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To My Grandpa who must have seen this...

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Presentations

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10. P.O. Saygin, "Gender Differences in College Applications: Evidence from the Centralized System in Turkey ," at *Job Talk, HEC Business School in Montreal*, Montreal, Canada, 2012.
11. P.O. Saygin, "Gender Differences in College Applications: Evidence from the Centralized System in Turkey ," at *Job Talk, Mannheim University*, Mannheim, Germany, 2012.

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Abstract

In Turkey, as in many other countries, gender gap in participation in education has remained persistent even though female students have been outperforming male students in terms of many measures of educational outcomes. The aim of this thesis is to provide an overview of the trends in gender gap in educational attainment in particular in higher education in Turkey and to elaborate their potential causes and consequences. The analysis of gender differences in educational outcomes, enrollment decisions and preferences for higher education programs, the centralized standardized test based university entrance system is used as a tool to design the empirical approach. First, I show that in Turkey, as in many other countries, female students perform better in high school and have higher test scores than males and are more likely to enroll in higher education programs controlling for test scores. 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. Secondly, using detailed unique administrative data from the centralized college entrance system, I also 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. Finally, I also document the gender differences in preferences for university program attributes. I 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 which has important implications for the persistency of gender wage gap and occupational differences in Turkish labor market in spite of the improvements in gender gap in educational achievements.

Chapter 1

Gender Differences in Education in Turkey

It is well acknowledged that education of women is crucial especially for developing world as the social benefits of women's schooling are significant for several reasons such as fertility, infant mortality and child health and education, social cohesion, and crime (De Walque 2007; Filmer 2006; Herz and Sperling 2004; Schultz 1993, 2002; Sen 1999; Subbarao and Raney 1995; Summers 1994; Thomas 1990; UNESCO 2000; Watson 2005).

Moreover, also private returns to education is higher for women than men. Although results vary by country, women receive higher returns to their schooling investment in terms of earnings: their return, on average, is 9.8%, compared with 8.7% for men (Psacharopoulos and Patrinos 2004). Therefore, participation of women in education in lower rates causes also economic inefficiency.

Even though lower rates of participation of women in education is unequal, inefficient, and detrimental for development, women participate in education less than men in many countries. According to Psacharopoulos and Patrinos (2004), on average, women obtain less schooling than men on average. Nevertheless, the gender gap in educational outcomes has disappeared and even reversed in many developed countries. At the moment, female educational attainment clearly dominates male educational attainment in a majority of industrialized countries and it holds for several measures of educational outcomes. Women are in clear majority among secondary school graduates, among students enrolled in tertiary education, and among tertiary graduates. Moreover, females obtain better scores at standardized tests and higher GPAs with resect to males.

On the other hand, a sizable gap remains in schooling levels in most developing countries. Also in Turkey, gender gap in participation rates in education is still significantly high. However, similar to developed countries, there has been a sharp increase in female educational outcomes such as GPAs and standardized test scores with respect to males.

The aim of this dissertation is to provide an overview of the trends in gender gap in educational attainment in particular in higher education in Turkey and to elaborate their potential causes and consequences. In order to conduct the analysis of gender differences in educational outcomes, enrollment decisions and preferences for higher education programs, the centralized standardized test based university entrance system is used as a tool to design the empirical approach.

The dataset employed in this study was obtained from a merge of the 2008 Student Selection Examination for university entrance (OSS in Turkish) 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% 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). I constructed a unique dataset by merging the characteristics of university programs from Higher Education Programs dataset by each university program that applicants list.

In the first chapter, I document the trends in educational outcomes using both National Education Statistics and individual level econometric analysis using the dataset of Student Selection and Placement System (OSYS in Turkish) for the year 2008. I show that in Turkey, as in many other countries, female students outperform males in high school. They also have higher test scores than males and are more likely to enroll in higher education programs controlling for test scores. Nevertheless, men still predominate at highly selective programs that lead to high-paying careers.

In the second chapter, I elaborate the gender gap at elite schools which is particularly puzzling because college admissions are based entirely on nationwide exam scores. Using detailed unique 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.

In the third chapter, I analyze the heterogeneity in preferences for higher education program characteristics. Using the matched administrative dataset including the choice lists submitted by university applicants, I 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 which has important implications for the persistency of gender wage gap and occupational differences in Turkish labor market.

1.1 Education System in Turkey

Formal education system in Turkey consists of primary education, high school education and university. Primary education is only compulsory part and gives education for 8 years. Until 1997, primary education was only 5 years and middle schools that give 3 years education were not compulsory. In 1997 compulsory education has been extended to 8 years of basic education covering also the middle school education.

After compulsory education, the secondary level of schooling consists of general high school with an additional 4 years of education or a vocational high school. Before 2006, there were also vocational and general type of high schools where the education duration was 3 years. In 2006, all high schools started to give 4 years of education. There are also general and vocational high schools where the medium of instruction is a foreign language. Entry to certain high schools is by a centralized examination.

General high schools offer a curriculum preparing students for university education with a tracking system where students are expected to be specialized in a major and choose a future education or labor market career accordingly. Similarly, the vocational high schools offer technical education preparing students for vocational higher education within the higher education system. There are also privately operated tutoring centers which both give additional support during the formal education and also prepare students both high school entrance and university entrance examination.

Turkish government provides formal education for all the citizens free of charge at each level. Primary and High school education is under Ministry of Education's control. Together with public schools, there are also private schools at each stage of the education system that is regulated again by Ministry of Education.

Access to university is provided with a centralized system since 1974. Private universities have started to operate in late 1980s. In 2008 there were around 160 universities in Turkey and around 35 of them were private universities. In last couple of years number of private universities have been sharply increasing and providing college placements for many applicants. Both private and public universities provide 4-years university programs as well as 2 years vocational programs. There is also the so-called Open Education which is a distance learning system granting four-year degree where students follow lectures broadcast on national TV or online and sit for the centrally administered examinations.

Access to any kind of higher education program is provided only through a test-based exam at a national level implemented by a central authority (Student Selection and Placement Center-OSYM in Turkish). After taking the test, applicants submit a list of higher education programs in an order of their preferences and OSYM assigns students to each program with limited capacities considering the preferences and test scores. Given the number of applications, the demand for higher education is quite far from to be met.

In 2008, about 1.5 million applicants took the university entrance examination where about 20% were high school seniors who take the exam for the first time and the rest of the applicants were retakers. Out of 1.5 million applicants t 12.5% were placed in a four-year university program, 9.0% were placed in a two-year program and 13.4% were placed in the

Open Education programs.

Considering this huge excess demand, in order to avoid the over-enrollment in higher education, the system designed in a restrictive way. Therefore, the national university entrance examination has a discarding structure with a doublefold objective: Firstly, it denies access to university for the least successful students with the presumption that they may drop out or generally perform poorly at university. Secondly it gives access to university to the most successful students and accordingly with their preferences offers them a place in a university and field of study that is presumed to maximize their utility. Driven by excess demand and high competition there is a large number of applicants every year retaking the test as they previously failed to obtain a sufficient test score to be placed in a desired program.

1.2 An Overview of Gender Gap in Educational Attainments in Turkey

There are several areas of concern within the education system in Turkey. The most important one is the low female enrollment rates especially in rural areas. Although returns to schooling is higher for females in Turkey, gender gap in participation rates in education is still significantly high.

In Turkey, in general, womens returns to education is not any lower than those of mens. Using 1987 Household Budget Survey, Tansel (1994) shows that womens returns to education is higher than those of men at the primary and middle school levels. Similar results are reported by Tansel (1996, 2004) using 1987 Household Labor Force Survey and 1994 Household Budget Survey. According to these results, for the wage earners, womens returns to education are higher at the middle school, high school and at the university level and also for the self-employed, womens returns to education are much higher than that of mens. Bakis et. al. (2010) analyze returns to education in Turkey using data from

Table 1: Gender ratio by educational year and level of education

Education Year	Primary Education	Secondary Education	Higher Education
1997/'98	85,63	74,70	69,58
1998/'99	86,97	75,50	69,44
1999/'00	88,54	74,74	70,96
2000/'01	89,64	74,41	73,56
2001/'02	90,71	75,87	75,17
2002/'03	91,10	72,32	74,33
2003/'04	91,86	78,01	74,09
2004/'05	92,33	78,72	74,66
2005/'06	93,33	78,76	77,20
2006/'07	94,11	79,65	77,65
2007/'08	96,39	85,81	78,74
2008/'09	97,91	88,99	80,08
2009/'10	98,91	88,59	83,38
2010/'11	100,42	88,14	-

Source: Ministry of Education. National Education Statistics 2001.

2006 Household Labor Survey and find that Turkish labor market is segmented by gender and returns to education are uniformly higher for women.

Table 1 shows the gender ratio of schooling at different levels of education for the period between 1997 and 2011. Although Female-Male ratio is considerably lower than 1 except for primary education level in 2010-2011 academic year, it has been considerably improving over these years: It has increased from 85.63 to 100.42 at primary education level, from 74.70 to 88.14 at secondary education level and from 69.58 to 83.38 at higher education level.

In Turkey, also female labor force participation (especially urban level) has been lower than any other country in the OECD or Europe. Female labor participation has been higher in rural areas of the country, as girls usually stay home and join family labor while boys are more likely to go to school in these areas. As for the wage inequality, it mainly comes from low levels of female education and the inequality in education starts at very early levels of education where girls fail to complete even 8 years of compulsory schooling. On the other hand, similarly with many other countries in the world, girls have been showing higher performance compared to boys in terms of general educational outcomes. For instance, females have a higher high school GPA on average with respect to boys, but are less likely to take the test for university entrance. The gender gap in terms of university applications as not as severe as earlier levels of education where 44% of high school graduates were girls while 38% of applicants (including retakers) were girls. Once females take the test, they are more successful than boys in all fields, but this better performance is not visible in the labor market. One of the most distinctive difference across gender at university applications appears to exist in retaking decision. Among the 2008 university entrance test applicants, 55% of girls were retakers while 66% of boys retook the test. Similarly for those who are placed in a program, 76% of girls and 84% of boys have taken the test at least once before.

A sharp increase in female educational outcomes such as GPAs and standardized test scores and a reduction in gender gap in higher education have been observed in many countries in the past decades and this trend has been analyzed with different approaches in order to understand the sources and implications of this catch up. In Turkey, especially at high school and university entrance level females have been outperforming males which can be easily seen in Table 2 where gender differences in achievements at the university entrance test in 2008 are reported.

From Table 2, it is clear that females have higher high school GPAs and test scores on average. 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.

One of the possible drivers causing the gender differences in test scores could be differences driven by the positive selection of females. Indeed, it seems females have better financial support and their parents are relatively better educated with respect to boys. Table 3 shows parents

Table 2: Descriptive Statistics for Achievements by Gender in 2008 University Entrance Test

	Female	Male	Diff
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)***

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 discriminated in terms of family support as one might expect.

1.3 Gender Differences in Achievements in Different Categories

As it is previously stated, there is a positive selection of females in the university applicants population. In order to avoid the effect of this positive selection on the gender differences in test scores I first estimated applicant's test scores in each category on individual characteristics controlling also for high school and high school type fixed effects. As there is a similar competitive system for the allocation of students in the transition from primary to secondary education in Turkey, controlling for high school and high school type provides a strong control for unobserved ability.

Estimation results are reported at the Table 4 where high school type, field and city fixed effects are included controlling for other individual characteristics such as retaking, private tutoring, and working status.

At the same table, positive and significant coefficient of the dummy variable taking value 1 of the applicant is a second taker, shows that there is a positive relationship between retaking and test scores in many categories. Controlling for other individual characteristics, second-takers have significantly higher test scores even though the level of this effect varies across categories. (e.g. there is a significant negative relationship between retaking and foreign language while the highest significant effect is seen on quantitative test scores.). As the university entrance test is a standardized test, it is not surprising that an applicant is more likely to obtain a higher test score with another year of preparation and thus many applicants choose to re-take the test in order to increase their test scores.

1.4 Gender Differences in Placements to Higher Education Programs by Categories

In the previous section, it is reported that female applicants obtain higher test scores on average with respect to males. In this section, it is aimed to provide evidence for gender differences in probability of getting an assignment. I estimated discrete placement outcome by categories with multinomial logit on gender controlling for all of the test scores and high school GPAs, and I found that there are significant differences between

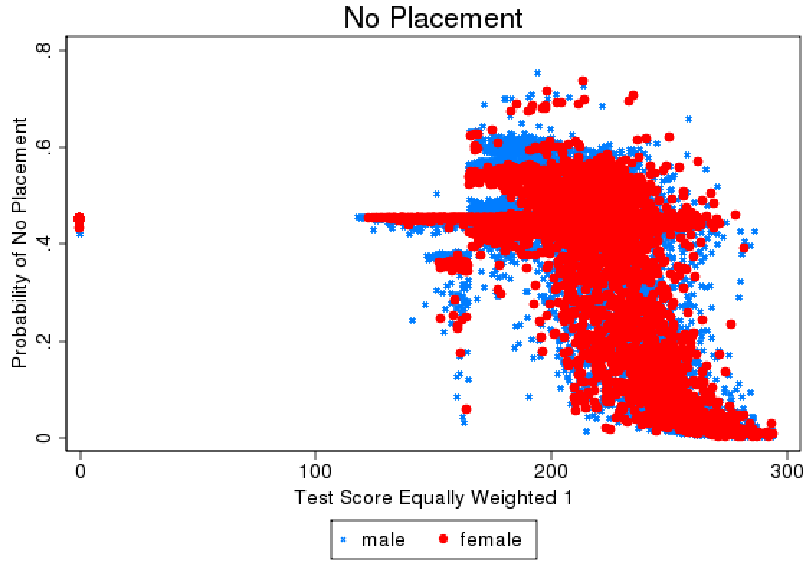

Figure 1: Predicted Probabilities of Getting No Assignment by Gender

boys and girls in terms of placement outcome. Table 5 shows the mean gender differences in predicted probabilities of placement in all categories. First line indicates that boys are significantly more likely to get no assignment with respect to girls.

The predicted probabilities of assignment outcome by categories for females and males are shown also in graphs in order to see how the predicted probabilities of assignment outcome changes by test scores. As one can easily observe from the Figure 1, the difference between boys and girls in terms of predicted probability of getting no assignment is more visible for low and high test score applicants.[1]

In the previous section, it is reported that female applicants are more likely to get an assignment controlling for test scores and other individual characteristics. As a final step, it is aimed to provide evidence for gender differences in probability of getting an assignment to a top major

[1]One might be concerned about the high share of male applicants in the sample when it comes to placement outcomes as it is a procedure of placement of applicants to a limited number of programs that have pre-announced capacities. On the other hand, this bias goes to a direction supporting the result.

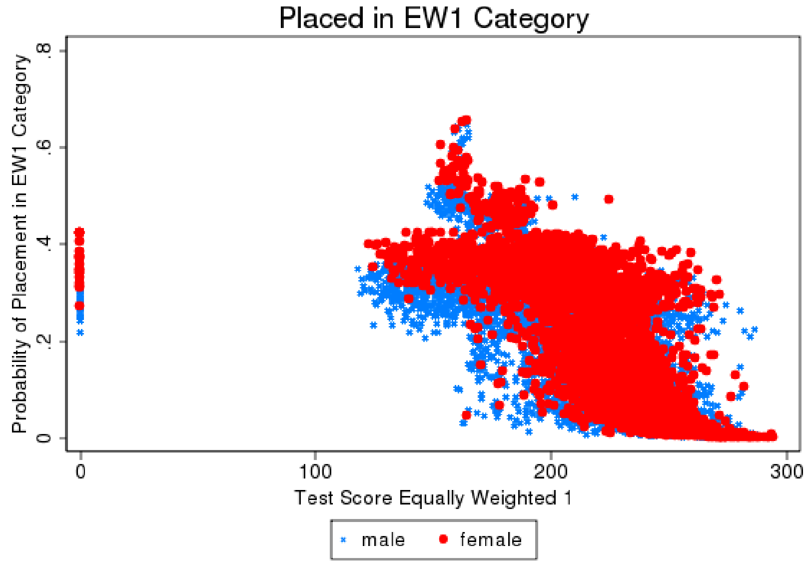

Figure 2: Predicted Probabilities of Getting An Assignment in Equally Weighted 1 Category by Gender

that has higher expected returns is reported in Table 6. I first estimated the probability of getting an assignment to one of the high return majors controlling for test scores, individual characteristics, parents education levels, high school types and high school specialization fields for the full sample of applicants. I find around 8% higher probability of getting assigned to a top major with respect females. In order to control for differences in test scores distributions between females and males, I also introduced the squares and cubes of test scores into the analysis and it reduced the difference to 7%. These results are shown in the first two columns of the Table 6.

Given that females are more likely to get an assignment, I applied the same estimations reducing the sample to the applicants who get an assignment. Doing so, it is possible to measure the gender differences in probability of getting an assignment to a top major given that they are assigned to a program. The estimation without controlling for test score squares and cubes gives a gender difference of 12% while when these controls added the difference is reduced to 11%. These results are reported in the 3rd and 4th columns of the Table 6.

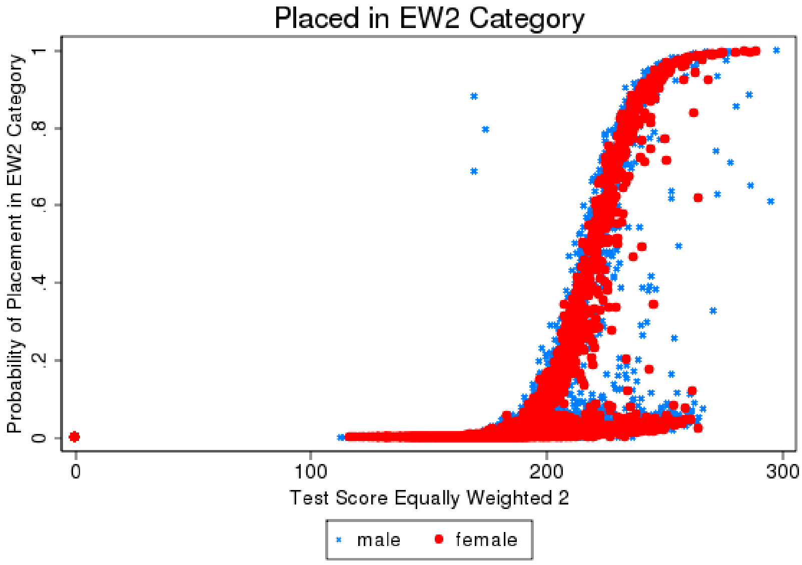

Figure 3: Predicted Probabilities of Getting An Assignment in Equally Weighted 2 Category by Gender

1.5 Conclusion

In this chapter, the gender differences in educational outcomes at different stages of education system in Turkey. With an emphasis on the gender differences in University Entrance Examination in Turkey, I show that female students outperform male students. They have higher test scores than males and are more likely to enroll in higher education programs controlling for test scores. Nevertheless, males still predominate at top majors university programs that lead to high-paying careers.

In the new era of technological developments, educational investments are becoming more and more important for labor market outcomes. In particular, the recent trend of employment polarization will likely lead to more pronounced differences between the labor market fortunes of high- and low-skilled workers. Gender differences in educational attainment imply that these highly rewarded high-skill workers

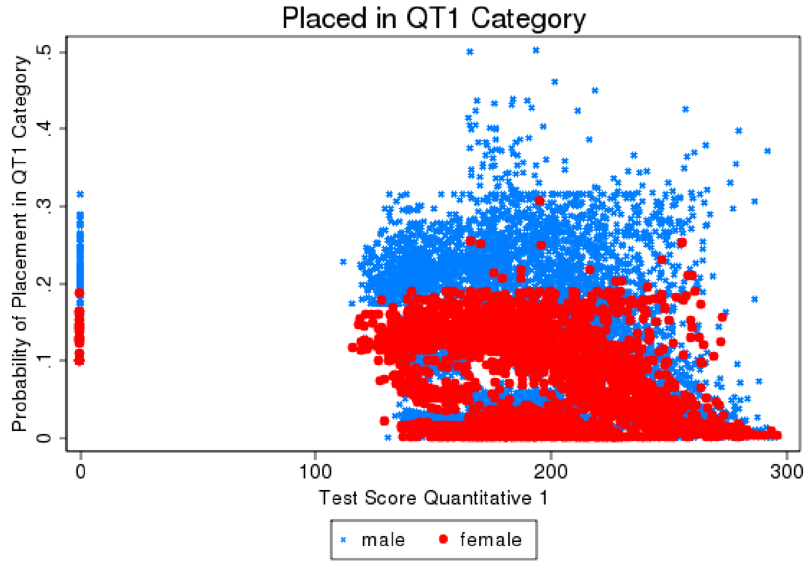

Figure 4: Predicted Probabilities of Getting An Assignment in Quantitative 1 Category by Gender

will be predominantly male and increasingly disadvantaged low-skill workers will be predominantly female. Gender gap in educational attainment can therefore have far reaching labor market implications.

The findings that are reported in this chapter imply a persistence in the gender gap of the skill supply in Turkish labor market. Therefore, the gender gap is likely to be persistent both in terms of wages and occupational choice even though females obtain better educational outcomes with respect to males. Given the higher returns to education for women and the importance of the education and labor market participation of women for economic development of a country, the potential reasons and consequences of the gender differences in university applications are a very relevant question to be studied in order to provide a policy framework for both education system and labor market.

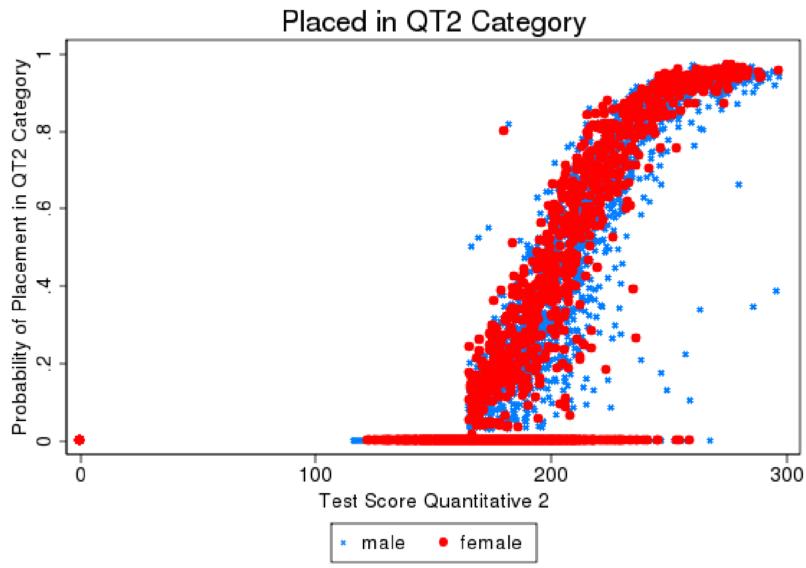

Figure 5: Predicted Probabilities of Getting An Assignment in Quantitative 2 Category by Gender

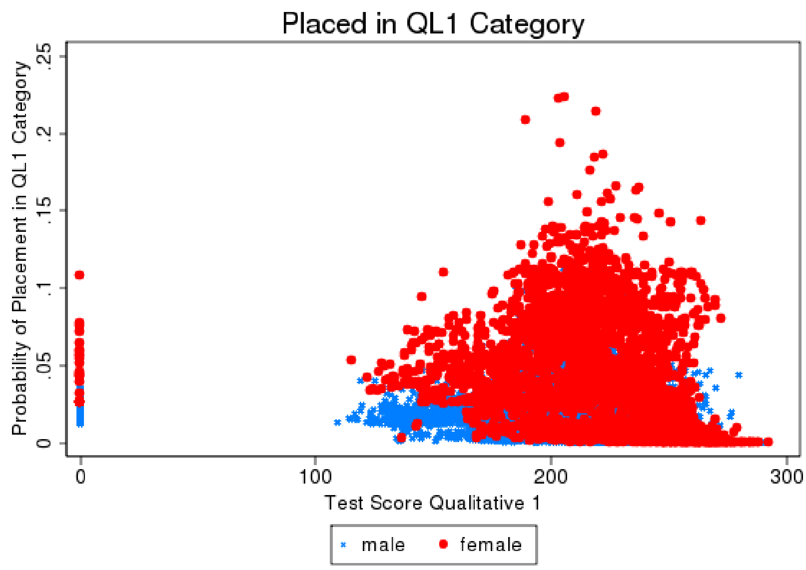

Figure 6: Predicted Probabilities of Getting An Assignment in Qualitative 1 Category by Gender

Table 3: Descriptive Statistics for Parents Education and Family Support by Gender in 2008 University Entrance Test

	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)***

Table 4: Test Score Estimations with High School Type, Field and City Fixed Effects

	EW1	EW2	QT1	QT2	QL1	QL2
Male	-1.7665	-3.4857	2.4427	-1.4566	-3.4238	-5.4855
	(.7494)**	(1.4129)**	(.7020)***	(1.4909)	(.7810)***	(1.4514)***
Second Takers	6.2576	9.1660	5.3675	4.9286	6.4145	8.3987
	(1.0233)***	(1.9294)***	(.9586)***	(2.0359)**	(1.0665)***	(1.9819)***
Private Tutoring	8.6684	5.6147	8.1351	8.9813	7.4719	2.5257
	(.8143)***	(1.5354)***	(.7628)***	(1.6201)***	(.8487)***	(1.5772)
if working	-12.4801	-8.5422	-11.5245	-10.9928	-11.8655	-2.0844
	(.8104)***	(1.5279)***	(.7591)***	(1.6122)***	(.8446)***	(1.5695)
Parents Education	Yes	Yes	Yes	Yes	Yes	Yes
HS Background	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9983	9983	9983	9983	9983	9983
F statistic	34.0915	57.8012	60.5828	83.2523	22.849	98.0605

Table 5: Gender Differences in Predicted Probabilities from Multinomial Logit Estimation of Placement by Categories: Females w.r.t. Males

	Mean difference wrt males	P-value
Probability of No Placement	-0.0125	0.0000
Probability of Placement in FL Category	0.0121	0.0000
Probability of Placement in EW1 Category	0.0204	0.0000
Probability of Placement in EW2 Category	0.0232	0.0000
Probability of Placement in QT1 Category	-0.0575	0.0000
Probability of Placement in QT2 Category	-0.0107	0.0000
Probability of Placement in QL1 Category	0.0231	0.0000
Probability of Placement in QL2 Category	0.0018	0.0000

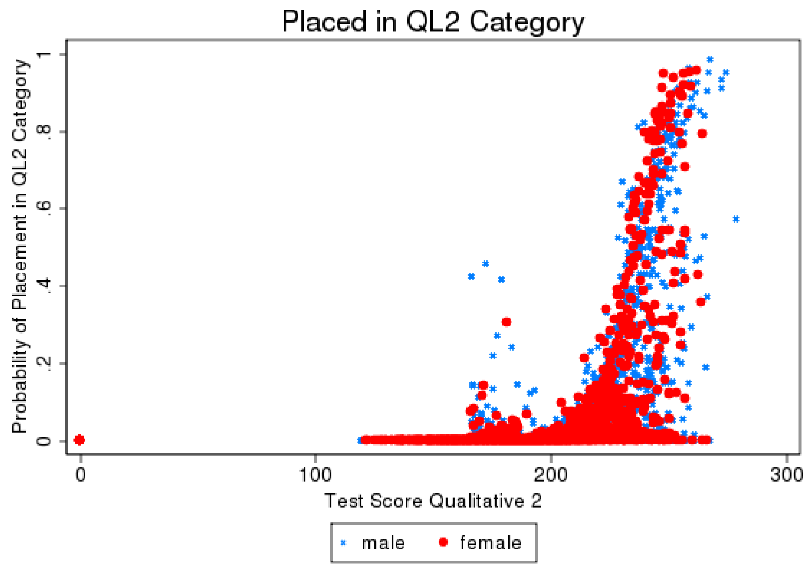

Figure 7: Predicted Probabilities of Getting An Assignment in Qualitative 2 Category by Gender

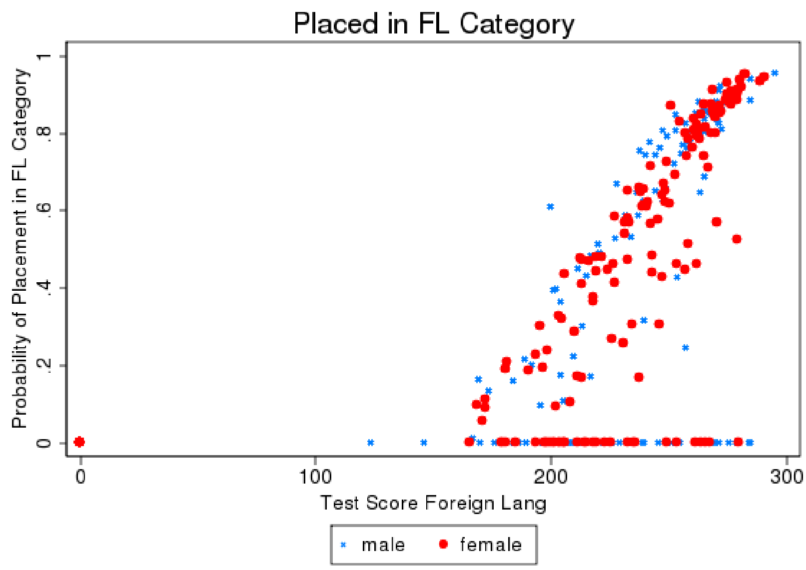

Figure 8: Predicted Probabilities of Getting An Assignment in Foreign Languages Category by Gender

Table 6: Gender Differences in Probability of Assignment to a Top Major

	All-1	All-2	Placed-1	Placed-2
Male	.0785	.0661	.1236	.1052
	(.0069)***	(.0064)***	(.0099)***	(.0094)***
Second Takers	.0356	.0280	-.0147	-.0171
	(.0098)***	(.0089)***	(.0138)	(.0130)
Third Takers	-.0445	.0172	-.0742	-.0213
	(.0096)***	(.0089)*	(.0138)***	(.0132)
Fourth Takers	-.0611	-.0032	-.0999	-.0430
	(.0125)***	(.0115)	(.0185)***	(.0175)**
Private Tutoring	.0095	.0138	.0231	.0235
	(.0074)	(.0068)**	(.0112)**	(.0105)**
All-HS-GPAs	Yes	Yes	Yes	Yes
All-Test-Scores	Yes	Yes	Yes	Yes
All-Test-Scores-Powers		Yes		Yes
Parents-Education-Controls	Yes	Yes	Yes	Yes
High-School-Type	Yes	Yes	Yes	Yes
HS-Background	Yes	Yes	Yes	Yes
Obs.	9983	9983	6184	6184
F statistic	23.5551	36.0187	22.9477	29.2023

Chapter 2

Gender Differences in Retaking Decision and It's Effect on Placement Outcomes

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

[1]Recent studies provide evidence suggesting that there are significant gender differ-

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 university programs with lower cutoff scores.

In this chapter, 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 field, 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

ences 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).

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 this chapter 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 chapter 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.

This chapter is organized as follows: in Section 2.1 , I provide details about the institutional setting in Turkey; in Section 2.2 , I describe the data and show some descriptive statistics to motivate the rest of the chapter. In Section 2.3 and 2.4, I explain the research design and report the main results. In Section 2.5 , I conclude this chapter.

2.1 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 Turkish university

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

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 field. 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 chapter 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. 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 dead-

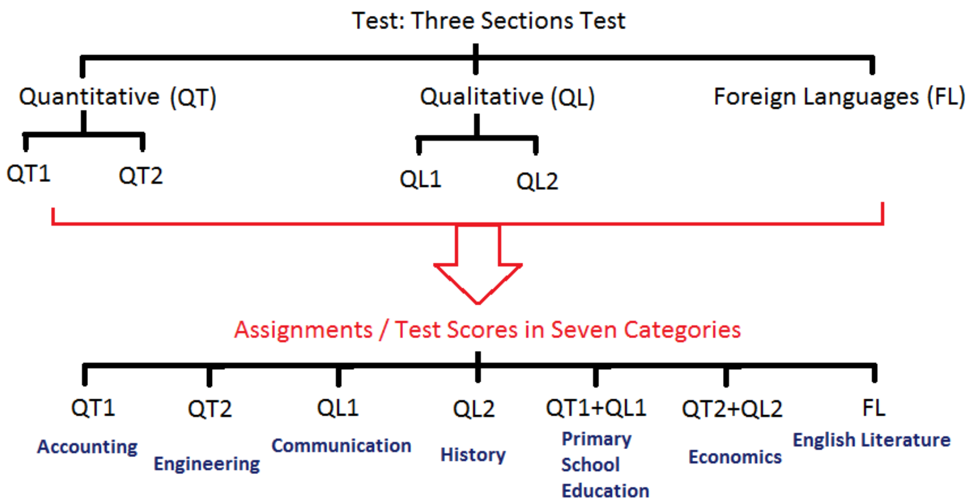

Figure 9: University Entrance Test: Sections and Categories

line 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 field 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 9).

Two mains sections each have 2 sub-sections. Regardless a student's choice of field 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 fields. Two mains sections each have 2 sub-sections in the following fields: Social Sciences (history, geography and philosophy), Science (Biology, Chemistry and Physics), Mathematics, and Literature. The Foreign Language section is an additional test. Regardless a student's choice of field in high school, each student answers essentially 4 sections which are Literature 1, Social Sciences 1, Mathematics 1, and Science 1. Section 2 with its subsections such as Literature 2, Social Sciences 2, Mathematics 2, and Science 2 and foreign language test are more advanced requiring more detailed knowledge in these fields. Therefore students choose to answer the questions of the subsections that pertain to their high school field.

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 field 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 fields. The weighted GPA is calculated with lower coefficients in an off-field main category. For example, an applicant having studied Sciences in high school field would

[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

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-field categories, it strongly discourages applicants to choose off-field university programs as the field test score 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.

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

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 retake the exam in the following years. A relevant 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.

2.2 Data and Descriptive Statistics

2.2.1 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% 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 7 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 7 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 3 in the previous chapter 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.

2.2.2 Theory and Evidence on the Willingness to be Unassigned to Retake the Test

In order to motivate the analysis, I 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:

$$\tilde{w_i} = w_i + s_i \tag{2.1}$$

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

$$E(s_i) = \mu_{si} \tag{2.2}$$

$$Var(s_i) = \sigma_{si}^2 \tag{2.3}$$

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

$$E(\tilde{w_i}|\sigma_i) = w_i + \mu_{si} \tag{2.4}$$

$$Var(\tilde{w_i}|\sigma_i) = \sigma_{si}^2 \tag{2.5}$$

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 $V^i\left(w_i\right)$ 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:

$$V^i\left(w_i\right) = \int_{w_R}^{\bar{w}} P(\tilde{w_i}|w_i, X_i)U^i(\tilde{w_i})d\tilde{w_i} + \int_{\underline{\mathbf{W}}}^{w_R} P(\tilde{w_i}|w_i, X_i)V^i\left(\tilde{w_i}\right)d\tilde{w_i} - c \tag{2.6}$$

$$V^i\left(w_i^R\right) = U^i(w_i^R) \tag{2.7}$$

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-field 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 8, 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 be-

cause of anxiety?

The differences by gender in the share of applicants answering these questions as "absolutely agree" are summarized in the end of Table 7. 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.

2.3 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:

$$C_{lt}^i > s_t^i \tag{2.8}$$

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 field 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 field f is denoted by R_{ihf}, then the model is given by:

$$R_{ihf} = \delta M_i + x_i'\beta + \mu_h + \mu_f + \epsilon_{ihf} \tag{2.9}$$

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 9 gives the results from simple OLS, probit and OLS with high school fixed effects and high school field fixed effects[6] where standard errors are clustered by high school city. According to these results reported in first three col-

[6]In a given high school, student might choose different fields in the end of first year and the students are assigned to the classrooms based on the field choice. Therefore controlling for retaking status, high schools and high school fields 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.

umn of Table 9 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 squares and cubes of all test scores are also included in the OLS estimation with high school and high school field fixed effect and results from this estimation is reported in the last column. The gender difference is around 3% and it's a significant number given that the total share of applicants willing to be unassigned is about 30%.

Another feature of the institutional setting is that there is a strong tracking system discouraging applicants to choose majors that do not pertain their high school field. 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 in their own field. 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 school 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 field fixed effects are run with dummy variables for the technical high schools and an interaction term with gender.

Another confounding effect might be driven by 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

[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.

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. Table 10 reports the results for the 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.

A 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 field fixed effects. I define the number of safe choices as the number of university programs 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 11 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 11 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 field 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 suggest 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.

2.4 Gender Differences in Reservation University Programs

2.4.1 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 field fixed effects, and majors are reported in the first columns of the Table 12 and Table 13 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

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

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 and an interaction term with gender[9].

Second columns of Table 12 and Table 13 report the results showing that gender difference in cutoff scores of last choice and assigned university programs are still significant for applicants 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 difference in cutoff scores of last and placement choices is not driven by the potential differences in constraints of distance to better schools in big cities.

2.4.2 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.

[9] I also exclude the technical high school graduates from this analysis as they might confound the results because of affirmative action as explained in the previous section

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 sam-

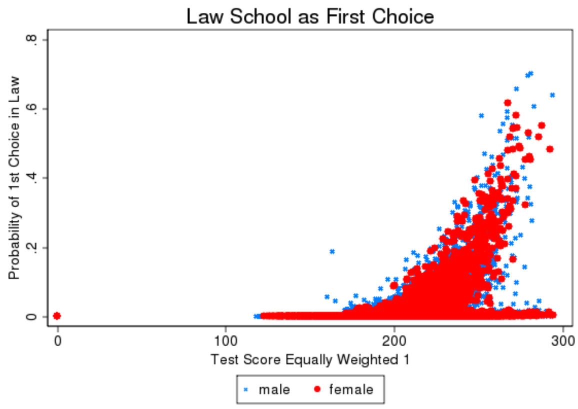

Figure 10: Predicted Probabilities of Choosing Law School as the first choice

ple are reported in Table 14. All specifications such as simple OLS, high school, high school type, and high school field 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 10 to 17 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

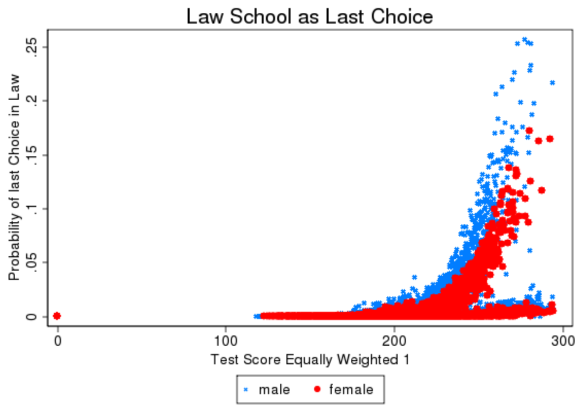

Figure 11: Predicted Probabilities of Choosing Law School as the last choice

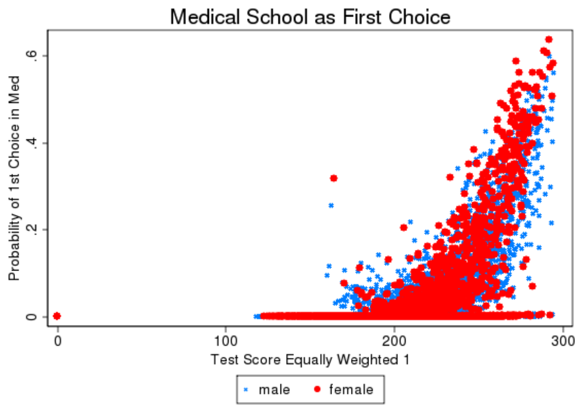

Figure 12: Predicted Probabilities of Choosing Medical School as the first choice

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

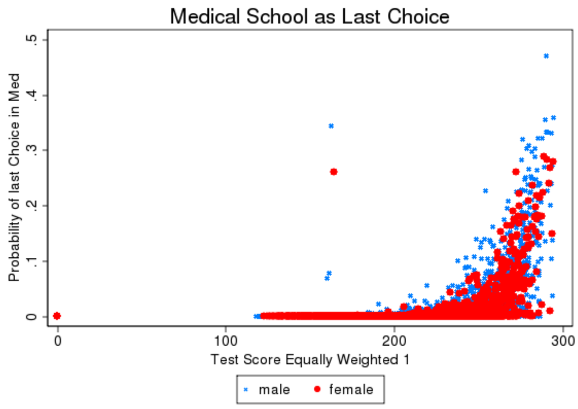

Figure 13: Predicted Probabilities of Choosing Medical School as the last choice

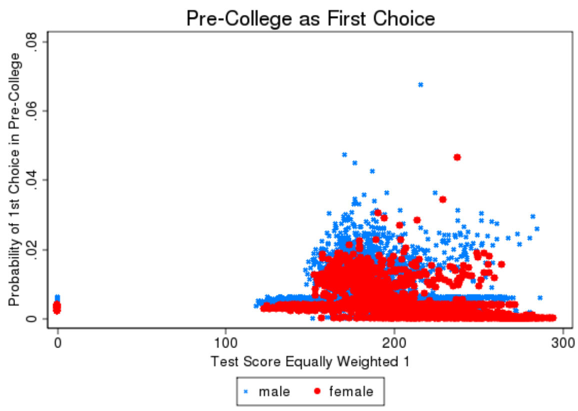

Figure 14: Predicted Probabilities of Choosing Pre-College as the first choice

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.

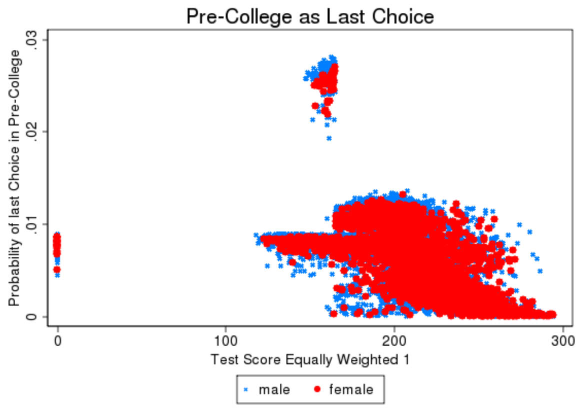

Figure 15: Predicted Probabilities of Choosing Pre-College as the last choice

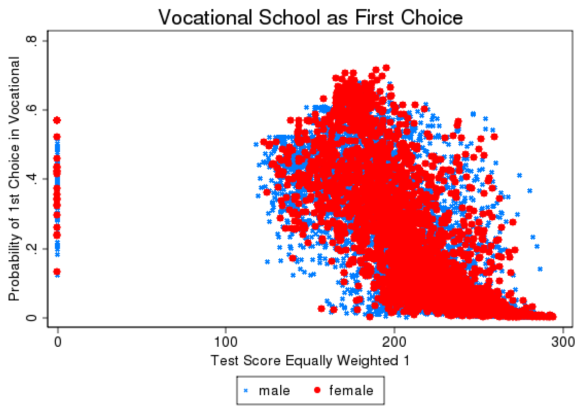

Figure 16: Predicted Probabilities of Choosing Vocational School as the first choice

2.5 Remarks

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 females outperform males in scholastic success at high school and on the university entrance test on average, university placement outcomes do not seem to reflect these improvements in gender gap. The gender gap is still apparent and large when we look at the general statistics on the number of quality university degrees hold by men and women. In order to

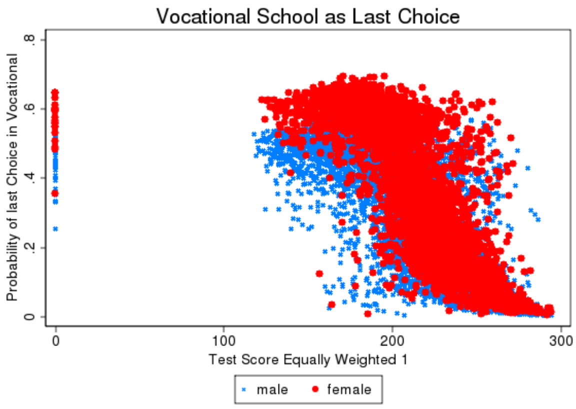

Figure 17: Predicted Probabilities of Choosing Vocational School as the last choice

understand the forces driving these gaps, one should analyze potential gender differences that might 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.

In this chapter, 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.

Table 7: 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)***

Table 8: 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	

Table 9: 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 Powers	No	No	No	Yes
Household Controls	Yes	Yes	Yes	Yes
High School FEs	No	No	Yes	Yes
High School Field FEs	No	No	Yes	Yes
Obs.	8496	8496	8496	8496
F statistic	67.1634		1.2569	1.3394

Table 10: 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 Field FEs	Yes	Yes	Yes	Yes
Obs.	8496	8496	8496	8496
F statistic	1.2569	1.2566	1.2564	1.2558

Table 11: 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 Field FEs	Yes	Yes
Obs.	8496	8496
F statistic	1.2612	1.1806

Table 12: Cutoff Score of Last Choice

	Last Choice	Only 3 Big Cities	No Tech High School
Male	3.0946	5.2397	2.9530
	(1.2042)**	(1.9539)***	(1.2005)**
If Retaker	-7.3685	-8.2222	-7.3583
	(1.5639)***	(2.4057)***	(1.5589)***
Private Tutoring	1.1371	1.0288	.8654
	(1.3870)	(2.2564)	(1.3832)
If working	-3.2911	-2.6655	-3.1202
	(1.3847)**	(2.3096)	(1.3804)**
All High School-GPAs	Yes	Yes	Yes
All Test Scores	Yes	Yes	Yes
Cutoff Score of First Choice			.0592
			(.0091)***
Majors	Yes	Yes	Yes
High School Fields	Yes	Yes	Yes
Obs.	6380	2209	4980
F statistic	233.2906	95.9372	231.1719

Table 13: Cutoff Score of Placement Outcome

	Placement Outcome	Only 3 Big Cities	No Tech High School
Male	2.0033	3.5058	2.1921
	(.9413)**	(1.5515)**	(.7407)***
If Retaker	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)***
Majors	Yes	Yes	Yes
High School Fields	Yes	Yes	Yes
Obs.	5959	2176	4530
F statistic	187.0551	90.2989	617.8444

Table 14: 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 Field FEs	Yes	Yes	No
High School Type FEs	No	Yes	No
e(N)	2994	2994	2994
e(F)	1.3895	11.3691	115.5524

Chapter 3

Heterogeneity in Preferences for Attributes of University Programs

The literature on gender inequality provides different economic theories. One of them is the discrimination hypothesis where the prejudices such as cultural norms bring about gender inequalities, suggesting a need for policy intervention. Another hypothesis suggests that gender-differentiated outcomes result from personal preferences rendering implications for public policy less clear. According to an alternative theory based on the constraints, it is also argued that income and credit constrained households invest in sons over daughters education in order to maximize future earning potential in an environment where males have higher incomes than females.

Therefore the economic questions one should ask are most of the time based on gender behavioral differences: Many of the studies find significant differences in outcomes between men and women. Evidence suggests that women and men may have different preferences with respect to health, savings, education, timing of marriage, and the number of children they would like to have. It is difficult to distinguish whether these differences stem from differences in underlying preferences or in constraints between the genders, particularly when preferences themselves are potentially endogenous to constraints. Nevertheless, it is still possible to measure and report the differences in preferences that can lead to gender differences in terms of important economic outcomes. In this chapter, I provide an evidence on gender differences in preferences for university program attributes which eventually determines their university and major choice that has a substantial effect on their future career on labor market.

The data employed in this chapter comes from the same dataset as in the previous chapter that is obtained from a merge of the 2008 OSS (Student Selection Examination) dataset, 2008 Survey of the OSS Applicants and Higher Education Programs dataset and the Higher Education Programs dataset from 2007 and 2008. Higher Education Programs dataset provides the information about the characteristics of the universities and higher education programs (such as major, the city where university is located and distance to high school city, whether private or public university and tuition status, instruction language, cutoff scores, capacities,...etc). I merged the characteristics of university programs from Higher Education Programs dataset by each university program chosen by the applicants.

After sitting for the university entrance test, students with a test score higher than a certain threshold are eligible to list university programs on her choice form in order of preference and the algorithm mechanism assigns applicants to programs depending on their choices and test scores. As it is explained previously, each university program is associated with one of the subject categories and it has a pre-announced limited enrollment capacity. 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. 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. In 2008, there were 10.670 university programs in total provided by 156 universities including both public and private universities.

Given the advantage of the dataset containing all choices in their order of preferences, in this chapter I analyze the preferences for university programs using both the choice of university programs from a large set of alternatives and the ranking of these choices. It is organized as follows: in Section 3.1, I report the results for the gender differences in preferences for university program attributes using a rank ordered logit model that uses only the chosen university programs for each individual as an alternative set and define the choice with highest utility according the ranking of alternatives. In section 3.2, I introduce the decision of willingness to be unassigned to the choice model. I first provide a research design based on a discrete choice model and then report the mixed logit estimation results. Mixed logit estimation yields estimates of individual coefficients of the random utility model and I report the gender differences by their willingness to get no assignment in the coefficients of attributes of university programs. In Section 3.3 , I conclude this chapter.

3.1 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 only 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 girls and boys. Although the effect of gender is not identified, it is still possible to draw some general conclusions from the results reported in Table 15 and Table 16. As the model is estimated separately for females and males, comparing the magnitudes of the coefficients of university program attributes for girls and boys does not provide any significant information about how differently they value the attributes of university programs. Yet, results can still provide 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 [1], scholarship status) are significantly different from zero having the same sign for both female and male

[1]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.

Table 15: Rank Ordered Logit Estimation: Attributes

	Girls	Boys	ALL
Test Score-Cutoff Score	-.0008	-4.00e-06	-.0002
	(.0002)***	(.0001)	(.0001)*
If University is in Big City	.3711	.4943	.4543
	(.0185)***	(.0130)***	(.0106)***
Distance from High School City	-.00005	1.00e-05	-5.00e-06
	(.00003)*	(.00002)	(1.00e-05)
Capacity	.0012	.0006	.0008
	(.0002)***	(.0001)***	(.00009)***
Foreign Instruction Language	-.0658	.1692	.1031
	(.0542)	(.0336)***	(.0285)***
Night School	-.1973	-.2353	-.2222
	(.0193)***	(.0133)***	(.0110)***
Private University with No Scholarship	-25.0750	-25.7682	-25.2286
	(.1774)***	(.1367)***	(.1083)***
Private University with Scholarship	-25.4407	-26.2224	-25.6551
	(.2062)***	(.1597)***	(.1263)***

samples.

On the other hand, some coefficients are different in terms of the statistical significance between girls and boys. First of all, as it is shown in Table 15, 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 the likelihood of assignment 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. [2].

[2]Usually English language

Finally, as it is reported in Table 16, coefficients of indicator variables for majors differ in terms of significance between females and males. As it is described previously, 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 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[3].

One might think that these differences in coefficients for the majors might be driven by the differences in high school fields.[4] Therefore one can argue that differences in comparative advantages in different fields 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 fields, 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 so-

[3]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

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

ciety even though it usually leads to a very modest wage and career.

3.2 Preferences for the Attributes of University Programs: Introducing Willingness to be Unassigned

3.2.1 Model

In this section, I provide a deeper analysis of the decision making for the choice of university programs by introducing the willingness to be unassigned. Considering the willingness to get no assignment of the applicant, the choice of a university program from an individualized alternative set can be modeled as following:

There are 7 categories broadly defined in accordance with the sections of the test such as quantitative, qualitative, foreign languages etc. and every university 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 cutoff score C_{jt}. Program l_t^i with the lowest cutoff score chosen by individual i from category t is expected to be the last program for individual i to be assigned in category t.

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:

$$C_{lt}^i > s_t^i \tag{3.1}$$

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

I describe the decision of willingness to take the risk of getting no assignment as following:

Applicant i obtaining a test score s_t^i in category t has following options within each category:

- Choose at least one or more programs j from category t that are feasible with s_t^i which implies $C_{jt} \leq s_t^i$,

- Choose one or more program j from category t only with $C_{jt} > s_t^i$ and be willing to get no assignment from this category,

- Choose no program and get no assignment from this category.

In the discrete choice setting of the reservation university program, assume an individual i with test scores s_t^i has the individual choice sets from each category that are restricted to include only the lowest cutoff score choice program chosen by the applicant and programs below. Applicant i assigns utility u_{ijt} to a feasible university program j from category t with $C_{jt} \leq s_t^i$ and selects the highest expected utility. The event that applicant i chooses j from category t is denoted by the indicator $d_{ijt} = 1$ with

$$\sum_{j=0}^{J_i^t} d_{ijt} = 1 \tag{3.2}$$

where $C_{jt} \leq s_t^i$ for all $j_t^i = \{0, 1, ..., J_i^t\}$ and $t = \{1, ..., 7\}$

For individual i, utility of the the lowest cutoff score program l chosen by the applicant from this category t will have higher expected utility than any other program j in this choice set. In other words, lowest cutoff score program that is also defined as the reservation university program will have a higher utility than any other university program that has a lower cutoff score and not chosen by the applicant.

$$U(C_{lt}|C_{lt} \leq s_t^i, X_i) > U(C_{jt}|C_{jt} \leq C_{lt}, X_i) \tag{3.3}$$

for all $j_t^i = \{0, 1, ..., J_i^t\}$ where $t = \{1, ..., 7\}$.

The utility that applicant i assigns to a feasible university program j from category t is given by:

$$u_{ijt} = X_i'\beta_{jt} + R_{jt}\alpha_i + Z_{jt}\gamma_i + \epsilon_{ijt} = v_{ijt} + \epsilon_{ijt} \tag{3.4}$$

The term α_i is the individual coefficient for the parameter $R_{jt}\alpha_i$ which defines the university program j in category t as either risky or safe choice. The parameter R_{jt} takes value 1 if the cutoff score C_{jt} is higher than s_t^i and 0 otherwise.

The term ϵ_{ijt} is unobserved component of tastes and assumed to be randomly distributed across the population.

Thus we can write for each category t:

$$P(d_{ijt} = 1|C_{jt} \leq s_t^i, X_i, Z_{jt}) = P(v_{ijt} + \epsilon_{ijt} > v_{ikt} + \epsilon_{ikt})\, for\, all\, j \neq k \tag{3.5}$$

The probability of making a choice list M_i containing the best alternatives from 7 categories will be given by the multiplication of probabilities written for each category t:

$$P(M_i|C_{jt} \leq s_t^i, X_i, Z_{jt}) = \prod_{t=1}^{7} P(d_{ijt} = 1|C_{jt} \leq s_t^i, X_i, Z_{jt}) \tag{3.6}$$

3.2.2 Data Setting and Results

The data used in this section also comes from the same dataset that contains the information for a random sample of 9983 individuals. For the analysis of mixed logit, I use only 2% of this sample and I also drop the applicants who fail to obtain a sufficiently high test score to make a choice list and those who do not submit any choice list even though they have sufficiently high test scores. Finally, I analyze the choices of 126 applicants.

For an individual i, I define an individual alternative set depending on the lowest cutoff score choice that is reservation university program for each category. I analyze the reservation university program choice for a given category. I arrange the dataset by expanding for each individual by the number of alternatives in each individual alternative set for 11 categories. Finally, I drop the lines of categories from which the applicant has no program listed.

Given the huge number of available alternatives, 10670 university programs in 11 categories, I define individual choice sets that are compatible with the decision of taking risk of getting no assignment. Even after defining individual choice sets, it is still not feasible to run the mixed logit model due to the large number of alternatives. Therefore, I take a random sample of each alternative set for each category for an applicant i.

The data setup for mixed logit estimation is also identical to that required by conditional logit estimation. In this analysis, an applicant i faces n choices situations where $n = \{1, ..., 11\}$.[5]. e.g. If an applicant list 7 programs from 3 different categories, I define this applicant as facing 3 choice situation. Each observation in the data corresponds to an alter-

[5]In practice there are 7 categories in total but I divided the EA1, QL1, QT1, FL categories in two parts as the cutoff scores and allocation algorithms can differ for certain programs that are associated with these 4 categories. Therefore, in the data analysis, I use a setting where there are 11 categories.

native, and the dependent variable is 1 for the chosen alternative in each choice situation (category) and 0 otherwise.

Given the research design explained above, using the mixed logit setting I obtain the estimates of the individual parameters for the attribute of university programs fitting a model in which all the coefficients for university program attributes are normally distributed (Hole: 2007). I estimated two different model where I consider different attributes and major choices separately. The following explanatory variables representing some attributes of university programs enter the first model:

- Whether University Program is a Risky Choice (0-1 dummy)
- Whether University is in a Big City (0-1 dummy)
- Distance between University City and High School City
- Whether University is a Public University (0-1 dummy)
- Tuition Status (Scaled 1 to 8)

The coefficients' summary statistics for the first model are reported by gender in Table 17. The second model includes the majors as explanatory variables. In this analysis, I only take the high profile majors such as Medical School-Dentistry-Pharmacy, Business-Economics, Engineering, and Law School. Similarly, the coefficients' summary statistics for the second model are reported by gender in Table 18.

As it is reported in Table 17 there is no opposite preferences for any attribute even though size of the coefficients seem to be different on average for male and female applicants. Male applicants dislike less the risky choices as their reservation choice of university program with respect to female applicants. Another interesting finding is that the coefficients for risky choices are not significantly changing by test score.

As for the choice of big cities for going to college, male applicants prefers going to the universities in big cities more than female applicants. Given that the most of the top ranked universities are located in big cities in Turkey, differences in these coefficients would yield differences in outcomes. Also Figure 19, shows the coefficients for females and males applicants by their test scores. For almost every level of test scores, male applicants have higher coefficients with respect to female applicants. The coefficients of dummy variable for public universities and the variable for tuition status are higher for female applicants. Similarly Figure 21, 20 and Figure 22 shows these coefficients for females and males by their test scores. Gender differences for tuition and distance coefficients are not significant although there is a significant difference for the tuition coefficients for applicants with higher test scores.

Table 18, reports the results for the second model where I estimated the coefficients for high profile majors such as Medical School, Economics-Business, Engineering, and Law School. Female applicants dislike engineering and economics and business majors while, male applicants like to choose these majors. Even though there is no opposite preferences for Law and Medical Schools, the size of the coefficients seem to be higher for male applicants indicating that males like to choose these majors more than female applicants. Similarly Figure 23, Figure 24, Figure 25 and Figure 26 shows the coefficients for females and males by test scores.

3.3 Remarks

In this chapter, I first 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

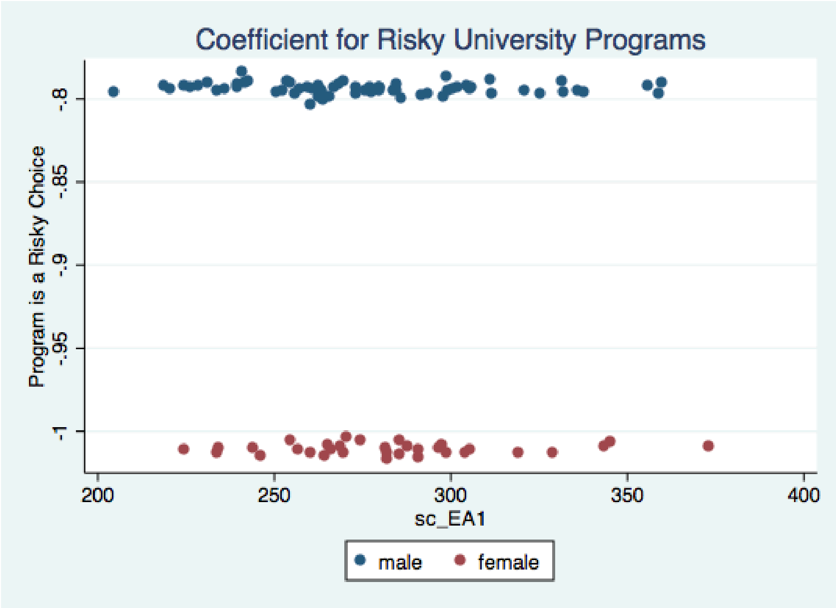

Figure 18: Coefficients by Gender and Test Score

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.

After showing the gender differences in preferences for university program attributes using their choice list to map their preferences from the ranking of the university programs, I also analyze the heterogeneity in preferences for university programs considering also the decision for taking the risk of getting no assignment. In particular, I analyze the decision making for taking the risk of being unassigned and it's potential effect on the decision making for the university program choice and preferences for these university program's attributes. I find that female applicants seem to weigh the characteristics that matter during university even more when it comes to choose the reservation university program and they sacrifice other qualities of the programs that might pro-

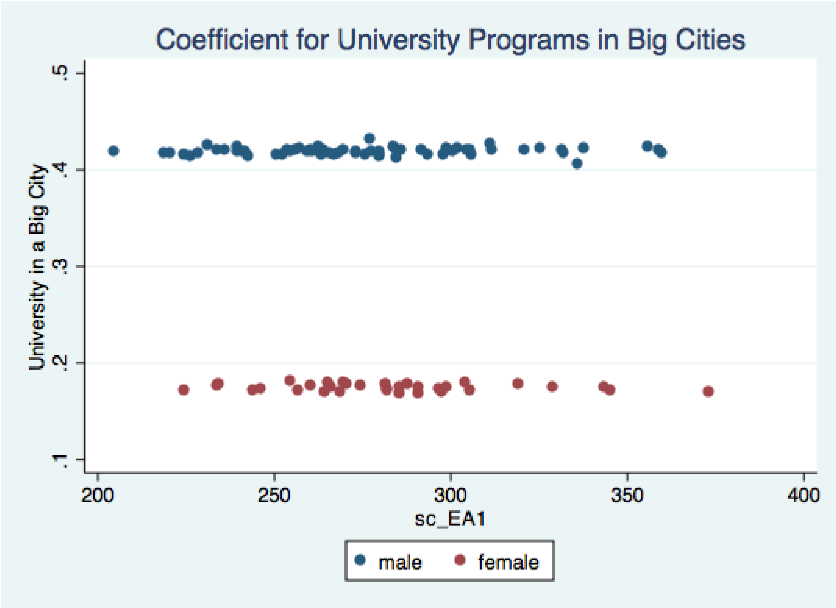

Figure 19: Coefficients by Gender and Test Score

vide them a good profile later in labor market.

3.4 Conclusion

Despite the underlined importance of female participation in education and labor market for the economic development, sizable gap remains in schooling levels in most developing countries. Also in Turkey, gender gap in participation rates in education is still significantly high. However, there has been a sharp increase in female educational outcomes such as GPAs and standardized test scores with respect to males.

In this dissertation I aimed to give an overview of gender differences in education in Turkey and it's potential causes and consequences. First, I reported the trends in educational outcomes showing that in Turkey, as in many other countries, female students perform better in high school. They also have higher test scores than males and are more likely to enroll in higher education programs controlling for test scores. Nevertheless, men still predominate at highly selective programs that lead to high-

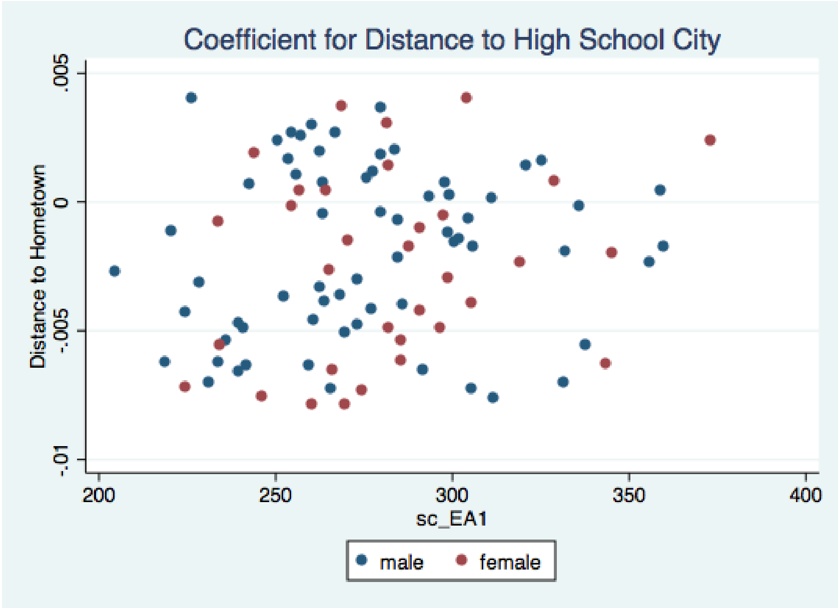

Figure 20: Coefficients by Gender and Test Score

paying careers.

Second, I elaborate the gender gap at elite schools which is particularly puzzling because college admissions are based entirely on nationwide exam scores. Using detailed unique 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 retaking the test and applying again next year.

Finally, I analyze the heterogeneity in preferences for higher education program characteristics. Using the matched administrative dataset including the choice lists submitted by university applicants, I 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.

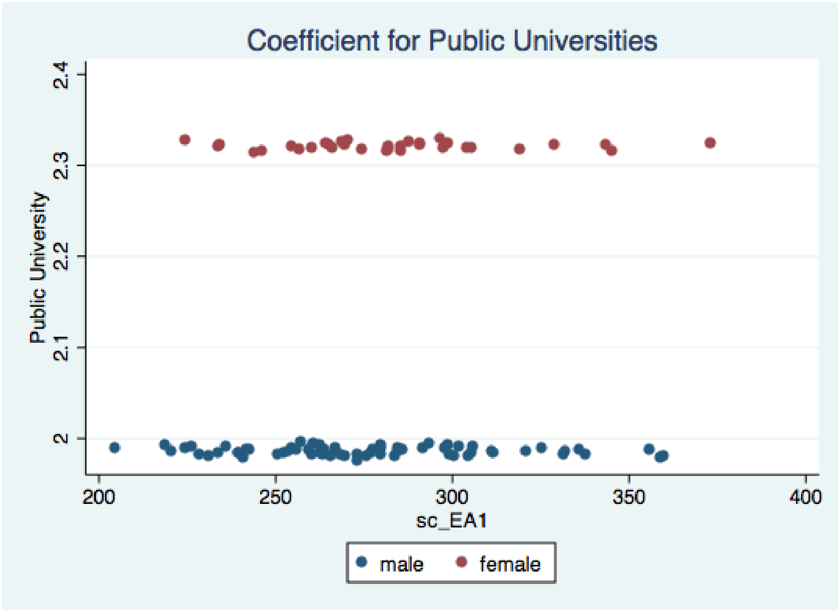

Figure 21: Coefficients by Gender and Test Score

Together, these differences in willingness to be unassigned and in relative preferences for school attributes that are reported and evaluated in details in this dissertation can explain much of the gender gap at the most elite programs which has important implications for the persistency of gender wage gap and occupational differences in Turkish labor market.

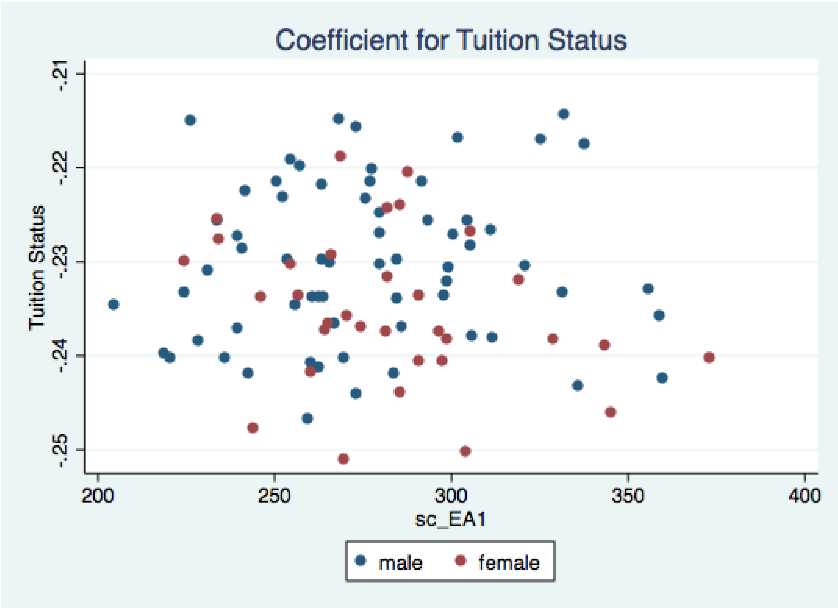

Figure 22: Coefficients by Gender and Test Score

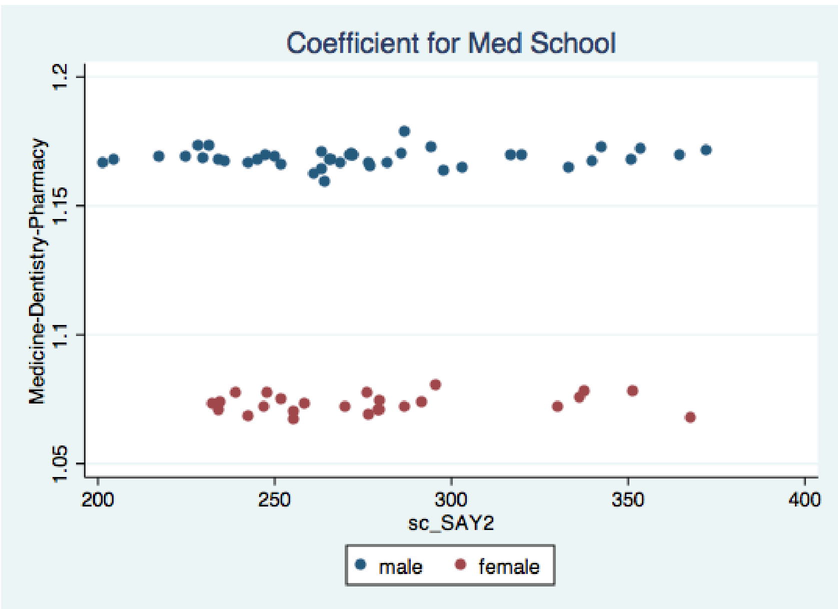

Figure 23: Coefficients for Majors(Medical School) by Gender and Test Score

Table 16: Rank Ordered Logit Estimation: Majors

	Girls	Boys	ALL
Majors			
Agriculture-Environment	.0234	.0306	.0176
	(.0683)	(.0482)	(.0393)
Communication	-.4392	-.5321	-.5399
	(.3603)	(.2228)**	(.1896)***
Dentist-Pharmacy	.8427	1.0203	.9514
	(.0821)***	(.0697)***	(.0528)***
Econ-Business	.0088	.2224	.1227
	(.0453)	(.0400)***	(.0299)***
Econ-Administrative	.0851	.1855	.1455
	(.0924)	(.0675)***	(.0543)***
Engineering	.0700	.1762	.1283
	(.0517)	(.0360)***	(.0293)***
Architecture	1.1569	1.3095	1.2687
	(.1858)***	(.2183)***	(.1410)***
Health School	-.1002	.1010	.0145
	(.0574)*	(.0504)**	(.0376)
Law School	-.2578	.0399	-.0759
	(.0842)***	(.0714)	(.0542)
Literature	.2926	.5220	.4059
	(.0569)***	(.0562)***	(.0398)***
Medical School	.1151	.4441	.3248
	(.0919)	(.0642)***	(.0526)***
Open Education	-.2612	.5301	.4661
	(.3483)	(.3698)	(.2257)**
Pre-College	-.1115	-.2071	-.1935
	(.2776)	(.1239)*	(.1126)*
Natural Sciences	.2593	.4388	.3610
	(.0508)***	(.0408)***	(.0317)***
Tourism	.1857	.2003	.1705
	(.1003)*	(.0650)***	(.0542)***
Vocational	-.0327	-.0522	-.0630
	(.0527)	(.0378)	(.0305)**
e(N)	30181	57276	87457
e(F)			

Table 17: Coefficients by Gender

Program is a Risky Choice	-1.0109	-0.7946	-0.8650
StdDev	0.0032	0.0032	0.1018
University in a Big City	0.1732	0.4184	0.3386
StdDev	0.0035	0.0037	0.1154
Distance to Hometown	-0.0025	-0.0019	-0.0021
StdDev	0.0035	0.0035	0.0035
Public University	2.3196	1.9846	2.0936
StdDev	0.0037	0.0042	0.1576
Tuition Status	-0.2342	-0.2304	-0.2316
StdDev	0.0085	0.0083	0.0085

Table 18: Coefficients for Majors by Gender

	Female	Male	All sample
Medicine-Dentistry-Pharmacy	1.0726	1.1683	1.1364
StdDev	0.0032	0.0031	0.0454
Econ-Business	-0.0011	1.9900	1.3263
StdDev	0.0035	0.0037	0.9423
Engineering	-0.0626	0.8097	0.5189
StdDev	0.0035	0.0035	0.4129
Law	1.2492	2.7527	2.2516
StdDev	0.0037	0.0042	0.7116

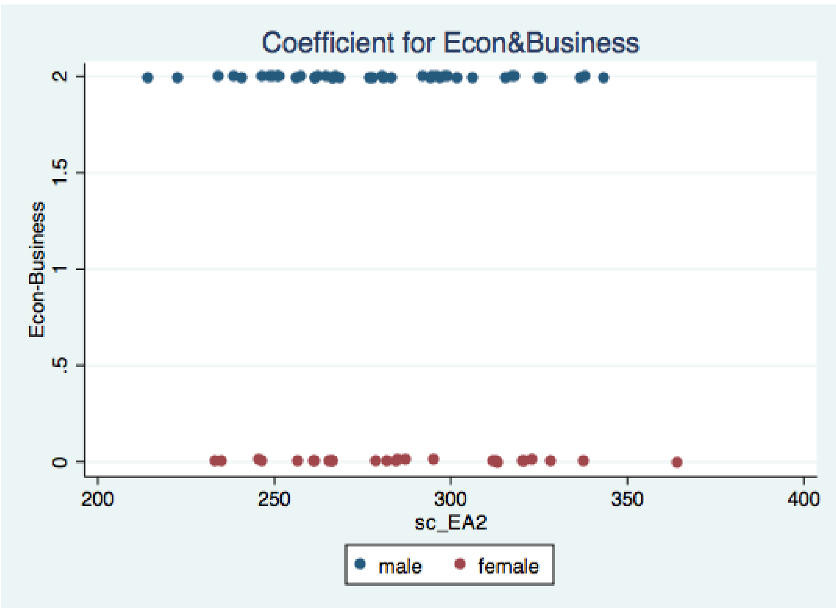

Figure 24: Coefficients for Majors(Econ-Business) by Gender and Test Score

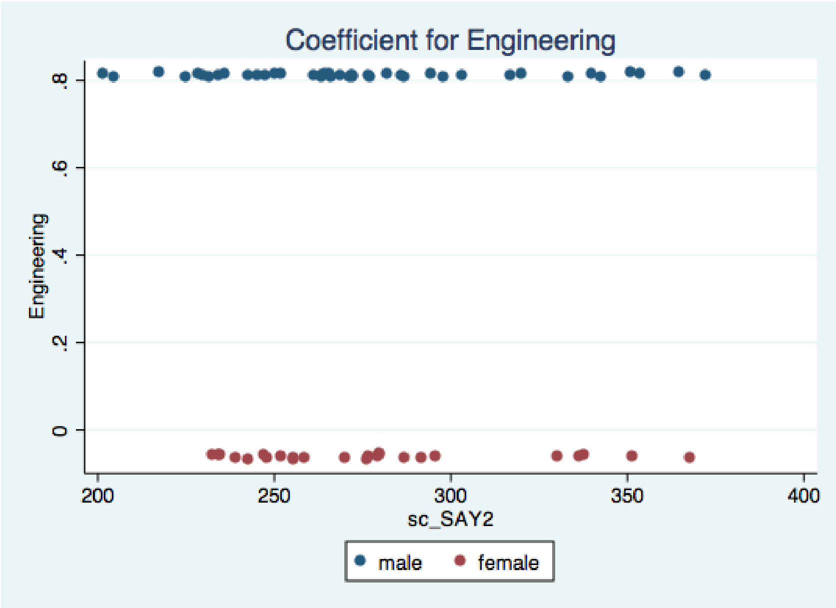

Figure 25: Coefficients for Majors(Engineering) by Gender and Test Score

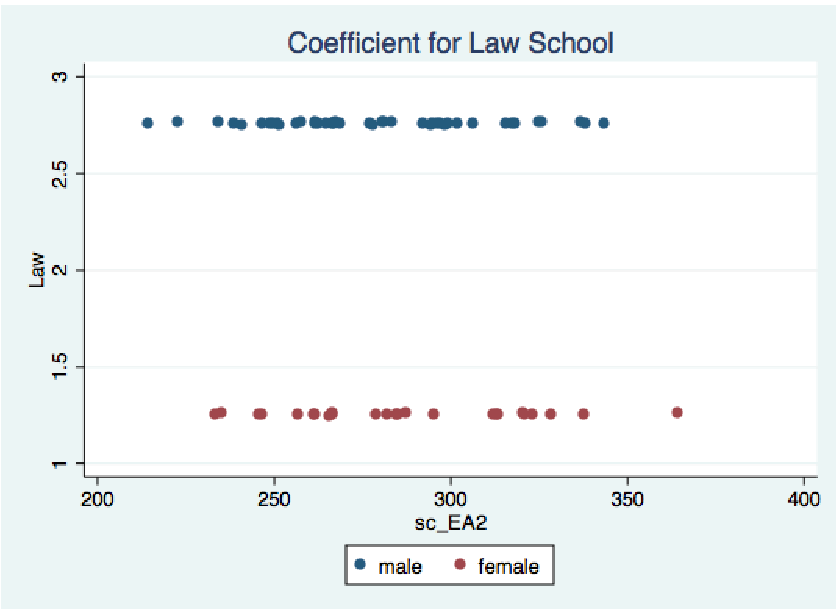

Figure 26: Coefficients for Majors(Law School) by Gender and Test Score

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