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The gender gap in college major choice in Chile

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ABSTRACT

This paper studies gender differences in college applications in Chile. We use the revealed preferences of students for college major choice by taking advantage of Chile's Centralized Admission System, and estimate a nested logit model to predict the first preference of applicants. We find that males apply to selective programs even when they are marginal candidates, while equally qualified female candidates tend to apply less often to these programs. Using counterfactual exercises, we conclude that to successfully address the gender gap, along with promoting females' participation in STEM careers, we must increase males' willingness to consider non-STEM fields. Closing the gender gap does not imply a loss in terms of talent distribution by area of knowledge.

1. Introduction

Over the past decades, many countries have made relevant progress in narrowing or closing gender gaps in years of schooling, as well as in secondary and postsecondary school attendance. However, the opposite is true in regard to the areas of study pursued; empirical evidence shows that in many countries women are underrepresented in the fields of science, technology, engineering and mathematics (STEM), whereas they are over-represented in humanities, education, health and the arts. According to OECD data, women make up 78% of students in education and 76% of students in health and welfare. Meanwhile, only 24% in engineering and 19% of students in information and communications technologies (ICT) are women. In 2015, an average of 27% of new university entrants in OECD countries selected a field of study in STEM, with most going into engineering, manufacturing and construction only 24% of the latter were women (OECD, 2017). Moreover, there is gender segregation within the sciences: Sikora and Pokropek (2012a) show that in all 50 countries that took the PISA test, 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 overrepresentation of one gender has been called horizontal sex segregation in education. This phenomenon can explain gender segregation in the labor market, as the content of schooling accounts for a substantial part of the gender gap in jobs and earnings. Arcidiacono (2004) finds positive returns to STEM fields and (Peri, Shih & Sparber, 2015) show that STEM workers boost economic growth by increasing productivity, particularly that of college-educated workers. In general, stereo-typically 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. This paper aims to shed light on the drivers of the gender gap in college major applications by studying how males and females behave in their probability of choosing a university career, and then by analyzing what would happen if males and females had the same preferences. In this analysis we understand preferences as the basis of people's behavior, in accordance with the choice-salience interpretation of preferences described by Sen (1994). This allows us to consider that students' preferences are affected both by their own well-being, as well as by social expectations, including gender stereotypes, which influence their university applications.

We contribute to the literature by estimating a college major choice model, which allows us to estimate the parameters that affect college applications by gender, considering many of the relevant variables found in the literature. Furthermore, we use our estimations to examine, using counterfactuals, what would happen if females pursued male preference strategies (male parameters) in college applications and vice versa, an under-explored topic in the literature. This exercise quantifies the impacts of reducing gender stereotypes in college major

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applications.

To perform this analysis we use the revealed preferences of students for college major choices by taking advantage of Chile's Centralized Admission System (SUA, for its acronym in Spanish) from which we have data on the entire cohort of applicants to enter Chilean universities in 2015. In the application process students must first take a series of admission tests; when they receive their final scores -based on their high school GPA and the university entrance test- they must submit a ranked preference list of up to 10 college major combinations they wish to be considered for.

To estimate a college major choice model we rely on a nested logit methodology because the university preference is correlated to the major preference. In fact, in Chile enrollment is universally a paired college major program, unlike admissions in most universities in the United States where enrollment to a university allows students to change their majors throughout their college career.

Our results are in line with what has been found in the literature; there are masculinized (i.e. engineering) and feminized (i.e. non-physician health) careers. We also found that fathers influence the decisions of male students while female students are influenced by both parents; however, those students with good academic performance tend to reproduce the choices of the parent of the same sex to a lesser extent. The gender composition of high school classes also has an effect on the college major choice. Finally, proficiency in math, measured through both GPA and test scores, has a large effect on both male and female preferences to apply to engineering majors.

The model allows us to analyze what happens with college major choices for different students according to their academic achievement, thus, we can better understand how male and female students make decisions based on their academic performance. In fact, we find that given similar characteristics and academic performance, gender matters when choosing a career. Male students tend to apply to a higher extent to the most selective majors when they have good academic achievement, compared to female students with similar academic achievement.

Likewise, we use the estimated structural model to construct a series of counterfactuals that shed light on the most effective ways to reduce the gender gap in college major choices. In particular, we analyze the role of preferences (as defined above and therefore including social stereotypes) in the choice of majors and universities. Our estimates allow us to conclude that, in order to successfully address the gender gap, along with promoting females' participation in STEM careers, we must increase males' willingness to consider non-STEM fields. Furthermore, in this exercise we show that closing the gap does not imply a loss in terms of talent distribution (measured by cognitive performance) by area of knowledge.

The rest of the paper is organized as follows. Section 2 reviews the literature, Section 3 presents a description of the Chilean higher education system and the application process, Section 4 describes the data, Section 5 presents the model and the estimation procedure used in this paper. Section 6 provides the estimation results, Section 7 provides the counterfactuals exercises, and Section 8 presents conclusions.

2. Review of the literature

Recently, there has been much focus on the under-representation of women in STEM fields and its contributing effect to the gender gap on earnings in the labor market, since STEM fields are associated with more valuable job-related human capital leading to higher monetary returns. (Arcidiacono, 2004). The main question is why females 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 issue is whether these differences are explained by nature or nurture. Research in the fields of 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 underperform relatively in technical and quantitative subjects from childhood and gradually disengage from these subjects (Killgore & Yurgelun-Todd, 2004; Lenroot et al., 2007).

However, in some countries and economies with the best performance on PISA, girls have the same or higher scores in math as their male classmates; this is the case of Hong Kong, Shanghai, Singapore and Taipei-China. These results suggest that the gender gap in mathematics is not determined by innate differences in ability. (Dossi, Figlio, Giuliano & Sapienza, 2019) conclude that socialization at home can explain a relevant part of the observed gender disparities in mathematics performance. Likewise, (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. Turner and Bowen (1999) and Dickson (2009) find that SAT scores play a small role in major gap; also, (Justman & Méndez, 2018) find that female students require stronger prior signals of mathematical ability to choose male-dominated subjects. Thus, girls and boys performing equally in the same subjects choose majors differently and according to their own gender stereotype.

In fact, many studies associate career choices with gender stereotypes.[1] The argument is that gender specific attributes develop during childhood and affect boys' and girls' choices throughout their lifecycles (Gneezy & Rustichini, 2004; Sutter & Rützler, 2010). The literature shows that females are generally more risk averse than males and more likely to shy away from competition. Some authors suggest that these characteristics are related to a gender gap in self-confidence (Booth & Nolen, 2011)and (Booth & Nolen, 2012; Croson & Gneezy, 2009; Gneezy, Niederle, & Rustichini, 2003; Niederle & Vesterlund, 2007) and (Niederle & Vesterlund, 2010; Gupta, Poulsen & Villeval, 2005), Niederle and Yestrumskas (2008). (Kurtz-Costes, Rowley, Harris-Britt & Woods, 2008) also suggest that girls' perception of their own mathematics and science abilities is lower than that of boys. Saltiel (2019) finds that math problem solving ability and self-efficacy are strong predictors of STEM enrollment for both males and females; in addition, he finds a relative shortfall of high-achieving women who are confident in their math ability.

Gneezy et al. (2003) and (Gneezy, Leonard & List, 2009) present experimental evidence supporting the idea 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) and Niederle and Vesterlund (2010) argue that women have lower faith in their own math abilities (conditional on actual abilities), due to extensive gender-stereotyping in math related jobs and less taste for competition, which play a substantial role in mathematics. (Örs, Palomino & Peyrache, 2013) and Jurajda and Münich (2011) find that females underperform on high-stake tests relative to males with similar abilities.

Additionally, experimental evidence suggests that the gender gap in college major choice is mainly due to differences in non-pecuniary preferences and tastes; several papers highlight the importance of preferences in driving STEM gaps (Bartolj & Polnec, 2012; Wiswall & Zafar, 2014; 2017; Zafar, 2009). 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

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

pecuniary versus non-pecuniary benefits (Turner & Bowen, 1999); that is, economic incentives are not sufficient for girls to enroll and stay in traditionally male fields of study ((NOE), 2010). In this regard, (Humlum, Kleinjans, Nielsen, 2012), using Danish data, derive a model of career choice and identity; they find that while students with a career-oriented identity choose according to the financial incentive associated with their choice, this was not the case for students with social-oriented identity.[2]

(Favara, 2012) finds that gender stereotyping affects educational choices from the age of 14, and its effect is greater 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. However, Park, Behrman, and Choi (2018) assess causal effects of single-sex schools on different STEM outcomes in Seoul, where assignment to single-sex or coeducational high schools is random; they find significantly positive effects for all-boys schools but not for all-girls schools. Furthermore, (Ardila Brene & Zölitz, 2020) show that having a larger proportion of female peers decreases girls' probability of enrolling in and graduating from STEM programs.

In terms of the role of pre-college factors there is no agreement. Speer (2017), using a broad array of pre-college test scores (the ASVAB), shows that differences in college preparation can actually account for a large portion of gender gaps in college major choice. Whereas Delaney and Devereux (2019), using a preference ranking for all secondary school students who apply for college in Ireland, conclude that students preferences are more important than grades in explaining the gender gap in STEM applications.

Finally, in relation to the intergenerational transfer of preferences for science careers, Sikora and Pokropek (2012b) find that this factor varies 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

There are two types of high schools in Chile: scientific-humanist (regular), and technical-professional (vocational). Most students who intend to continue their studies at a university attend the scientific-humanistic type. In 11th grade, students choose to follow a certain academic track -humanities, sciences or arts- based on their interests. That way, students receive more advanced training in subjects corresponding to their tracks. Therefore, students are already choosing certain areas of study and can prepare for the college admission tests in the last two years of high school.

The higher education system consists of three types of institutions: universities, professional institutes, and technical formation centers. Universities offer professional title and academic degrees programs.[3] There are two types of universities: traditional (25 public and private universities created before the year 1980), and non-traditional (over 30 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.

Chile has a single centralized admission system for its traditional universities, administered by the Department of Educational Evaluation, Measurement and Registration (DEMRE for its acronym in Spanish) at the University of Chile, which is under the authority of CRUCH. Since 2003, the 25 traditional universities of CRUCH have used a group of standardized tests that comprise the University Selection Exam (PSU for its acronym in Spanish) -which is similar to the United States' SAT test- and the high school GPA (NEM for its acronym in Spanish) 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.[4]

All students who take the college entrance exam (PSU) must complete mandatory tests in mathematics and language; they may also take optional tests in other subjects (social sciences and/or science). Scores are scaled to a distribution with a range of 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 the degree programs it offers, and choose the weightings it deems appropriate in accordance with the rules established by CRUCH.

The application score is calculated by applying the weightings to an applicant's 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 a 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. The program then 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 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[5]). 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.

In our analysis, we only consider the 33 universities (traditional and private) that use this single centralized system to select their students since we want to examine the factors that affect the gender gap on college major applications, thus we need students' preferences and constraints that are only available through the centralized system. In fact, we use the first preference or most desired college program to estimate our model.

4. 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 who graduated from high school in December 2014, and applied to enter university in March 2015. The data about the characteristics of university candidates, their applications and final acceptance was provided by DEMRE.

Students apply to the centralized admission system ranking their

[2] For career-oriented people, career and work are important for a meaningful life. Conversely social-oriented people assign more importance to cooperation, social responsibility and social issues, such as other people's well-being.

[3] In this paper, we refer to universities and colleges indistinctly.

[4] Starting 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. This factor has a strong correlation with the high-school GPA.

[5] The most selective schools only consider the first four preferences, that is, if students apply to a major in the fifth preference to a highly selective school, the school does not consider that application.

college major choices. To have a reasonable number of possible options, we group majors into disciplines or areas of study: (1) medicine and odontology, (2) health[6], (3) sciences, (4) civil engineering,[7] (5) technology, (6) business, (7) arts, (8) social sciences and humanities, (9) law, (10) education. Universities were clustered into four groups, where groups 1–3 have the CRUCH institutions grouped by selectivity,[8] and group 4 has the private non-traditional ones.[9]

There were 76,680 students who graduated from high school in 2014 and applied to a colege major through the centralized admission system, but only 68,730 of them applied as a first option to an area and group of universities in which they satisfied the entrance requirements. Only 54,991 of that set have no missing values in the variables needed, and therefore they can be used for the estimation of the model.

Table 1 shows some descriptive statistics in terms of applications, enrollment and the gender gap for each area of study. There are important gender gaps in health, civil engineering, technology and education. Gender gaps are generally higher in the application process than in enrollment, which means that the selection process seems to decrease the gender gap. The reduction of the gender gap is greater in the female dominated areas. Moreover, 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.

5. Model

This section presents our model for college-major application, guided by the institutional rules described above.[10] 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 group of universities, each with A areas of study (group of majors). Let $j \in A$ be a major, and $k \in U$ be any university. Let (j, k) denote a program (college-major pair). Each program differs by admission requirements, fields of study and college quality. Thus, students choose among $A \times U$ options.

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

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

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

Students apply to a program as their first preference in order to maximize their expected utility:

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

where x_{ijk} is the vector of students' characteristics relevant to their college major choice: gender, father's area of occupation, mother's area of occupation, mixed high school class (between 40% and 60% of females in a class), female high school class (more than 60% of females in the class), geographic location (region of the country where the student currently lives), high school type (public, private-voucher or private), PSU scores s_i = (language, math, science, social sciences), high school class ranking[11], high school GPA (biology-chemistry, math-physics, music-arts, humanities), and per capita income.

z_{ij} is the vector of program characteristics relevant to students' choice of major: application scores (a_{ij}), cutoff scores[12], average score of programs, vacancies per region, tuition, student aid[13] and the percentage of students from the same high school that enrolled in this group of universities the previous year. Finally, 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 on the different tests (s_i=(s_{i1}, s_{i2}, ..., s_{iS}), (ii) their average high school GPA, (iii) the vector of major-j-specific weights ($\omega_j = [\omega_{j1}, \ldots, \omega_{jS}]$) and (iv) the application score of the last student enrolled in each program the year before (cutoff score).

This model is estimated through a nested logit (see Appendix A for further details of the model).

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%	36

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

6. Results

6.1. Estimation results

We estimate the model for an entire cohort of students, and also for males and females separately; Tables 3, B.1 and B.2 in Appendix B present the marginal effects by area of study for these models,

[6] Health refers to non-physician health majors.

[7] Civil engineering refers to all the engineering programs in Chile that last 6 years; specialties include mathematics, computer science, industrial, mechanics, electrical, civil works, mining, geology, biotechnology, chemistry, etc. These majors are highly selective, whereas the engineering majors that last 4 years are included in the technology area of study.

[8] Group 1 includes the Universidad de Chile and the Pontificia Universidad Católica de Chile; group 2 includes Universidad de Concepción, Universidad de Talca, Pontificia Universidad Católica de Valparaíso, Universidad Austral de Chile, Universidad de Santiago, Universidad Técnica Federico Santa María, and Universidad de la Frontera; group 3 includes the remaining universities belonging to the CRUCH system.

[9] Only the eight universities that use the centralized system in 2015.

[10] For a similar model of college-major application see Bordón and Fu (2015).

[11] Standarized 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.

[12] We use the difference between the application score of the student minus the application score of the last student enrolled at the area-university group in 2015 (cutoff).

[13] Using tuition and student aid we compute the out-of-pocket costs for each major in each school.

Table 3
Average Marginal Effects by Area of Study (all students).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	2.1%	14.8%	−0.4%	−14.1%	−7.6%	−0.6%	0.7%	2.4%	−0.1%	2.9%
Parent's area same sex	3.2%	2.4%	0.3%	1.4%	0.3%	1.6%	0.2%	1.6%	3.3%	0.5%
Parent's area different sex	3.2%	1.7%	0.4%	−0.02%	−0.3%	0.6%	1.2%	0.5%	2.1%	1.1%
Female high school class	0.4%	2.5%	−0.6%	−1.4%	0.1%	−1.7%	0.2%	0.03%	−0.7%	1.1%
Mixed high school class	0.3%	1.8%	−0.7%	−0.5%	−0.1%	−1.1%	0.3%	−0.1%	−0.6%	0.7%
High school ranking	0.9%	−1.2%	0.01%	1.9%	−0.8%	−0.6%	0.5%	−0.4%	−0.3%	0.1%
Language PSU Score	1.0%	0.3%	0.2%	−2.4%	−1.8%	−3.4%	0.6%	3.7%	0.4%	1.5%
Math PSU Score	−4.4%	−11.9%	0.03%	16.1%	0.5%	7.1%	−0.3%	−4.5%	−2.9%	0.2%
Science PSU Score	6.9%	3.6%	0.5%	−2.8%	−1.0%	−2.1%	−0.6%	−1.8%	−0.7%	−2.0%
Social Sciences PSU Score	−0.5%	−2.1%	−0.2%	−0.9%	−0.4%	−0.1%	−0.4%	0.1%	5.4%	−1.0%
Biology-Chemistry GPA	2.4%	4.2%	0.5%	−4.2%	−0.1%	−0.9%	−0.4%	−0.9%	0.1%	−0.8%
Math-Physics GPA	−2.1%	−4.9%	−0.03%	7.5%	0.9%	2.3%	−0.5%	−1.7%	−0.5%	−0.9%
Arts-Music GPA	−0.3%	0.6%	−0.1%	−0.5%	0.02%	−0.1%	0.6%	−0.1%	−0.2%	0.1%
Humanities GPA	1.0%	1.0%	−0.4%	−2.5%	−1.1%	−0.9%	−0.5%	2.7%	1.1%	−0.4%
Per capita income	0.1%	−0.2%	−0.04%	0.4%	−0.3%	0.3%	0.3%	0.4%	0.1%	−1.0%
Private subsidized high school	0.5%	−0.3%	0.2%	−0.6%	−0.5%	0.9%	0.1%	−0.5%	0.5%	−0.3%
Private paid high school	0.8%	−2.0%	0.6%	−3.2%	−1.6%	5.6%	1.3%	−0.04%	1.8%	−3.0%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

respectively. Pseudo R^2 of the model for all students, males and females are: 0.25, 0.24 and 0.22, respectively. The prediction errors are smaller than 1%. These estimations allow us to analyze how gender affects students' application to different programs.[14]

In line with the literature, we find that females are more likely to apply to health majors and less likely to apply to civil engineering and technology programs. The mother's field of occupation have higher effects than the father's field of occupation on daughters in health, business, social sciences and humanities, and law. The father's field of occupation has a higher effect on daughters than the mother's field of occupation in sciences, civil engineering and education. For male students, having a father related to the area has higher effects than the mother's area of occupation in almost all areas. Males and females who graduated from a mostly female high school class have higher probabilities of applying to programs in the area of health and lower probabilities of applying to civil engineering programs.[15]

We also analyzed results by academic performance tercile, as measured by the average PSU score in language and mathematics. For the lowest performing female student tercile, having a mother linked to the area of study tends to have a greater effect than having a father in a related area; this occurs in most of the areas of study and to a greater extend than in the other terciles. For male students belonging to the lowest performing tercile, having a father linked to the area of study has a greater effect on the choice of major than for the other two terciles, while the effect of the mothers is low. Hence, there is a stronger tendency to reproduce the area of study of the parent of the same gender in the case of students who belong to the lowest performing tercile. It appears to be easier to escape intergenerational influence for those with higher academic achievement.[16]

Higher GPA and PSU test scores in subjects related to an area are associated with a higher probability of applying to that area. Proficiency in math, measured through GPA and test scores, has a large effect on both female and male students' probability of applying to engineering majors. Since females tend to have lower scores than males on the mathematics and science PSU tests[17], performance on these tests could partially explain why females tend to apply less to civil engineering and technology majors than males.

The estimation results by tercile of previous achievement show similar trends for all students. Nevertheless, this highlights that the marginal effects of PSU scores in selective areas (like medicine and odontology, civil engineering and law) tend to be higher for the terciles with higher achievement.

Table 4 shows the average marginal effects by group of universities for these models. We find that both female and male students increase their probability of applying to a university group when their score is above the cutoff score. However, the effect of this variable is also quadratic and negative, indicating that this probability decreases when a score is much higher than the cutoff. The selectivity of the university group, the percentage of regional vacancies in the program, co-payment options, and former high school classmates' enrollment in the same university group also affect applications.[18]

6.2. Predicted choice probabilities

In this section we carry out two exercises. First, we estimate the predicted choice probabilities for each area of study and university group for students with average values in all variables except gender (male or female). This exercise allows us to isolate the unobservable preferences in college-major choices that are tied specifically to gender. Second, we analyze male and female students' predicted choice probability according to their academic achievement.

For the first exercise, Fig. 1 shows the simulated probability of applying to each area of study and group of universities, for males and females with average values in all the remaining control variables. In Fig. 1A, we can observe important differences in the probabilities by gender in health, civil engineering, technology, social sciences and humanities and education. In fact, an average male student is much more likely to apply to engineering and technology majors than a female with the same average characteristics, and an average female student is much more likely to apply to health majors than a male with the same average characteristics.[19]

As Fig. 1B shows, the differences between genders in the probability

[14] To analyze the robustness of our analysis we replicated our estimations using 2 different grouping of universities. We first aggregate universities in four groups by their years of accreditation, and then based on tuition fees. Appendix G shows those estimations. The results are robust to the different grouping of universities.

[15] The results are robust for different gender composition, that is, mainly male classes (0-40% females), mixed classes (40-60% females) and mainly female classes (60-100% females). The results for female students are consistent with the Ardila 2020 findings.

[16] For the marginal effects per tercile of achievement and gender see Appendix B, tables B.3-B.11.

[17] See Appendix C.

[18] See Table B.12 for the marginal effects by group of universities per tercile of achievement.

[19] Figure B.1 in Appendix B shows the predicted probabilities by area of study per tercile of achievement.

Table 4
Average Marginal Effects in Applying to Different University Groups.

Variable	All students	Females	Males
Difference of score	3.81%	3.66%	3.93%
Difference of score^2	−1.38%	−1.41%	−1.34%
Program average score	4.60%	4.92%	4.32%
% of regional vacancies of the program	0.02%	0.03%	0.02%
Copayment	0.02%	0.02%	0.02%
% Previous school generation of the group	0.02%	0.02%	0.02%

All coefficients are statistically significant at a 99% confidence level.

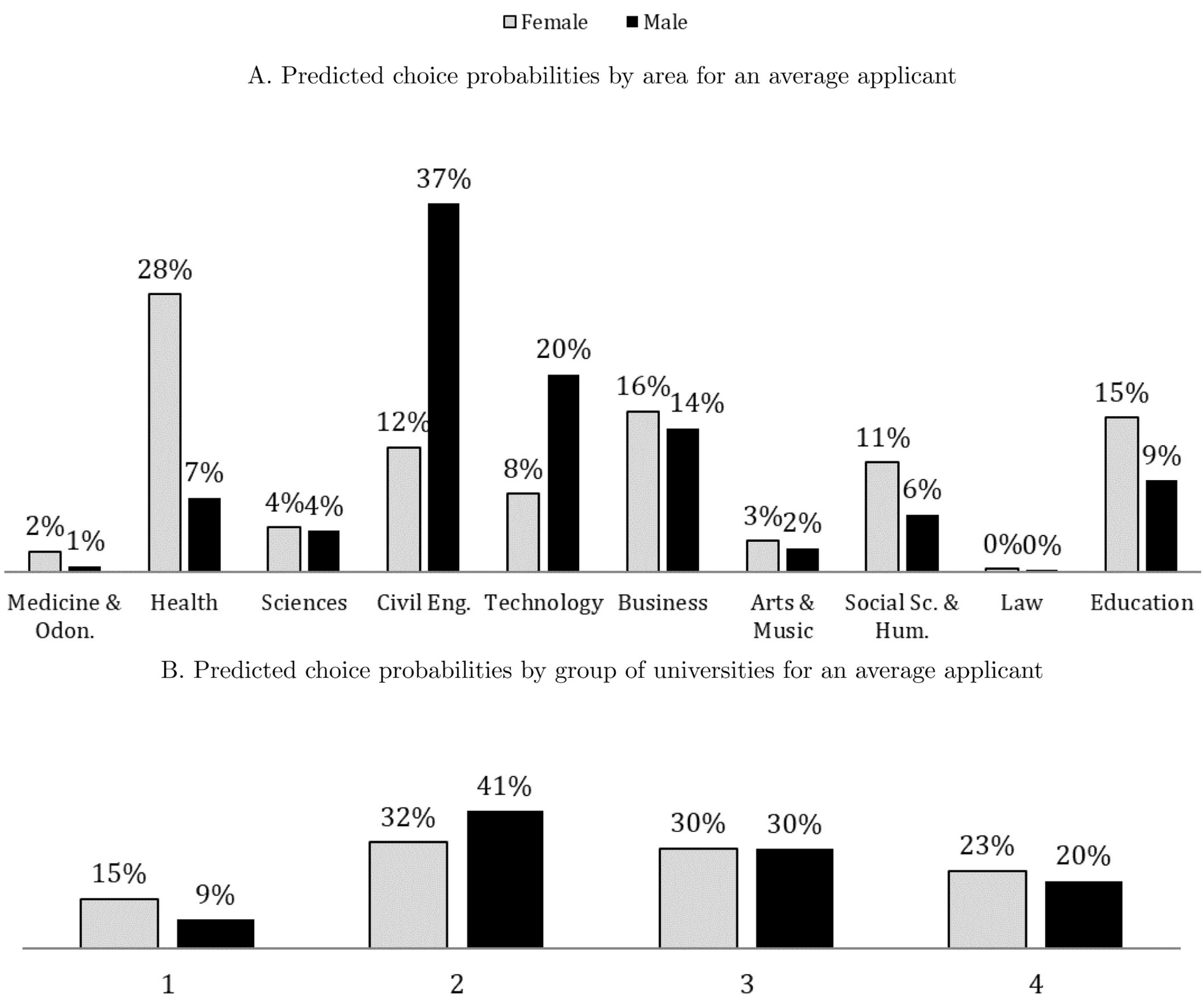

Fig. 1. Predicted Choice Probabilities for an Average Applicant by Gender.

of applying to university groups 3 and 4 tend to be small.[20] However, for the first university group an average female student has a probability of application higher than a comparable male, while the opposite happens for group 2. This tendency is affected by the gender differences in the areas of preference: male students have a higher probability of application to group 2 in technology and civil engineering, while females have a higher probability of applying to group 1 in health, social sciences and humanities, business, arts and education.[21]

In the second exercise, we go further and analyze male and female students' predicted choice probability according to their academic achievement. In particular, we consider male and female students with average characteristics, but who have different academic performance in a given area of study, measured by the PSU and GPA score of the subject most related to the area. The results can be seen in Fig. 2A, which shows that an average applicant, male or female, with a higher PSU score and GPA in the subject related to the area, has a higher probability of applying to the most selective major in the area of study; that is, to medicine and odontology considering the science PSU score and GPA in biology or chemistry, to civil engineering considering the

[20] Figure B.2 in Appendix B shows the predicted probabilities by university group per tercile of achievement.

[21] In addition, we simulate the probabilities for each area of study and university group for students of different gender, gender composition of the class (mostly female or mixed high school class), and parent's area of occupation (of the same and different gender of the student), and average values for the rest of the variables. This exercise allows us to create 180 different student's profiles. We find that if we only change the gender variable, the probability of choosing a certain area of study can change up to 41%, while the probability of choosing a certain university group can change up to 16%.

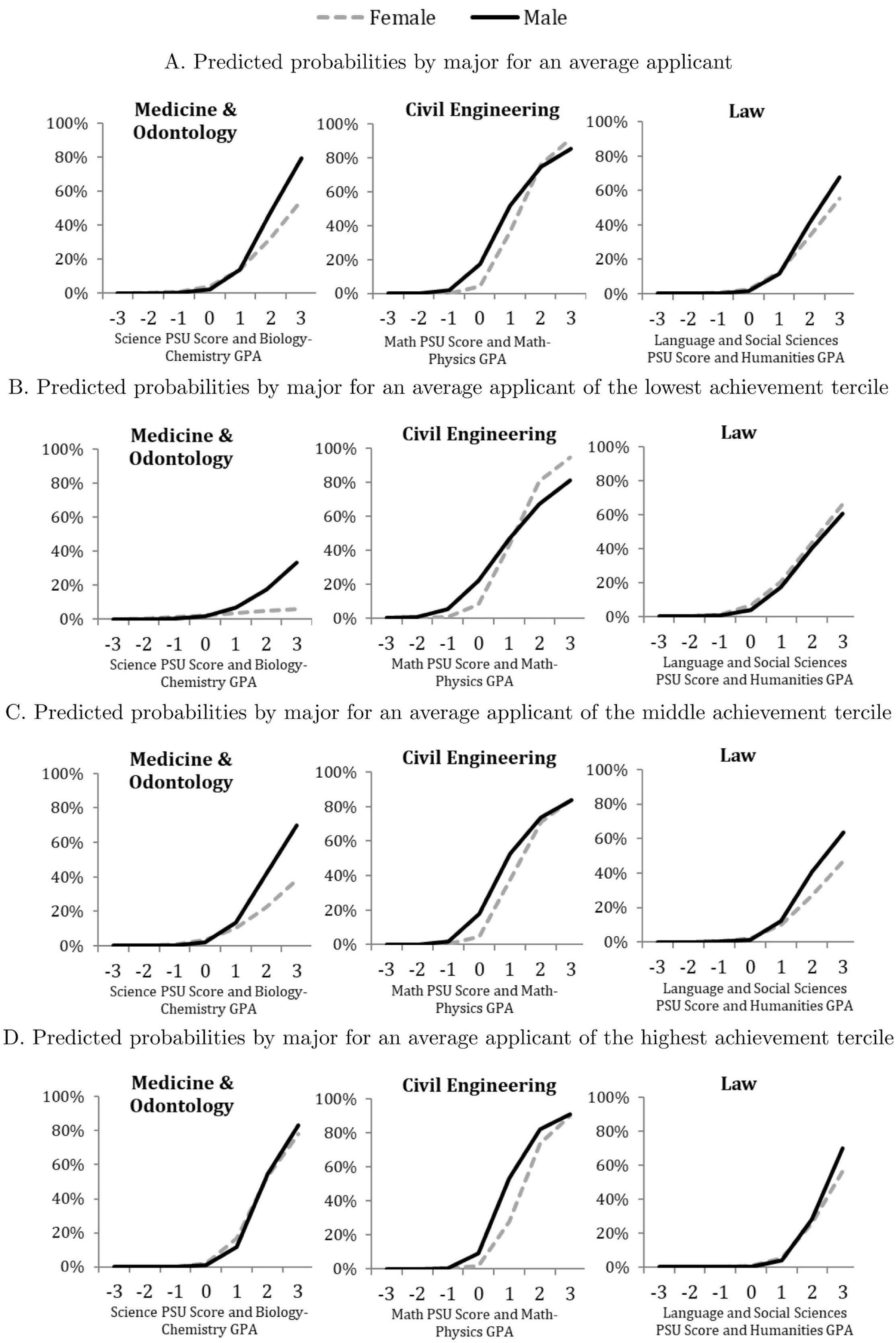

Fig. 2. Predicted Probabilities of the Most Selective Major for an Average Applicant by Previous Achievement Measured by GPA and PSU Scores. Note: Predictions made using average values for all variables except gender, PSU score and GPA for the corresponding area.

Table 5
Decomposition Analysis to Explain the Gender Gap by Area of Study .

	Average probability for		Gender difference in probability	$(\overline{X}_M - \overline{X}_F)\hat{\beta}_M$	$(\hat{\beta}_M - \hat{\beta}_F)\overline{X}_F$	Contribution of the	
	Males ($\hat{\overline{Y}}_M$)	Females ($\hat{\overline{Y}}_F$)				Data	Parameters
Medicine & Odon.	7%	9%	−3%	−1%	−2%	32%	68%
Health	10%	30%	−19%	−4%	−15%	22%	78%
Sciences	4%	3%	1%	0%	1%	33%	67%
Civil Eng.	32%	10%	22%	9%	13%	41%	59%
Technology	13%	4%	8%	1%	8%	7%	93%
Business	11%	8%	3%	1%	1%	51%	49%
Arts & Music	2%	3%	−1%	−1%	0%	69%	31%
Social Sc. & Hum.	10%	16%	−6%	−3%	−3%	52%	48%
Law	6%	6%	0%	0%	0%	220%	−120%
Education	6%	10%	−5%	−2%	−3%	38%	62%

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

Table 6
Percentage of Female and Male Applicants by Area of Study for the Counterfactual Scenarios.

Area	Percentage of Applicants											
	True parameters			Female parameters			Male parameters			Mean parameters		
	Female	Male	Gap	Female	Male	Gap	Female	Male	Gap	Female	Male	Gap
Medicine & Odon.	61%	39%	−23%	54%	46%	−8%	56%	44%	−12%	55%	45%	−10%
Health	77%	23%	−54%	58%	42%	−16%	62%	38%	−24%	60%	40%	−20%
Sciences	47%	53%	6%	49%	51%	2%	52%	48%	−4%	50%	50%	0%
Civil engineering	26%	74%	48%	39%	61%	22%	45%	55%	10%	42%	58%	16%
Technology	28%	72%	44%	48%	52%	4%	52%	48%	−4%	50%	50%	0%
Business	46%	54%	8%	47%	53%	6%	50%	50%	0%	48%	52%	4%
Arts	65%	35%	−30%	56%	44%	−12%	62%	38%	−24%	59%	41%	−18%
Social Sc. & Hum.	65%	35%	−30%	60%	40%	−20%	60%	40%	−20%	60%	40%	−20%
Law	54%	46%	−8%	54%	46%	−8%	55%	45%	−9%	55%	45%	−10%
Education	67%	33%	−34%	58%	42%	−16%	60%	40%	−20%	59%	41%	−18%

math PSU and GPA in mathematics and physics, and to law considering the social sciences PSU and GPA in the humanities.[22] It is noteworthy that this trend is more pronounced for males than females, which implies that a male student with the same average characteristics, same GPA and test results as a female student will tend to have higher probability of choosing the most selective major in each area, including humanities. This result coincides with Justman and Méndez (2018) findings for mathematics, in the case of male dominated subjects, and extends the results to other majors such as medicine and odontology and law, which are not masculinized.

Figs. 2 B-2 D show the probability of application to the most selective majors (medicine and odontology, civil engineering and law), by tercile of previous achievement measured by GPA and the required PSU for that major. From the figures, we can see that, in the case of medicine, for the lowest and middle achievement terciles, the effect of increasing the associated PSU and GPA is higher for male than female students, but there are no gender differences for the students in the highest achievement tercile. In the case of civil engineering, the effect of increasing the associated PSU and GPA tends to be higher for male students than female students in all terciles. In law, we see increasing effects of PSU and GPA for male students compared with female students, except in the lowest achievement tercile, where there is no gender difference. Thus, in general, male students are more prone to apply to the most selective majors than female students with equivalent achievement, with two exceptions: (i) women in the highest achievement tercile apply to the same extent as males to medicine and odontology, a selective major with significant participation by women, and (ii) women of the lowest achievement tercile apply to the same extent as men to law, a slightly feminized major.

In summary, these gender gaps in college major choices are based on a differentiated behavior of males and females: we find that high achievement students (both males and females) increase their probability of applying to the most selective majors (medicine and odontology, civil engineering and law).[23] However, when we compare average male and female students with the same academic results, this tendency is stronger for males, showing that they are more likely than females to bet on the most selective majors. That is, males apply to competitive programs even when they are marginal candidates while equally qualified females will tend not to apply to those same competitive programs. Therefore, talented female do not apply to the same extent to the most competitive majors, leaving these positions to less talented males.

These results suggest that decisions could be influenced by social stereotypes, as males can feel more social pressure to be successful, and therefore choose the most selective option. Also, there may be gender differences in the relative importance of pecuniary versus non-pecuniary benefits (NOE), 2010; Turner and Bowen, 1999). In addition, females might feel more insecure about their own knowledge, tending to believe that they are less competent for the more selective options. As already mentioned, the literature shows that females are generally more risk averse than men and more likely to shy away from competition; the literature also suggests that these characteristics are related to a gender gap in self-confidence based on gender stereotyping (Booth & Nolen, 2011; Booth & Nolen, 2012; Croson & Gneezy, 2009; Gneezy

[22] Appendix D, Table B.1 displays the average PSU scores by area of study. It is easy to see that for the case of Chile, the three majors mentioned are the most selective ones.

[23] See Appendix E.

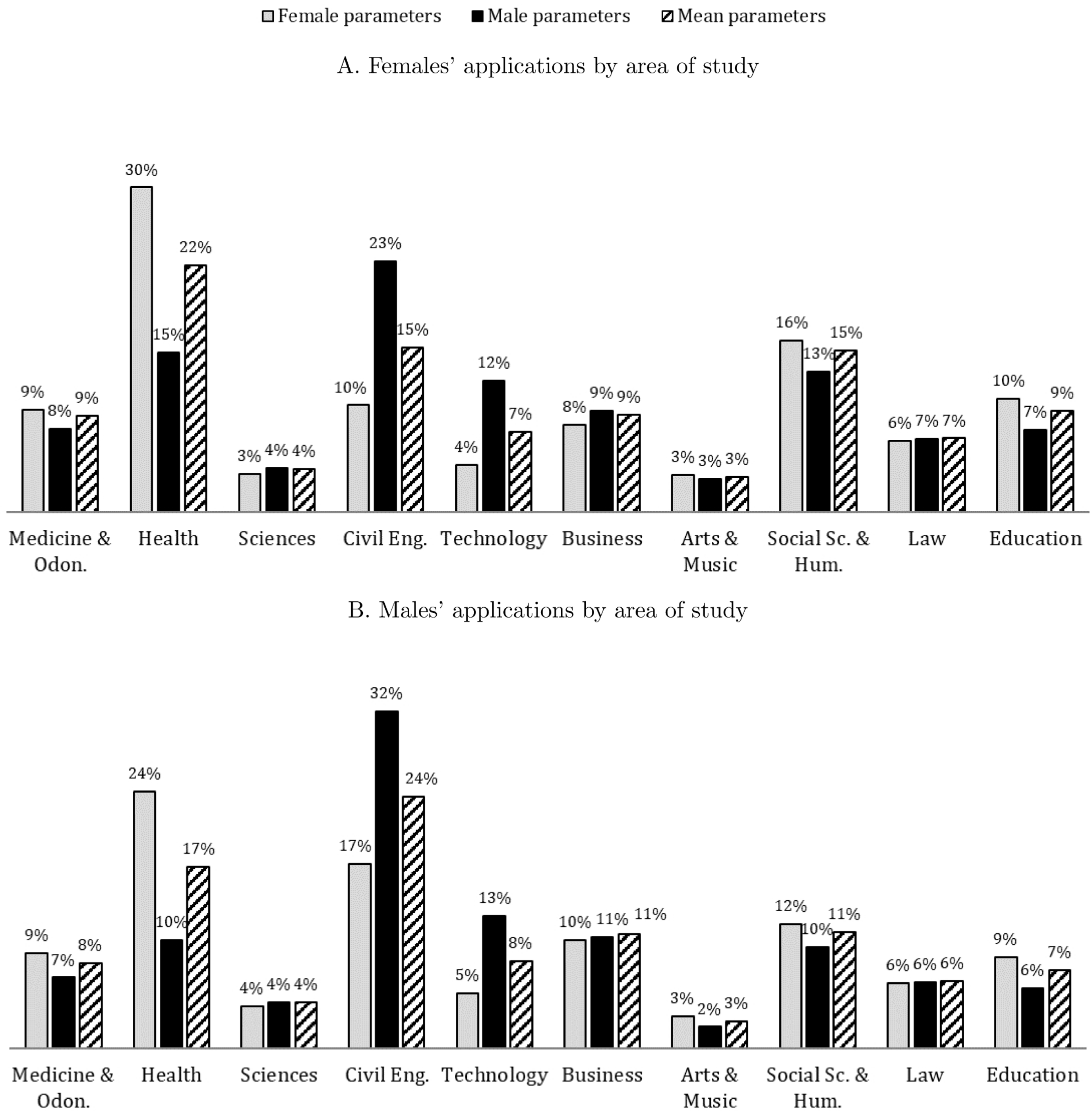

Fig. 3. Percentages of Applicants by Area of Study for the Counterfactuals Exercises.

et al., 2003; Niederle & Vesterlund, 2007; Niederle & Vesterlund, 2010; (Gupta, Poulsen & Villeval, 2005); Niederle & Yestrumskas, 2008).

6.3. 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:

$$\overline{\hat{Y}_M} - \overline{\hat{Y}_F} = (\overline{X}_M - \overline{X}_F)\hat{\beta}_M + \overline{X}_F(\hat{\beta}_M - \hat{\beta}_F) \quad (3)$$

where $\overline{\hat{Y}_M}$ and $\overline{\hat{Y}_F}$ are the average predicted value of choosing an area of study and a group of universities for males and females, respectively. $\overline{X}_M$ and $\overline{X}_F$ correspond to the average values of the independent and observable variables for males and females, respectively. $\hat{\beta}_M$ and $\hat{\beta}_F$ are the estimated coefficients for males and females. Note that the first term on the right-hand side of Eq. (3) is the gender difference in 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 college-major choice.

Table 5 displays the results of this exercise for the 10 areas of study considered. It shows that, in most areas the gender gap could be attributed more to the parameters than to the data, even though it is

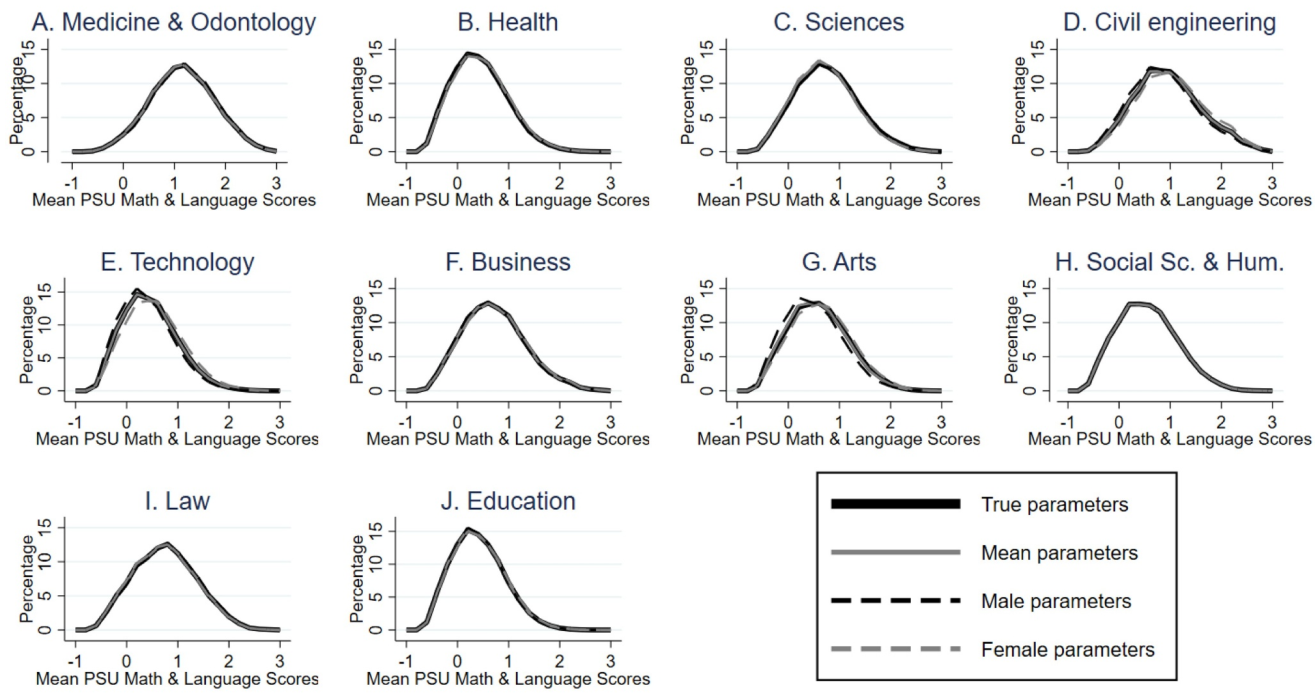

Fig. 4. Distribution of Mean Language and Mathematics PSU Scores by Area of Study for the Counterfactual Exercises.

known that in the data, particularly in the PSU tests scores, there are gender differences that affect the observable differences in application.[24] In contrast, the gender gap in the area of arts and music could be attributed more to observable differences between female and male applicants than to the estimated parameters, which include the students' preferences. Our results are consistent with those of Delaney and Devereux (2019).

7. Counterfactuals

We run three different counterfactual exercises. First, we look at the effects on the probability of applying to each area of study if female students had the same preference parameters as male students, that is, if females consider the same factors and to the same degree as males. Second, we look at the effect of applying to each area of study if male students had female students' preference parameters. Third, we look at the effect of applying to each area of study using the weighted average of male and female preference parameters.[25]

In what follows, we present the results of these three scenarios compared with the base scenario, i.e. the true parameters. These outcomes are shown in Tables 6 to 9 and Figs. 3 and 4.

7.1. Counterfactual exercise: If female students had male preference parameters

For the first counterfactual exercise, Fig. 3A depicts the percentage of applicants if female students had male preference parameters. We find that females would apply less to health, social sciences and humanities, education and medicine and odontology while applying more to civil engineering and technology. Table 7 depicts the percentage of all applicants by area of study in each scenario. For these cases, we find that considering both male and female students, there would be less applicants for health (13% vs 21% in the original case), education (7% vs 8%), and social sciences and humanities (11% vs 13%).

Table 6 presents the percentage of female and male applicants and the gender gap by area of study. Columns 1 and 7 show the results of this counterfactual exercise: (i) female-dominated majors would continue to be dominated by females, but with a lower proportion of women: 62% vs 77% in health, 62% vs 65% in arts and music, 60% vs 67% in education, 56% vs 61% in medicine and odontology, 60% vs 65% in social sciences and humanities; (ii) civil engineering would continue to be male-dominated, although with a higher proportion of women, 45% vs 26%; (iii) Business would close the gender gap and technology would reverse the gap; more women would apply to technology if they had male parameters, 52% vs 28%.

Table 9 presents the average PSU test scores by area of study. Even though we find small changes in the average scores, there are no substantial changes in the distribution of cognitive ability. This can be seen in Fig. 4, which shows the distribution of the average language and math PSU test score by area of study.[26]

7.2. Counterfactual exercise: If male students had female preference parameters

The second counterfactual exercise shows that if males had female preference parameters, males would apply more to health, education, medicine and odontology, social sciences and humanities and arts; they would apply less to civil engineering and technology (see Fig. 3B). In aggregate terms, as shown in Table 7, there would be more applicants for health (27% vs 21%), education (10% vs 8%), social sciences and humanities (14% vs 13%) and medicine and odontology (9% vs 8%).

Regarding the percentage of female applicants, Table 6, columns 1 and 4 show that: (i) female-dominated majors would continue to be dominated by females, but to a lesser extent: 58% vs 77% in health,

[24] In appendix C we present the distribution of PSU score by gender.

[25] We use the proportion of males and females in the cohort to compute the weighted average.

[26] The average mathematics PSU score would decrease in civil engineering, technology, and arts. The average science PSU score would increase in medicine and odontology, health and sciences, but decrease in civil engineering and technology. The average Social Science PSU score would increase in business, social sciences and humanities and law, but decrease in arts and music and education. See columns 1 and 3 of Table F.1, and figures F.1 y F.2 in Appendix F.

Table 7
Percentage of Applicants by Area of Study.

Area	Parameters True	Female	Male	Mean
Medicine & Odon.	8%	9%	7%	8%
Health	21%	27%	13%	20%
Sciences	4%	4%	4%	4%
Civil engineering	20%	13%	27%	19%
Technology	8%	5%	12%	8%
Business	9%	9%	10%	10%
Arts & Music	3%	3%	3%	3%
Social Sc. & Hum.	13%	14%	11%	13%
Law	6%	6%	6%	7%
Education	8%	10%	7%	8%
Total	100%	100%	100%	100%

Table 8
Gender Gap in Feminized and Masculinized Areas of Study for the Counterfactual Scenarios.

Majors	Parameters True	Female	Male	Mean
Feminized	30%	13%	18%	16%
Masculinized	26%	8%	4%	5%
All	28%	11%	13%	12%

Notes: This table summarizes Table 7, clustering majors by gender dominance. The Gap is shown in absolute values.

54% vs 61% in medicine and odontology, 56% vs 65% in arts and music, 60% vs 65% in social sciences and humanities, and 58% vs 67% in education; (ii) male-dominated majors would continue to be dominated by men, but with a higher proportion of females: 39% vs 26% in civil engineering, 48% vs 26% in technology, and 49% vs 47% in sciences.

Regarding the tests scores, we find small variations, although the distribution is almost the same by area of study, see Table 9, columns 1 and 2, and Fig. 4.[27]

7.3. Counterfactual exercise: If male and female students had average preference parameters

The third counterfactual exercise shows the scenario where male and female students have average parameters. Overall, the percentage of applicants for each area would remain the same (with less than 1% difference), see Table 7. Table 6, columns 1 and 10 show the responses of the applicants to this counterfactual exercise: (i) female-dominated majors would continue to be dominated by females, but with a lower proportion of woman: 60% vs 77% in health, 55% vs 61% in medicine and odontology, 59% vs 65% in arts, 60% vs 65% in social sciences and humanities, and 59% vs 67% in education; (ii) civil engineering majors would continue to be dominated by men, but with a higher proportion of females 42% vs 26%. (iii) sciences and technology would close the gender gap, 50% vs 47% and 50% vs 28%, respectively.

Therefore, if males and females choose majors according to the average preference parameters, we could expect that the gender gap would decrease for both feminized and masculinized majors (see Table 8). This exercise also shows that there is no impact on the PSU

[27] The average mathematics PSU score would increase in civil engineering, technology, and arts. The average science PSU score would increase in health and civil engineering and technology, but decrease in sciences. The average social science PSU score would increase in arts and education, but decrease in business and social sciences & humanities. See columns 1 and 2 of Table F.1, and figures F.1 y F.2 in Appendix F.

Table 9
Average PSU Scores by Area of Study for the Counterfactual Scenarios.

Area	Mathematics True Par.	Female Par.	Male Par.	Mean Par.	Language True Par.	Female Par.	Male Par.	Mean Par.
Medicine & Odon.	1.32	1.32	1.34	1.32	1.20	1.17	1.24	1.20
Health	0.57	0.63	0.53	0.58	0.52	0.52	0.54	0.52
Sciences	0.97	0.95	0.97	0.95	0.72	0.67	0.76	0.70
Civil engineering	1.31	1.43	1.19	1.30	0.80	0.85	0.76	0.80
Technology	0.71	0.80	0.60	0.70	0.41	0.49	0.37	0.42
Business	0.98	1.02	0.95	0.98	0.66	0.67	0.64	0.64
Arts & Music	0.58	0.68	0.44	0.57	0.80	0.84	0.73	0.78
Social Sc. & Hum.	0.45	0.48	0.43	0.46	0.85	0.83	0.88	0.85
Law	0.63	0.62	0.63	0.63	1.08	1.05	1.12	1.08
Education	0.43	0.46	0.41	0.43	0.59	0.59	0.59	0.58

Note: Scores were standardized.

scores (see Table 9, columns 1 and 4, and Fig. 4). This means that the gender gap does not imply a loss in terms of talent distribution (measured by cognitive performance) by area of knowledge.

8. Conclusions

This paper looks at the gender gap in applications to university majors in Chile. We estimate a structural model using a nested logit and simulate counterfactuals. Our results suggest that the gender differences we observe in college major application and enrollment are highly affected by students' preferences, since males and females show different patterns of application to the areas of study. In particular, females are more likely to apply to health majors and less likely to apply to civil engineering and technology. It is worth pointing out that by preferences we mean the behavior pattern we observe in the decisions that male and female students make, patterns that can be based on individual motivations, but can also be the result of social constructions. In this sense, the probability of applying to different areas of study according to student gender, suggests the existence of gender stereotypes that affect college major application.

These stereotypes are also linked with parents as role models; the mother's field of occupation has higher effects on daughters in health, business, social sciences and humanities, and law, while for male students having a father related to the area has a strong effect on their choices in almost all areas. Hence, while males seem to have a higher tendency to reproduce gender patterns of the previous generation, females seem to be influenced by both, their father's and mother's area of occupation. We also find that those students with good academic performance tend to reproduce to a lesser extent the choices of the parent of the same sex.

We also find that females and males from mostly-male high school classes are less likely to apply to health majors, and more likely to apply to civil engineering. Consequently, a higher interaction with students of certain gender, increases the probabilities of following the application pattern of that gender.

More importantly, looking at the area of study and university group, we see that males have a higher tendency, compared to similar females, to choose the most selective program if they have good results on the PSU tests. This also suggests that decisions could be influenced by social stereotypes, as males could feel more social pressure to be successful, choosing the most selective option. In addition, females may feel more insecure about their own knowledge, tending to believe that they are less apt for more selective options. The literature shows that women are generally more risk averse than men and more likely to shy away from competition; the literature also suggests that these characteristics are related to a gender gap in self-confidence based on gender stereotyping.

Our counterfactual analysis allows us to conclude that the gender gap in college major choice is related not only to the female choice, but also to the choice of males. Thus, in order to successfully address the gender gap, along with promoting females' participation in STEM careers, we must increase males' willingness to consider non-STEM fields. In the counterfactual exercise where males and females choose majors using the average preference parameters, we find that the gender gap decreases for both feminized and masculinized majors, and we also show that closing the gap this way does not imply a loss in terms of talent distribution (measured by cognitive performance) by area of knowledge.

This means that we need to promote policies that reduce gender stereotypes and encourage gender equality, bearing in mind that gender biases are unconscious. In this sense, it is important to carry out campaigns and activities that raise awareness. We must produce changes from early childhood; the task is to open up the world to girls and boys, broadening their view. In this sense, it is relevant to sensitize parents to support their sons and daughters in relation to their professional aspirations. Finally, it is relevant to include the gender issue in the curriculum of pedagogy careers, as well as teachers' professional development programs. All these factors should contribute to reducing gender stereotypes.

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Appendix A Nested Logit Model

In the model, students apply to a college-major combination (program) as their first preference in order to maximize their expected utility:

$$U_{ijk} = \alpha_j z_{ij} + \beta_k x_{ijk} + \epsilon_{ijk} = V_{ijk} + \epsilon_{ijk} \tag{1}$$

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 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.

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

$$p_{ijk} = \theta_k (a_{ij} - \bar{a}_{ij}) + \eta_{ijk} \tag{2}$$

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^*} = 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 Gumbels extreme-value distribution (see Eq. 3). This assumption corresponds to a nested logit model.

$$F_{U|A}(\epsilon_{jk}|j) = exp\left[-\left(\sum_{k\in U_j} exp\left(\frac{\epsilon_{jk}}{\tau_j}\right)\right)^{\tau_j}\right] \tag{3}$$

In this type of model, we have that

$$P[C_{ijk}=1|C_{ij} = 1] = \frac{exp(x_{ijk}\beta/\tau_j)}{\sum_{l\in U_j} exp(x_{jk}\beta)/\tau_j)} \tag{4}$$

$$P[C_{ij} = 1] = \frac{exp(\tau_j IV_j)}{\sum_{n\in A} exp(\tau_n IV_n)} \tag{5}$$

where

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

$$P[C_{ijk} = 1] = P[C_{ij} = 1]P[C_{ijk} = 1|C_{ij} = 1] \tag{6}$$

Appendix B. Average Marginal Effects for Area of Study by Gender

The math PSU score has the highest effect on the area of study to which students apply. An increase in one standard deviation in math PSU score increases, on average, by 19.6% the likelihood of applying to civil engineering for males and by 13.4% for females. Also, it decreases the likelihood of applying to health, medicine and odontology, social sciences and humanities and law.

Similarly, an increase in one standard deviation in math-physics GPA increases by 8.9% the likelihood of applying to civil engineering for males and by 6.5% for females. Additionally, it decreases the likelihood of applying to health majors by around 5%.

Also, one standard deviation increase in biology-chemistry GPA increases the likelihood of applying to health majors by 3%, on average, for males and 5.1% for females while decreasing the likelihood of applying to civil engineering by 4.6% for males and 3.9% for females. An increase in one standard deviation in the science PSU score increases by 7.2% the likelihood of applying to medicine and odontology for males and 6.5% for females.

Table B.1
Average Marginal Effects by Area of Study (Males).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	2.8%	2.8%	0.5%	2.5%	0.3%	1.9%	−0.2%	1.6%	2.9%	1.1%
Parent's area different sex	2.2%	2.0%	−0.1%	−2.6%	−1.1%	1.2%	1.1%	1.0%	2.8%	1.0%
Female high school class	0.5%	2.4%	−0.6%	−1.2%	−0.1%	−1.4%	0.1%	−0.1%	−0.7%	1.2%
Mixed high school class	−0.05%	0.4%	−0.7%	0.4%	0.02%	−0.9%	0.1%	0.3%	−0.3%	0.7%
High school ranking	0.3%	−0.2%	0.2%	2.4%	−1.2%	−1.2%	0.3%	−0.1%	−0.4%	0.1%
Language PSU Score	0.8%	0.7%	0.5%	−2.4%	−2.8%	−4.1%	0.6%	3.9%	0.8%	1.9%
Math PSU Score	−5.5%	−10.6%	−0.6%	19.6%	−0.5%	6.6%	−0.9%	−4.1%	−3.1%	−0.9%
Science PSU Score	7.2%	4.2%	0.8%	−4.6%	−1.6%	−2.3%	−0.5%	−1.4%	−0.7%	−1.3%
Social Sciences PSU Score	−0.4%	−1.0%	−0.2%	−1.5%	−0.7%	−0.02%	−0.4%	−0.1%	5.0%	−0.7%
Biology-Chemistry GPA	2.8%	3.0%	0.8%	−4.6%	−0.2%	−0.5%	−0.2%	−0.6%	−0.1%	−0.4%
Math-Physics GPA	−2.8%	−4.4%	−0.3%	8.9%	1.0%	1.6%	−0.4%	−1.9%	−0.8%	−0.9%
Arts-Music GPA	−0.3%	0.3%	−0.1%	−0.6%	0.3%	−0.04%	0.5%	−0.02%	−0.2%	0.2%
Humanities GPA	1.5%	1.1%	−0.3%	−3.2%	−1.5%	−0.3%	−0.2%	1.9%	1.4%	−0.4%
Per capita income	0.1%	−0.4%	0.2%	0.8%	−0.6%	0.5%	0.1%	0.03%	0.2%	−0.9%
Private subsidized high school	0.8%	−1.0%	−0.1%	−0.8%	−0.5%	1.6%	0.5%	−0.8%	0.3%	0.02%
Private paid high school	1.0%	−2.6%	0.3%	−2.8%	−1.2%	7.7%	0.5%	−1.2%	1.8%	−3.4%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table B.2
Average Marginal Effects by Area of Study (Females).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	3.7%	2.6%	0.1%	−1.0%	0.2%	1.2%	1.1%	1.6%	3.8%	0.1%
Parent's area different sex	3.9%	0.2%	1.0%	0.6%	0.01%	0.3%	1.2%	−0.1%	1.8%	1.4%
Female high school class	1.1%	4.5%	−0.4%	−3.5%	−0.7%	−0.9%	−0.2%	0.1%	−0.3%	0.3%
Mixed high school class	1.3%	4.4%	−0.5%	−3.1%	−0.9%	−0.3%	−0.1%	−0.4%	−0.3%	−0.2%
High school ranking	1.6%	−1.9%	−0.1%	1.3%	−0.5%	−0.1%	0.6%	−0.7%	−0.2%	0.1%
Language PSU Score	1.2%	−0.3%	−0.03%	−2.3%	−0.9%	−2.8%	0.5%	3.5%	0.2%	1.0%
Math PSU Score	−3.2%	−13.4%	0.6%	13.4%	1.5%	7.6%	0.2%	−4.8%	−2.8%	1.0%
Science PSU Score	6.5%	3.8%	0.1%	−1.9%	−0.5%	−1.9%	−0.6%	−2.2%	−0.7%	−2.5%
Social Sciences PSU Score	−0.6%	−3.1%	−0.2%	−0.3%	−0.1%	−0.1%	−0.3%	0.2%	5.8%	−1.2%
Biology-Chemistry GPA	2.0%	5.1%	0.3%	−3.9%	0.1%	−1.2%	−0.5%	−1.1%	0.2%	−1.0%
Math-Physics GPA	−1.7%	−5.4%	0.2%	6.5%	0.8%	2.8%	−0.6%	−1.5%	−0.1%	−1.0%
Arts-Music GPA	−0.3%	0.6%	−0.1%	0.04%	−0.2%	−0.2%	0.6%	−0.3%	−0.1%	0.01%
Humanities GPA	0.4%	0.9%	−0.5%	−1.7%	−0.6%	−1.5%	−0.8%	3.5%	0.6%	−0.3%
Per capita income	0.2%	−0.1%	−0.3%	0.04%	−0.01%	0.03%	0.5%	0.7%	−0.1%	−1.1%
Private subsidized high school	0.1%	0.3%	0.3%	−0.3%	−0.6%	0.3%	−0.1%	−0.02%	0.6%	−0.6%
Private paid high school	0.5%	−1.5%	0.7%	−3.4%	−1.9%	3.7%	1.8%	1.2%	1.9%	−2.9%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table B.3
Average Marginal Effects by Area of Study (lowest tercile of achievement, all students).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	0.8%	18.5%	−0.3%	−11.8%	−13.2%	−1.2%	−0.2%	3.1%	0.6%	3.6%
Parent's area same sex	3.6%	4.7%	−0.2%	4.8%	−0.03%	1.5%	0.2%	2.6%	3.5%	0.5%
Parent's area different sex	0.1%	0.7%	1.3%	−2.4%	−0.4%	1.0%	1.2%	−0.1%	0.1%	2.5%
Female high school class	0.9%	3.7%	−0.4%	−2.0%	−1.0%	−1.9%	0.01%	0.3%	−0.6%	0.9%
Mixed high school class	0.8%	2.4%	−0.1%	−1.6%	−0.8%	−0.7%	−0.1%	−0.1%	−0.5%	0.7%
High school ranking	0.1%	0.02%	−0.01%	1.3%	−0.2%	−0.5%	0.1%	−1.1%	−0.4%	0.7%
Language PSU Score	0.5%	2.2%	−1.4%	−1.6%	−2.0%	−3.8%	0.3%	2.7%	−0.4%	3.5%
Math PSU Score	−0.6%	−10.1%	−0.4%	10.2%	3.1%	4.5%	−0.5%	−5.3%	−1.6%	0.6%
Science PSU Score	1.6%	6.1%	0.3%	−0.2%	−0.7%	−1.2%	−0.6%	−2.2%	−0.7%	−2.3%
Social Sciences PSU Score	−0.3%	−3.1%	−0.3%	−0.6%	−0.6%	0.04%	−0.4%	1.0%	5.2%	−0.9%
Biology-Chemistry GPA	0.2%	5.2%	0.5%	−1.6%	−0.4%	−1.0%	−0.3%	−1.0%	−0.2%	−1.4%
Math-Physics GPA	−0.3%	−5.5%	−0.1%	4.4%	2.0%	2.6%	−0.7%	−1.6%	−0.01%	−0.8%
Arts-Music GPA	−0.2%	0.4%	−0.1%	−0.3%	−0.2%	−0.1%	0.7%	−0.2%	−0.2%	0.2%
Humanities GPA	0.3%	0.9%	0.05%	−2.1%	−1.7%	−0.8%	−0.1%	3.2%	1.2%	−0.9%
Per capita income	0.1%	−0.02%	0.1%	0.04%	−0.4%	0.9%	0.3%	0.2%	0.3%	−1.4%
Private subsidized high school	0.2%	0.3%	−0.3%	−0.5%	−0.3%	−0.2%	0.4%	−0.3%	0.8%	−0.1%
Private paid high school	0.8%	−1.9%	1.4%	−4.1%	−2.2%	1.8%	2.3%	2.0%	1.1%	−1.3%

All coefficients are statistically significant at a 99% confidence level, except the effect of Math-Physics GPA on Law which is not significant (even at a 90% confidence level). Estimations have fixed effects by region.

Table B.4
Average Marginal Effects by Area of Study (middle tercile of achievement, all students).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	1.7%	16.6%	−0.6%	−15.5%	−7.2%	−0.8%	0.9%	1.7%	−0.3%	3.5%
Parent's area same sex	4.4%	2.2%	−0.9%	1.9%	0.5%	1.2%	1.2%	0.6%	2.9%	0.9%
Parent's area different sex	2.7%	3.7%	1.3%	2.3%	−0.5%	−0.2%	1.9%	0.8%	3.8%	0.8%
Female high school class	0.2%	0.4%	−0.4%	−0.3%	0.5%	−1.4%	0.5%	−0.05%	−0.6%	1.1%
Mixed high school class	−0.1%	1.1%	−0.8%	−0.1%	0.2%	−0.9%	0.7%	−0.4%	−0.4%	0.8%
High school ranking	0.9%	−0.9%	0.2%	1.6%	−1.6%	−1.0%	0.8%	−0.1%	0.2%	−0.1%
Language PSU Score	1.1%	−0.9%	0.6%	−4.0%	−1.9%	−3.1%	0.8%	4.7%	0.4%	2.2%
Math PSU Score	−3.3%	−16.2%	0.2%	15.6%	1.3%	9.5%	−0.1%	−4.4%	−3.6%	1.1%
Science PSU Score	5.4%	5.0%	0.4%	−2.2%	−1.2%	−2.1%	−0.6%	−1.9%	−0.7%	−2.2%
Social Sciences PSU Score	−0.5%	−2.2%	−0.3%	−0.8%	−0.5%	−0.1%	−0.4%	−0.3%	6.4%	−1.4%
Biology-Chemistry GPA	1.5%	4.4%	0.4%	−3.7%	0.2%	−1.0%	−0.5%	−0.8%	0.1%	−0.6%
Math-Physics GPA	−1.0%	−5.5%	−0.1%	8.0%	0.9%	2.0%	−0.4%	−2.1%	−0.3%	−1.5%
Arts-Music GPA	−0.4%	0.9%	−0.1%	−0.7%	0.4%	−0.3%	0.4%	−0.1%	0.03%	−0.3%
Humanities GPA	0.6%	1.2%	−0.5%	−2.2%	−0.9%	−0.8%	−0.7%	3.1%	0.5%	−0.1%
Per capita income	0.2%	−0.1%	−0.1%	0.6%	−0.6%	0.1%	0.4%	0.4%	0.1%	−1.0%
Private subsidized high school	0.5%	−1.0%	0.3%	−0.3%	−0.7%	1.8%	0.05%	0.3%	−0.3%	−0.6%
Private paid high school	1.4%	−1.8%	1.3%	−3.4%	−1.7%	5.8%	1.2%	−0.2%	1.1%	−3.7%

All coefficients are statistically significant at a 99% confidence level, except the effect of Arts-Music GPA on Social Sciences & Humanities which is not significant (even at a 90% confidence level). Estimations have fixed effects by region.

Table B.5
Average Marginal Effects by Area of Study (highest tercile of achievement, all students).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	3.7%	9.2%	−0.5%	−14.6%	−2.4%	0.0%	1.5%	2.3%	−0.9%	1.6%
Parent's area same sex	3.7%	0.8%	1.4%	0.5%	0.3%	2.0%	−0.2%	1.7%	3.3%	−0.1%
Parent's area different sex	5.6%	0.5%	−0.6%	−1.2%	0.1%	1.2%	0.6%	0.5%	2.4%	0.3%
Female high school class	0.4%	3.1%	−0.6%	−2.4%	0.3%	−1.5%	0.0%	−0.1%	−0.5%	1.3%
Mixed high school class	0.4%	1.7%	−0.9%	−0.1%	0.0%	−1.4%	0.1%	0.4%	−0.6%	0.5%
High school ranking	0.9%	−2.33%	−0.47%	2.9%	−0.3%	−0.1%	0.4%	0.0%	−0.6%	−0.3%
Language PSU Score	3.0%	−2.2%	0.5%	−2.4%	−0.6%	−3.1%	0.4%	2.6%	1.5%	0.2%
Math PSU Score	−6.9%	−13.7%	−0.6%	22.1%	−1.1%	7.2%	−0.5%	−4.2%	−3.3%	1.0%
Science PSU Score	12.1%	4.1%	1.9%	−9.3%	−1.1%	−3.0%	−0.6%	−1.6%	−0.8%	−1.7%
Social Sciences PSU Score	−0.6%	−1.0%	−0.1%	−1.1%	−0.2%	−0.2%	−0.4%	−0.5%	4.8%	−0.7%
Biology-Chemistry GPA	6.3%	2.5%	0.4%	−7.4%	0.1%	−1.1%	−0.2%	−0.9%	0.4%	0.0%
Math-Physics GPA	−5.7%	−2.9%	0.6%	9.9%	−0.4%	1.8%	−0.3%	−1.3%	−1.1%	−0.5%
Arts-Music GPA	0.3%	−0.2%	−0.2%	−0.1%	−0.2%	0.3%	0.6%	−0.3%	−0.5%	0.3%
Humanities GPA	2.0%	0.6%	−0.75%	−2.5%	−0.7%	−0.9%	−0.8%	2.0%	1.5%	−0.4%
Per capita income	0.2%	−0.41%	−0.2%	0.38%	0.1%	0.0%	0.2%	0.3%	−0.1%	−0.5%
Private subsidized high school	0.6%	−0.7%	0.7%	−1.2%	−0.2%	1.3%	−0.2%	−1.7%	1.1%	0.1%
Private paid high school	0.3%	−1.7%	−0.2%	−3.2%	−0.7%	6.3%	0.5%	−1.5%	2.7%	−2.6%

All coefficients are statistically significant at a 99% confidence level, except the effect of Female on Business which is not significant (even at a 90% confidence level). Estimations have fixed effects by region.

Table B.6
Average Marginal Effects by Area of Study (lowest tercile of achievement, males).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	6.4%	1.8%	0.3%	7.4%	−0.1%	0.8%	−0.1%	2.1%	3.7%	4.7%
Parent's area different sex	−0.4%	2.4%	0.8%	−4.6%	−1.5%	2.9%	1.4%	1.4%	−1.1%	2.1%
Female high school class	0.7%	3.7%	0.1%	−2.2%	−1.3%	−1.2%	−0.2%	0.2%	−0.5%	0.8%
Mixed high school class	0.3%	0.6%	0.6%	−1.3%	−1.0%	−0.4%	−0.4%	0.9%	0.1%	0.6%
High school ranking	0.1%	0.4%	0.4%	2.2%	−0.1%	−2.5%	0.2%	−0.6%	−1.0%	0.9%
Language PSU Score	0.1%	3.4%	−0.7%	−1.9%	−3.5%	−4.8%	−0.2%	4.5%	−1.0%	4.0%
Math PSU Score	−1.2%	−9.0%	−1.0%	14.1%	3.8%	3.8%	−1.5%	−4.8%	−2.4%	−1.8%
Science PSU Score	2.3%	5.5%	0.5%	−0.6%	−1.7%	−1.5%	−0.9%	−1.7%	−0.5%	−1.4%
Social Sciences PSU Score	−0.1%	−1.4%	−0.3%	−1.3%	−1.3%	−0.1%	−0.7%	0.7%	5.1%	−0.6%
Biology-Chemistry GPA	0.4%	4.1%	1.0%	−1.8%	−0.8%	−0.5%	−0.4%	−1.1%	−0.2%	−0.8%
Math-Physics GPA	−0.5%	−5.7%	−0.4%	5.9%	3.1%	2.2%	−0.9%	−1.9%	−0.5%	−1.2%
Arts-Music GPA	−0.3%	0.02%	−0.3%	−0.5%	−0.1%	0.2%	0.8%	0.004%	−0.1%	0.2%
Humanities GPA	0.7%	1.8%	−0.1%	−3.3%	−3.2%	0.4%	0.2%	2.6%	1.9%	−1.1%
Per capita income	0.1%	−0.6%	0.4%	0.6%	−0.7%	1.3%	−0.1%	−0.2%	0.5%	−1.4%
Private subsidized high school	0.4%	−1.3%	−0.4%	−1.3%	0.1%	1.0%	1.1%	−1.2%	0.9%	0.5%
Private paid high school	1.2%	−1.8%	1.9%	−5.7%	−2.0%	5.6%	0.5%	1.0%	1.6%	−2.3%

All coefficients are statistically significant at a 99% confidence level, except the effect of Arts-Music GPA on Social Sciences & Humanities which is not significant (even at a 90% confidence level). Estimations have fixed effects by region.

Table B.7
Average Marginal Effects by Area of Study (middle tercile of achievement, males).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	3.9%	4.4%	−0.9%	3.2%	0.8%	1.0%	−0.1%	0.6%	2.0%	0.6%
Parent's area different sex	−0.7%	3.5%	1.5%	−3.1%	−2.3%	−0.2%	3.3%	1.0%	6.0%	0.8%
Female high school class	−0.6%	0.9%	−0.3%	−0.1%	0.5%	−2.1%	0.4%	0.6%	−1.0%	1.6%
Mixed high school class	−0.3%	−0.03%	−1.4%	1.6%	0.6%	−1.2%	0.4%	−0.002%	−0.5%	0.9%
High school ranking	0.7%	0.8%	0.9%	0.9%	−2.5%	−1.6%	0.6%	−0.4%	0.6%	0.02%
Language PSU Score	1.4%	0.1%	0.2%	−5.2%	−3.0%	−3.6%	1.3%	5.1%	1.2%	2.6%
Math PSU Score	−3.2%	−14.9%	−0.6%	19.4%	−0.1%	8.4%	−1.0%	−4.3%	−3.5%	−0.3%
Science PSU Score	5.0%	6.3%	0.8%	−3.4%	−2.0%	−2.4%	−0.4%	−1.4%	−0.7%	−1.7%
Social Sciences PSU Score	−0.2%	−1.3%	−0.3%	−1.6%	−0.9%	−0.2%	−0.4%	−0.2%	6.4%	−1.2%
Biology-Chemistry GPA	1.7%	3.2%	0.5%	−4.1%	0.3%	−0.7%	−0.3%	−0.3%	0.02%	−0.4%
Math-Physics GPA	−1.0%	−5.6%	−0.8%	9.9%	0.9%	1.1%	−0.2%	−2.5%	−0.6%	−1.2%
Arts-Music GPA	−0.5%	0.7%	0.1%	−0.9%	0.8%	−0.4%	0.4%	−0.2%	−0.1%	−0.03%
Humanities GPA	0.9%	1.3%	−0.5%	−2.4%	−1.5%	0.04%	−0.4%	2.4%	0.3%	−0.1%
Per capita income	0.1%	−0.3%	0.2%	1.0%	−0.9%	0.3%	0.3%	0.01%	0.2%	−1.1%
Private subsidized high school	0.7%	−0.3%	−0.4%	−1.0%	−1.1%	2.7%	0.4%	−0.3%	−0.2%	−0.5%
Private paid high school	3.0%	−2.1%	0.7%	−5.0%	−2.0%	8.4%	0.9%	−1.3%	1.7%	−4.2%

All coefficients are statistically significant at a 99% confidence level, except the effect of Math PSU score on Technology which is significant at a 95% confidence level and the effect of Mixed high school class on Social Sciences & Humanities, which is not significant (even at a 90% of confidence level). Estimations have fixed effects by region.

Table B.8
Average Marginal Effects by Area of Study (highest tercile of achievement, males).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	3.5%	1.8%	1.5%	0.4%	0.2%	2.9%	−0.17%	1.8%	2.9%	−0.03%
Parent's area different sex	4.7%	0.3%	−1.3%	−1.53%	0.1%	1.3%	−0.5%	0.6%	3.6%	0.4%
Female high school class	1.5%	2.3%	−1.4%	−2.0%	0.2%	−0.5%	0.2%	−1.2%	−0.4%	1.4%
Mixed high school class	0.1%	0.5%	−0.8%	0.2%	0.3%	−0.8%	0.2%	0.2%	−0.4%	0.6%
High school ranking	0.2%	−1.5%	−0.9%	3.5%	−0.8%	0.2%	0.1%	0.3%	−0.7%	−0.5%
Language PSU Score	2.5%	−1.0%	0.5%	−1.7%	−1.21%	−4.7%	0.6%	2.4%	1.9%	0.7%
Math PSU Score	−7.4%	−12.6%	−1.3%	24.2%	−2.2%	5.9%	−0.6%	−3.5%	−3.0%	0.5%
Science PSU Score	11.7%	4.6%	2.4%	−11.4%	−1.2%	−2.8%	−0.3%	−1.2%	−0.8%	−1.1%
Social Sciences PSU Score	−0.6%	−0.4%	−0.1%	−1.5%	−0.2%	0.05%	−0.3%	−0.5%	3.9%	−0.4%
Biology-Chemistry GPA	6.2%	1.8%	0.4%	−7.4%	0.1%	−0.5%	−0.1%	−0.4%	0.01%	−0.01%
Math-Physics GPA	−6.4%	−1.6%	0.7%	10.0%	−0.8%	1.1%	−0.1%	−1.2%	−1.3%	−0.4%
Arts-Music GPA	0.2%	0.00%	−0.3%	−0.2%	−0.2%	0.1%	0.3%	−0.01%	−0.5%	0.4%
Humanities GPA	2.5%	0.3%	−0.3%	−3.1%	−0.5%	−1.0%	−0.4%	0.8%	1.8%	−0.2%
Per capita income	0.1%	−0.3%	−0.01%	0.5%	−0.1%	0.04%	0.2%	0.2%	0.00%	−0.5%
Private subsidized high school	1.3%	−1.4%	0.4%	−0.7%	0.1%	0.5%	−0.1%	−0.8%	0.5%	0.3%
Private paid high school	0.1%	−2.6%	−0.5%	−1.0%	−0.1%	6.6%	−0.1%	−1.8%	2.0%	−2.7%

All coefficients are statistically significant at a 99% confidence level, except the effect of Biology-Chemistry GPA on Education which is significant at a 90% confidence level). Estimations have fixed effects by region.

Table B.9
Average Marginal Effects by Area of Study (lowest tercile of achievement, females).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	−0.3%	5.7%	−0.6%	4.0%	−0.4%	1.8%	0.9%	2.7%	2.3%	−0.6%
Parent's area different sex	−0.2%	−2.6%	1.6%	−0.9%	−0.1%	−0.5%	0.8%	−1.3%	0.6%	2.3%
Female high school class	1.6%	5.7%	−1.2%	−2.9%	−1.4%	−1.2%	−0.2%	−0.3%	−1.2%	1.2%
Mixed high school class	1.6%	5.1%	−0.9%	−2.8%	−1.3%	0.2%	−0.2%	−1.2%	−1.3%	0.8%
High school ranking	0.2%	−0.02%	−0.2%	0.7%	−0.3%	0.5%	0.1%	−1.3%	−0.2%	0.6%
Language PSU Score	0.8%	1.4%	−1.9%	−1.6%	−1.0%	−3.2%	0.5%	1.5%	0.1%	3.3%
Math PSU Score	−0.2%	−10.8%	−0.02%	8.2%	2.5%	4.9%	0.2%	−5.5%	−1.0%	1.9%
Science PSU Score	1.4%	6.5%	0.2%	−0.3%	−0.1%	−1.1%	−0.5%	−2.6%	−0.8%	−2.8%
Social Sciences PSU Score	−0.5%	−4.2%	−0.3%	−0.1%	−0.03%	0.1%	−0.1%	1.1%	5.1%	−1.0%
Biology-Chemistry GPA	0.1%	5.9%	0.1%	−1.7%	−0.2%	−1.1%	−0.3%	−0.9%	−0.2%	−1.7%
Math-Physics GPA	−0.1%	−5.4%	0.1%	3.6%	1.2%	2.8%	−0.6%	−1.4%	0.4%	−0.6%
Arts-Music GPA	−0.2%	0.68%	−0.01%	0.04%	−0.4%	−0.3%	0.5%	−0.380%	−0.3%	0.3%
Humanities GPA	0.1%	0.3%	0.1%	−1.3%	−0.7%	−1.6%	−0.4%	3.5%	0.6%	−0.6%
Per capita income	0.1%	0.4%	−0.2%	−0.4%	−0.1%	0.5%	0.5%	0.6%	0.001%	−1.5%
Private subsidized high school	−0.1%	1.5%	−0.2%	0.1%	−0.8%	−1.0%	−0.02%	0.3%	0.8%	−0.6%
Private paid high school	0.6%	−1.8%	1.0%	−3.0%	−2.2%	−0.9%	3.2%	2.7%	1.1%	−0.7%

All coefficients are statistically significant at a 99% confidence level, except the effect of Per Capita Income on Law which is not significant (even at a 90% confidence level). Estimations have fixed effects by region.

Table B.10
Average Marginal Effects by Area of Study (middle tercile of achievement, females).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	5.2%	1.7%	−1.0%	−2.1%	0.4%	1.3%	4.0%	0.5%	5.1%	0.8%
Parent's area different sex	6.7%	2.8%	1.0%	3.2%	0.04%	0.1%	1.7%	0.5%	3.2%	1.6%
Female high school class	1.5%	0.9%	0.3%	−2.4%	−0.1%	0.6%	0.4%	−1.9%	0.9%	−0.2%
Mixed high school class	1.0%	2.4%	0.2%	−3.2%	−0.6%	1.1%	0.7%	−2.3%	1.0%	−0.4%
High school ranking	1.4%	−2.2%	−0.3%	2.0%	−1.1%	−0.5%	1.0%	−0.05%	−0.2%	−0.1%
Language PSU Score	1.0%	−2.0%	1.0%	−2.9%	−1.0%	−2.6%	0.3%	4.5%	−0.1%	1.9%
Math PSU Score	−3.2%	−17.7%	0.8%	12.5%	2.6%	10.5%	0.4%	−4.3%	−3.6%	1.9%
Science PSU Score	5.8%	4.8%	0.05%	−1.7%	−0.7%	−1.9%	−0.7%	−2.3%	−0.7%	−2.6%
Social Sciences PSU Score	−0.7%	−2.9%	−0.3%	−0.2%	−0.2%	−0.01%	−0.3%	−0.4%	6.4%	−1.4%
Biology-Chemistry GPA	1.2%	5.3%	0.5%	−3.6%	0.2%	−1.2%	−0.8%	−1.3%	0.3%	−0.7%
Math-Physics GPA	−1.1%	−5.3%	0.4%	6.7%	0.8%	2.6%	−0.5%	−1.8%	−0.1%	−1.8%
Arts-Music GPA	−0.2%	0.8%	−0.3%	−0.3%	0.1%	−0.2%	0.3%	0.2%	0.1%	−0.5%
Humanities GPA	0.2%	1.1%	−0.6%	−2.0%	−0.4%	−1.7%	−0.9%	3.7%	0.6%	−0.1%
Per capita income	0.3%	0.01%	−0.3%	0.1%	−0.3%	−0.2%	0.5%	0.8%	0.02%	−1.0%
Private subsidized high school	0.03%	−1.4%	0.8%	0.4%	−0.3%	1.0%	−0.2%	0.8%	−0.4%	−0.8%
Private paid high school	−0.3%	−1.2%	1.9%	−2.1%	−1.5%	3.7%	1.4%	0.6%	0.8%	−3.4%

All coefficients are statistically significant at a 99% confidence level, except the effect of Per Capita Income on Health which is significant at a 95% confidence level. Estimations have fixed effects by region.

Table B.11
Average Marginal Effects by Area of Study (highest tercile of achievement, females).

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	4.6%	0.6%	1.2%	−2.0%	0.3%	0.9%	0.05%	1.7%	3.9%	−0.3%
Parent's area different sex	6.2%	0.6%	0.4%	−0.05%	0.13%	1.4%	1.0%	0.3%	1.7%	0.2%
Female high school class	0.6%	6.2%	−0.3%	−4.8%	−0.4%	−2.2%	−0.9%	2.4%	−0.3%	−0.3%
Mixed high school class	1.7%	4.8%	−1.0%	−2.7%	−0.7%	−2.3%	−0.7%	2.7%	−0.5%	−1.4%
High school ranking	2.4%	−3.5%	0.1%	2.0%	0.2%	−0.6%	0.8%	−0.72%	−0.5%	−0.1%
Language PSU Score	3.6%	−3.4%	0.6%	−3.1%	−0.03%	−1.3%	0.2%	2.7%	1.2%	−0.4%
Math PSU Score	−5.8%	−15.6%	0.2%	19.9%	0.4%	9.0%	−0.4%	−5.1%	−3.8%	1.2%
Science PSU Score	12.5%	3.7%	1.18%	−7.0%	−1.1%	−3.3%	−0.9%	−2.1%	−0.8%	−2.3%
Social Sciences PSU Score	−0.7%	−1.7%	−0.1%	−0.6%	−0.1%	−0.56%	−0.5%	−0.6%	6.0%	−1.1%
Biology-Chemistry GPA	6.4%	3.4%	0.4%	−7.8%	0.3%	−1.9%	−0.3%	−1.4%	1.0%	−0.1%
Math-Physics GPA	−5.1%	−4.5%	0.2%	10.4%	−0.2%	2.5%	−0.5%	−1.3%	−0.9%	−0.5%
Arts-Music GPA	0.4%	−0.8%	−0.3%	0.7%	−0.3%	0.6%	1.0%	−0.9%	−0.3%	−0.1%
Humanities GPA	1.2%	1.1%	−1.6%	−1.7%	−1.0%	−0.7%	−1.4%	4.0%	0.8%	−0.7%
Per capita income	0.3%	−0.54%	−0.3%	0.2%	0.3%	−0.1%	0.3%	0.6%	−0.22%	−0.5%
Private subsidized high school	−0.09%	0.5%	0.9%	−2.0%	−0.8%	2.2%	−0.3%	−2.0%	1.8%	−0.2%
Private paid high school	0.7%	−0.4%	0.1%	−6.1%	−1.5%	6.0%	1.1%	−0.5%	3.5%	−2.9%

All coefficient are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table B.12
Average Marginal Effects by Group of Universities for Each Tercile of Achievement.

	Tercile 1			Tercile 2			Tercile 3		
Variable	All students	Males	Females	All Students	Males	Females	All Students	Males	Females
Difference of score	2.96%	2.72%	3.13%	4.24%	4.24%	4.11%	4.21%	4.30%	3.99%
Difference of score ^{2}	−1.18%	−1.02%	−1.26%	−1.68%	−1.66%	−1.67%	−1.27%	−1.23%	−1.31%
Program average score	3.26%	3.72%	3.36%	4.89%	4.96%	5.05%	4.56%	4.13%	5.07%
% of regional vacancies of the program	0.02%	0.02%	0.03%	0.03%	0.02%	0.03%	0.02%	0.02%	0.03%
Copayment	0.05%	0.04%	0.05%	0.07%	0.07%	0.07%	0.00%	0.00%	−0.01%
% Previous school generation of the group	0.02%	0.01%	0.02%	0.02%	0.02%	0.02%	0.03%	0.03%	0.03%

All coefficients are statistically significant at a 99% confidence level.

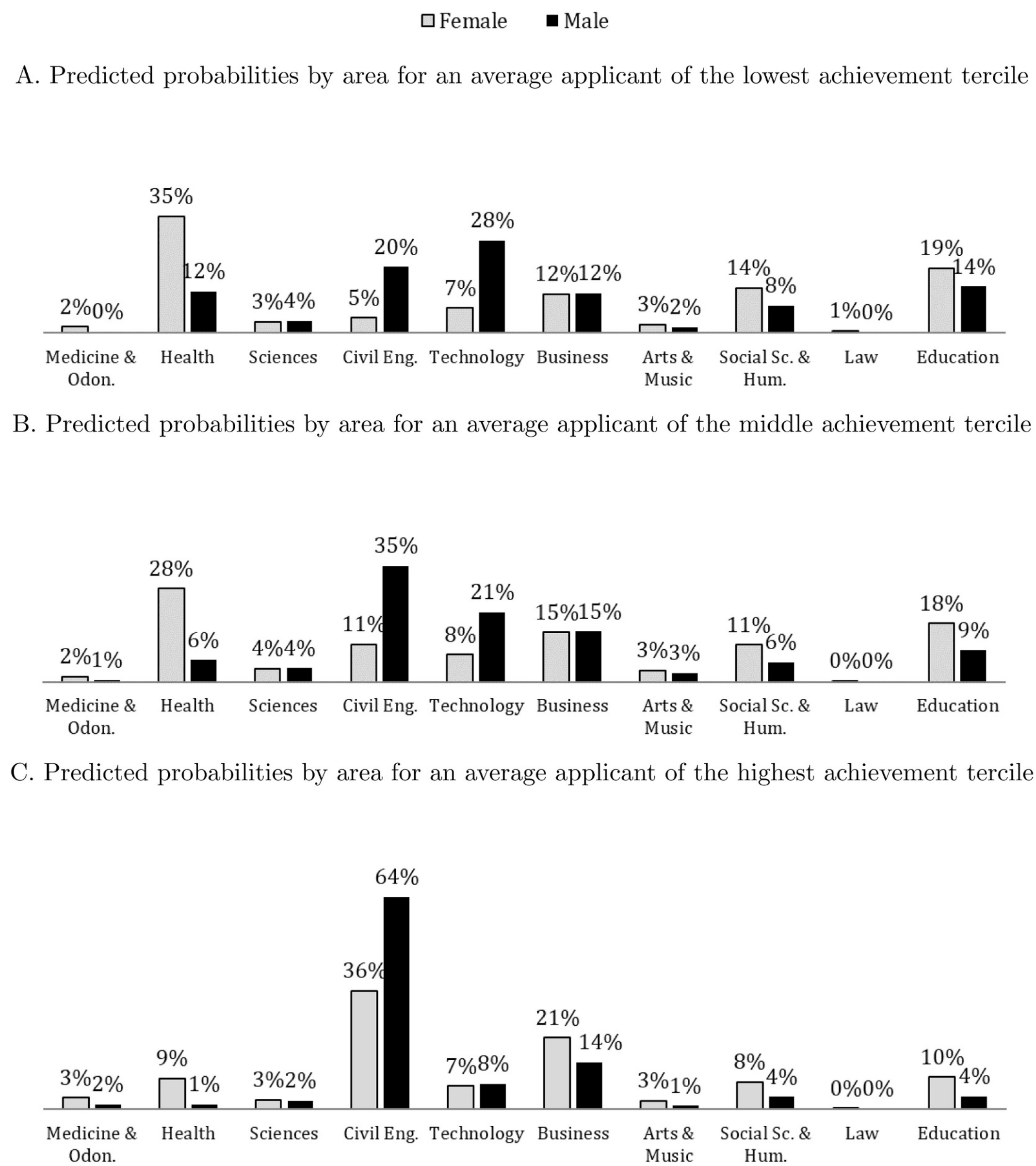

Fig. B.1. Predicted choice probabilities by area of study.

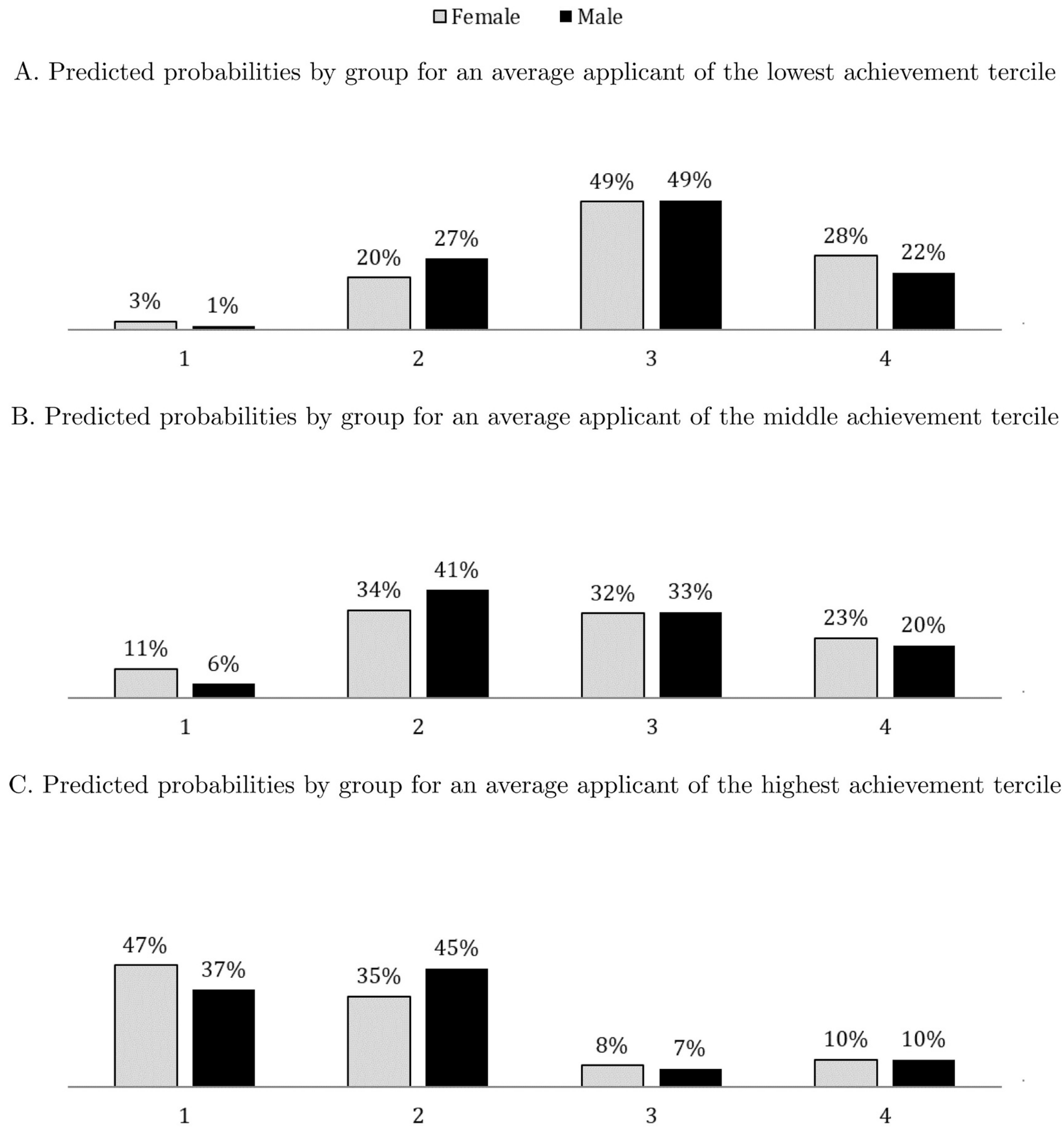

Fig. B.2. Predicted choice probabilities by university group.

Appendix C. Gender Differences in PSU Scores

Fig. C.1 shows that female students tend to have lower math and sciences PSU Scores than male students.

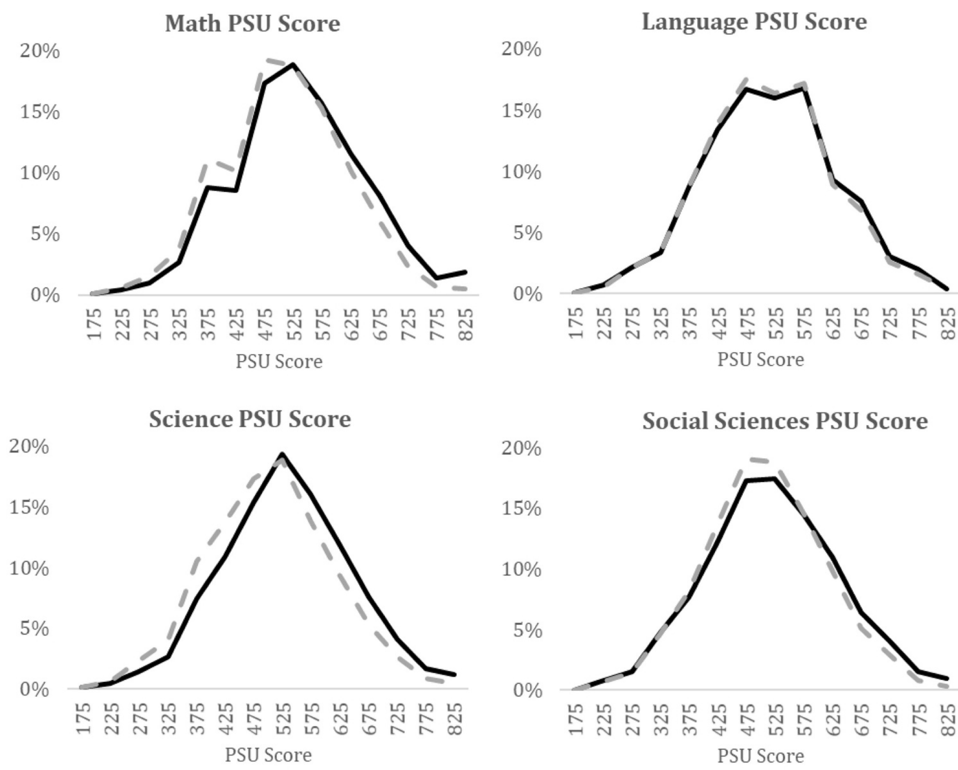

Fig. C.1. PSU Scores for the Admission Process of 2015.

Appendix D. PSU Scores by Area

As can be seen in Table D.1, medicine and odontology is the area with the highest average of PSU scores in language, math and science. Civil engineering is the area with the second highest average of math PSU scores. Law is the area with the highest social sciences PSU scores and the area with the second highest average PSU score in language.

Table D.1
Average of PSU Scores by area.

Area	Language	Math	Social Sciences	Science
Medicine & Odon.	667.7	686.3	614.0	691.7
Health	585.0	587.4	542.6	583.5
Sciences	588.3	611.9	562.2	601.9
Civil engineering	581.8	630.1	558.8	583.1
Technology	577.1	614.1	553.8	581.0
Business	576.3	603.8	578.9	546.3
Arts & Music	606.0	573.4	600.1	549.7
Social Sc. & Hum.	615.5	564.7	624.4	536.4
Law	634.4	576.9	658.6	540.2
Education	586.0	560.6	577.7	536.6

Note: PSU Scores have a normal distribution with a mean equal to 500 points and a maximum score of 850 points. Estimations only consider the students who applied through the Unique Admission System (SUA) in 2015.

Appendix E. Majors Applied to by Students with Outstanding Achievement

From Table E.1, in particular for the case of the areas related to mathematics (sciences, civil engineering, technology and business), we see that outstanding male students have a higher tendency than females to apply to Civil engineering, the most selective degree of these areas. The same phenomenon is observed for degrees related to science (sciences, health and medicine and odontology) and humanities (social sciences and humanities and law), in which outstanding male students apply more than females to medicine and odontology in the former case and law in the latter. However, in those two last cases the differences are lower.

Table E.1
Specific Majors Applied to by Students with Outstanding Achievement.

Students with at least 700 points on Math PSU test who applied to the areas of sciences, Civil engineering, technology or business		
	Male	Female
Civil Engineering	41%	24%
Economics or Administration[a]	12%	14%
Physics and/or Astronomy	1%	1%
Pedagogy in Mathematics	1%	1%
Biochemistry	0%	1%
Other	45%	59%
Students with at least 700 points on science PSU test and who applied to the areas of sciences, medicine & odontology or health		
	Male	Female
Medicine	71%	69%
Nursing	2%	8%
Odontology	5%	7%
Biochemistry	2%	2%
Medical Technology	3%	2%
Other	17%	13%
Students with at least 700 points on social sciences and/or language PSU test who applied to the areas of social sciences and humanities or Law		
	Male	Female
Law	21%	18%
Psychology	4%	7%
Journalism	2%	3%
Literature	1%	2%
Sociology	2%	2%
Other	71%	68%

[a] In Chile this mayor is called “Ingenieria Comercial”.
Estimations only consider the students who applied through the Unique Admission System (SUA) in 2015.

Appendix F. Average PSU scores of Science and Social Sciences by Counterfactual Scenario

Figs. F.1 and F.2 show the distribution of math and language PSU scores in the different counterfactual scenarios.

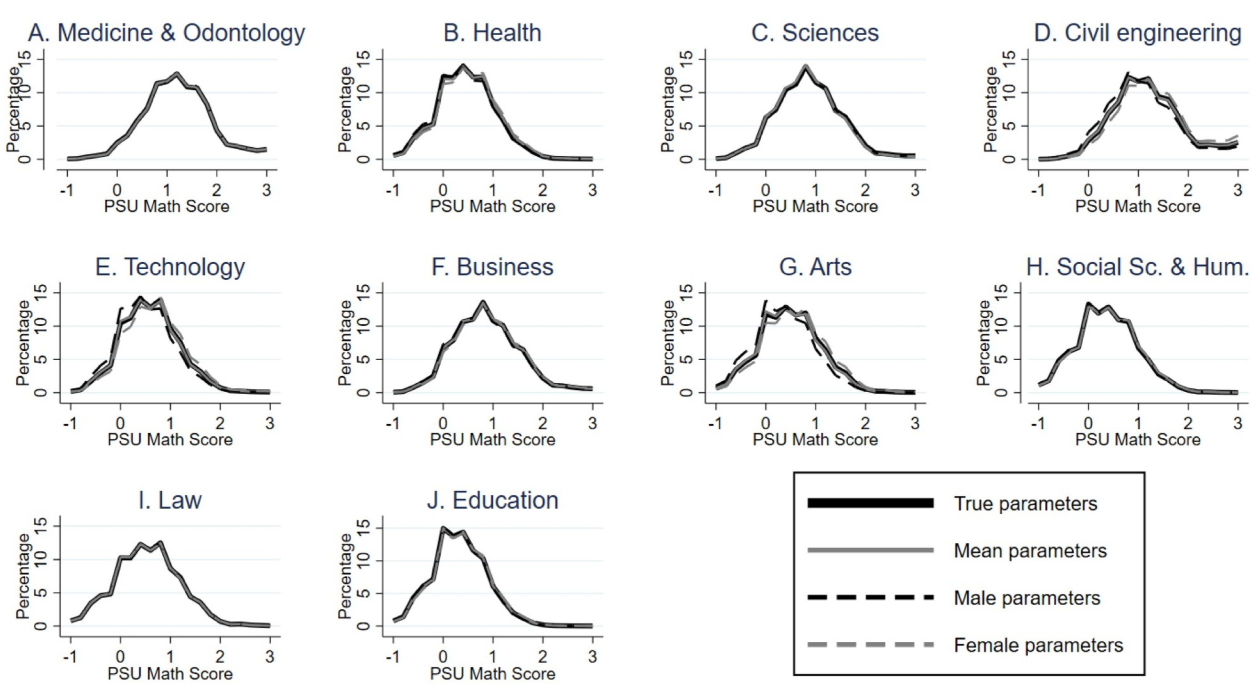

Fig. F.1. Distribution of Mathematics PSU Scores by Area of Study for the Counterfactual Exercises.

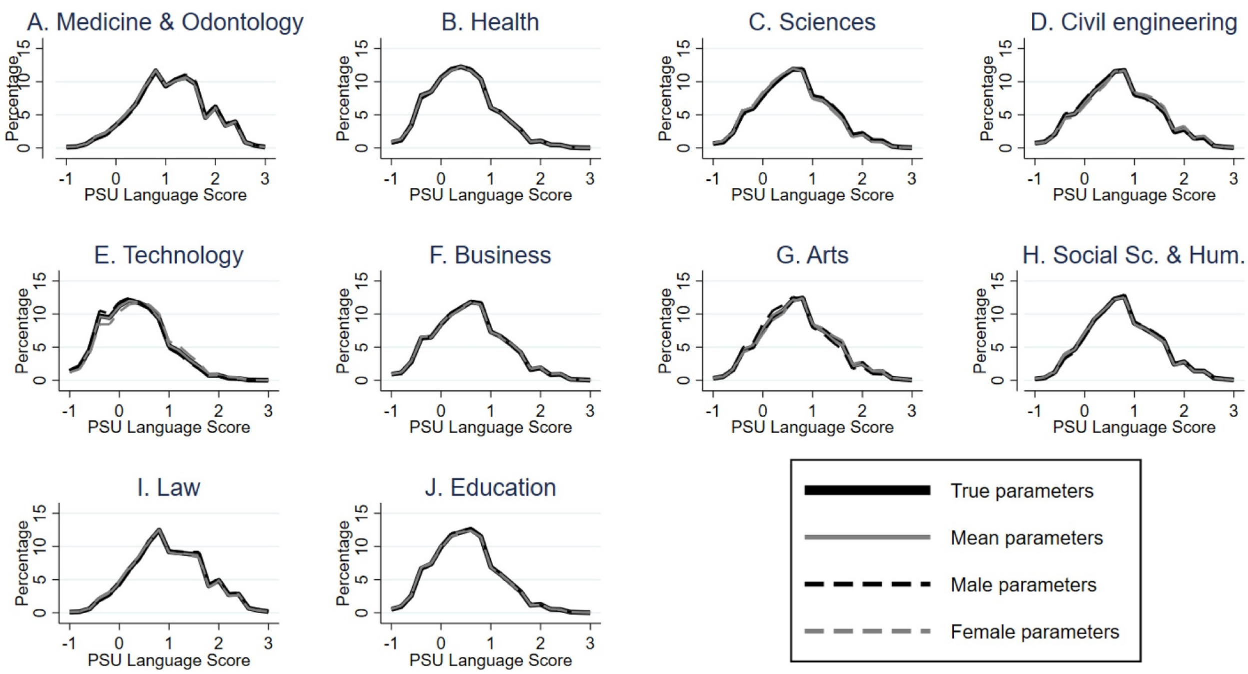

Fig. F.2. Distribution of Language PSU Scores by Area of Study for the Counterfactual Exercises.

Table F.1
Average PSU Scores.

Area	True Par.	Female Par.	Male Par.	Mean Par.
		Science		
Medicine & Odon.	1.31	1.28	1.38	1.32
Health	0.39	0.41	0.45	0.43
Sciences	0.69	0.64	0.72	0.67
Civil engineering	0.72	0.84	0.59	0.72
Technology	−0.15	0.17	−0.38	−0.06
Area		**Social Sciences**		
Business	−0.62	−0.83	−0.48	−0.70
Arts & Music	0.31	0.47	0.02	0.26
Social Sc. & Hum.	0.66	0.63	0.72	0.66
Law	1.29	1.25	1.32	1.28
Education	−0.42	−0.31	−0.65	−0.50

Note: Scores were standardized. Columns show the parameters of each counterfactual.

Appendix G. Robustness of Results by Different University Groups

To analyze the robustness of our analysis we replicated our estimations using 2 different university grouping. We first aggregate universities in four groups by their years of accreditation, and then based on prices (tuition fees). Table G.1 shows the average characteristics of each group of universities, based on different groupings. In the following, we present the results in both cases.

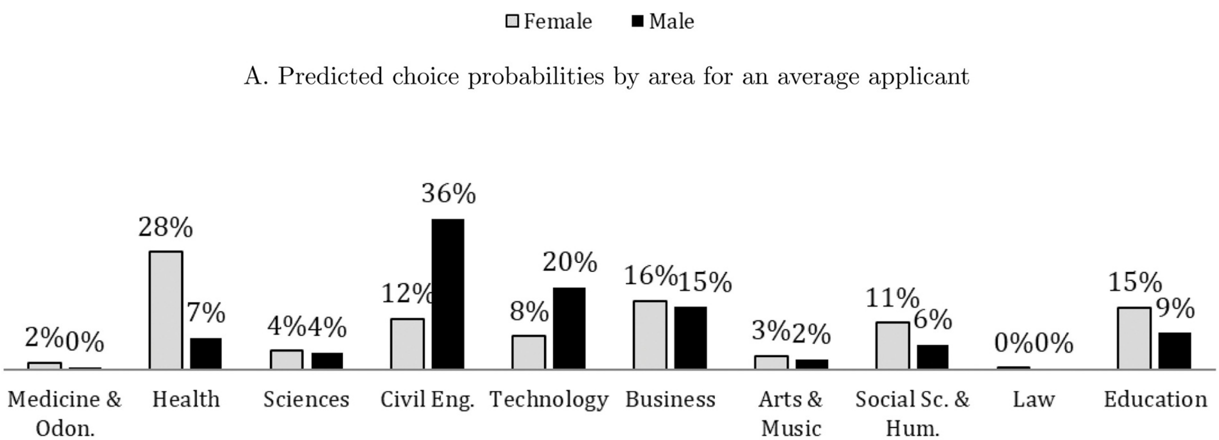

Fig. G.1. Predicted Choice Probabilities for an Average Applicant (estimation made using university grouping based on years of accreditation).

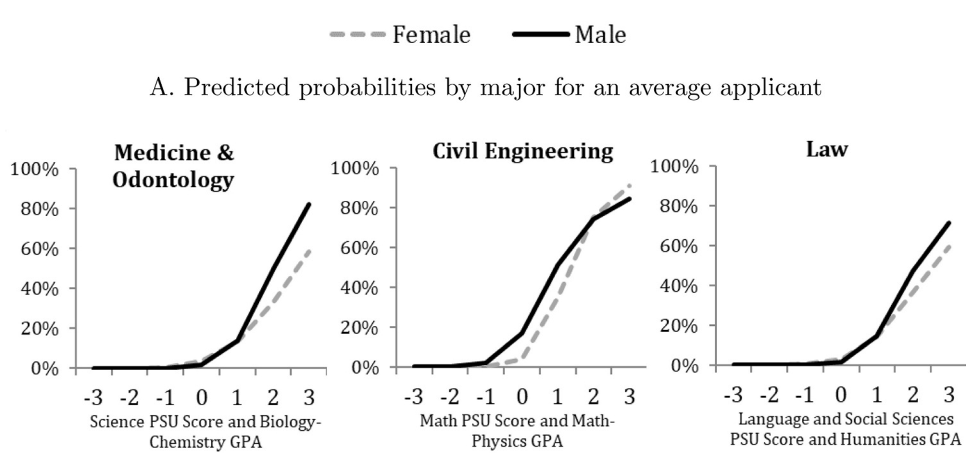

Fig. G.2. Predicted Probabilities of the Most Selective Major for an Average Applicant by Previous Achievement Measured by GPA and PSU Scores (estimation made using university grouping based on years of accreditation). Note: Predictions made using average values for all variables except gender, PSU score and GPA for the corresponding area.

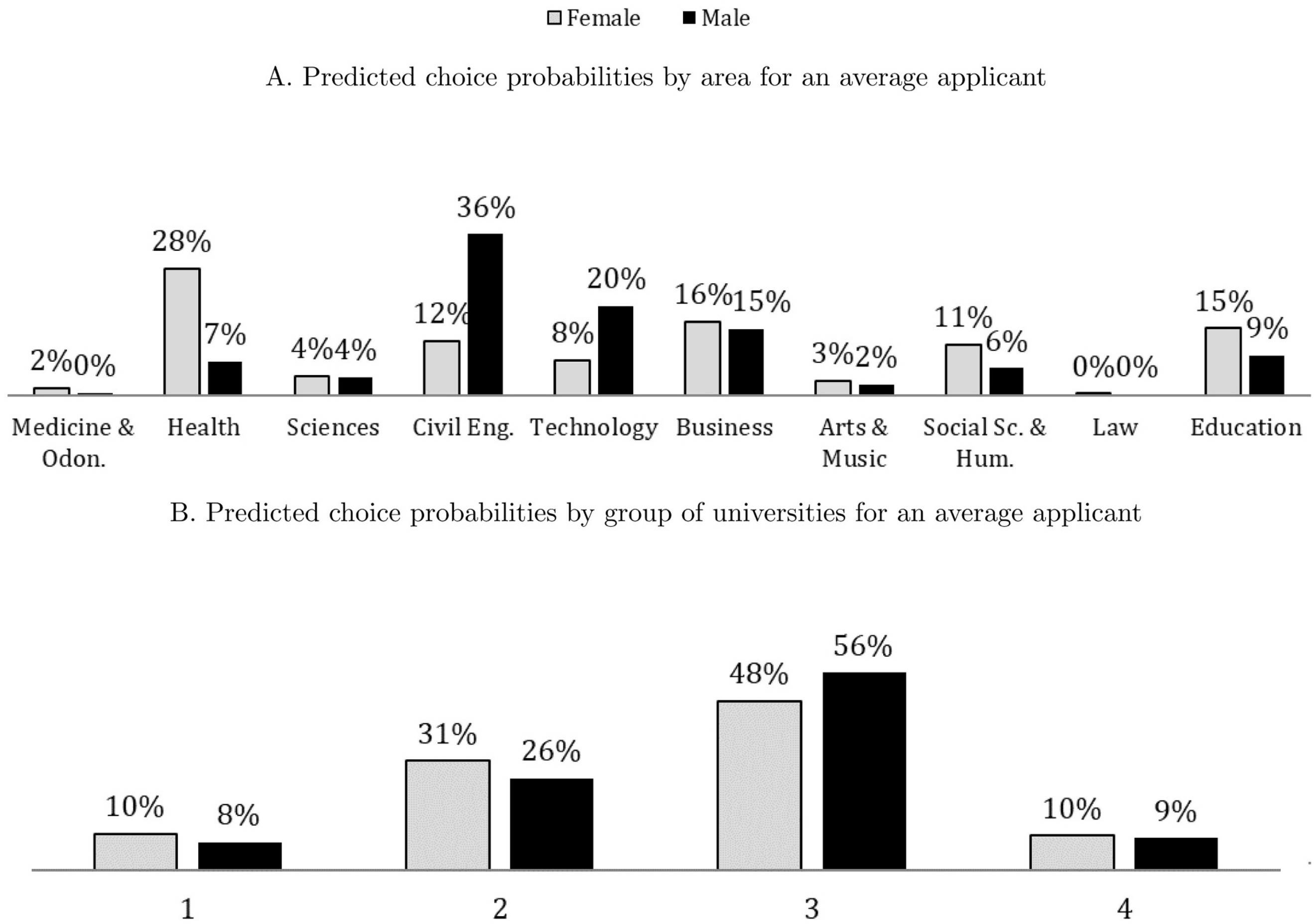

Fig. G.3. Predicted Choice Probabilities for an Average Applicant (estimation made using university grouping based on price).

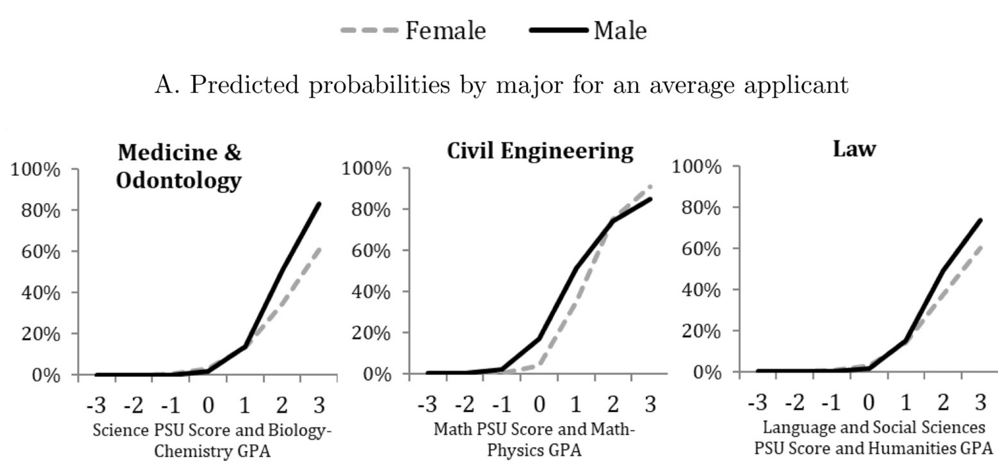

Fig. G.4. Predicted Probabilities of the Most Selective Major for an Average Applicant by Previous Achievement Measured by GPA and PSU Scores (estimation made using university grouping based on price). Note: Predictions made using average values for all variables except gender, PSU score and GPA for the corresponding area.

Table G.1
Universities Characteristics by Different Grouping.

Grouping	Group number	Number of universities	Application score (2014)		Years of accreditation (Dec. 2014)		Price (Millions CLP 2015)		Proportion of Traditional universities
			Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Selectiveness & Tradition (original)	1	2	699.2	4.7	7	0	4	0.2	1
	2	7	623.7	18.1	5.7	0.8	2.6	0.3	1
	3	16	577.2	19.3	4.2	1	2.1	0.3	1
	4	8	606.9	34.3	5	0.5	3.2	0.9	0
Years of accreditation	1	3	675.7	40.9	7	0	3.7	0.5	1
	2	5	625.8	27.5	6	0	3	0.9	0.8
	3	14	601.9	25.2	5	0	2.6	0.7	0.57
	4	11	570.2	17.8	3.6	0.7	2.1	0.5	0.91
Prices (tuition fees)	1	3	652.5	52	6	1	4.3	0.2	0.33
	2	5	626.1	53.1	5.6	1.3	3.4	0.3	0.4
	3	18	598.1	27.1	4.9	0.8	2.4	0.2	0.89
	4	7	571.7	16.4	3.9	1.1	1.8	0.2	0.88

Estimation results

Tables G.2–G.7 show the average marginal effects by area of study, for all students, females and males according to our university grouping. The results show that the main effects described in the article are robust, independent of the grouping of universities considered. Indeed, using years of accreditation or prices, almost all average marginal effects in major choice have differences lower than 1% with the original estimation.

Table G.8 shows the average marginal effects by university group, and again, most effects described in the main article remain, independent of the universities grouping. Using years of accreditation, all marginal effects in program choice have an equal or higher magnitude than in the original model. These changes, in most cases are lower than 1% with the original estimation, except one: for all students and males the quadratic effect of difference of score has a higher magnitude than in the original estimation.

Using the criterion of prices, almost all average marginal effect in university choice also have differences lower than 1% with the original estimation, but, for all students and male, the effect of the difference of the score has a lower magnitude than in the original estimation.

Table G.2
Average Marginal Effects by Area of Study (all students, estimation made using university groups based on accreditation years) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	2.1%	14.8%	−0.5%	−14.0%	−7.7%	−0.6%	0.7%	2.4%	−0.1%	2.9%
Parent's area same sex	3.1%	2.5%	0.3%	1.2%	0.2%	1.6%	0.2%	1.7%	3.4%	0.4%
Parent's area different sex	3.1%	1.6%	0.5%	−0.2%	−0.4%	0.7%	1.2%	0.6%	2.1%	1.2%
Female high school class	0.3%	2.6%	−0.6%	−1.4%	0.1%	−1.7%	0.2%	−0.02%	−0.7%	1.1%
Mixed high school class	0.3%	1.9%	−0.7%	−0.5%	−0.1%	−1.0%	0.3%	−0.2%	−0.5%	0.6%
High school ranking	2.6%	−1.5%	−0.01%	1.1%	−1.3%	−0.9%	0.5%	−0.5%	−0.1%	0.1%
Language PSU Score	1.3%	0.4%	0.2%	−3.0%	−2.1%	−3.6%	0.7%	4.2%	0.6%	1.2%
Math PSU Score	−3.9%	−12.0%	−0.01%	16.1%	0.3%	7.4%	−0.2%	−4.7%	−2.9%	−0.1%
Science PSU Score	7.6%	3.5%	0.4%	−2.7%	−1.2%	−2.3%	−0.6%	−2.0%	−0.8%	−2.1%
Social Sciences PSU Score	−0.5%	−2.2%	−0.2%	−0.9%	−0.5%	−0.1%	−0.4%	0.2%	5.6%	−1.1%
Biology-Chemistry GPA	2.4%	4.2%	0.5%	−4.1%	−0.2%	−0.9%	−0.3%	−0.9%	0.1%	−0.8%
Math-Physics GPA	−2.0%	−5.0%	−0.03%	7.4%	0.9%	2.3%	−0.6%	−1.8%	−0.4%	−0.9%
Arts-Music GPA	−0.2%	0.5%	−0.1%	−0.5%	0.04%	−0.1%	0.6%	−0.2%	−0.1%	0.1%
Humanities GPA	1.0%	1.0%	−0.4%	−2.5%	−1.0%	−1.0%	−0.5%	2.8%	1.1%	−0.4%
Per capita income	0.2%	−0.2%	−0.02%	0.4%	−0.3%	0.3%	0.3%	0.4%	0.1%	−1.0%
Private subsidized high school	0.7%	−0.3%	0.1%	−0.7%	−0.6%	0.9%	0.1%	−0.4%	0.6%	−0.4%
Private paid high school	0.9%	−1.7%	0.5%	−3.4%	−1.8%	5.6%	1.3%	0.3%	2.1%	−3.7%

All coefficients are statistically significant at a 99% confidence level, except the effect of Math PSU Score on Science which is significant at 95% confidence level.
Estimations have fixed effects by region.

Table G.3
Average Marginal Effects by Area of Study (females, estimation made using university groups based on accreditation years) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	3.6%	2.6%	0.1%	−1.0%	0.1%	1.3%	1.2%	1.6%	3.9%	0.1%
Parent's area different sex	4.0%	0.3%	1.1%	0.6%	−0.02%	0.2%	1.1%	−0.1%	1.9%	1.6%
Female high school class	1.1%	4.5%	−0.3%	−3.5%	−0.7%	−1.1%	−0.3%	0.2%	−0.2%	0.3%
Mixed high school class	1.3%	4.4%	−0.4%	−3.0%	−0.9%	−0.4%	−0.1%	−0.3%	−0.2%	−0.3%
High school ranking	3.3%	−2.5%	−0.2%	0.8%	−0.8%	−0.4%	0.6%	−0.8%	−0.1%	0.05%
Language PSU Score	1.6%	−0.3%	−0.04%	−2.7%	−1.1%	−3.0%	0.6%	3.9%	0.3%	0.7%
Math PSU Score	−2.7%	−13.7%	0.5%	13.5%	1.4%	7.7%	0.3%	−4.9%	−2.7%	0.6%
Science PSU Score	7.2%	3.7%	0.1%	−1.9%	−0.6%	−2.1%	−0.8%	−2.5%	−0.9%	−2.7%
Social Sciences PSU Score	−0.6%	−3.2%	−0.3%	−0.3%	−0.1%	−0.2%	−0.3%	0.3%	6.0%	−1.3%
Biology-Chemistry GPA	2.1%	5.1%	0.3%	−3.9%	0.02%	−1.2%	−0.4%	−1.1%	0.3%	−1.1%
Math-Physics GPA	−1.6%	−5.4%	0.2%	6.4%	0.8%	2.8%	−0.6%	−1.5%	−0.1%	−1.0%
Arts-Music GPA	−0.2%	0.6%	−0.1%	0.04%	−0.2%	−0.2%	0.6%	−0.3%	−0.1%	−0.01%
Humanities GPA	0.4%	0.9%	−0.5%	−1.7%	−0.6%	−1.5%	−0.8%	3.5%	0.7%	−0.3%
Per capita income	0.3%	−0.1%	−0.3%	0.00%	−0.01%	0.03%	0.5%	0.7%	−0.1%	−1.1%
Private subsidized high school	0.3%	0.4%	0.3%	−0.4%	−0.7%	0.2%	−0.2%	−0.01%	0.7%	−0.7%
Private paid high school	0.7%	−1.2%	0.7%	−3.5%	−2.0%	3.5%	1.8%	1.5%	2.1%	−3.5%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table G.4
Average Marginal Effects by Area of Study (males, estimation made using university groups based on accreditation years) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	2.8%	2.7%	0.6%	2.4%	0.3%	1.9%	−0.2%	1.6%	3.0%	1.1%
Parent's area different sex	2.1%	1.9%	−0.1%	−3.4%	−1.2%	1.3%	1.1%	1.1%	3.0%	1.0%
Female high school class	0.4%	2.4%	−0.7%	−1.2%	−0.05%	−1.3%	0.2%	−0.3%	−0.7%	1.2%
Mixed high school class	−0.1%	0.5%	−0.7%	0.3%	0.02%	−0.8%	0.1%	0.3%	−0.3%	0.7%
High school ranking	2.0%	−0.3%	0.2%	1.4%	−2.0%	−1.5%	0.4%	−0.2%	−0.1%	0.2%
Language PSU Score	1.2%	0.9%	0.5%	−3.2%	−3.2%	−4.3%	0.7%	4.5%	1.0%	1.9%
Math PSU Score	−5.2%	−10.7%	−0.7%	19.9%	−0.8%	7.1%	−0.9%	−4.4%	−3.1%	−1.2%
Science PSU Score	8.0%	4.3%	0.8%	−4.4%	−2.1%	−2.7%	−0.6%	−1.5%	−1.0%	−1.6%
Social Sciences PSU Score	−0.4%	−1.0%	−0.2%	−1.6%	−0.8%	−0.1%	−0.4%	0.1%	5.2%	−0.8%
Biology-Chemistry GPA	2.8%	3.1%	0.8%	−4.6%	−0.2%	−0.5%	−0.2%	−0.6%	−0.1%	−0.4%
Math-Physics GPA	−2.6%	−4.4%	−0.4%	8.8%	1.0%	1.6%	−0.5%	−1.9%	−0.8%	−0.9%
Arts-Music GPA	−0.3%	0.3%	−0.1%	−0.7%	0.3%	−0.1%	0.5%	−0.04%	−0.1%	0.2%
Humanities GPA	1.5%	1.1%	−0.3%	−3.2%	−1.4%	−0.4%	−0.2%	1.9%	1.4%	−0.5%
Per capita income	0.1%	−0.3%	0.2%	0.8%	−0.7%	0.5%	0.2%	0.03%	0.2%	−1.0%
Private subsidized high school	1.0%	−1.0%	−0.1%	−0.9%	−0.5%	1.6%	0.4%	−0.8%	0.5%	0.01%
Private paid high school	1.1%	−2.4%	0.2%	−3.1%	−1.6%	8.0%	0.5%	−1.0%	2.2%	−3.8%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table G.5
Average Marginal Effects by Area of Study (all students, estimation made using university groups based on prices) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Female	2.1%	14.8%	−0.5%	−14.0%	−7.7%	−0.6%	0.7%	2.4%	−0.1%	2.9%
Parent's area same sex	3.1%	2.5%	0.3%	1.3%	0.3%	1.6%	0.2%	1.7%	3.4%	0.5%
Parent's area different sex	3.1%	1.6%	0.5%	−0.3%	−0.4%	0.7%	1.2%	0.6%	2.1%	1.2%
Female high school class	0.3%	2.5%	−0.6%	−1.4%	0.1%	−1.7%	0.2%	0.03%	−0.7%	1.1%
Mixed high school class	0.2%	1.8%	−0.7%	−0.5%	−0.1%	−1.0%	0.3%	−0.1%	−0.5%	0.6%
High school ranking	2.7%	−1.4%	−0.04%	1.0%	−1.4%	−1.0%	0.5%	−0.5%	−0.02%	0.1%
Language PSU Score	1.4%	0.5%	0.2%	−3.0%	−2.1%	−3.7%	0.7%	4.2%	0.7%	1.2%
Math PSU Score	−3.7%	−11.9%	−0.05%	16.0%	0.2%	7.3%	−0.2%	−4.7%	−2.8%	−0.1%
Science PSU Score	7.8%	3.5%	0.4%	−2.8%	−1.2%	−2.3%	−0.6%	−2.0%	−0.7%	−2.1%
Social Sciences PSU Score	−0.5%	−2.2%	−0.2%	−0.9%	−0.5%	−0.1%	−0.4%	0.2%	5.6%	−1.1%
Biology-Chemistry GPA	2.5%	4.2%	0.5%	−4.2%	−0.2%	−0.9%	−0.3%	−0.9%	0.1%	−0.8%
Math-Physics GPA	−2.0%	−5.0%	−0.03%	7.4%	0.9%	2.3%	−0.6%	−1.8%	−0.4%	−0.9%
Arts-Music GPA	−0.2%	0.5%	−0.1%	−0.5%	0.03%	−0.2%	0.6%	−0.2%	−0.1%	0.1%
Humanities GPA	1.0%	1.0%	−0.4%	−2.5%	−1.0%	−1.0%	−0.5%	2.8%	1.1%	−0.4%
Per capita income	0.2%	−0.2%	−0.02%	0.4%	−0.3%	0.3%	0.3%	0.4%	0.1%	−1.0%
Private subsidized high school	0.7%	−0.3%	0.2%	−0.6%	−0.5%	0.9%	0.1%	−0.5%	0.6%	−0.4%
Private paid high school	0.9%	−1.6%	0.4%	−3.4%	−1.8%	5.6%	1.2%	0.2%	2.1%	−3.6%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table G.6
Average Marginal Effects by Area of Study (females, estimation made using university groups based on prices) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	3.5%	2.8%	0.04%	−1.0%	0.1%	1.2%	1.1%	1.6%	3.9%	0.1%
Parent's area different sex	3.9%	0.3%	1.1%	0.5%	−0.03%	0.2%	1.2%	−0.1%	1.8%	1.5%
Female high school class	1.1%	4.5%	−0.3%	−3.4%	−0.7%	−1.1%	−0.3%	0.1%	−0.2%	0.3%
Mixed high school class	1.3%	4.4%	−0.4%	−2.9%	−0.9%	−0.4%	−0.1%	−0.4%	−0.2%	−0.3%
High school ranking	3.2%	−2.3%	−0.2%	0.8%	−0.8%	−0.5%	0.6%	−0.8%	−0.03%	−0.04%
Language PSU Score	1.5%	−0.1%	−0.1%	−2.7%	−1.1%	−3.0%	0.6%	3.9%	0.3%	0.6%
Math PSU Score	−2.7%	−13.5%	0.5%	13.4%	1.4%	7.6%	0.3%	−4.9%	−2.7%	0.6%
Science PSU Score	7.4%	3.5%	0.1%	−1.9%	−0.6%	−2.1%	−0.7%	−2.3%	−0.7%	−2.6%
Social Sciences PSU Score	−0.6%	−3.2%	−0.3%	−0.3%	−0.1%	−0.2%	−0.3%	0.3%	6.0%	−1.3%
Biology-Chemistry GPA	2.1%	5.2%	0.3%	−3.9%	0.03%	−1.2%	−0.5%	−1.1%	0.3%	−1.1%
Math-Physics GPA	−1.5%	−5.4%	0.2%	6.4%	0.8%	2.8%	−0.6%	−1.6%	−0.1%	−1.0%
Arts-Music GPA	−0.2%	0.6%	−0.1%	0.03%	−0.2%	−0.2%	0.6%	−0.3%	−0.1%	0.03%
Humanities GPA	0.4%	0.9%	−0.5%	−1.7%	−0.6%	−1.6%	−0.8%	3.6%	0.6%	−0.3%
Per capita income	0.3%	−0.1%	−0.3%	0.01%	−0.01%	0.03%	0.5%	0.7%	−0.1%	−1.1%
Private subsidized high school	0.3%	0.4%	0.3%	−0.4%	−0.7%	0.3%	−0.2%	−0.04%	0.7%	−0.8%
Private paid high school	0.6%	−1.1%	0.6%	−3.5%	−2.0%	3.5%	1.8%	1.5%	2.1%	−3.5%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table G.7
Average Marginal Effects by Area of Study (males, estimation made using university groups based on prices) .

Variable	Medicine & Odon.	Health	Sciences	Civil Eng.	Technology	Business	Arts & Music	Social Sc. & Hum.	Law	Education
Parent's area same sex	2.8%	2.8%	0.6%	2.4%	0.3%	1.9%	−0.2%	1.7%	3.0%	1.1%
Parent's area different sex	2.0%	1.8%	−0.05%	−3.3%	−1.2%	1.4%	1.1%	1.1%	2.9%	1.0%
Female high school class	0.4%	2.4%	−0.7%	−1.2%	−0.1%	−1.3%	0.2%	−0.2%	−0.7%	1.2%
Mix high school class	−0.1%	0.5%	−0.7%	0.3%	0.1%	−0.8%	0.1%	0.3%	−0.3%	0.7%
High school ranking	2.2%	−0.2%	0.2%	1.1%	−2.1%	−1.6%	0.4%	−0.2%	0.03%	0.1%
Language PSU Score	1.3%	1.0%	0.5%	−3.3%	−3.3%	−4.4%	0.8%	4.4%	1.2%	1.9%
Math PSU Score	−4.9%	−10.7%	−0.8%	19.7%	−0.8%	7.0%	−0.9%	−4.3%	−3.1%	−1.2%
Sciences PSU Score	8.2%	4.3%	0.8%	−4.5%	−2.1%	−2.6%	−0.5%	−1.5%	−0.7%	−1.5%
Social Sciences PSU Score	−0.4%	−1.0%	−0.2%	−1.6%	−0.8%	−0.1%	−0.4%	0.1%	5.2%	−0.8%
Biology-Chemistry GPA	2.8%	3.1%	0.8%	−4.6%	−0.2%	−0.5%	−0.2%	−0.6%	−0.1%	−0.4%
Math-Physics GPA	−2.5%	−4.4%	−0.4%	8.9%	0.9%	1.6%	−0.5%	−1.9%	−0.8%	−0.9%
Arts-Music GPA	−0.3%	0.3%	−0.1%	−0.7%	0.3%	−0.1%	0.5%	−0.05%	−0.1%	0.2%
Humanities GPA	1.5%	1.1%	−0.3%	−3.2%	−1.4%	−0.3%	−0.2%	1.9%	1.4%	−0.4%
Per capita income	0.2%	−0.4%	0.2%	0.7%	−0.7%	0.5%	0.2%	0.03%	0.2%	−1.0%
Private subsidized high school	0.9%	−1.0%	−0.1%	−1.0%	−0.5%	1.6%	0.4%	−0.8%	0.5%	−0.02%
Private paid high school	1.1%	−2.3%	0.2%	−3.1%	−1.5%	7.8%	0.4%	−1.0%	2.2%	−3.8%

All coefficients are statistically significant at a 99% confidence level. Estimations have fixed effects by region.

Table G.8
Average Marginal Effects for Group. Estimations made using different university groups.

	Universities grouped based on years of accreditation			Universities grouped based on prices		
Variable	All students	Females	Males	All students	Females	Males
Difference of score	4.26%	3.92%	4.54%	2.77%	3.01%	2.61%
Difference of score^2	−2.39%	−2.17%	−2.62%	−1.12%	−1.28%	−0.99%
Program average score	5.28%	5.36%	5.23%	5.10%	5.11%	5.07%
% of regional vacancies of the program	0.03%	0.03%	0.02%	0.01%	0.02%	0.01%
Copayment	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
% Previous school generation of the group	0.02%	0.02%	0.02%	0.03%	0.03%	0.03%

All coefficients are statistically significant at a 99% confidence level.

Predicted choice probabilities

Predicted choice probabilities of major applications are very similar between these two models and the original one. Figs. G.1A and G.2 A show the predicted probabilities of an average student of applying to different majors, only varying their gender, using different criteria of university grouping. Although there is some difference in magnitude, the predictions follow the same pattern that we found in the estimations made with the original 4 groups of universities. In the same sense, Fig. G.2 and G.4 show the probability of application to the most selective areas (medicine and odontology, civil engineering and law), depending on the PSU score and GPA of a related subject, and the pattern is almost the same as that observed in the original estimation.

Figs. G.1 B and G.2 B show the predicted probabilities of an average student of applying to different groups of universities, only varying their sex, using different universities grouping. In the first place, if we group universities based on accreditation years, we have the same pattern as in the main article: females and males have similar probabilities for application for groups 3 and 4 (not more than 3% of difference), females have higher probabilities than males of applying to group 1, but less to group 2. Also, if we group universities based on prices, females and males have similar application probabilities for groups 1 and 4, females have higher probabilities than males of applying to group 2, but less to group 3. Note that in all cases the higher gender gap is in the group which includes some universities that are prominent in civil engineering and technology areas (group 2 in the original grouping, group 2 in the grouping based on years of accreditation and group 3 based on prices), traditionally male fields.

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