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Gender Differences in College Applications: Evidence from the Centralized System in Turkey

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Abstract

In Turkey, as in many other countries, female students perform better in high school and have higher test scores than males. Nevertheless, men still predominate at highly selective programs that lead to high-paying careers. The gender gap at elite schools is particularly puzzling because college admissions are based entirely on nationwide exam scores. Using detailed administrative data from the centralized college entrance system, I study the impact of gender differences in preferences for programs and schools on the allocation of students to colleges. Controlling for test score and high school attended, I find that females are more likely to apply to lower-ranking schools, whereas males set a higher bar, revealing a higher option value for re-taking the test and applying again next year. I also find that females and males value program attributes differently, with females placing more weight on the distance from home to college, and males placing more weight on program attributes that are likely to lead to better job placements. Together, these differences in willingness to be unassigned and in relative preferences for school attributes can explain much of the gender gap at the most elite programs.

JEL Classification: C35, I20, I24
Keywords: gender gap, college admissions, school choice

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1 Introduction

In the last few decades, the gender gap in education has changed remarkably in favor of females. Females have begun to outperform males in general achievements. However, while the share of males in total higher education enrollment has fallen considerably in many countries, females still remain underrepresented in many high-wage occupations.

There are a number of studies that provide explanations for the reduction in gender gap in higher education enrollment (Blau 1998; Goldin et. al. 2006; Jacob 2002; Peter and Horn 2005; Reynolds and Burge 2004) and gender differences in major choices (Barres 2006; Friedman 1989; Polachek 1978, 1981; Turner and Bowen 1999; Xie and Shauman 2003; Zafar 2009). This literature could suggest two plausible explanations for the gender differences in highly selective higher education programs: Differences in preferences for college majors and differences in abilities and achievement distributions. However, there is no comprehensive analysis incorporating both explanations to elaborate the differences in higher education enrollment and major choice decisions in order to understand the reasons behind the persistent underrepresentation of females in highly selective university programs and the poor reaction of the gender gap in labor markets given the remarkable turn in female educational achievements.

To address this issue, I use detailed administrative data from the Turkish university entrance test in 2008. Data includes applicants' choices over all university programs, so that I can directly investigate the potential differences in choices made by males and females conditional on test scores.

In Turkey, the transition to higher education from high school is highly centralized and only possible through a standardized test conducted at a national level. After taking the test and receiving their scores, applicants submit a list of higher education programs in order of preferences and a central authority applies an algorithm to assign students to each program taking into consideration the student's preferences and their test score. Given the large number of university applicants, the demand for higher education is quite far from being met. In order to avoid over-enrollment in higher education, the system is designed in a restrictive way. Driven by high competition for getting into a quality program, there are a large number of applicants every year who retake the test because they have failed to obtain a high enough test score to be placed in their desired program. This is why, many applicants who are not satisfied with their test score choose to be unassigned at the cost of not enrolling at all and retake the test the following year.

Retaking the test is costly and risky since applicants have to spend another year preparing for the exam in a very competitive environment, and face also the uncertainty of their new test score. Since the effect of uncertainty and competition could vary across gender[1], it is reasonable to expect that the willingness to be unassigned, reflected initially in choice of university programs, and eventually in labor market outcomes, could differ by gender. Applicants less willing to be unassigned to a university should, for example, have a lower reservation university program, which means that they should apply to lower-ranking university programs.

In this paper, the institutional setting is used as a tool to investigate gender differences in decision making that goes behind the universities listed on applications. I particularly focus on describing the gender differences in the reservation university program and on the potential effect that school choice might have on placement outcomes, and thus the labor market. For this, I construct a measure that allows me to describe the willingness to be unassigned to a university, and show that there are significant differences across gender in this measure. I also elaborate the link between willingness to be unassigned and school choice. This approach is used on the search to answer the following crucial questions: Are there gender differences in willingness to be unassigned and if so are there any gender differences in university program choices driven by differences in the willingness to be unassigned? I assemble a unique dataset that allows me to address these questions. I use the 2008 Student Selection Test (Ogrenci Secme Sinavi-OSS in Turkish) Applicant Survey provided by Student Selection and Placement Center (Ogrenci Secme ve Yerlestirme Merkezi-OSYM in Turkish) together with administrative data containing the choice lists submitted by each applicant and the information on test scores in each

[1] Recent studies provide evidence suggesting that there are significant gender differences in attitudes towards risk and competition and in performance in competitive environments. Literature on gender differences in risk preferences and reaction to competition shows that females are more risk-averse than males and they do not only avoid competition but also perform worse under competition (Dohmen and Falk 2006; Gneezy et al. 2003; Niederle and Vesterlund 2005).

subject, high school information, and personal achievements. I also consider the characteristics of different cities, universities, and programs from each student's choices.

My results show that, controlling for test scores, high-school and other individual characteristics, girls are less willing to be unassigned and they are more likely to choose low profile schools as their lowest option and to get assigned to lower cutoff score programs. Finally, according to results from rank ordered logit model estimations, girls are more likely than boys to be concerned about admission probability rather than other attributes, such as foreign language as the instruction language, which is potentially a valuable asset for the labor market.

The focus of the paper is on the effect of heterogeneity in the willingness to be unassigned on the observed differentials in school choices, university placements, and thus labor market outcomes among males and females. Even though it is reasonable to remain agnostic on the reasons behind the differences in willingness to be unassigned, it is also possible to provide different possible explanations behind the obtained results. This paper documents for the first time the existence of a gender gap in the willingness to be unassigned when it comes to choosing universities and it's effects on placement outcomes. Additionally, I offer a new perspective on heterogeneity in school choice[2] by measuring the differences in reservation university programs.

The paper is organized as follows: in Section 2, I provide details about the institutional setting in Turkey; in Section 3, I describe the data and show some descriptive statistics to motivate the rest of the paper. In Section 4 and 5, I explain the research design and report the main results. In Section 6, I conclude.

2 Procedure to Apply to Universities in Turkey

Ensuring equal opportunity in access to education is one of the major challenges of the Turkish educational system, which is characterized by crucial income, regional, and gender disparities. In the last 30 years, the gender gap has been a persistent characteristic of

[2]Cullen et al. 2003, Hastings et al. 2008, Kehinde 2011

Turkish university enrollment and of its labor markets. Female labor force participation (especially at the urban settings) has been lower than in any other OECD country. In rural areas, for example, girls are more likely to stay home and join family labor while boys are more likely to go to school. In the past few years, however, this story seems to have been changing. As in many other countries, girls in Turkey have begun performing better than boys in terms of general education achievements. For instance, girls now have higher high school GPAs on average. As for the university applications, the gender gap is not as severe; in 2008, 44% of high school graduates were girls while 38% of university applicants were girls. Also, girls outperform boys on average on the university entrance test in almost every subject. Given these recent improvements in the relative performance of girls, what remains puzzling is that there has been very little reduction in the gender gap in terms of enrollment rates in highly selective college programs that are linked to high-wage occupations.

In this section, I briefly explain the university entrance system in Turkey. Some features of the application and admission procedure will be important to understand how I answer the research question of the paper and will also shed some light on the decision-making of applicants.

The national university entrance test is called as "Student Selection Exam" (OSS in Turkish) and the central authority, named Student Selection and Placement Center (OSYM in Turkish) conducts the test and placement process. Given that there is a large demand excess, this exam is highly competitive and the system has a discarding structure with a double-fold objective: Firstly, it denies access to university enrollment to the least successful students with the presumption that they may drop out or generally perform poorly in college. Secondly it gives access to university enrollment to the most successful students and according to their preferences offers them a place in a university and field of study that is presumed to maximize their utility. The only requirement for an OSS application is to have graduated and/or be eligible to graduate from high school. Applications are received by OSYM with a strict deadline all around the country (around March). All high schools submit the GPA's of their students to OSYM which are used to calculate the final test scores of applicants. The test is conducted at a national level on the same date/time (in June) in all regions of the country.

High school students choose a broad subject of study in their second year such as: Sciences, Turkish-Mathematics, Social Sciences, Foreign Languages, or Arts. The university entrance test has 2 main sections as Quantitative and Qualitative in addition to a foreign language section (See Figure 1).

Two mains sections each have 2 sub-sections. Regardless a student's choice of subject in high school, each student answers essentially Quantitative-1 and Qualitative-1 sections. Quantitative-2 and Qualitative-2 sections are more advanced requiring more detailed knowledge in these subjects.

Based on the number of correct and incorrect answers in these sections, 7 different test scores are calculated for each individual in the following categories: OSS Quantitative-1 score, OSS Qualitative-1 score, OSS Equally Weighted-1[3] score, OSS Quantitative-2 score, OSS Qualitative-2 score, OSS Equally Weighted-2 score[4], and Foreign Language score. As the coefficients that are multiplied with the number of correct answers in each section are higher for the sections that pertain to applicant's high school subject and they are also penalized for incorrect answers, applicants tend to give priority to answer relevant sections of the test in order to maximize their score.

For those with a test score higher than 160 in OSS Qualitative-1, OSS Equally Weighted-1, OSS Foreign Language and a test score higher than 185 in OSS Quantitative-2, OSS Qualitative-2, OSS Equally Weighted-2, OSS placement scores are calculated while those with test scores below these thresholds are considered as "failed". Placement scores are calculated in each category as a sum of OSS test score with the student's weighted high school GPA. Three different weighted GPA's are calculated for quantitative, qualitative and equally weighted placement scores. Weights control for OSS scores and the GPAs of all students of a given high school as well as within high school subjects. The weighted GPA is calculated with lower coefficients in an off-subject main category. For example, an

[3]It is calculated as a weighted average based on the correct and incorrect answers from Quantitative-1 and Qualitative-1 sections

[4]It is calculated as a weighted average based on the correct and incorrect answers from Quantitative-2 and Qualitative-2 sections

applicant having studied Sciences in high school subject would have the highest coefficient for the OSS Quantitative categories (e.g. 0.8) while it is the lowest for OSS Qualitative categories (0.2). Since weighted high school GPA leads to a lower placement score for off-subject categories, it strongly discourages applicants to choose off-subject university programs as the test score in related subjects is required to apply.

Each university program is associated with one of the 7 subject categories and it has a pre-announced limited enrollment capacity which is determined by Higher Education Council. Applicants receive their final placement scores in all categories together with a booklet where they can see the capacity and the cutoff score of each university program from last year's admissions.[5] After knowing their final placement score in each category and each program's previous years' cut-off scores of each program, applicants make a list of programs up to 24 from 7 categories.

The allocation algorithm is based the on college optimal allocation mechanism. All students who choose a university program are ranked according to their placement scores in the the department's associated category with that department and the students with higher scores are tentatively assigned to that program under the university program's capacity constraint. (For example, the computer engineering department is associated with the category Quantitative-2 and all applicants choosing the engineering department of university A are ranked according to their Quantitative-2 placement score.) Tentative assignments continue at each step of the algorithm mechanism until each applicant gets either one final assignment or no assignment. Since the demand for many programs is higher than the capacity of the programs, OSYM gives priority to the applicants with higher test scores. Therefore an applicant will be assigned to the program closest to the top of her preference list where her test score is sufficiently high compared to the other applicants who have the same department in their choice list given the capacity constraint.

On average around half of the applicants are placed in a university program. The applicants who do not have sufficiently high test scores to be assigned in any department on their list get no assignment and can re-take the exam in the following years. A relevant

[5]Each university program has a cutoff score which is determined by the placement score of the last admitted student in last year

feature of the system is the punishment for re-taker applicants who are assigned to a university program in the previous year. If an applicant does not enroll in her placement and retakes the test in the following year, applicant's weighted high school GPA is calculated with a lowered coefficient. This rule highly discourages applicants to have a program that they are not willing to attend on their list. Therefore, applicants are encouraged to get no assignment this year, remain unenrolled for a year and retake the test next year in which case their test score in the next year remains "unaltered" instead of attending an undesired program or rejecting the assignment and retaking the test with lower weighted high school GPA.

3 Data and Descriptive Statistics

3.1 Dataset

The dataset employed in this study was obtained from a merge of the 2008 OSS (Student Selection Examination) dataset and 2008 Survey of the OSS Applicants and Higher Education Programs dataset. The OSS dataset provides administrative individual information on test scores, high school weighted GPA's, the submitted choice list of university programs and the placement outcome for the 1,646,376 applicants. On the other hand, the Survey of OSS applicants is a survey conducted by OSYM where the applicants are asked questions about the socioeconomic characteristics of their household, high school achievements, private tutorials, applicant's views about high school education and private tutorials. This is a survey conducted online and 62,775 applicants answered the survey questions in 2008. I have access to only a random sample of about 16 percent with 9983 observations. Finally, the Higher Education Programs dataset provides the information about the characteristics of the universities and higher education programs (such as whether it is private or public, instruction language, cutoff grades for previous years, capacities,...etc).

Table 1 provides the summary statistics for applicants by gender. From this table, it is clear that girls have higher high school GPAs on average, test scores and a lower rate for retaking the test than boys. As it was previously stated, girls are less likely to obtain a high school degree and take the university entrance test and this might create a selection bias. In order to avoid the positive selection in the favor of female applicants, my analysis will be based on an empirical approach that conditions on the test scores. In other words, it aims to investigate the differences in university applications controlling for the standardized test scores obtained by individuals.

As it was previously mentioned, an applicant can put up to 24 choices on their application. In the sample of 9983 applicants, 1306 applicants did not submit a choice list at all. 1217 of these did not submit a list although they had a higher test score than the minimum of 160 in at least one of the basic categories (Equally Weighted-1, Qualitative-1, Quantitative-1, Foreign Language). 3238 applicants (one third of sample) submitted a full list of 24 departments where the average number of choices in the list was 14.28.

Table 1 also gives the summary statistics of characteristics related to the choices made across gender. 9% of females and 11% of males do not submit a choice list so that they do not receive an assignment although they passed the threshold test score. Also, females seem to list a higher number programs from a higher number of subject categories which implies a more diversified choice list.

One of the possible drivers causing the gender differences in choice and willingness to be unassigned could be differences in family support by gender in favor of boys. On the other hand, given the positive selection of females, it is reasonable to argue that girls are not as discriminated as one would expect. Indeed, it seems females have better financial support and their parents are relatively better educated with respect to boys. Table 2 shows parents education and some family support indicators by gender and it shows that the mean differences in parents education levels are positive and significant. Female applicants do not only have better educated parents but also they are significantly more likely to attend private tutoring centers. Also, it seems that their parents are more likely to be willing to pay a private university tuition which is considerably higher than public universities. These descriptive statistics could arguably support the idea that girls are not as restricted in terms of family support as one might expect.

3.2 Descriptive Evidence on Gender Differences in Willingness to be Unassigned to Retake the Test

In this section, it is aimed to provide a frame describing the retaking decision of applicants and report some descriptive statistics in order to motivate the research question. I first describe a very simple model in a search model context for the decision to get no assignment instead of choosing a university program that has a feasible cutoff score given the obtained test score. Let $w_i \in [\underline{w}, \bar{w}]$ denote the test score that applicant i obtains this year and the utility of attending a university program that is attainable with w_i is given by $U(w_i)$ with $U' > 0$ and $U'' < 0$. Applicants are risk averse so that $U(w_i)$ is concave and has decreasing absolute risk aversion.

An applicant with the test score w_i either accepts to choose a program that is feasible with w_i or to retake the test in the following year. Applicant i is assumed to obtain a test score $\tilde{w_i}$ in the next year which is a random variable given by:

$$\tilde{w_i} = w_i + s_i \tag{1}$$

where s_i is the shock to the test score that has following mean and variance:

$$E(s_i) = \mu_{si} \tag{2}$$

$$Var(s_i) = \sigma_{si}^2 \tag{3}$$

Therefore, $\tilde{w_i}$ is a random variable with cumulative distribution function $F(\tilde{w_i})$ and conditional mean and variance given by:

$$E(\tilde{w_i}|\sigma_i) = w_i + \mu_{si} \tag{4}$$

$$Var(\tilde{w_i}|\sigma_i) = \sigma_{si}^2 \tag{5}$$

Given individual characteristics X_i, an applicant i with the test score w_i compares $U(w_i|X_i)$ the utility of attending a program that is feasible with w_i and the expected value of retaking the test in the next year. Let $V^i(w_i)$ denote the value of retaking the test, given test score w_i obtained today, and let w_i^R be the reservation test score of student i, i.e. if $w_i < w_i^R$ the student decides to retake the exam. Given these definitions, we have the following equations that fully characterize the problem faced by student i:

$$V^i\left(w_i\right) = \int_{w_R}^{\bar{w}} P(\tilde{w}_i|w_i, X_i)U^i(\tilde{w}_i)d\tilde{w}_i + \int_{\underline{\mathrm{W}}}^{w_R} P(\tilde{w}_i|w_i, X_i)V^i\left(\tilde{w}_i\right)d\tilde{w}_i - c \tag{6}$$

$$V^i\left(w_i^R\right) = U^i(w_i^R) \tag{7}$$

where c is the fixed financial cost of preparing for the test.

Facing such a problem, for a given variance in test scores, applicants are expected to be less willing to be unassigned if the mean test scores obtained by re-takers is lower. Similarly, for a given mean, a higher variance in test scores of re-takers would lead applicants to be less willing to be unassigned.

In the dataset, there is only information for test scores in 2008. To figure out the potential changes in the mean and variances of test scores by retaking, I estimate the test scores on individual characteristics controlling for high school and high-school-subject fixed effects and I calculate the differences in the residuals for first-time takers and second-time takers for both boys and girls. According to the calculations summarized in Table 3, I find that there is a significant increase in mean residual test scores for re-takers both for among boys and girls while there is no significant difference in the increase by gender. As for the variance of residuals, there is no significant change in the variance of residual test scores between first taker females and re-taker females while re-taker males seem to have significantly higher variance with respect to their first-taker pairs.

Considering these results together, with the fact that males tend to retake the test more than females, it is possible to argue that males tend to retake the test more than females even though they potentially face a test-score distribution with a higher variance by retaking with the same increase in mean score with females.

Other interesting descriptive statistics are obtained from the survey questions related to the applicants' self-assessments. In the survey, the applicants are asked the following questions:

- Would you define yourself as "a hardworking student"?
- Would you define yourself as feeling pressure during the exams?
- Would you define yourself as being extremely nervous during the exams?
- Would you define yourself as underperforming on the exams because of anxiety?

The differences by gender in the share of applicants answering these questions as "absolutely agree" are summarized in the end of Table 1. Girls are considerably more likely to define themselves as "a hardworking student" while they also seem to be more influenced by the exams by feeling pressure and being nervous which also they believe, affects their performances. Looking at these descriptive statistics, one might expect that females could be less willing to be unassigned because they might want to avoid another year of stressful preparation for the test in a competitive environment. Also, defining themselves as "a hardworking student", females might believe they have already put maximum effort into preparing for the test and another year of preparation would not change their results as much.

The attitude towards willingness to be unassigned is highly related to the reaction to competition as it requires preparing for the test another year in a very competitive environment. In addition to the cost of another year of preparation, the decision to retake also represents an example for a decision related to risk taking where an applicant expects to obtain a higher test score with an uncertainty in the next year. As a result, any difference in preferences for risk, competition, and waiting an additional year would also lead to the differences in willingness to be unassigned. According to the evidence that DellaVigna and Paserman (2005) report, more impatient job seekers set lower reservation wages. Also, Paserman (2007) argues that for US job seekers there is a lot of heterogeneity - the degree of discounting for low and medium wage workers is very high, while high wage workers are relatively more patient. Similar to job searching, it is expected here that the more the applicant avoids being unassigned, the lower the reservation university program of the applicant since safer choices will necessarily have lower rankings.

Given these descriptive statistics, it is reasonable to expect to find gender differences in reservation university programs that might explain the remaining gender differences in highly selective university programs in spite of the reversal of the gap in scholastic achievements.

4 Willingness to be Unassigned

The question that I seek to answer in this section is: Whether boys are more willing to be unassigned instead of being placed in a program that has a cutoff score which is attainable with the test score obtained that year. In order to answer this question, one should elicit the list of university programs applicants submitted.

Since applicants do not know the exact cutoff scores for university programs for the year that they take the exam, they infer a probability of being assigned to a university program looking at previous cutoff scores and their own test score. Thus, each student makes a choice list considering the assignment probabilities with the constraint that the list can include up to 24 choices from 10,617 programs belonging to one of the 7 categories provided by 147 universities. The choice list typically includes university programs having cutoff scores around their placement scores in corresponding categories according to applicants' expectations about the cutoff scores that are mostly determined by the popularity of the programs and universities.

The most crucial part of the analysis in this section is the definition of an individual's willingness to be unassigned. To proceed more formally, I describe how the applicants make their choice list in a simple framework:

There are 7 categories broadly defined in accordance with the sections of the test such as quantitative, qualitative, foreign languages etc. and every major is associated with one of these categories. Individual i receives a set of test scores S^i that contains a test score s_t^i calculated for each category t where $t = \{1, 2, 3, 4, 5, 6, 7\}$. From the 7 categories, individual i choose program(s) j with expected cutoff score C_{jt}.

Given the properties of algorithm mechanism that assigns applicants, it is possible to identify the last program for which an applicant is to be assigned. As it is mentioned in the previous section, the algorithm mechanism is based on the college optimal algorithm with multiple categories. All applicants choosing a program j from category t, regardless of the order of the programs in their list for a given category, are ranked according to their test score s_t^i. Thus, for this category, an applicant would be assigned to the program j with highest cutoff score in her list that her test score s_t^i attains. Similarly, if the test score s_t^i does not attain any of the programs chosen from a given category t, then applicant would get no assignment from this category.

Let program l_t^i with the lowest cutoff score chosen by individual i from category t. l_t^i is expected to be the last program in category t for individual i to be assigned. In other words, algorithm mechanism would yield no assignment if the program with the lowest expected cutoff score in a given category in the choice list would be above the test score.

As it was previously mentioned, the punishment rule for re-takers who were assigned to a university program in the previous year discourage applicants to choose a program that they are not willing to attend. Therefore, it is reasonable to assume that the applicant is willing to get no assignment from a given category, if not assigned to the last program with the lowest expected cutoff score in that category.
I define an applicant i as willing to be unassigned if the lowest cutoff score programs in all categories chosen to be higher than applicant's test scores in corresponding categories which implies:

$$C_{lt}^i > s_t^i \tag{8}$$

for all $t = 1, 2, ...7$.

The empirical model presented in this section is a reduced form model where I estimate the gender gap in the probability of being willing to be unassigned based on the definition above. Thus, I estimate the probability that the expression given by (8) is fulfilled on the dataset described in the previous section which allows to control for both high school and high school subject fixed effects.

The variable of interest M is an indicator variable taking the value of 1 for male applicants, and 0 else. The indicator variable for willingness to be unassigned of applicant i at school h with the subject field f is denoted by R_{ihf}, then the model is given by:

$$R_{ihf} = \delta M_i + x_i'\beta + \mu_h + \mu_f + \epsilon_{ihf} \tag{9}$$

where $i = 1, ...N$, $h = 1, ...H$, $f = 1, ..., F$, and ϵ_{ihf} is a random error term and the empirical hypotheses to be tested is $\delta > 0$.

Further, I test whether the estimates of δ change by different specifications of the model where I introduce the controls that are supposed to proxy the gender specific impacts on the probability of willingness to be unassigned.

Based on the model above, the probability of willingness to be unassigned is estimated conditional on test scores and individual characteristics controlling for fixed effects related to high school. Table 4 gives the results from simple OLS, probit and OLS with high school fixed effects and high school subject fixed effects[6] where standard errors are clustered by high school city. According to these results reported in first three column of Table 4 that are robust to different specifications, the probability of being willing to be unassigned is higher for boys. As the distribution of test scores can be different for females and males, the second and third order polynomials in all test scores are also included in the OLS estimation with high school and high school subject fixed effect and results from this estimation is reported in the last column. The gender difference is around 3% and it is a significant number given that the total share of applicants willing

[6]In a given high school, student might choose different subjects in the end of first year and the students are assigned to the classrooms based on the subject choice. Therefore controlling for retaking status, high schools and high school subjects brings the analysis almost to the level of comparing the students in the same classroom. Given the fact that the procedure for placement in high schools in Turkey is based on a very similar centralized test based system, controlling for high school related fixed effects allows me to control for unobserved individual characteristics.

to be unassigned is about 30% in the sample of applicants who are eligible to submit a list.

I also provide a robustness check considering the fact that girls are potentially more restricted to stay in their hometown and attend a local college instead of attending a university in a big city where the best universities are cumulated[7]) To control for this effect, a dummy variable if the high school city is one of the 3 big cities (Istanbul, Ankara and Izmir) and an interaction term with gender are included in the analysis.

An additional robustness check takes into account another feature of the institutional setting. There is a strong tracking system discouraging applicants to choose majors that do not pertain their high school subject. This feature is even stronger with an affirmative action for technical high school students where applicants' placement scores are calculated adding some extra points in case they choose the vocational university programs related to their own high school subject. Since the applicants from technical high schools know that they will receive some extra points in case they choose vocational programs, they might be choosing programs that have relatively higher cutoff scores which does not necessarily mean that they are willing to be unassigned. Moreover, the fact that technical high schools are mostly male dominated high schools might confound our results for gender differences in willingness to be unassigned. In order to avoid this confounding effect, the same estimation with high school and high school subject fixed effects are run with dummy variables for the technical high schools and an interaction term with gender.

Table 5 reports the results for the robustness check estimations where the coefficient of dummy variables for technical high schools and big cities and interaction terms are insignificant with an ignorable change in the gender coefficient.

An alternative way of comparing boys and girls in terms of the level of willingness to be unassigned is to estimate the number of safe choices on gender conditional on test score and individual characteristics controlling for high school and high school subject fixed effects. I define the number of safe choices as the number of university programs

[7]Attending a college in a city different from hometown is more costly for students than attending a college in hometown and families can have less control on their kids if they leave the hometown. Therefore parents usually prefer that their kids stay in their hometown to attend a local college for not only financial reasons but also to keep their kids close to them.

that are listed by applicant and that have lower cutoff scores than applicant's test score. It is assumed that the more is the number of safe choices listed by applicant are, the less the applicant is willing to be unassigned. The first column of the Table 6 shows that female applicants list a higher number of safe choices than male applicants.

Another measure of how much an applicant is willing to be unassigned is the negative differences between lowest cutoff scores programs' cutoffs scores and applicants' test scores for all categories. This is to measure how much higher the cutoff scores of the lowest cutoff score programs in all categories listed by the applicant are than her test scores in corresponding categories. As the sum of negative differences increase, the probability of no assignment increases. The second column of the Table 6 reports the results for the estimation of sum of negative differences between lowest cutoff score programs' cutoffs scores and applicants' test scores for all categories on gender conditional on individual characteristics and high school and high school subject fixed effects. Consistently with the previous findings, this difference is higher for male applicants by 6.80 on average.

Summarizing the evidence that is obtained in this section, it is suggested that female applicants avoid being unassigned and they make a "safer" choice list to guarantee an assignment. Although it is difficult to disentangle the reasons underlying the aversion from willingness to be unassigned, these results are strong enough to argue that this aversion might imply a lower reservation university programs for females with respect to males. Although several arguments can be suggested as a source the differences in willingness to be unassigned such as girls avoiding risk and competition, or some cultural norms that might affect their choices[8], it is very crucial to interpret the implications of this evidence of gender differences in willingness to be unassigned on gender differences in school choice therefore gender differences in outcomes in higher education enrollment, major choice and eventually labor market outcomes.

[8]e.g. Females have lower reservation university programs because males are more likely to be the breadwinner of the family

5 Gender Differences in Reservation University Programs

5.1 Differences in Choices within Same Majors

As it was previously noted above, the fact that females are less willing to be unassigned eventually implies that they also tend to target lower cutoff score university programs. This difference might be well driven by the differences in preferences for different majors as female applicants might differ in preferences with respect to males. In order to eliminate the gender differences that results from the differences in preferences for majors, the gender analysis of the cutoff scores of chosen programs is made by controlling for majors. The results of the estimations of the cutoff score of the last choice and the cutoff score of the university program where the applicant get assigned on gender conditional on test scores together with individual characteristics, high school and high school subject, and university program major fixed effects are reported in the first columns of the Table 7 and Table 8 respectively. The results show that female applicants target lower cutoff score programs within the same major as their last choices with respect to male applicants. They are also placed in lower cutoff score programs within the same major. The gender difference is around 3 points for last choice program on average while it is around 2 points for assignment program.

Dogan and Yuret (2011) descriptively shows that girls are less mobile than boys when choosing the location of college and it might potentially restrict the availability of the alternatives for female applicants. Therefore it might affect their choices as they will not consider the universities that are out of their home city and/or region as an alternative in the choice set. In order to control for the potential constraint of distance to good universities in big cities, I reduced the sample of applicants that attended to a high school in one of the three big cities: Istanbul, Ankara and Izmir where almost all top-ranking universities are located.[9]

Second columns of Table 7 and 8 report the results showing that gender difference in cutoff scores of last choice and assigned university programs are still significant for ap-

[9] I also run the same analysis excluding the technical high school graduates from the sample as they might confound the results because of affirmative action as explained in the previous section. These results are also presented in Table 7 and Table 8.

plicants attending high schools in 3 big cities and moreover the gender difference is even higher in these cities which is 3.28 and 3.50 respectively for programs chosen as last choice and programs where they are placed. This evidence suggests that the gender differences in cutoff scores of last and placement choices are not driven by the potential differences in constraints of distance to better schools in big cities.

5.2 Differences in Choosing Majors

Since applicants differ in willingness to be unassigned, the choice lists reflects these differences holding test scores constant. The aim of this section is to elaborate the potential effect of differences in willingness to be unassigned on the major choice and the focus is on the last choice that is assumed to be reservation university program.

It is well reported that there are significant gender differences in major choices where girls are more likely to choose literature and human sciences whereas boys tend to choose engineering and natural sciences. In order to disentangle the differences driven by the differences in willingness to be unassigned, the first choice will be used as a control. The main challenge in a logistic setup is the huge choice set. Each student makes a choice list under the constraint that the list can include up to 24 choices from 10,617 programs. In order to reasonably narrow down the choice set to a feasible set in a logit setup, initially I created a choice set of majors rather than university programs. The question that this setup can answer is whether girls tend to choose relatively lower profile majors as their last choice controlling for the first choice.

The choice set of 18 majors is defined as following: Agricultural Sciences, Communication Sciences, Dentist and Pharmacy, Economics-Business, Economics-Administration, Engineering, Architecture, Health School, Literature and Social Sciences, Law School, Medical School, Open Education, Pre-College Programs, Religion, Natural Sciences, Tourism, Vocational Schools, Education. Finally "no placement" is also included as an alternative. As major such as Dentist-Pharmacy, Economics-Business, Engineering, Law School and Medical School potentially lead to high-paying careers among the alternatives, these majors are defined as "High Profile Majors". These majors can be also considered as majors that are characterized by a higher probability of dropping out as it requires more effort to graduate because of the difficulty level of classes.

As a first stage, it is aimed to investigate if there is a gender difference in the probability of choosing at least one high profile majors in their last three choices. Since I aim to investigating the effect of differences in willingness to be unassigned on major choice, I constrained my analysis for those who choose at least one high profile majors in their top three choices in order to control for the other factors that might affect the preferences for majors. The estimation results for probability of choosing at least one high profile major in their last three choices for this sample are reported in Table 9. All specifications such as simple OLS, high school, high school type, and high school subject fixed effects estimations are reported in this table and the coefficient of gender is positive, significant and robust to all specifications suggesting that male applicants who choose high profile majors at least as one of their top three choices are more likely to choose high profile majors also in their last three choices. In other words, female applicants, even though they choose at least one high profile majors in their top three choice, are less likely to choose high profile majors as their last choices since they might find those majors less secure than low profile majors to guarantee an assignment.

As a further step, multinomial logistic model is used for the first, last, and placement choices controlling for gender, test scores and retaking status where the choice set is the same as described above. I calculated predicted probabilities for each alternative and obtained following graphs where it is possible to see differences in predicted probabilities for male and female applicants. The Figure 2 presents the graphs showing the predicted probabilities by gender of choosing Law School, Medical School, Pre-College and Vocational College programs as the first and last option.

As for the vocational school, girls are more likely than boys to choose as their last option, while they are equally likely to choose as the first option. As for the pre-college, girls are less likely than boys to choose as the first choice while they are equally likely to choose as their last option. Pre-college and vocational college programs can be assumed to be the least advantageous majors in terms of labor market outcomes and these findings state that girls are willing to choose these majors as their last option more than boys. As for the law school, girls are equally likely with boys to choose as first option, while they are less likely to choose as the last option. As for the medical school, girls are less likely to choose as the last option, while more likely to choose as the first option. Since the high profile majors such as law school and medical school have higher cutoff scores, choosing these majors as last option would yield an assignment with a relatively lower probability with respect to low profile majors. Combining these results with those reported in the previous section, females tend to choose lower profile majors and lower ranked programs within the same major as their last choices controlling for the first choices.

5.3 Ranking University Programs

In this section, I use a rank-ordered conditional logit model to estimate how applicants value university program characteristics and how the weights placed on these characteristics vary across gender. Rank-ordered logistic model is also known as exploded logit model. Exploded refers to a logit model that incorporates multiple-ranked choices for each person but not only the first choice that gives the highest utility. (McFadden and Train 2000, Train 2003)

The setting of rank-ordered conditional logit model is very similar to a conditional logit model where a coefficient is obtained for each attribute of the alternatives. In this rank-ordered model, each applicant is assumed to have an individual choice set and the individual choice set is assumed to include the university programs that are chosen by the applicant and coefficients are mapped from the ranking of these alternatives. Using this method, I obtain the coefficients for university program attributes such as tuition status, distance from high school city, instruction language, whether university is a public or private university, whether university is in a big city etc.

The advantage of using this method is double-fold compared to a conditional logit model: First of all, large choice set in our setting that consists of more than 10 thousands university programs is not feasible for a logistic regression. Second, since conditional logit model allows to analyze only one choice from a choice set, one would loose an important part of the information about preferences as most of the applicants make more than one choice. On the other hand, rank-ordered logistic regression use all the information about the programs that are chosen by applicants mapping the coefficients from their ranking.

I estimated the rank-ordered conditional logit model separately for the sample of females and males. Although the effect of gender is not identified, it is still possible to draw some general conclusions from the results reported in Table 10. As the model is estimated separately for females and males, comparing the magnitudes of the coefficients of university program attributes for these two samples does not provide any statistically significant information about how differently they value the attributes of university programs. Yet, results can still provide convincing evidence for gender differences if one compares the signs and significance levels of the coefficients. Coefficients of some attributes (such as whether the university is in a big city, distance from home city to university city, capacity of the program, whether it is a night school [10], scholarship status) are significantly different from zero having the same sign for both female and male samples.

On the other hand, some coefficients are different in terms of the statistical significance between girls and boys. First of all, the coefficient of the difference between cutoff score of program and applicant's test score which measures how likely that applicant could be assigned to that program is significantly different from zero for female applicants while male applicants are not as much concerned about admission probability when they make their choice list. Likewise, distance from home to college is an attribute that females value significantly while males seem not to place a significant weight on it. Another difference in significance levels is observed on the coefficient of foreign language attribute. While the coefficient is positive and significant for male applicants, it seems that female applicants do not necessarily prefer university programs where the instruction is in a foreign language.[11]

Finally, coefficients of indicator variables for majors differ in terms of significance between females and males. As it is described above there are 18 main majors where some of them are defined as high profile since they lead to high-paying careers. In this model, education major is taken as the base major since it can be related to both in quantitative and qualitative categories therefore it is relatively more comparable to all majors

[10] Night schools usually has the same instruction programs as normal programs but only difference is the classes are scheduled in the evening and the tuition is relatively more expensive than the normal programs.

[11] Usually English language

as an alternative. The coefficients for Agricultural Sciences, Communication Sciences, Dentist and Pharmacy, Architecture, Law School, Literature and Social Sciences, Open Education, Natural Sciences, and Tourism majors are significant and has the same sign for both boys and girls. The coefficients of following majors are insignificant for girls and positive and significant for boys: Economics-Business, Economics-Administration, Engineering, Health School, Medical School, Pre-College Programs, Vocational Schools. Boys place more weight on choice of majors that are higher profile than education such as Economics, Engineering, Medical School[12].

One might think that these differences in coefficients for the majors might be driven by the differences in high school subjects.[13] Therefore one can argue that differences in comparative advantages in different subjects across gender might yield differences in major choices. However rank-order logistic setup takes the chosen alternatives as the choice set and maps coefficients from the ranking. Therefore, this feature of the model is essential to avoid potential confounding factors that might affect major choice. Yet, even if these differences were assumed to be driven by differences in high school subjects, females still do not prefer high profile majors in equally weighted categories (such as Economics, Business) to education. The reason that females find education major more appealing is that it is considered as the most convenient job for a female in the society even though it usually leads to a very modest wage and career. These results are also in line with the findings reported in the previous sections that suggest that females have lower reservation university program.

6 Conclusion

Despite the reversing gender gap in educational outcomes where currently females perform better on average in many countries, highly selective colleges consequently high-wage occupations and industries remained dominated by males. In Turkey, similarly, although

[12] Males also tend to prefer pre-college programs or vocational schools rather than education major. This result is expected given that males tend to apply low profile majors such as two-years pre-college programs or open education programs to keep their student status in order to be able to delay the compulsory military service

[13] Girls are more likely to choose qualitative or equally weighted subjects while boys tend to choose quantitative subjects at high school

females outperform males in scholastic success at high school and on the university entrance test on average, placement to top-ranking university programs do not seem to reflect these improvements in gender gap. In order to understand the forces driving this gap, one should analyze gender differences that might potentially affect school choice. The particular institutional setting in Turkey allows me to abstract from the two-sided problem which usually complicates the question of preferences vs. discrimination since I perfectly observe individual's choices and test scores and the placement is based on a computer-calculated algorithm that allocates applicants only according to their choices and test scores.

Using a unique administrative dataset from a centralized system that allows to control for test scores and to determine the reservation university program, I created a measure for willingness to be unassigned and I find that females are less willing to be unassigned. I incorporate the willingness to be unassigned to the analysis of choices so that I distinguish between preferences and to a certain extent willingness to wait an additional year. By this approach, I find that females tend to target lower cutoff score programs within the same major as their last choice that guarantee an assignment with a higher probability when controlling for their first choices. With respect to males, females are also more likely to choose lower profile majors as their last choice when controlling for the first choice.

Finally, I provide evidence that females tend to be more concerned about university program characteristics such as admission probability and distance from home to university city rather than other characteristics such as foreign language as the instruction language which could be an asset when they look for a job after graduation. Also, they do not give a significant weight to the choice of major to be a high profile major. The characteristics found to be valued by girls in their choices can be classified as characteristics that matter during the university education while other characteristics such as instruction language and major are important after university as they will provide important advantages in the labor market.

In this paper, I document the existence of a gender gap in the willingness to be unassigned and wait an additional year for a better college enrollment. I present also evidence on differences in reservation university programs that are defined through the willingness to be unassigned. Reported evidence on differences in reservation university programs do not only provide an explanation for the persistent gender gap in highly selective college enrollments and high-wage occupations and industries but also it offers a new perspective on heterogeneity in school choice.

Figure 1: University Entrance Test: Sections and Categories

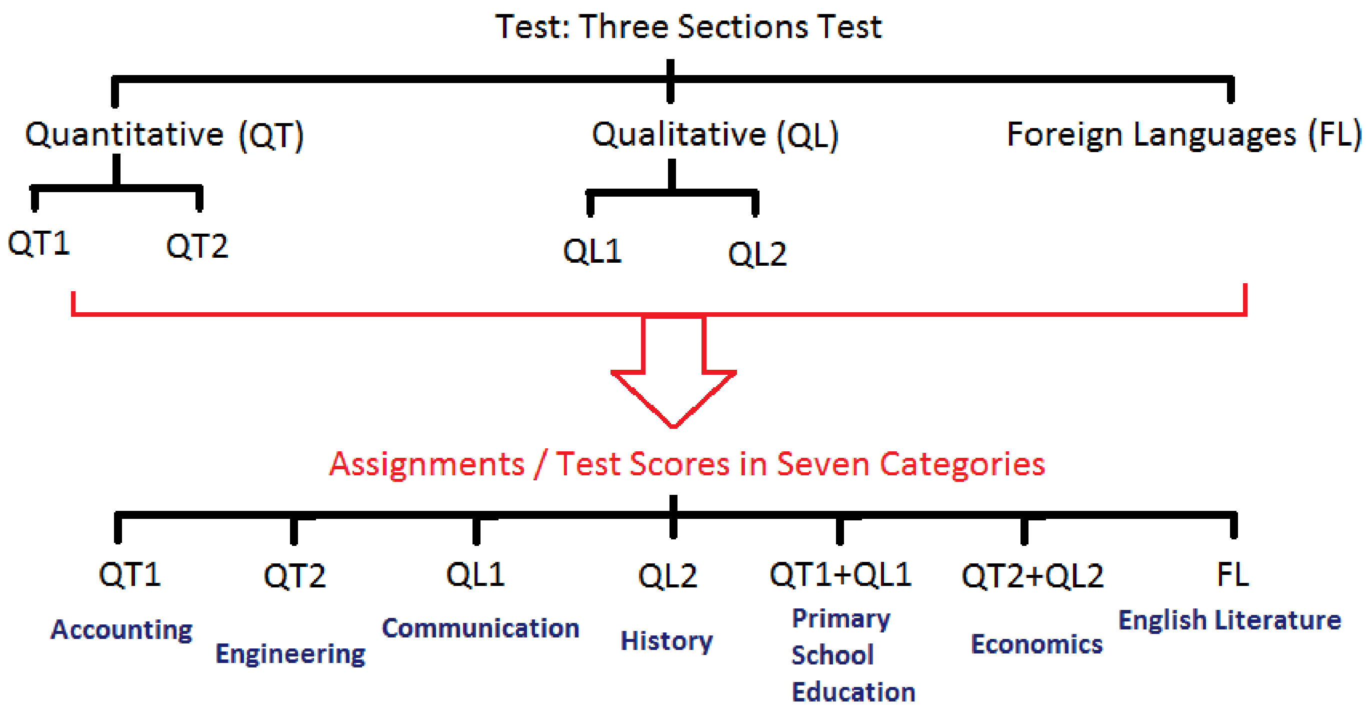


Table 1: Descriptive Statistics by Gender

	Female	Male	Diff
Achievements			
High school GPA	76.53	72.03	4.50
	(11.21)	(11.58)	(0.0000)***
Test Score Equally Weighted-1	212.55	206.03	6.53
	(35.90)	(42.80)	(0.0000)***
Test Score Equally Weighted 2	153.68	145.22	8.46
	(83.63)	(86.58)	(0.0000)***
Test Score Quantitative 1	188.20	188.75	-0.55
	(38.71)	(45.26)	(0.0008) ***
Test Score Quantitative 2	111.46	106.15	5.31
	(98.32)	(100.30)	(0.0000)***
Test Score Qualitative 1	219.11	209.58	9.53
	(34.24)	(42.05)	(0.0000)***
Test Score Qualitative 2	111.57	96.25	15.32
	(101.90)	(101.46)	(0.0000)***
If assigned	0.63	0.62	0.01
	(0.48)	(0.49)	(0.0000)***
Retaking			
Birth year	1988.23	1987.68	0.55
	(2.55)	(2.99)	(0.0000)***
If retake	0.78	0.84	-0.06
	(0.41)	(0.37)	(0.0000)***
Number of trials	3.02	3.44	-0.42
	(2.33)	(2.77)	(0.0000)***
If previously assigned	0.24	0.32	-0.08
	(0.43)	(0.47)	(0.0000)***
Choices			
Satisfy threshold but no choice	0.09	0.11	-0.02
	(0.29)	(0.31)	(0.0000)***
If choices from only one category	0.44	0.47	-0.03
	(0.50)	(0.50)	(0.0000)***
Number of categories	1.58	1.41	0.16
	(1.01)	(1.00)	(0.0000)***
24 prefs submitted	0.30	0.34	-0.04
	(0.46)	(0.47)	(0.0000)***
Number of Choices	14.46	14.18	0.28
	(8.90)	(9.44)	(0.0000)***
Survey Answers about Themselves			
If define as hardworking	0.43	0.34	0.09
	(0.50)	(0.47)	(0.0000)***
If define as under pressure at exams	0.42	0.39	0.03
	(0.49)	(0.49)	(0.0000)***
If define as nervous at exams	0.45	0.41	0.04
	(0.50)	(0.49)	(0.0000)***
If define as underperforming at exams	0.41	0.40	0.01
	(0.49)	(0.49)	(0.0000)***

Notes: Standard deviations for females and males and p-values for differences are in parentheses.

Table 2: Parents Education and Family Support by Gender

	Female	Male	Diff
Parents Education and Support			
if working	0.19	0.34	-0.15
	(0.40)	(0.47)	(0.0000)***
Private Tutoring	0.73	0.66	0.07
	(0.45)	(0.47)	(0.0000)***
Ratio of Number of Choices in Private Universities	0.33	0.32	0.01
	(0.41)	(0.41)	(0.0000)***
Ratio of Number of Choices in Other Cities	2.43	2.41	0.02
	(4.19)	(4.41)	(0.0715)*
Ratio of Number of Choices in Big Cities	0.54	0.48	0.06
	(0.36)	(0.36)	(0.0000)***
Mother education not reported	0.004	0.008	0.004
	(0.07)	(0.09)	(0.0000)***
Mother No Schoolling	0.11	0.23	-0.12
	(0.32)	(0.42)	(0.0000)***
Mother Primary School	0.47	0.43	0.04
	(0.50)	(0.50)	(0.0000)***
Mother Middle School	0.12	0.11	0.01
	(0.32)	(0.31)	(0.0000)***
Mother High School	0.20	0.15	0.05
	(0.40)	(0.36)	(0.0000)***
Mother College or beyond	0.10	0.07	0.03
	(0.30)	(0.25)	(0.0000)***
Father education not reported	0.02	0.03	-0.01
	(0.14)	(0.16)	(0.0000)***
Father No School	0.03	0.07	-0.04
	(0.18)	(0.26)	(0.0000)***
Father Primary School	0.29	0.32	-0.04
	(0.45)	(0.47)	(0.0000)***
Father Middle School	0.16	0.14	0.02
	(0.37)	(0.35)	(0.0000)***
Father High School	0.28	0.25	0.03
	(0.45)	(0.43)	(0.0000)***
Father College or beyond	0.22	0.19	0.03
	(0.42)	(0.40)	(0.0000)***

Notes: Standard deviations for females and males and p-values for differences are in parentheses.

Table 3: Differences in Mean and Variance of Residual Test Scores by Gender and Retaking

	FT Girls	RT Girls	DIff	FT Boys	RT Boys	Diff	Diff-in-Diff
Mean							
	-0.723	1.871	2.594*	-1.542	0.141	1.682*	0.912
	(1.183)	(1.028)	(1.567)	(1.019)	(0.781)	(1.284)	(2.026)
Variance							
S. D.	28.367	29.580		30.3803	34.813		
p-value			0.117			0.000	

Notes: Standard errors are in parentheses for the mean differences. For differences in variance, p-values are reported in the last row.

Table 4: Taking Risk of Getting No Assignment

	OLS	Probit	FEs1	FEs2
Male	.0455	.0483	.0356	.0338
	(.0103)***	(.0109)***	(.0152)**	(.0153)**
Years Since Graduation=1	-.1152	-.1150	-.1325	-.1220
	(.0184)***	(.0181)***	(.0225)***	(.0222)***
Years Since Graduation=2 to 4	-.0375	-.0368	-.0688	-.1001
	(.0199)*	(.0202)*	(.0220)***	(.0219)***
Years Since Graduation=5 or more	.0276	.0315	-.0486	-.0773
	(.0244)	(.0252)	(.0294)*	(.0293)***
Private Tutoring	.0237	.0252	.0165	.0144
	(.0101)**	(.0108)**	(.0171)	(.0169)
If working	-.0261	-.0281	-.0247	-.0292
	(.0123)**	(.0131)**	(.0166)	(.0164)*
All High School GPAs	Yes	Yes	Yes	Yes
All Test Scores	Yes	Yes	Yes	Yes
All Test Scores Polynomials (2nd-3rd)	No	No	No	Yes
Household Controls	Yes	Yes	Yes	Yes
High School FEs	No	No	Yes	Yes
High School Subject FEs	No	No	Yes	Yes
Obs.	8496	8496	8496	8496
F statistic	67.1634		1.2569	1.3394

Notes: First column is the simple OLS where the standard errors are clustered by high school city. The second column is the probit estimation results. The third column shows the results with high school and high school subject fixed effects and the fourth column takes into account also 2nd and 3rd order polynomials in all test scores to control for differences in test score distributions as well as high school and high school subject fixed effects. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Dependent variable is a dummy variable that takes value 1 if the applicant is willing to take the risk of getting no assignment. Standard errors are in parentheses.

Table 5: Taking Risk of Getting No Assignment: Different Specifications

	(1)	(2)	(3)	(4)
Male	.0356	.0448	.0355	.0347
	(.0152)**	(.0195)**	(.0152)**	(.0160)**
If HS in one of 3 big cities	-1.4140	-1.3897		
	(1.0664)	(1.0669)		
If HS in one of 3 big cities by gender		-.0222		
		(.0294)		
If Technical HS			.2751	.2671
			(.6549)	(.6569)
If Technical HS by gender				.0076
				(.0478)
Years Since Graduation=1	-.1325	-.1329	-.1325	-.1325
	(.0225)***	(.0225)***	(.0225)***	(.0225)***
Years Since Graduation=2 to 4	-.0688	-.0691	-.0687	-.0687
	(.0220)***	(.0220)***	(.0220)***	(.0220)***
Years Since Graduation=5 or more	-.0486	-.0492	-.0485	-.0484
	(.0294)*	(.0294)*	(.0294)*	(.0294)*
Private Tutoring	.0165	.0166	.0167	.0167
	(.0171)	(.0171)	(.0171)	(.0171)
If working	-.0247	-.0247	-.0247	-.0246
	(.0166)	(.0166)	(.0166)	(.0166)
All High School GPAs	Yes	Yes	Yes	Yes
All Test Scores	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
High School FEs	Yes	Yes	Yes	Yes
High School Subject FEs	Yes	Yes	Yes	Yes
Obs.	8496	8496	8496	8496
F statistic	1.2569	1.2566	1.2564	1.2558

Notes: All column shows the results with high school and high school subject fixed effects. In the first two columns, controls for applicants graduated from high schools in three big cities, Istanbul, Ankara, and Izmir are included. Last two columns control for applicants graduated from technical high schools that has a affirmative action for university programs that are related to their high school subject. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Dependent variable is a dummy variable that takes value 1 if the applicant is willing to take the risk of getting no assignment. Standard errors are in parentheses.

Table 6: Taking Risk of Getting No Assignment: Other Measures

	Number of Safe Choices	Differences between TS and CS
Male	-.5297	6.1764
	(.1677)***	(1.4407)***
Years Since Graduation=1	.4009	-5.0414
	(.2476)	(2.1268)**
Years Since Graduation=2 to 4	.1798	-9.7177
	(.2420)	(2.0793)***
Years Since Graduation=5 or more	-.8850	-18.4346
	(.3236)***	(2.7800)***
Private Tutoring	-.1973	1.1047
	(.1885)	(1.6192)
If working	-.0142	-6.8747
	(.1822)	(1.5653)***
All High School GPAs	Yes	Yes
All Test Scores	Yes	Yes
Household Controls	Yes	Yes
High School FEs	Yes	Yes
HS Subject FEs	Yes	Yes
Obs.	8496	8496
F statistic	1.2612	1.1806

Notes: In both columns high school and high school subject fixed effects are included. In the first column, dependent variable is the number of safe choices that has lower cutoff scores than applicant's test scores. In the second column, dependent variable is the negative sum of differences between test scores and cutoff scores of programs chosen by applicant. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Standard errors are in parentheses.

Table 7: Cutoff Score of Last Choice

	All Sample	Only 3 Big Cities	No Tech High School
	(1)	(2)	(3)
Male	2.2824	3.4037	2.9530
	(1.1963)*	(1.9872)*	(1.2005)**
Retaking	-2.5441	-3.6500	-7.3583
	(1.4887)*	(2.3635)	(1.5589)***
Private Tutoring	.8573	1.2319	.8654
	(1.2795)	(2.1350)	(1.3832)
If working	-2.1696	-1.9205	-3.1202
	(1.2960)*	(2.2037)	(1.3804)**
All High School GPAs	Yes	Yes	Yes
All Test Scores	Yes	Yes	Yes
Cutoff Score of First Choice			.0592
			(.0091)***
Category Dummies	Yes	Yes	Yes
HS Subject FEs	Yes	Yes	Yes
Obs.	8367	2910	6380
F statistic	110.2373	50.5149	231.1719

Notes: First column gives the results for the whole sample of applicants submitting a choice list. In the second column, only the applicants graduated from high schools in three big cities, Istanbul, Ankara, and Izmir are taken from the sample. Third column, technical high school graduates are excluded from the sample of applicants submitting a choice list to discard the potentially confounding effect of affirmative action for technical high schools. I also included the first choice cutoff score to this estimation. In all specifications, the dependent variable is the cutoff score of the last choice where the high school subjects and the major of the last choice are included in the controls. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Standard errors are in parentheses.

Table 8: Cutoff Score of Placement Outcome

	All Sample	Only 3 Big Cities	No Tech High School
	(1)	(2)	(3)
Male	2.0033	3.5058	2.1921
	(.9413)**	(1.5515)**	(.7407)***
Retaking	1.1727	-1.7143	-5.4800
	(1.1510)	(1.8468)	(.9510)***
Private Tutoring	.9752	.4148	-1.5520
	(1.0362)	(1.7271)	(.8806)*
If working	-2.0106	-1.0925	-4.4417
	(1.0393)*	(1.7785)	(.8693)***
All High School GPAs	Yes	Yes	Yes
All Test Scores	Yes	Yes	Yes
Cutoff Score of First Choice			.0562
			(.0061)***
Category Dummies	Yes	Yes	Yes
HS Subject FEs	Yes	Yes	Yes
Obs.	5959	2176	4530
F statistic	187.0551	90.2989	617.8444

Notes: First column gives the results for the whole sample of applicants who get an assignment. In the second column, only the applicants who get an assignment and graduated from high schools in one of the three big cities, Istanbul, Ankara, and Izmir are taken to the sample. Third column, technical high school graduates are excluded from the sample of assigned applicants to discard the potentially confounding effect of affirmative action for technical high schools. I also included the first choice cutoff score to this estimation. In all specifications, the dependent variable is the cutoff score of the university program where the applicant is assigned and high school subjects and the major of the university program that the applicant gets assigned are included in the controls. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Standard errors are in parentheses.

Table 9: Differences in Major Choice As First 3 and Last 3 Choices by Gender

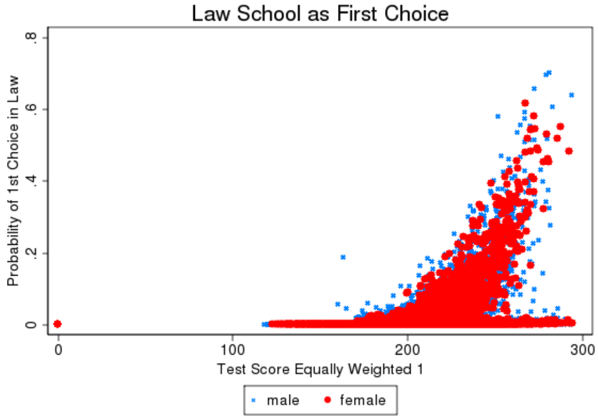
	(1)	(2)	(3)
Male	.1552	.1527	.1671
	(.0292)***	(.0190)***	(.0170)***
Private Tutoring	.0393	.0079	.0081
	(.0437)	(.0275)	(.0330)
Years Since Graduation=1	-.0409	-.0851	-.1203
	(.0392)	(.0246)***	(.0238)***
Years Since Graduation=2 to 4	-.0665	-.0908	-.1185
	(.0418)	(.0264)***	(.0221)***
Years Since Graduation=5 or more	-.1239	-.1309	-.1156
	(.0715)*	(.0452)***	(.0448)***
If Working	-.0005	-.0422	-.0456
	(.0365)	(.0244)*	(.0192)**
All Test Scores	Yes	Yes	Yes
All High School GPAs	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
High School FEs	Yes	No	No
High School Subject FEs	Yes	Yes	No
High School Type FEs	No	Yes	No
e(N)	2994	2994	2994
e(F)	1.3895	11.3691	115.5524

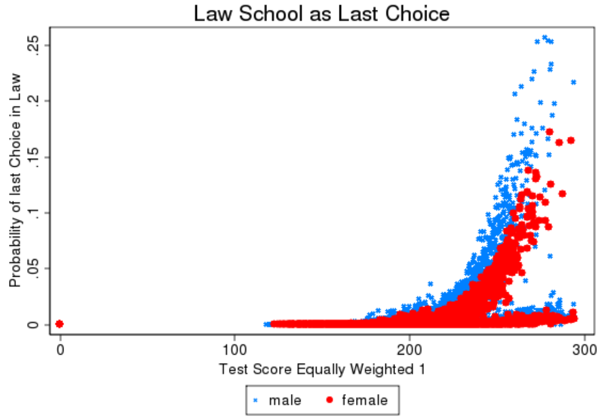
Notes: The sample consists of applicants who has at list one high profile major in top three choices and the dependent variable takes value one if the applicant has a high profile major in the last three choices. First column reports the results where the high school and high school subject fixed effects are included. In the second column, high school type and high school subject fixed effects are included. Third column gives the simple OLS results where the standard errors are clustered by high school city. Household controls include mother and father education categorical variables and an availability measure such as internet, own room in the house etc. Standard errors are in parentheses.

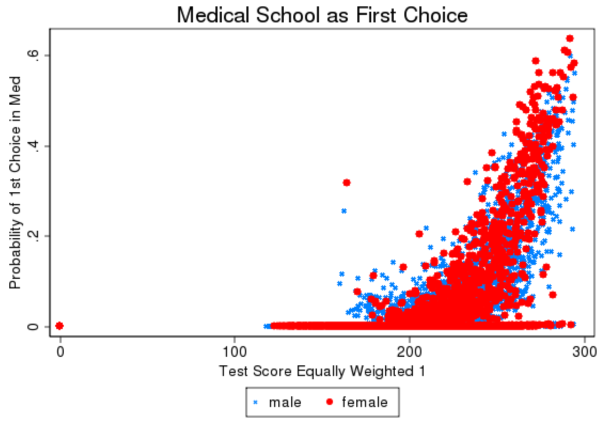
Table 10: Rank Ordered Logit Estimation

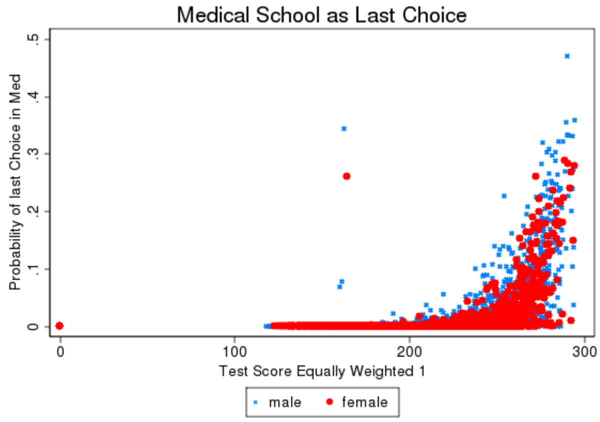
	Girls	Boys	ALL
Difference of Test Score-Cutoff Score	-.0008 (.0002)***	-4.00e-06 (.0001)	-.0002 (.0001)*
If University is in Big City	.3711 (.0185)***	.4943 (.0130)***	.4543 (.0106)***
Distance from High School City	-.00005 (.00003)*	1.00e-05 (.00002)	-5.00e-06 (1.00e-05)
Capacity	.0012 (.0002)***	.0006 (.0001)***	.0008 (.00009)***
Foreign Instruction Language	-.0658 (.0542)	.1692 (.0336)***	.1031 (.0285)***
Night School	-.1973 (.0193)***	-.2353 (.0133)***	-.2222 (.0110)***
Private University with No Scholarship	-25.0750 (.1774)***	-25.7682 (.1367)***	-25.2286 (.1083)***
Private University with Scholarship	-25.4407 (.2062)***	-26.2224 (.1597)***	-25.6551 (.1263)***
Majors			
Agriculture-Environment	.0234 (.0683)	.0306 (.0482)	.0176 (.0393)
Communication	-.4392 (.3603)	-.5321 (.2228)**	-.5399 (.1896)***
Dentist-Pharmacy	.8427 (.0821)***	1.0203 (.0697)***	.9514 (.0528)***
Econ-Business	.0088 (.0453)	.2224 (.0400)***	.1227 (.0299)***
Econ-Administrative	.0851 (.0924)	.1855 (.0675)***	.1455 (.0543)***
Engineering	.0700 (.0517)	.1762 (.0360)***	.1283 (.0293)***
Architecture	1.1569 (.1858)***	1.3095 (.2183)***	1.2687 (.1410)***
Health School	-.1002 (.0574)*	.1010 (.0504)**	.0145 (.0376)
Law School	-.2578 (.0842)***	.0399 (.0714)	-.0759 (.0542)
Literature	.2926 (.0569)***	.5220 (.0562)***	.4059 (.0398)***
Medical School	.1151 (.0919)	.4441 (.0642)***	.3248 (.0526)***
Open Education	-.2612 (.3483)	.5301 (.3698)	.4661 (.2257)**
Pre-College	-.1115 (.2776)	-.2071 (.1239)*	-.1935 (.1126)*
Natural Sciences	.2593 (.0508)***	.4388 (.0408)***	.3610 (.0317)***
Tourism	.1857 (.1003)*	.2003 (.0650)***	.1705 (.0542)***
Vocational	-.0327 (.0527)	-.0522 (.0378)	-.0630 (.0305)**

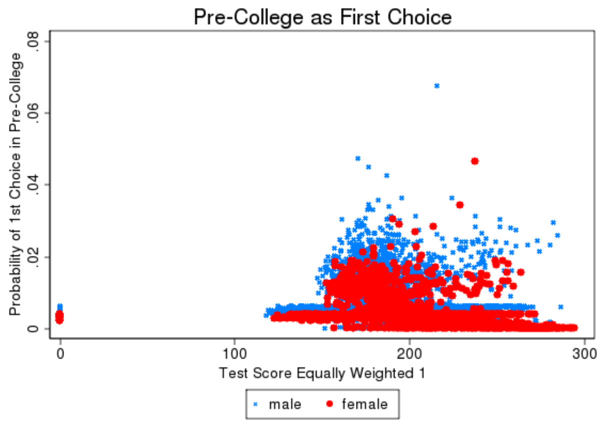
Notes: First two columns give the estimation results for only female and male applicants respectively. The third column shows the results for the whole sample. Standard errors are in parentheses. The difference between test score and cutoff score of the university program is defined as an attribute of the university programs that varies at individual level for each university program. It measures the perceived probability of admission of a given applicant to a university program.

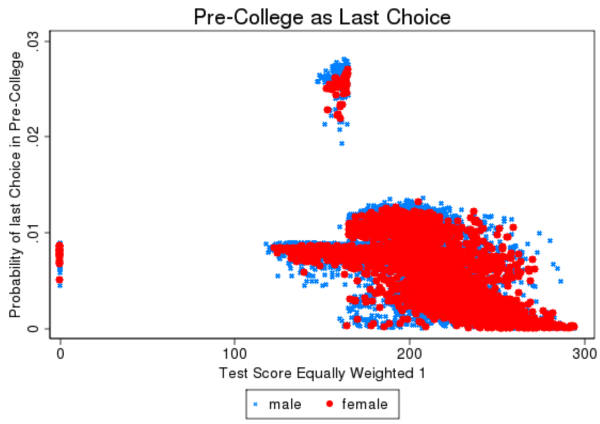

Law School as First Choice
Probability of 1st Choice in Law
0
.2
.4
.6
.8
0
100
200
300
Test Score Equally Weighted 1
male
female

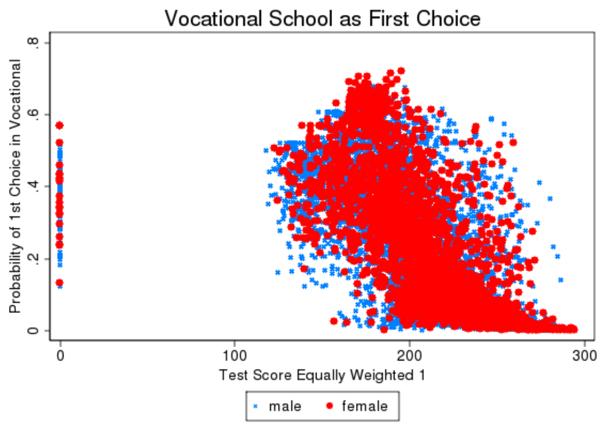

Law School as Last Choice
Probability of last Choice in Law
0
.05
.1
.15
.2
.25
0
100
200
300
Test Score Equally Weighted 1
male
female

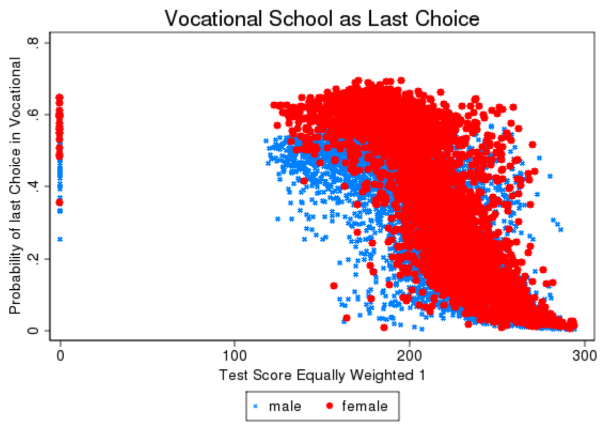

Medical School as First Choice
Probability of 1st Choice in Med
0
.2
.4
.6
0
100
200
300
Test Score Equally Weighted 1
male
female


Medical School as Last Choice
Probability of last Choice in Med
0
.1
.2
.3
.4
.5
0
100
200
300
Test Score Equally Weighted 1
male
female


Pre-College as First Choice
Probability of 1st Choice in Pre-College
0
.02
.04
.06
.08
0
100
200
300
Test Score Equally Weighted 1
male
female


Pre-College as Last Choice
Probability of last Choice in Pre-College
0
.01
.02
.03
0
100
200
300
Test Score Equally Weighted 1
male
female


Vocational School as First Choice
Probability of 1st Choice in Vocational
0
.2
.4
.6
.8
0
100
200
300
Test Score Equally Weighted 1
male
female


Vocational School as Last Choice
Probability of last Choice in Vocational
0
.2
.4
.6
.8
0
100
200
300
Test Score Equally Weighted 1
male
female

References

Ajayi, K. (2011) *School Choice and Educational Mobility: Lessons from Secondary School Applications in Ghana*, Working Paper.

Barres, B. (2006) *Does Gender Matter?*, Nature, 442: 133-13

Blau, F. D. (1998) *Trends in the Well-Being of American Women, 1970-1995*, Journal of Economic Literature 36 (March): 112-65.

Cullen, J., B. Jacob, and S. Levitt (2003) *The Effect of School Choice on Student Outcomes: Evidence from Randomized Lotteries*, National Bureau of Economic Research Working Paper No.10113.

Dellavigna, S., and M. Daniele Paserman (2005) *Job Search and Impatience*, Journal of Labor Economics, University of Chicago Press, vol. 23(3), pages 527-588.

Dogan, M. K. and Yuret T. (2011) *The Causes of Gender Inequality in College Education in Turkey*, Procedia Social and Behavioral Sciences 5 691-691ZA.

Dohmen, T. and Falk A. (2006) *Performance Pay and multidimensional sorting: Productivity, Preferences, and Gender*, IZA Discussion Papers No. 2001.

Friedman, L. (1989) *Mathematics and the Gender Gap: A Meta-Analysis of Recent Studies on Sex Differences in Mathematical Tasks*, Review of Educational Research 59: 185-213.

Gneezy, U., M. Niederle, and A. Rustichini (2003) *Performance in Competitive Environments: Gender Differences*, Gender Differences" Quarterly Journal of Economics, 118 (3), 1049-1074.

Goldin, C., L. Katz, and I. Kuziemko (2006) *The Homecoming of American College Women: The Reversal of the College Gender Gap*, Journal of Economic Perspectives, 20(4), 133-156.

Hastings, J. S. Thomas J. Kane, and Douglas O. Staiger (2006) *Heterogeneous Preferences and the Efficacy of Public School Choice*, National Bureau of Economic Research Paper Working Papers No. 12145.

Jacob, B. A. (2002) *Where the boys arent: noncognitive skills, returns to school and the gender gap in higher education*, Economics of Education Review 21:5899.

McFadden, D. and Train, K. E. (2000) *Mixed MNL Models for Discrete Response*, Journal of Applied Econometrics, 15, 447-470.

Niederle, M., and L.Vesterlund (2007) *Do Women Shy away from Competition? Do Men Compete too Much?*, Quarterly Journal of Economics, 122(3): 1067-1101.

Paserman, M. D. (2007) *Gender Differences in Performance in Competitive Environments: Evidence from Professional Tennis Players*, IZA Discussion Papers No. 2834.

Peter, K., and Horn, L. (2005) *Gender differences in participation and completion of undergraduate education and how they have changed over time*, NCES No. 2005-169 Washington, DC National Center for Education Statistics, U.S. Department of Education.

Polachek, S. W. (1978) *Sex Differences in College Major*, Industrial and Labor Relations Review 31 (4):498-508.

Polachek, S. W. (1981) *Occupational self-selection: A human capital approach to sex differences in Occupational Structure*, Review of Economics and Statistics, 68 (1), 60-69.

Reynolds, J. R., and Burge, S. W. (2008) *Educational expectations and the rise in womens post-secondary attainments*, Social Science Research, 37, 485499.

Train, K. E. (2003) *Discrete Choice Methods with Simulation*, Cambridge, United Kingdom: Cambridge University Press.

Turner, S. and W. Bowen (1999) *Choice of Major: The Changing (Unchanging) Gender Gap*, Industrial and Labor Relations Review 52(2): 289-313.

Waldfogel, J. (1998) *The Family Gap for Young Women in the United States and Britain: Can Maternity Leave Make a Difference?*, Journal of Labor Economics, 16 (3), 505-545.

Xie, Y. and K. Shauman (2003) *Women in Science: Career Processes and Outcomes*, Cambridge, MA Harvard University Press.

Zafar, B. (2009) *College Major Choice and the Gender Gap*, Federal Reserve Bank of New York Staff Reports, no. 364