap studies conducted in Turkey. However, there has not been much discrimination focus to date in Turkish studies, given they mostly focus on explaining participation difference and the wage gap between women and men via observed characteristics. 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 have taken a big step in labor markets in the recent decades, we still observe a gender gap in employment and earnings. Early work on discrimination mainly used regression analysis and decomposition techniques such as Oaxaca (1973) and Blinder (1973) on survey or registry data. However, limitations of this approach as explained in Bertrand and Duflo (2016) have shifted the emphasis to field experiments such as direct audit and correspondence audit studies.

There is a growing literature relying on the correspondence audit methodology, studying the gender discrimination at the hiring stage. For example, 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 a discrimination in favor of women in vacancies for computer analyst programmers, secretaries, and accounting positions and in favor of men for 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 of applications for construction worker, sales assistant, IT professional, high school teacher, restaurant worker, driver, accountant, nurse, pre-school teacher, and cleaner positions. While female applicants have a slightly higher probability to receive a call back compared to men for the pooled sample for all occupations, male applicants have a slight (insignificant) advantage in male-dominated professions.

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 resumes 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 measure gender discrimination are carried out in developed countries except for China. However, due to different labor market regulations, it is hard to generalize Chinese results to other developing countries. In this respect, our study also contributes to the literature by providing evidence from a developing country.

Likewise there exist only a handful of studies on labor market discrimination (ethnic, religion and gender) in Turkey. Gender discrimination analysis mainly focuses on the wage gap via Oaxaca-Blinder type decomposition tools. The rest of the gender discrimination research aims to understand main problems and characteristics of the female labor force participation in Turkey.

Dayioglu and Kasnakoglu (1997), using 1987 Household Income and Expenditure Survey dataset, estimate a wage regression on human capital variables. They show that 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 sizable and lowers the degree of the wage gap. Yamak and Topbas

(2004) analyze the extent of the male-female wage gap, using the 1994 Household Consumption Expenditures Survey. Appliying the same decomposition method, 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 in male-female earnings gap using 1996 Household Consumption Expenditure Survey. Their results also indicate a significant wage gap, particularly in the private sector. The main reason underlying the gender wage gap in the private sector is the higher returns to wage-determining characteristics for male workers. Kara (2006) using Turkish Household Expenditure and Income Survey analyze the gender wage gap, and he also concludes that the gender wage gap decreases with education. Cudeville and Gurbuzer (2007), using the 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 South European countries. However, they also emphasize that wage discrimination is only an insufficient indicator of discrimination against women and that the most prominent concern is, instead, the under-representation of women in the labor market.

Dayioglu and Kirdar (2011) examine the labor supply behavior of women using cohort analysis and show that younger cohorts of women are participating more than older cohorts in urban areas.

After controlling for education, however, they find that women participation rates do not change between cohorts.

Ilkkaracan (2012) and Toksoz (2011) indicate 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 export-oriented firms, female participation rate tends 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 is seen only among the university graduate. Guner and Uysal (2014) analyze the causal relationship between culture and female labor force participation for female migrants and find that female employment rates in migrants' province of origin around the time of their birth has a positive impact on the labor supply behavior of these individuals.

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 the 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 in the education system) increases the importance of this result with the possible and continuing future effects. Her second important finding is a negative association between patriarchal values and labor force participation. Dildar's findings indicate that urbanization does not weaken the effect of conservatism and so women's labor force participation continue to be weak in urban areas.

In short, female labor force participation and gender discrimination literature has 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 are aiming to fill this gap in literature in Turkey by providing the first experimental evidence on hiring stage discrimination against women via a correspondence audit study.

3. Experimental Design

In this study, we employ 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 mainly 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, the 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 and correspondence audits are no exception. For example, people with a normal body mass index are taken as the reference group when examining discrimination against overweight people. Similarly, males constitute the reference group in a gender study.

The prime benefit of audit studies is that the subjects (firms in the current experiment) 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 the reference and investigated applicants can be minimized. Finally, sending a small number of resumes prevent 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 can estimate 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 direct audit studies where fictitious applicants take interviews with the prospective employers. In direct audit studies, trained individuals take part in interviews and job offers are counted. Besides being costly, slow and prone to distortions; direct audits might carry signals more than the 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 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 to get a job offer or a wage offer before finalizing the recruitment process, it is also not possible to quantify discrimination in those steps. Moreover, it is not feasible to apply for 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 imperfect, 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 to 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 for 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 to understand whether the inequality of opportunity influences the 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 with 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 a list of the most common female and male names in Turkey. We further restricted this list to neutral-sounding names. Neutral names should not signal any ethnic or religious affiliation to anyone in Turkey. In other words, those names can be used by the majority of the population without a reference group in mind. Some examples of these 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 allow the survey-takers to assign any characteristics they want to a name including but not limited to the religious, ethnic or socioeconomic background. When we collected the responses back, we only kept the names, which signals either no affiliation or only an affiliation to the Turkish majority. 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 most frequently 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 diverse geographical areas. 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 can 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 regarding their identity signaling power.

3.2 Resume Characteristics

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

- Gender
- Birthplace
- 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[3]. 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 can be found in the appendix.

Like birthplace and educational institution selection, we assigned addresses from similar neighborhoods regarding socioeconomic characteristics to our resumes. We have selected addresses from Istanbul, and we matched vacancies from the Anatolian side of Istanbul to addresses from the Anatolian side and vacancies from the European side to addresses from the European side. That might seem slightly odd to someone who is not familiar with the city, but it is one of the most important job requirements for most job openings[4].

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

[3] We controlled the high school quality by the required threshold points in the high school entrance exam for enrollment.
[4] It is not rare to see specific address requirements in the vacancy advertisements.

3.3 Applying for Vacancies

As we noted above, we first limited our interest to Istanbul. Istanbul had roughly half of the vacancies available on the job portal, and it is the largest market in the country. Then, we limited our interest into entry-level jobs (no experience requirement), which are eligible for all college graduates (no specific college major requirement). Finally, we also chose new advertisements on 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.[5] 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 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.

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 can 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, both or neither of them could get interview requests, which is fairly common in audit studies. When neither of the candidate gets a callback, we consider that observation as a no observable discrimination observation. When only one of the candidates gets a phone call we count that as a discrimination observation, given that fictitious candidates are observably identical except their gender. The difference between the calls to females and males is the callback measure of discrimination that we generate in line with the existing 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 quantify discrimination. The web portal we are using for applications allows 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 applicants and they can only see limited information about the applicant when they list the applications, including but not limited to the name of the applicant. For example, if they list only the male applicants they will not see a female application at all on their list even though that person has ideal qualifications for the job. The listing measure is the first click information provided by the job application portal. Next, 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 by the website. Both pieces of click information suggest interest in the application, and we use these pieces of information to create two new measures of discrimination.

[5] In the original design, we sent four resumes per application. In addition to neutral female and male resumes, we sent either Kurdish male and female resumes or Muslim female and male resumes in each application. However, we only discuss the gender discrimination for neutral candidates in this paper.

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

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

4. Data

4.1 Household Labor Force Survey

We utilize microdata 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 the unemployment rate and labor market participation are calculated monthly from LFS.

LFS captures the noninstitutionalized 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 can 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 continue to labor market outcomes. We find that 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 pf notice in 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 the individual is working and 0 otherwise and graph it in Figure 2. Figure 2 shows that the share of working individuals is significantly higher among males compared to females (71.9 percent vs. 28 percent), confirming that the low labor force participation rate of females is one of the main problems of the Turkish labor market.

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

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

The low education level of females is also evident in Figure 5. 30.85 percent of the females are working as unpaid family workers. For males, this ratio is only 4.39 percent. As expected for both genders, wage earners have the biggest share, but the share is higher for males. On the other hand, working as an employer is rare among females. Only 1.26 percent of the women are employers 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 than the male unemployment rate (8.47 percent). The overall unemployment rate in the data is 9.93 percent which is close to the official rate of 10.1 percent. The higher unemployment rate for women could indicate discrimination against women, but it could also arise from the aforementioned differences in education as well.

To control for the education effect, we create two groups. The first group consists of individuals with the education below high school; the second group consists of individuals with a high school degree or above. 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; 7.48 percent for males and 16.78 percent for females. 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. The unemployment rate of less educated women is even lower than that of less educated men. That seems a natural outcome of women working in low-skilled jobs, in the informal sector and working as unpaid family workers.

On the other hand, for higher educated individuals, the unemployment rate of females (16.68 percent) is more than two times the unemployment rate of males (7.48 percent). This observation could be interpreted as an indicator of discrimination against educated females or preference difference between males and females in the labor market. Remember that higher educated individuals are also the group we focus in the correspondence audit.

The survey asks the unemployed individuals "for how long have you been looking for a job", with the results reported in months. We see that not only are female unemployment rates higher than males, but also their unemployment spells are longer (Figure 6). When we focus on the two aforementioned education groups, we see that for both genders, the 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 region fixed effects. We first run this model by adding a gender dummy that takes the value 1 for females and 0 for males, therefore trying to see estimates are suggestive of the existence of discrimination between genders. Then, we run the same model for females and males separately to see how the possible effects of 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 a university degree on employment probability is higher for males than females. The 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 the probability of being employed for males, it has a negative effect on 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 a 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, the average application resume listing rate for males is 65 percent and 62 percent for females. Although the female access rate is 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 again not statistically significant.

The callbacks by the 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 in favor of females. The average callback rate for 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 an 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 who 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 can be seen that more than 90 percent of the time, either both or none of our fictitious applicants are get a response. While only the male applicant got a callback from the employer 2.5 percent of the time, 3.2 percent of the time only the female applicant got a callback. That means, opposed to expectations, we observed net discrimination against men, albeit it is 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 a university degree, suggesting that they are highly educated individuals. However, the entry level jobs that we were applying do not require high human capital and offer minimum wage more often than not. That might explain why we do not observe a difference between males and females at the callback rates[6].

The second explanation comes from the stark difference between female and male labor force participation rates in Turkey. Even if employers have a 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.

In Table 6, we run regressions on our discrimination measures to make inference on the statistical significance of our results. We find that the probability of getting a callback is 1.7 percent higher for female applicants on average. However, the probability of being listed is 2.4 percent lower for females, albeit the significance of listing is sensitive to the error structure we choose for the estimations. In other words, firms favor 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, the probability of callback is 1.7 percentage points 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. That is both economically and statistically significant difference in callback rates in favor of females[7].

We have the chance to see how many applicants were applying for each vacancy. To use this observation, we followed the jobs we applied to 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 seen 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 percentage points lower for a female applicant in comparison to a male applicant if the vacancy has less than 500 applications but the significance is sensitive to the assumed error structure selection again. Differential treatment disappears, however, if the number of applicants is higher than 500 cut-off.

When we look at the callbacks by applicant pool size, we see that females are favored regarding the callback by the vacancies with less than 500 applicants. Particularly, the probability of getting a callback is 3.4 percent higher for the 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 is 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.

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

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

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, the positive treatment of women in manufacturing is confusing at face value. However, this observation is also in line with our previous prediction on employer tastes and employee preferences. Even if employers have a distaste for women - which we have no evidence for - it cannot be as strong as the lack of women who are 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 workspace environment slightly.

6. Conclusion

In this study, we try to shed light on a possible mechanism for labor force participation rate of women in Turkey, namely gender discrimination at the hiring stage. We first showed that relative to men, women in Turkey have lower labor force participation rates, higher unemployment rates, and longer unemployment spells. We then conducted a correspondence audit study in Istanbul and measured callbacks, resume screening and resume listing responses by employers to produce hiring stage discrimination measures. We show that there is no difference between males and females for listing rate and screening rate measures, which represent the hiring process prior to callback. Moreover, we show that females are positively treated at the callback stage, which is in line with the existing literature. We calculate that for every three resumes sent by a female applicant, male applicants need to send four 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 favor of females in callbacks, we conclude that gender discrimination might not be a good medium for explaining the gender gap in the Turkish labor market.

Taking the results at the face value, it looks like audit and survey results are contradictory. Yet, it is important to note that correspondence audit results are driven from a specific set of individuals.

First, we focus on educated individuals in the correspondence audit. Hence, we cannot conclude there is no gender discrimination towards lower educated females in Turkey. If that is the case, both higher and lower educated females might have higher unemployment rates due to composition effect at the equilibrium. Second, our correspondence audit study focuses on Istanbul, which is the largest market in Turkey. Still, gender discrimination might be higher in smaller cities of Turkey. This difference might also cause worse labor market outcomes for females, higher and lower educated alike. As a result, we believe future research should focus on different education levels and a broad set of cities to get a better understanding of gender discrimination in Turkey.

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Table 1: Determinants of Employment by Gender

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 2: Listings by Applicant Name

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 3: Screenings 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 4: Callbacks 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 5: Net Discrimination

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 6: 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 7: Listing by Applicant Pool Size

	(1)	(2)	(3)	(4)
VARIABLES	**<500 Applicants**	**<500 Applicants**	**>500 Applicants**	**>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 8: Screenings by the Applicant Pool Size

	(1)	(2)	(3)	(4)
VARIABLES	**<500 Applicants**	**<500 Applicants**	**>500 Applicants**	**>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 9: Callbacks by the Applicant Pool Size

	(1)	(2)	(3)	(4)
VARIABLES	<500 Applicants	<500 Applicants	>500 Applicants	>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 10: Callbacks by Sectors

	(1)	(2)	(3)	(4)
VARIABLES	Manufacturing	Manufacturing	Services	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 11: Correlations between Discrimination Measures

	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

Figure 1: Educational Attainments by Gender

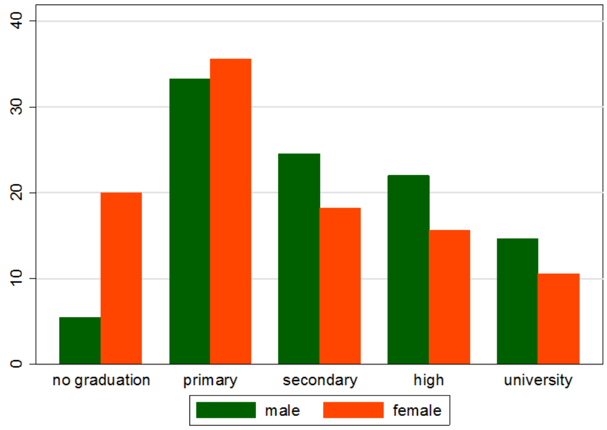


Figure 2: Employment by Gender

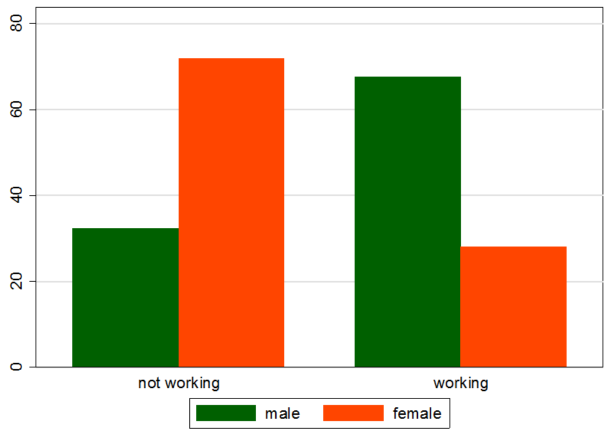


Figure 3: Share of Private vs. Public Workers by Gender

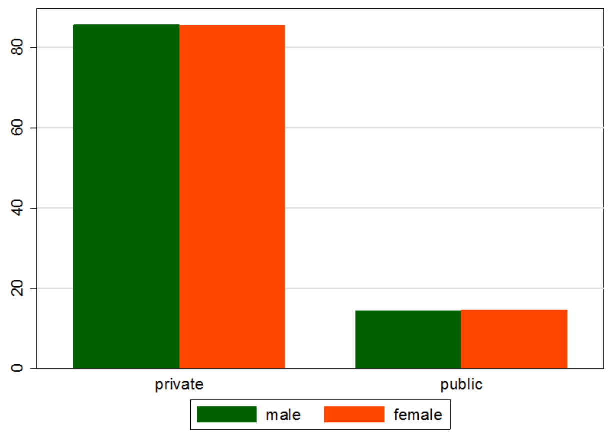


Figure 4: Sectoral Distribution by Gender

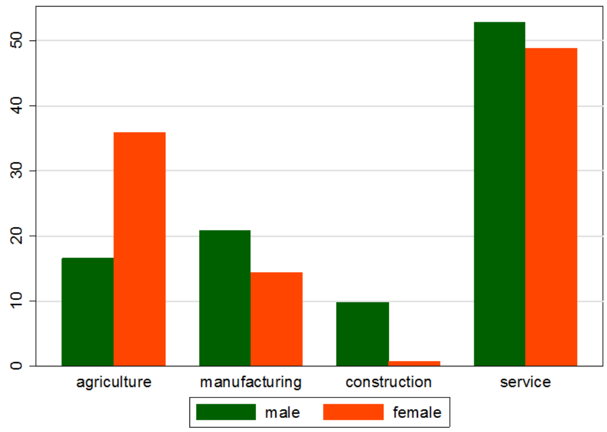
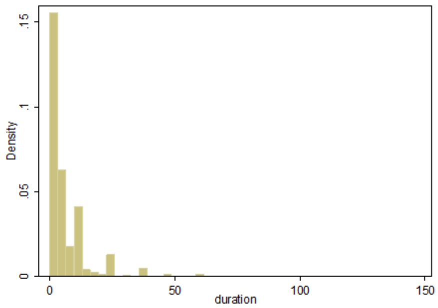
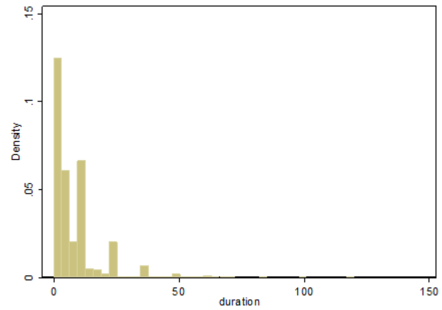


Figure 5: Employment Status by Gender

Figure 6: Duration of Unemployment by Gender

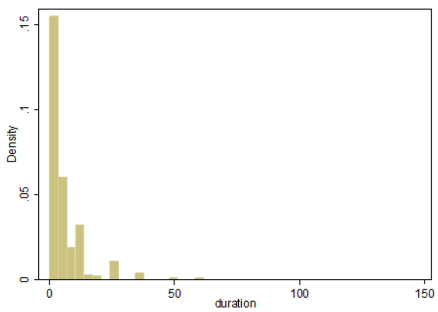


(a) Males

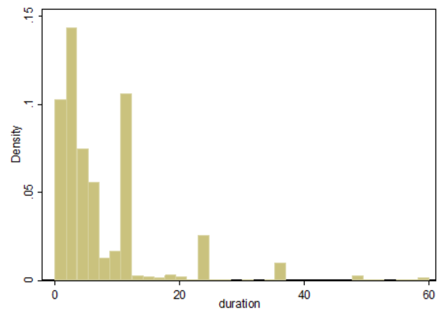


(b) Females

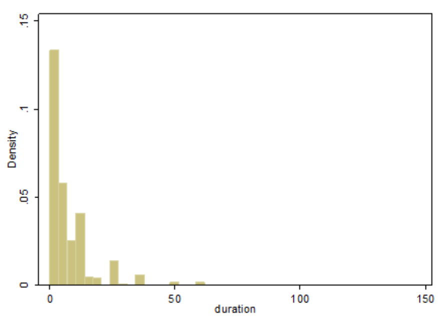
Figure 7: Duration of Unemployment by Gender and Education



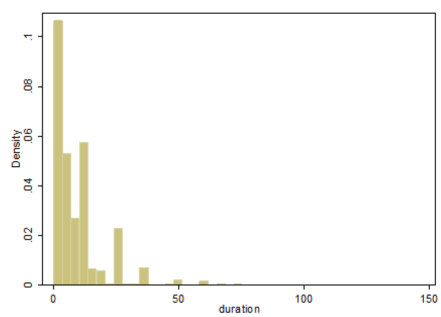
(a) Below High School Males



(b) Below High School Females



(c) Above High School Males



(d) Above High School Females

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
- Çukurova University
- Dokuz Eylül University
- Akdeniz University
- Anadolu University
- Selçuk University
- 19 Mayıs University
- Ege University
- Gazi University
- Pamukkale University