

Gender Differences in College Major Choices. The case of Chile ¹

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November, 2018

Abstract

This paper studies the causes of gender differences in college applications in Chile. We developed a model for college-major application based on the Chilean institutional setting. We group majors into disciplines or areas of knowledge, group traditional universities into three tiers according to their quality and selectivity and we include a fourth group with private universities created after 1981. We consider several factors that affect the paired choice (major, university group). We then estimate a nested logit model to predict the pair (area, university group) to which students apply as their first preference. Our results show that females are 14.8% more likely to apply to health majors, 14.7% less likely to apply to civil engineering and 7.9% less to technology. We also find that the score on the math selection test has the highest effect on college application; it increases the likelihood of applying to civil engineering and business, and decreases the probability of applying to health, medicine & odontology, social sciences & humanities and law. Our counterfactuals show that the gender gap decreases more in female dominated areas if males had female's preference parameters rather than female having male's preferences. Furthermore, the gender gap decreases more in engineering and technology if female has male's preferences rather than male having female's parameters.

JEL Classification: I20, I23, J16.

Keywords: Gender differences, gender preferences, college-major choice.

¹Alejandra Mizala acknowledges financial support from FONDECYT Project N 1140834 and from PIA-CONICYT (Basal Project FB0003). Paola Bordón acknowledges support from (CONICYT/FONDAP/15130009) and the Millemium Nucleus on Social Development. This research was also partially supported by the supercomputing infrastructure of the NLHPC (ECM-02) at the Faculty of Physical and Mathematical Sciences, Universidad de Chile. Also, we would like to thank the participants at SECHI and PEGNet conferences for their valuable comments.

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1 Introduction

Empirical evidence has shown that women tend to be underrepresented in science, technology, engineering and math (STEM) and overrepresented in the humanities, education, and social sciences. This is important since underrepresentation of women in STEM fields can explain gender segregation in the labor market, given that the content of schooling accounts for a substantial part of the gender gap in jobs and earnings (Arcidiacono, 2004); in fact, STEM fields are associated with more valuable job-related human capital and generate a higher monetary return. Therefore, it is relevant to understand why girls do not choose the most rewarding majors in terms of future wage and labor market opportunities.

Are these gender differences generated by the underlying preferences of men and women, or instead, are they a result of selection processes in higher education? In other words, is it that women do not want to apply to STEM fields or is it that they cannot apply due to selection standards? Understanding the causes of underrepresentation of women in STEM fields becomes crucial for policy makers, educators and employers if the goal is to increase women's participation in those areas of study.

This paper analyzes these questions for the case of Chile. In particular, we estimate the gender gap if female had male's preferences and vice versa. To this end, we consider the cohort of students who applied to universities in 2015 through the Chilean Single Admission System (SUA). The SUA is a unified single application system used by universities belonging to the Council of Chancellors of Chilean Universities (CRUCH), which includes 25 public and private universities created before 1980 (also known as traditional universities). In 2012, eight non-traditional private universities have joined the SUA. To apply, students sort their preferences, indicating their desired major-university pair.

In order to identify the factors that influence the students' application choices, we group majors into disciplines or areas of study, group traditional universities into three tiers according to their quality and selectivity, and we include a fourth group with the private universities created after 1981; we distinguish gender factors that affect the paired choice (area of study, university group) or program. We then estimate a nested logit model to predict the pair (area, group) to which students apply as their first preference.

Our results show that gender affects application choices in several dimensions: (i) females are 14.8% more likely to apply to health majors, 14.7% less likely to apply to civil engineering and 7.9% to technology; (ii) mother's area of study or work have higher effects on daughters in female dominated majors and law (2-4%), whereas father's area of study or work have higher effects on daughters in medicine & odontology, civil engineering and education (3-7%); (iii) females from mostly-female high schools classes are 5.8% more likely to apply to health majors, but 3% less likely to apply to civil engineering.

The selection process also influences students' application choices: students are more likely to apply to an program when they are likely to be admitted. Thus, if women tend to have lower scores on the University Math Selection Test (PSU) than men, their probability of applying to areas where this test has a major impact on selection (such as science and civil engineering) will be lower. In fact, an increase in one standard deviation in Math PSU

score increases 20.1% the likelihood of applying to civil engineering for males and 13.6% for females and decreases 14.6% the likelihood of females to apply to health careers.

This paper is organized as follows. Section ?? reviews the literature, section ?? presents a description of the Chilean higher education system and the application process, section ?? presents the model and estimation procedure used in this paper, section ?? describes the data, section ?? provides the estimation results, section ?? shows some profiles or different combinations of simulated choice probabilities for average students differentiated by gender, section ?? provides the counterfactuals exercises, section ?? studies the gender differences in light of our findings, and section ?? concludes.

2 Review of the Literature

Over the past decades many countries have made progress in narrowing or closing gender gaps in years of schooling, secondary and post-secondary school attendance. However, the opposite is true for the content of education received; empirical evidence shows that in many countries women are under-represented in the fields of science, technology, engineering and mathematics (STEM) whereas they are over-represented in humanities, languages, education and the arts. In 2012, only 14 percent of women who entered university for the first time in OECD countries chose STEM fields of study vis a vis 39 percent of men (OECD, 2015). Furthermore, there is gender segregation in science. Sikora and Pokropek (2012a) shows -using data from PISA 2006 that included 50 countries- that in all countries science-oriented girls prefer biology, agriculture or health careers, whereas boys favor careers in computing, engineering or mathematics.

The proportion of female and male students across fields of study with over-representation of one gender has been called horizontal sex segregation in education. This phenomenon can explain gender segregation in the labor market, given that the content of schooling accounts for a substantial part of the gender gap in jobs and earnings (Arcidiacono, 2004). In general, stereotypically male subjects create more valuable job-related human capital and generate a higher monetary return.

Therefore, it is relevant to understand why girls do not choose the most rewarding majors in terms of future wage and labor market opportunities. The literature on this issue has not yet come to definitive answers.

The basic question is if these differences are explained by nature or nurture. Research in Psychology and Medicine has explained gender segregation by the presence of biological and neurological gender differences. According to this approach, boys use more cortical areas dedicated to spatial and mechanical functioning (Kimura, 2000). On the contrary, girls develop more the part of the brain devoted to verbal and emotional functioning. For this reason, girls may under perform relatively in technical and quantitative subjects from childhood and gradually disengage from these subjects (Killgore and Yurgelun-Todd, 2004; Lenroot, et al. 2007).

However, in some of the top-performing countries and economies in PISA girls perform equal to their male classmates in mathematics, attaining higher scores than all boys in most other countries around the world, this is for instance the case of Hong Kong, Shanghai, Singapore and Chinese Taipei. These results suggest that the gender gap in mathematics is not determined by innate differences in ability. Furthermore, Favara (2012) finds that the belief that men are naturally more skilled at technical/quantitative domains is empirically unfounded and attainments, such as performance and grades, are not able to explain subject choices alone. Girls and boys performing equally in the same subjects, choose per their own gender stereotype. Nonetheless, girls and boys at the top of grade distribution behave similarly in terms of subject choice.

Other literature associates career choices with gender stereotypes.⁵ The argument is that gender specific attributes such as risk aversion, self-confidence and attitude towards competition contribute to sketch the gender identity. These attributes develop during childhood and affect boys' and girls' choices along their lifecycles (Sutter and Rützler, 2010; Gneezy and Rustichini, 2004).

The literature shows that women are generally more risk averse than men and more likely to shy away from competition, some authors suggest that these characteristics are related to a gender gap in self-confidence (Booth and Nolen, 2011 and 2012; Croson and Gneezy, 2009; Gneezy et al., 2003; Niederle and Vesterlund, 2007 and 2010; Datta Gupta et al., 2005). Niederle and Yestrumskas (2008) find that females are less likely to seek challenges than men with the same abilities and that this is because they have a higher risk aversion or higher uncertainty about their own abilities than men do. Kutz-Costes et al (2008) suggests that girls' perception of their own mathematics and sciences abilities is lower than boys perception. Thus, if advanced math courses are relatively challenging, this explains why females often opt out of those courses.

Gneezy et al (2003) presents experimental evidence supporting that women may be less effective than men in mixed-sex competitive environments, although they are able to perform similarly in non-competitive environments and better in single-sex environments. Niederle and Vesterlund (2007) argue that lower self-confidence and less taste for competition play a substantial role in mathematics – and more so at the right tail of distribution. Örs, Palomino and Peyrache (2013) and Jurajda and München (2011), find that females underperform in high-stake tests relative to males with similar abilities, and Niederle and Vesterlund (2010), conclude that the gap at the top of the math test score distribution does not necessarily imply a gap in the underlying math abilities. One reason is that girls have particularly little faith in their own math abilities -conditional on actual abilities- because of extensive gender-stereotyping in math. Another reason is that math tends to be a very competitive discipline because the answers to exercises are either right or wrong.

Alternatively, experimental evidence suggests that the gender gap in the choice of college major is mainly due to differences in non-pecuniary preferences and tastes, pointing

⁵Another possibility is that gender discrimination in the labor market generates sex-differences in subject choice. Female students anticipate potential gender discrimination in the labor market avoiding those majors which offer higher rewards for men than for women.

out the role of preferences and social interactions in explaining how individuals make decisions. Using unique experimental data of Northwestern University graduates, Zafar (2009) finds that gender differences in beliefs about ability cannot explain the gender gap in major choices. The same for gender differences in beliefs about future earnings associated with each major which are insignificant and explain less than 1 percent of the gender gap. Conversely, he finds that the main part of the gender gap can be explained by gender differences in tastes and preferences for studying different fields, a similar result is obtained by Bartolj and Polanec (2012). The gender specific attributes discussed above might explain why boys and girls have different educational preferences. Differences in attitudes and preferences might affect the relative importance of pecuniary versus non-pecuniary benefits (Turner and Bowen, 1999), that is, economic incentives are not sufficient for girls to enroll and stay in male traditional fields of study (Noe, 2010).

Favara (2012) studies the role of social identity in determining individual behaviors and gender differences in economic outcomes. She integrates the concept of gender identity into an economic model of educational choices, to test the hypothesis that students' preferences are shaped by notions of gender identity congruence. Students choose their major based on both their expected monetary returns and the pay-offs in terms of identity. If a student conforms to the social norms of the reference group, here identified by gender, she receives an indirect utility (non-pecuniary pay-off) due to a more rewarding self-image. Conversely, violating the prescriptions of gender identity generates a loss of utility. She finds that gender stereotyping affects educational choices from the age of 14, and its effect is larger for girls than for boys. She also finds evidence that gender preferences can be modified by the environment, single-sex schools lead students to a less stereotyped educational choice, after controlling for endogenous self-selection into single-sex schools.

In the same line, Humlum et al. (2012), using Danish data, derive a model of career choice and identity. They characterize two identities relevant for educational choice: career oriented and social oriented typology. For a career-oriented person, career and work are important for a meaningful life. Conversely social oriented persons assign more importance to cooperation, social responsibility and social issues, such as other people's well-being. They find that these two underlying factors vary systematically with the investments in level and field of education and they consider this result as evidence that identity pay-offs are an important part of educational decision making. According to their findings, students' educational choices are consistent with their self-images. Students with a career oriented identity, choose based on the financial incentive they believe is associated with their choice. This finding implies that policy makers and higher education institutions should seriously consider identity-related issues to attract high-ability students to certain careers.

Sikora and Pokropek (2012b) find that intergenerational transfers of preferences for science careers vary considerably across countries, but there are certain regularities. In many countries, relevant paternal employment enhances sons' interest in science careers regardless of their field. In contrast, maternal employment inspires daughters in fewer countries and the influence tends to be limited to biology, agriculture and health

careers.

3 Chilean Higher Education System and Application Process

Chile has a single centralized admission system for its traditional universities, administered by the Department of Educational Evaluation, Measurement and Registration (DEMRE, by its Spanish abbreviation) at the University of Chile, which is under the authority of the Central Admission System at the Council of Chancellors of Chilean Universities (CRUCH).⁶ Since 2003, the 25 traditional universities of CRUCH have used the group of standardized tests that comprise the University Selection Exam (PSU, by its Spanish abbreviation) -which is similar to the United States' SAT test- and the high-school GPA (NEM, by its Spanish abbreviation) to select students for admission. Starting in 2012, eight non-traditional private universities have joined the PSU admission system, thus, the 33 most selective universities of the country use this single centralized system to select their students.⁷

All entrance exam takers complete mandatory tests in mathematics and language, and they also take optional tests in other subjects (social sciences and/or sciences). Scores are scaled to a distribution with range 150 to 850 and a mean and median of 500. Entrance exam scores, along with high-school GPA, are the primary components of the composite scores used for postsecondary admissions, scholarships, and student loan eligibility. Each university must set the guidelines, requirements and selection factors for admittance to each degree program it offers and choose the weightings it deems appropriate in accordance with the rules established by CRUCH.

The score of an applicant to a degree program is calculated by applying the weightings to his or her results for each selection factor. After taking the entrance exam and receiving their scores, students choose where to apply and submit their application to the SUA. As in other postsecondary education systems, a choice indicates both an institution and a major; we will refer to an college-major combination as a program. Students submit one application with up to ten ranked program choices. Once students apply, their entrance exam scores and GPAs are used by the universities to assign a score for each program. Once the final application score is calculated, the candidates for each program are placed into a strictly decreasing order based on their scores. Then, the program proceeds to fill their vacancies by starting with the applicant ranked first on the list, following a rigorous order of precedence until they fill all vacant slots. Applicants who are selected for their

⁶There are two types of universities in Chile, 25 traditional (public and private) universities created before the year 1980 and the over 30 non-traditional private universities created after 1980. Traditional universities are coordinated by the Council of Chancellors of Chilean Universities (CRUCH), and are eligible to obtain partial funding from the state.

⁷Starting in 2013, CRUCH decided to include high school in-class rank (besides high-school GPA) as a new selection factor in the university admissions process.

first choice are eliminated from the lists of their remaining choices. Applicants who are not selected for their first choice are placed on a waiting list and move on to compete for a spot in their second-choice program, and so forth.

Students have an incentive to rank order their choices correctly (they should not list a less-preferred choice over a more-preferred choice), nevertheless they may incorporate overall probability of admission in deciding which options to list (as they are allowed to list a maximum of ten options). While students apply with some knowledge of where they might be admitted, cutoff scores may vary from year to year as demand shocks for various programs ripple through the system.

4 Model

This section presents our model for college-major application, guided by the institutional rules described above. In the model, there is a continuum of students with a set of high school history (h_{ij}), socioeconomic and demographic characteristics (g_{ij}), final score (a_{ij}) and academic interests. There are U universities, each with A areas of study (group of majors). Let $j \in A$ be a major, and $k \in U$ any university. Let (j, k) denote a college program. Each program differs by admission requirements, fields of study and university quality. Thus, students choose among $A \times U$ options.

Students have a certain level of knowledge in mathematics, language, social science and science, summarized by $s_i = (s_{i1}, s_{i2}, \dots, s_{iS})$, the vector of test scores. This knowledge generates student's final application score:

$$a_{ij} = \sum_{l=1}^S \omega_{jl} s_{il} \quad (1)$$

where $\omega_j = [\omega_{j1}, \dots, \omega_{jS}]$ is the vector of major- j -specific weights and $\sum_{l=1}^S \omega_{ml} = 1$.

Students apply to a college-major combination (program) as their first preference in order to maximize their expected utility:

$$U_{ijk} = \alpha_j z_{ij} + \beta_k x_{ijk} + \epsilon_{ijk} = V_{ijk} + \epsilon_{ijk} \quad (2)$$

where x_{ijk} is the vector of students characteristics relevant to their college-major choice, which encompasses a_{ij} ; z_{ij} is the vector of characteristics relevant to their choice of major, including h_{ij} and g_{ij} ; and ϵ_{ijk} is the error term.

Note that a student's relevant characteristic to choose an option (j, k) is the probability of being accepted by that option (p_{ijk}). In the Chilean case, the probability of being accepted by option j depends only on the PSU tests' scores. Before students apply to college, they have access to the following information: (i) their scores at the different tests ($s_i = (s_{i1}, s_{i2}, \dots, s_{iS})$), (ii) their average high school GPA, (iii) the vector of major- j -specific weights

($\omega_j = [\omega_{j1}, \dots, \omega_{jS}]$) and (iv) the application score of the last student enrolled at each program the year before (cutoff score).

Let $C_{ijk} \in \{0, 1\}$, $C_{ij} \in \{0, 1\}$ and $A_{ijk} \in \{0, 1\}$ be dummy variables. $C_{ijk} = 1$ indicates that the student i chooses as their first preference major j at k university group and $C_{ijk} = 0$ otherwise. $C_{ij} = 1$ indicates that the student i chooses as their first preference major j and $C_{ij} = 0$ otherwise. $A_{ijk} = 1$ indicates that the individual i was admitted to major j in k university group and $A_{ijk} = 0$ otherwise.

On the other hand, the probability of being accepted at program (j, k) can be described by the following equation:

$$p_{ijk} = \theta_k(a_{ij} - \bar{a}_{ij}) + \eta_{ijk} \quad (3)$$

where a_{ij} is the final application score of student i at major j , $\bar{a}_{ij}$ is the application score of the last student admitted the year before, and η_{ijk} is the error term as the cut-off score could change every year.

Although U_{ij} and p_{ij} are not observable, students decisions are observable. Therefore, if $U_{ijk*} = \text{Max } U_{ijk}$ student i applies to the program (j, k) . In other words, we used the revealed preference principle.

We will assume that the conditional distribution of ϵ_{ijk} given a choice of major j follows a generalized Gumbel's extreme-value distribution (see equation (??)). This assumption corresponds to a nested logit model.

$$F_{U|A}(\epsilon_{jk}|j) = \exp \left[- \left(\sum_{k \in U_j} \exp \left(\frac{\epsilon_{jk}}{\tau_j} \right) \right)^{\tau_j} \right] \quad (4)$$

In this type of model, we have that

$$P[C_{ijk} = 1 | C_{ij} = 1] = \frac{\exp(x_{ijk}\beta/\tau_j)}{\sum_{l \in U_j} \exp(x_{jkl}\beta/\tau_j)} \quad (5)$$

$$P[C_{ij} = 1] = \frac{\exp(\tau_j IV_j)}{\sum_{n \in A} \exp(\tau_n IV_n)} \quad (6)$$

where

$$IV_j = \ln \sum_{l \in U_j} \exp(x_{jkl}\beta/\tau_j)$$

$$P[C_{ijk} = 1] = P[C_{ij} = 1]P[C_{ijk} = 1 | C_{ij} = 1] \quad (7)$$

5 Data

We use data on students' characteristics and the schools they attended obtained from the Chilean Ministry of Education. Specifically, we use data of a cohort of students graduated from high school in 2014, and applied to enter university in 2015. The data about the characteristics of university candidates, their applications and the final acceptance was provided by DEMRE.

76,680 students graduated from high school in 2014 applied to a major-university through the centralized admission system, but only 67,426 of them applied as a first option to an area-group of universities in which they comply the entrance requirements and they are not in more than 100 points under the cutoff score, and they have more than an option in this situation. Only 53,942 of that set haven't lost values in the variables needed for our model. To have a sample size that would allow estimating the models in a reasonable time, we chose a random sample of 20,000 cases. All area-group have at least 50 cases in the sample.

Students apply to the centralized admission system ranking their major-university choices. To have a reasonable number of possible options, we group majors into disciplines or areas of knowledge: (1) Medicine & Odontology, (2) Health, (3) Sciences, (4) Civil Engineering, (5) Technology, (6) Business, (7) Arts, (8) Social Sciences & Humanities, (9) Law, (10) Education. Universities were clustered into four groups, where group 1-3 have the CRUCH institutions by selectivity, and group 4 has the non-traditional ones.

Table 1 shows some descriptive statistics in terms of applications, enrollment and the gender gap for each area of knowledge. Gender gaps are generally higher at the application process than in enrollment, which means that the selection process seems to decrease the gender gap. There are important gender gaps in health, civil engineering, technology and education. The reduction of the gender gap is higher at the female dominated areas. On the other hand, Table 2 depicts applications and enrollment and the gender gap for each university group. It becomes clear that the selection process increases the gender gap for females in group 2.

For the estimation, we consider a set of students' characteristics (z_{ij}) relevant to his/her choice of area of study. We organize these variables in 5 groups:

Gender Variables:

- Female: Dummy that indicates if the student is female.
- Parent's area same sex: Dummy that takes the value of 1 if the student is male and his father has a job or studies related to the area of knowledge, or if the student is female and her mother has a job or studies related to the area.
- Parent's area same sex: Dummy that assumes the value of 1 if the student is male and his mother has a job or studies related to the area of knowledge, or if the student is female and her father has a job or studies related to the area.

- Female high school class: Dummy that takes the value of 1 if student was in a school class with more than 60% of women.
- Mix high school class: Dummy that takes the value of 1 if student was in a school class that had between 40% and 60% of women.

Selection factors of the university admissions process:

- High school ranking: Standardized score of the student ranking in high school according to their academic performance considering his/her high school cohort. The higher the grades, the higher the ranking and higher scores.
- High school GPA of Mathematics and Physics, Biology and Chemistry, Social Sciences & Humanities, Arts and Music: Standardized scores of GPA in the respective subjects.
- University Selection Test (PSU) scores of Math, Language, History and Science: Standardized Scores of the respective test.

High school related variables:

- Voucher or Private high schools: Dummies that indicate if the student studied either at voucher (private-subsidized) or at a private school. The default choice is public high school.

Student's characteristics:

- Per capita Income: Per capita income in hundred thousand Chilean pesos of 2014.
- Region II-XV: Dummies that indicates the region of the country where the student lives (reference category region I). This variables allow to control for geographical effects.

We also consider students' characteristics relevant to their college-major choice, the x_{ijk} vector:

- Difference of Score: Difference between the application score of the student minus the application score of the last student enrolled at the area-university group in 2008 (cutoff). Standardized Scores.
- Difference of Score squared.
- Program average score: Average PSU scores of Math and Language of the area-group. Standardized Scores.
- Percentage of regional vacancies of the program: Percentage of vacancies of the program relative to the total of vacancies of the program in the student's region.

- Copayment: Annual tuition that students expect to pay in the program in hundred thousand Chilean pesos. We assumed that students who applied for a state scholarship or credit expect to receive it.
- % of the previous high school class enrolled in the group: Percentage of students of the previous high school class of the student's school who enrolled at the group.

6 Estimation Results

We estimate the model for the entire sample and also for men and women, independently. Tables 3-5 present the marginal effects for these models. Pseudo R^2 of the model for the whole sample, male sample and female sample are: 0.25, 0.24 y 0.23, respectively. The prediction errors are smaller than 1%. These estimations allow us to analyse how gender affects students' application to different major or areas of knowledge in higher education.

Our most relevant results show that females are, in average, 14.8% more likely to apply to health majors, 14.7% less likely to apply to civil engineering and 7.9% less to technology. Mother's area of study or work have higher effects on daughters in female dominated majors and law (2-4%), while father's area of study or work have higher effects on daughters in medicine & odontology, civil engineering and education (3-7%). Females from mostly-female high schools class are 5.8% more likely to apply to health majors, but 3% less likely to apply to civil engineering.

We also find that Math PSU score is the test with higher effects on application for the areas of knowledge. Indeed, an increase in one standard deviation in Math PSU score increases, in average, 20.1% the likelihood of applying to civil engineering for males and 13.6% for females. Also, it decreases the likelihood of applying to health, medicine & odontology, social sciences & humanities and law. Similarly, Math-Physics GPA are the GPA with higher effects on area of knowledge application: an increase in one standard deviation in Math-Physics GPA increases 9.1% the likelihood of applying to civil engineering for males and 6.4% for females. Besides, it decreases 5.1% the likelihood of females of applying to health.

The results in other areas also affect the application. For example, an increase in one standard deviation in Biology-Chemistry GPA increases, on average, 3.4% the likelihood of applying to health for males and 4.1% for females, while it decreases 5.2% the likelihood of applying to civil engineering for males and 3.4% for females. Moreover, an increase in one standard deviation in Sciences PSU score increases 7.3% the likelihood of applying to medicine & odontology for males and 6.6% for females.

Finally, we corroborate that students from private high schools are 6.2% more likely to apply to business majors, 3.3% less likely to apply to civil engineering and 3.1% less likely to education.

Furthermore, we also study how different variables affect students' application to different university groups. Table 6 shows the average marginal effects for these models. We can

observe that, both female and male students increase their probability of applying to a group when their score is above the cutoff score (average marginal effect of difference of score near to 4%). However, there is also a quadratic and negative effect of this variable: this indicates that, when their score is much higher than the cutoff this probability will decrease.

Besides, the selectivity of the group of universities also affect the application: an increase of one standard deviation of the program average score will increase, on average, nearly 6% the probability of applying to a group. Otherwise, the effects of an increase in the percentage of regional vacancies in the program, co-payment and the percentage of previous high school class enrolled in the group of universities, are also positive but of a small magnitude.

7 Profiles

In this section we exhibit the simulated choice probabilities for each area of knowledge and university group for students with average coefficients in all variables except gender (male or female). Figure 1 and 2 show the simulated probability of applying to each area and group of universities, respectively, for males and females with average coefficients in all the remaining control variables. In Figure 1, we can observe that there are important differences in the choice probabilities by gender in health, civil engineering, technology, social sciences & humanities and education. However, as Figure 2 shows, the differences between both sexes in the probabilities for applying to different groups by an average student tend to be small.

Furthermore, we simulate the choice probabilities for each area of knowledge and university group for students of different gender, class composition (mostly female, male or mix high school class), and parent's area of occupation or study (of the same and different gender of the student). This exercise allows us to create 94 different student's profiles. We find that only changing the gender variable, the choice probability for an area of knowledge can change up to 41% while the choice probability for a university group can change up to 18%.

Moreover, we analyze students' profiles related to their achievement. In particular, we consider students with average characteristics, of different sexes, but with a outstanding achievement in certain area: (1) biology-chemistry (3.18 score at science PSU and 1.8 GPA in biology-chemistry); (2) math and sciences (3.18 score at science and math PSU, and 1.8 GPA in biology-chemistry and math-physics); (3) math-physics (3.18 score at math PSU and 1.8 GPA in math-physics); (4) history (3.18 score at history PSU and 1.8 GPA in humanities); (5) language (3.18 score at language PSU and 1.8 GPA in humanities); (6) Humanities (3.18 score at language and history PSU, and 1.8 GPA in humanities).

Our results of the latter analysis show that average male students with outstanding achievement in humanities and biology-chemistry are more likely than females to apply to the

most selective areas: a male student outstanding in humanities has higher probability than females of applying to law (79% vs 52%), but lower of applying to social sciences and humanities (16% vs 35%) and education (2% vs 7%). A male student outstanding in biology-chemistry has higher probability than females of applying to medicine & odontology (96% vs 85%), but lower of applying to health (2% vs 11%).

There are also differences in the other profiles: a male student outstanding at language has higher probability than a female student of applying to social sciences & humanities (41% vs 36%) and civil engineering (14% vs 2%), but lower of applying to health careers (9% vs 20%) and education (15% vs 25%). A male student outstanding at history has lower probability than a female student of applying to social sciences & humanities (17% vs 13%) and education (4% vs 2%). A male student outstanding at math-sciences has higher probability than a female student of applying to medicine & odontology (22% vs 15%), but lower to civil engineering (71% vs 76%).

Surprisingly, the predicted probabilities of applying to different areas of knowledge of males and females with outstanding results in math-physics are practically the same. This result suggests that the higher application of males compare to females to civil engineering is explained by gender differences in the applications of students with average results in math-physics.

Moreover, different achievement profiles also have gender differences in the probability of choosing a group of universities. A male student outstanding in biology-chemistry, history and humanities tends to have a higher probability (between 10% and 21%) of applying to the most selective group of universities than females. However, males and female students with outstanding achievement in math-physics, humanities and math-sciences have very similar predicted probabilities of applying to the different groups of universities.

Finally, we also analyzed the probability of an average student (male and female) of applying to different groups of universities. This average student has distinct values of the variable difference of Score at one group and average difference of score at the others groups (see Figure 3). The results show that higher scores increase application to groups of universities 2, 3 and 4, to a greater extent for females than for males, while the opposite occurs for group 1. Therefore, males are more sensitive than females to the difference of score, proxy for the probability of being accepted to the most selective group, but women are more sensitive than men in the less selective groups of universities.

8 Counterfactuals

We run three different counterfactuals. First, we look at the effects on the probability of applying to each area of knowledge if females had the same preference parameters as males, that is, if females consider the same factors and in the same magnitude as males. Second, we look at the effect of applying to each area of knowledge if males had female preference parameters. Third, we look at the effect of applying to each area of

knowledge if males had female preference parameters and, simultaneously, females had male preference parameters.

The first counterfactual shows that if females had male preference parameters, females would apply less to health, social sciences & humanities, education and medicine & odontology; more to civil engineering and technology (see figure 4). Over all, it would be less applicants for health (13% vs 21% on the original case), education (6% vs 8%), social sciences & humanities (12% vs 13%) and medicine & odontology (6% vs 7%). Female dominated majors would continue to be dominated by females: 62% vs 76% in health, 62% vs 68% in arts, 60% vs 64% in social sciences & humanities, and 59% vs 69% in education. Furthermore, civil engineering would continue to be male dominated, but less: 44% vs 25% female. Sciences and technology which are male dominated (49% and 26% female) would have equal or more females than males (53% and 50%). Finally, we find that the average of math and science PSU score of applicants would decrease in civil engineering, the average of science PSU score would decrease in business, technology and social sciences & humanities and increase in education, and the average of history PSU score would increase in medicine & odontology and business but decrease in arts & music and education.

The second counterfactual shows that if males had female preference parameters, males would apply more to health, education, medicine & odontology, social sciences & humanities and art; less to civil engineering and technology (see figure 5). In aggregate terms, it would be more applicants for health (28% vs 21%), education (10% vs 8%), social sciences & humanities (14% vs 13%), medicine & odontology (8% vs 7%) and arts & music (4% vs 3%). Female dominated majors would continued be dominated by females, but the women's proportion in most cases is lower: 57% vs 76% in health, 54% vs 68% in arts, 57% vs 69% in education, 52% vs 61% in medicine & odontology, 59% vs 64% in social sciences & humanities, but 54% vs 53% in Law. Moreover, civil engineering, technology and business would continue to be male dominated, but less: 39% vs 25% of females applying to civil engineering, 48% vs 26% to technology and 47% vs 46% to business. We also find that civil engineering and technology would have applicants with higher class ranking, math and science PSU scores, and higher GPA. The average of applicants' science PSU score would increase in business.

The third counterfactual shows that if males had female preference parameters while females had male preference parameters, in aggregate terms, the percentage of applicants for each area would remain the same (with less than 1% difference). However, there would be differences in the percentage of female applicants: social sciences & humanities and Law would continue being female dominated (55% and 55% vs 64% and 53% of women); other areas that used to be female dominated would be male dominated: 41% vs 76% of woman in health, 44% vs 61% in medicine & odontology, 47% vs 69% in education, and 48% vs 68% in art; the areas which used to be male dominated would be female dominated or equitable: 73% vs 26% in technology, 61% vs 25% in civil engineering, 53% vs 49% in sciences and 50% vs 46% in business. We also find that civil engineering and technology would have applicants with higher ranking and GPA, while health would have applicants with lower ranking and GPA. Also, technology would have applicants with

lower maths and science PSU scores, while business and education have applicants with higher science PSU score.

These counterfactual exercises allow us to compute the gender gap for each area in each case. We simulate the percentage of male and female applicants using their original preference parameters, using the female preference parameters for all students, using the male preference parameters for all students, and using the other sex's parameters. Table 7 shows the percentage of female and male applicants by area. Columns 2 and 3 display the original percentage of applicants by gender using their own parameters and column 4 shows the gender gap for each area as a comparison. Columns 5-6 display the percentage of applicants by gender using female parameters and column 7 shows the gender gap if male and female use female preference parameters. Columns 8-9 display the percentage of applicants by gender using male parameters and column 10 shows the gender gap if male and female use male preference parameters. Finally, columns 11-12 display the percentage of applicants by gender using other sex's parameters and column 13 shows the gender gap in this case. As a result of these exercises, we find that the gender gap decreases more in female dominated areas if males had female preference parameters or all students have the other sex's parameters rather than females having male parameters. Otherwise, the gender gap decreases usually more in male dominated areas if female had male preference rather than all students having the other sex's parameters or females having male parameters.

9 Understanding Gender Differences in College Major Choice

In order to understand the importance of the underlying factors that contribute to the difference in college major choices among females and males, we rely on the classic Oaxaca decomposition, that will allow us to express the difference in the average predicted value of the dependent variable as:

$$\bar{\hat{Y}}_A - \bar{\hat{Y}}_B = (\bar{X}_A - \bar{X}_B)\hat{\beta}_A + \bar{X}_B(\hat{\beta}_A - \hat{\beta}_B) \quad (8)$$

where $\bar{\hat{Y}}_A$ and $\bar{\hat{Y}}_B$ are the average predicted value of choosing an area of knowledge and a group of universities for males and females, respectively. $\bar{X}_A$ and $\bar{X}_B$ correspond to the average values of the independent and observable variables for males and females, respectively. $\hat{\beta}_A$ and $\hat{\beta}_B$ are the estimated coefficients for males and females. Note that the first term on the right-hand side of equation 8 is the gender difference on the mean probability of the choice of each program due to different observable characteristics ($X = [x_{ijk}; z_{ij}]$), while the second term is the difference due to unobservable variables that affect the university program choice.

Table 8 displays the results of this exercise for the 10 majors considered. For the cases of arts & music, social sciences & humanities and law the data (observables) explain most to the difference in the probabilities of choosing those major. On the other hand,

for medicine, health, sciences, civil engineering, technology, business and education, the gender differences we observed come from the unobservables (that can be measured by the discrepancies between the parameters of males and females). This decomposition shed lights on the importance of observables and unobservables that could be affected through different policies in order to reduce the gender differences on the probabilities of males and females of choosing social sciences versus technology.

10 Conclusions

This paper looks at the gender gaps in applications to college programs in Chile. We estimate the model using a nested logit and simulate counterfactuals.

Our results provide further evidence of important gender effects in higher education majors choices. Females are 14.8% more likely to apply to health majors, 14.7% less likely to apply to civil engineering and 7.9% less to technology. Also, mother's area of work or study have higher effects on daughters in female dominated majors and law (2-4%), whereas father's area have higher effects on daughters in medicine & odontology, civil engineering and education (3-7%). Besides, females from mostly-female high school classes are 5.8% more likely to apply to health majors, but 3% less likely to apply to civil engineering.

We also find evidence of the importance of previous achievement (related to the probability of being selected) in the application process. Math PSU score and Math-Physics GPA have the highest effect on area of application: considerably increases the likelihood of applying to civil engineering and business, and decreases the likelihood for less related areas. Also, scoring higher than the cutoff score of a program increases the probability of application.

However, we also observe gender effects related to achievement: (i) the magnitude of the effects of Math PSU score and math-physics GPA in the probability of applying to civil engineering is higher for males than females. (ii) males and females with excellent results on math and physics have similar probabilities of applying for different areas, nevertheless, a male student with average academic results has higher probability of applying to civil engineering. (iii) a male outstanding at biology-chemistry and humanities tend to have higher probabilities than females of applying to the most selective group of universities. (iv) Scores higher than the cutoff score increase - to a greater extent for men than for woman - the probability to apply to the most selective universities.

Our counterfactuals show that the gender gap decreases more in female dominated areas if males have female preference's parameters rather than females having male's parameters. Moreover, the gender gap decreases more in civil engineering and technology if females had male's preference parameters rather than males having female's parameters. These findings are relevant for policy makers, since we demonstrate that the effort to reduce the gender gap must seek not only that females are encouraged to pursue male dominated programs, but also that males choose female dominated programs.

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Table 1: Area Applications and Enrollment 2015

Area	% Applications			% Enrollment		
	Females	Males	Gap	Females	males	Gap
Medicine & Odon.	61%	39%	-22	58%	42%	-16
Health	78%	22%	-55	76%	24%	-51
Sciences	47%	53%	6	46%	54%	8
Civil engineering	24%	76%	52	25%	75%	51
Technology	27%	73%	46	27%	73%	46
Business	49%	51%	2	48%	52%	4
Arts & Music	63%	37%	-26	67%	33%	-34
Social Sc. & Hum.	64%	36%	-28	62%	38%	-24
Law	54%	46%	-8	52%	48%	-4
Education	68%	32%	-36	68%	32%	35

Source: Own elaboration.

Table 2: University Applications and Enrollment 2015

University	% Applications			% Enrollment		
	Females	Males	Gap	Females	males	Gap
Group 1	54%	46%	8	49.5%	50.5%	-1
Group 2	48%	52%	-4	43%	57%	-14
Group 3	56%	44%	12	51%	49%	2
Group 4	57%	43%	14	52%	48%	4

Source: Own elaboration.

Table 3: Average marginal effects for area (whole sample)

Variable	Medicine & Odon.	Health Sciences	Civil Eng.	Technology Business	Arts & Music	Social Sc & Hum.	Law	Education		
Female	2.4%	14.8%	-0.2%	-14.7%	-7.9%	-0.6%	1.1%	2.2%	-0.1%	3.4%
Parent's area same sex	1.3%	2.2%	0.3%	1.1%	0.5%	1.8%	-0.2%	1.9%	4.0%	0.03%
Parent's area different sex	4.9%	1.1%	0.2%	2.0%	-0.2%	0.4%	1.8%	0.8%	1.2%	1.0%
Female high school class	0.3%	3.4%	-0.2%	-0.8%	-0.6%	-1.5%	0.1%	-0.3%	-1.3%	1.1%
Mix high school class	0.6%	2.2%	-0.4%	-0.6%	-0.3%	-0.7%	0.3%	-0.5%	-1.0%	0.6%
High school ranking	0.3%	-0.9%	-0.3%	2.8%	-0.5%	-0.5%	0.4%	-0.3%	-0.2%	-0.7%
Language PSU Score	0.8%	0.6%	0.2%	-2.3%	-1.7%	-3.0%	0.4%	3.4%	0.1%	1.7%
Math PSU Score	-4.7%	-12.7%	0.1%	16.5%	0.6%	6.8%	-0.2%	-4.4%	-3.0%	0.4%
Sciences PSU Score	7.2%	3.4%	0.5%	-2.8%	-0.6%	-2.0%	-0.6%	-1.8%	-0.7%	-1.9%
History PSU Score	-0.5%	-2.3%	-0.1%	-0.8%	-0.4%	-0.1%	-0.4%	0.05%	5.4%	-1.0%
Biology-Chemistry GPA	2.5%	4.0%	0.8%	-4.2%	-0.01%	-0.7%	-0.5%	-1.1%	-0.04%	-0.4%
Math-Physics GPA	-1.9%	-5.0%	-0.1%	7.6%	0.5%	2.0%	-0.4%	-2.0%	-0.4%	-0.7%
Arts-Music GPA	-0.1%	0.5%	-0.1%	-0.6%	0.1%	0.1%	0.5%	-0.2%	-0.2%	-0.1%
Humanities GPA	1.4%	1.0%	-0.2%	-2.8%	-1.1%	-1.2%	-0.4%	2.8%	0.9%	-0.1%
Per capita income	0.1%	-0.4%	-0.03%	0.7%	-0.3%	0.1%	0.2%	0.3%	0.2%	-0.9%
Voucher high school	0.4%	-0.5%	0.4%	-0.8%	-0.2%	1.1%	0.04%	-0.3%	0.6%	-0.7%
Private high school	0.8%	-1.9%	0.4%	-3.3%	-1.2%	6.2%	1.2%	0.1%	0.9%	-3.1%

All coefficient are statistically significant at 99% confidence level, except the effect of History PSU score at Social Sc. & Humanities, which is statistically significant at 95% confidence level, and the effect of Biology-Chemistry GPA at Technology, which is statistically significant at 90% confidence level. Estimations have fixed effects by region.

Source: Own elaboration.

Table 4: Average marginal effects for area (female sample)

Variable	Medicine & Odon.	Health Sciences	Civil Eng.	Technology Business	Arts & Music	Social Sc & Hum.	Law	Education		
Parent's area same sex	0.6%	2.9%	-0.2%	-1.9%	0.3%	1.2%	0.8%	2.0%	4.2%	-0.4%
Parent's area different sex	7.1%	-0.7%	1.5%	3.2%	0.1%	-0.1%	1.9%	0.6%	0.6%	3.0%
Female high school class	0.8%	5.8%	-0.1%	-3.0%	0.03%	-0.7%	-1.5%	-2.2%	-0.3%	1.2%
Mix high school class	1.0%	5.6%	0.1%	-2.8%	-0.3%	0.1%	-1.3%	-2.8%	0.03%	0.4%
High school ranking	0.04%	-1.2%	-0.2%	1.9%	-0.2%	0.5%	0.3%	-0.4%	0.4%	-1.1%
Language PSU Score	1.4%	-0.03%	-0.2%	-2.3%	-0.8%	-2.1%	0.3%	3.5%	-1.1%	1.6%
Math PSU Score	-3.6%	-14.1%	0.9%	13.6%	1.3%	7.5%	0.2%	-4.4%	-2.7%	1.0%
Sciences PSU Score	6.6%	3.8%	0.2%	-1.9%	-0.2%	-1.9%	-0.6%	-2.1%	-0.7%	-2.4%
History PSU Score	-0.7%	-3.3%	-0.2%	-0.3%	-0.1%	-0.1%	-0.3%	0.2%	6.1%	-1.3%
Biology-Chemistry GPA	2.0%	4.1%	0.8%	-3.4%	0.7%	-0.9%	-0.9%	-1.4%	0.2%	-0.9%
Math-Physics GPA	-1.5%	-5.1%	0.1%	6.4%	0.2%	2.7%	-0.4%	-1.9%	-0.2%	-0.5%
Arts-Music GPA	-0.1%	0.6%	0.03%	0.1%	-0.4%	0.2%	0.7%	-0.03%	-0.5%	-0.5%
Humanities GPA	1.7%	0.6%	-0.8%	-2.1%	-0.6%	-2.4%	-0.3%	3.3%	0.4%	0.4%
Per capita income	0.3%	-0.2%	-0.2%	0.3%	-0.2%	0.1%	0.3%	0.4%	0.2%	-0.9%
Voucher high school	0.7%	0.6%	0.2%	-1.9%	-0.01%	0.3%	0.04%	0.6%	0.8%	-1.2%
Private high school	0.8%	-0.2%	0.00%	-5.9%	-0.9%	4.2%	2.2%	2.0%	0.9%	-3.0%
All coefficient are statistically significant at 99% confidence level, except the effects of Language PSU score in Health and Private high school in Science, which are not statistically significant. Estimations have fixed effects by region.										

All coefficient are statistically significant at 99% confidence level, except the effects of Language PSU score in Health and Private high school in Science, which are not statistically significant. Estimations have fixed effects by region.

Source: Own elaboration.

Table 5: Average marginal effects for area (male sample)

Variable	Medicine & Odon.	Health Sciences	Civil Eng.	Technology Business	Arts & Music	Social Sc & Hum.	Law	Education		
Parent's area same sex	2.2%	1.8%	0.6%	1.6%	0.6%	2.1%	-0.6%	1.6%	3.8%	0.3%
Parent's area different sex	2.9%	1.7%	-1.0%	-1.4%	-1.3%	1.4%	1.8%	0.9%	2.7%	0.2%
Female high school class	0.6%	3.5%	0.2%	-0.5%	-1.9%	-1.7%	0.4%	-0.2%	-1.0%	0.6%
Mix high school ranking	0.8%	0.3%	-0.6%	-0.1%	-0.2%	-0.8%	0.5%	0.4%	-0.8%	0.5%
High school ranking	0.3%	-0.02%	-0.4%	3.8%	-0.9%	-1.7%	0.4%	-0.4%	-0.9%	-0.2%
Language PSU Score	0.3%	1.1%	0.6%	-2.0%	-2.8%	-3.9%	0.5%	3.1%	1.4%	1.6%
Math PSU Score	-5.7%	-11.5%	-0.9%	20.1%	-0.02%	6.1%	-0.7%	-4.1%	-3.4%	-0.5%
Sciences PSU Score	7.3%	3.5%	1.0%	-4.2%	-1.0%	-2.1%	-0.5%	-1.4%	-0.6%	-1.2%
History PSU Score	-0.2%	-1.2%	-0.1%	-1.3%	-0.7%	0.02%	-0.4%	-0.3%	4.7%	-0.6%
Biology-Chemistry GPA	2.9%	3.4%	0.8%	-5.2%	-0.5%	-0.4%	-0.1%	-0.6%	-0.2%	0.2%
Math-Physics GPA	-2.3%	-4.8%	-0.3%	9.1%	0.6%	1.3%	-0.3%	-2.1%	-0.5%	-0.9%
Arts-Music GPA	-0.1%	0.1%	-0.2%	-1.0%	0.7%	0.1%	0.4%	-0.2%	0.04%	0.2%
Humanities GPA	1.1%	1.2%	0.3%	-3.5%	-1.7%	0.1%	-0.5%	2.4%	1.3%	-0.6%
Per capita income	0.1%	-0.7%	0.1%	1.3%	-0.4%	0.1%	0.1%	0.1%	0.2%	-1.0%
Voucher high school	0.01%	-1.5%	0.6%	0.1%	-0.4%	2.0%	0.02%	-1.1%	0.4%	-0.1%
Private high school	0.5%	-3.5%	0.7%	-0.6%	-1.4%	8.2%	-0.1%	-1.8%	1.1%	-3.2%

All coefficient are statistically significant at 99% confidence level, except the effect of High school ranking at Health, which is statistically significant at 95% confidence level, and the effects of Math PSU score at Technology and History PSU score in Business, which are not statistically significant. Estimations have fixed effects by region.

Source: Own elaboration.

Table 6: Average marginal effects for group

Variable	Whole sample	Female sample	Male sample
Difference of score	4.21%	4.06%	4.34%
Difference of score ²	-1.27%	-1.35%	-1.20%
Program average score	6.00%	6.14%	5.37%
% of regional vacancies of the program	0.03%	0.03%	0.03%
Copayment	0.02%	0.01%	0.03%
% Previous high school class enrolled in the group	0.03%	0.03%	0.03%
All coefficient are statistically significant at 99% confidence level.			

Source: Own elaboration.

Table 7: Counterfactuals Exercises: Percentage of female and male applicants by area

Area	% of Applicants											
	True parameters			Female parameters			Male parameters			Other sex's parameters		
	Female	Male	Gap	Female	Male	Gap	Female	Male	Gap	Female	Male	Gap
Medicine & Odon.	61%	39%	-22%	52%	48%	-4%	54%	46%	-8%	44%	56%	12%
Health	76%	24%	-52%	57%	43%	-14%	62%	38%	-24%	41%	59%	18%
Sciences	49%	51%	2%	49%	51%	2%	53%	47%	-6%	53%	47%	-6%
Civil engineering	25%	75%	50%	39%	61%	22%	44%	56%	12%	61%	39%	-22%
Technology	26%	74%	48%	48%	52%	4%	50%	50%	0%	73%	27%	-46%
Business	46%	54%	8%	47%	53%	6%	50%	50%	0%	50%	50%	0%
Arts & Music	68%	32%	-36%	54%	46%	-8%	62%	38%	-24%	48%	52%	4%
Social Sc. & Hum.	64%	36%	-28%	59%	41%	-18%	60%	40%	-20%	55%	45%	-10%
Law	53%	47%	-6%	54%	46%	-8%	54%	46%	-8%	55%	45%	-10%
Education	69%	31%	-38%	57%	43%	-14%	59%	41%	-18%	47%	53%	6%

Source: Own elaboration.

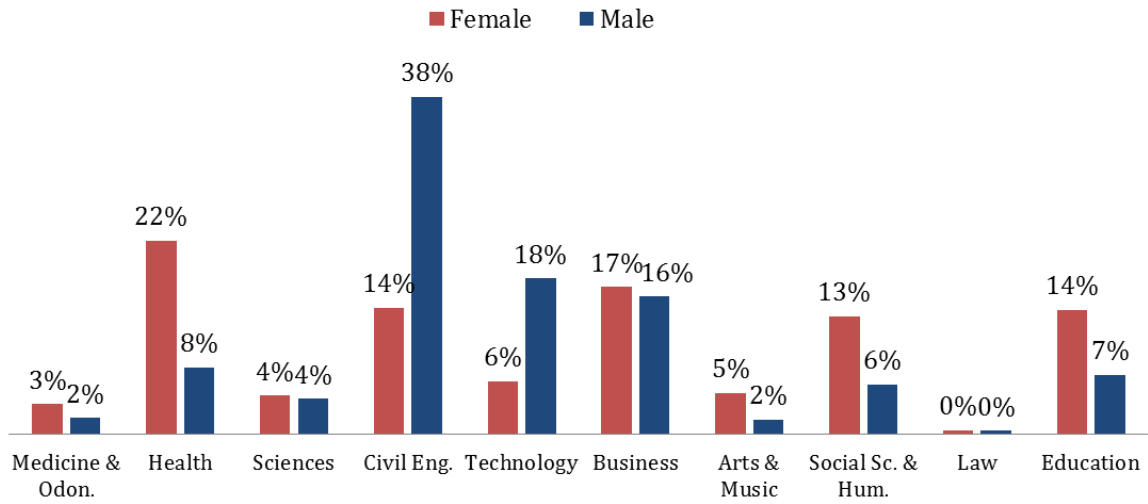
Table 8: Decomposition Analysis to explain gender differences

	Medicine & Odon.	Health Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc & Hum.	Law	Education
Average probability for males ($\hat{Y}_A$)	6.4%	10.7%	4.2%	12.6%	10.6%	2.0%	10.0%	6.3%	5.3%
Average probability for females ($\hat{Y}_B$)	8.8%	30.4%	3.7%	3.9%	8.2%	3.7%	15.9%	6.3%	10.5%
Gender difference in probability	-2.4%	-19.7%	0.5%	8.7%	2.4%	-1.7%	-5.8%	0.0%	-5.1%
$(\bar{X}_A - \bar{X}_B)\hat{\beta}_A$	-0.2%	-5.2%	0.0%	1.4%	1.1%	-1.0%	-3.4%	-0.3%	-1.6%
$\bar{X}_B(\hat{\beta}_A - \hat{\beta}_B)$	-2.2%	-14.4%	0.6%	7.3%	1.3%	-0.8%	-2.5%	0.3%	-3.5%
Contribution of the data	9.9%	26.6%	-6.3%	16.0%	46.5%	55.8%	57.8%	1081.1%	31.2%
Contribution of the parameters	90.9%	73.4%	-106.3%	84.0%	53.5%	44.2%	42.2%	-981.1%	68.8%

Notes: Gender difference in probability is defined as: $\hat{Y}_A - \hat{Y}_B$
A negative number means the contribution is in the opposite direction of the gender difference in probability.

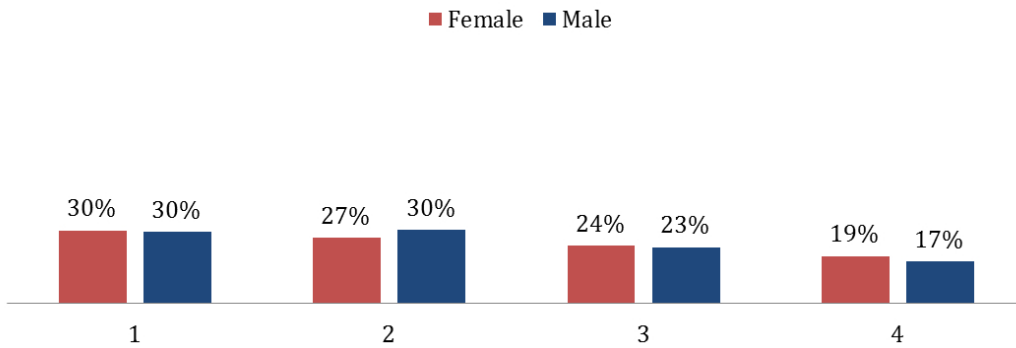
Source: Own elaboration.

Figure 1: Simulated choice probabilities by Area for an average student



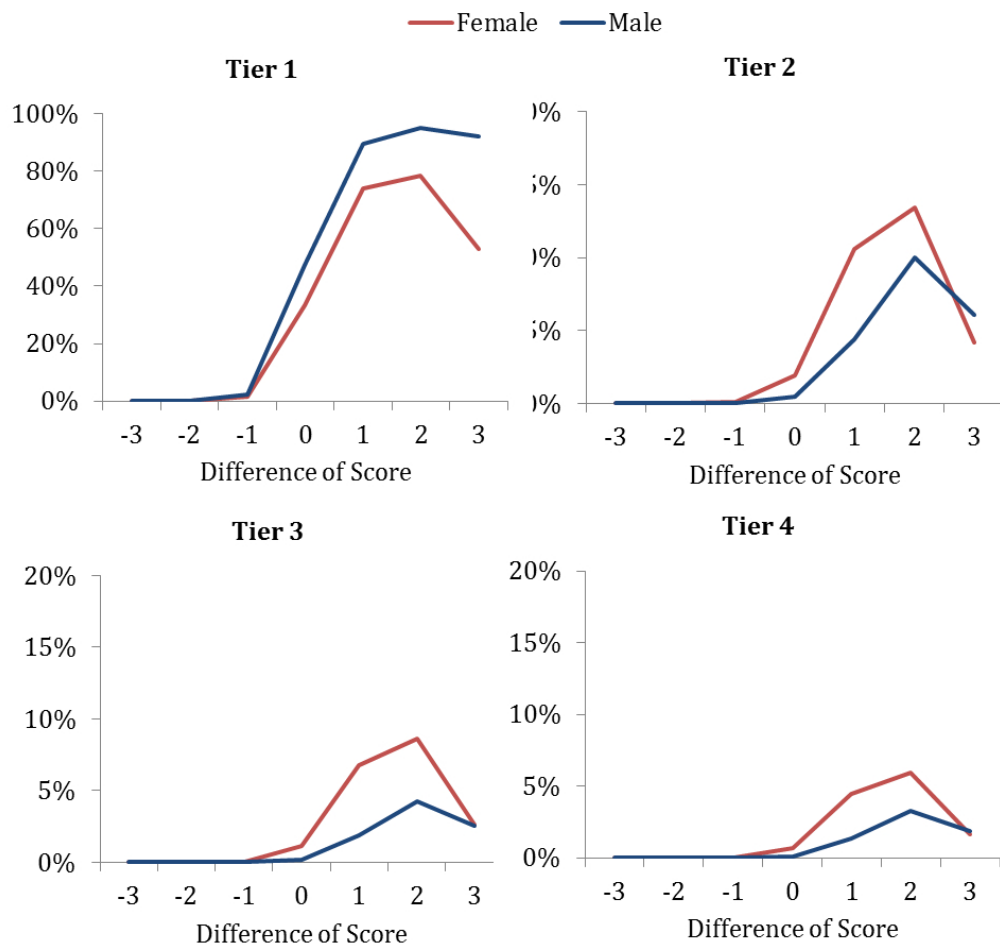
Source: Own elaboration.

Figure 2: Simulated choice probabilities by Group for an average student



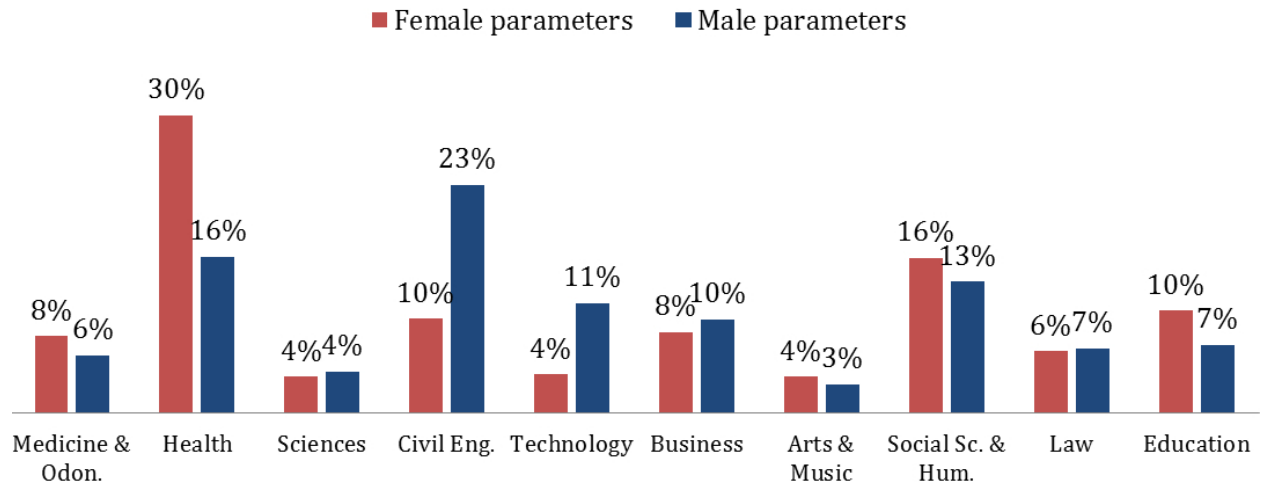
Source: Own elaboration.

Figure 3: Simulated choice probabilities by Group for an average student, with different Difference of Score



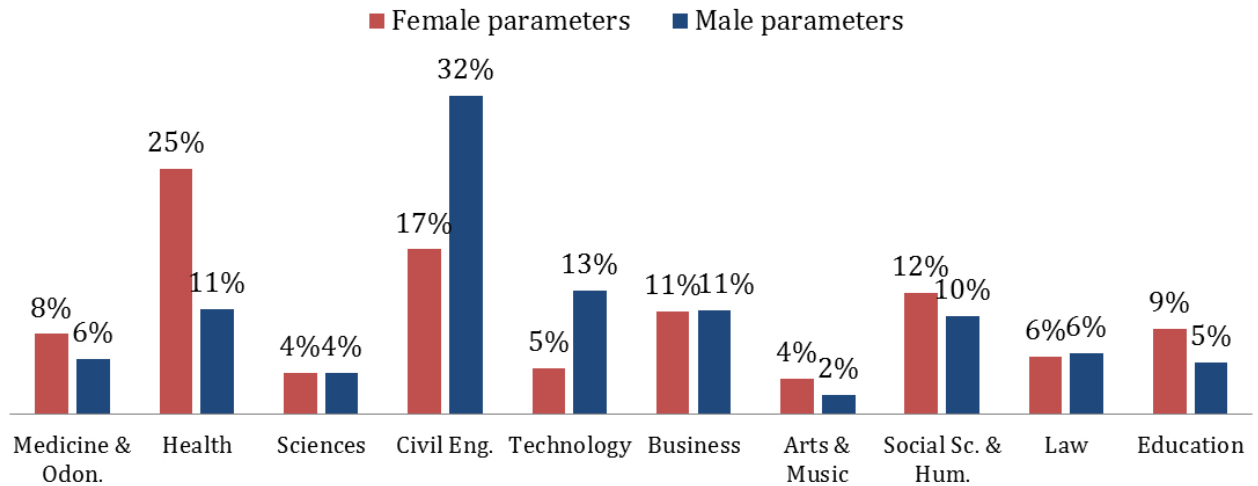
Source: Own elaboration.

Figure 4: Females' Applications if they had male preference parameters



Source: Own elaboration.

Figure 5: Males' Applications if they had female preference parameters



Source: Own elaboration.