Does the Gender Ratio at Colleges Affect High School Students' College Choices?*

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Abstract

Since STEM fields in colleges are male-dominated, female students may choose not to enter them to avoid being a minority. Using an incentivized discrete choice experiment, we study whether the gender ratio at colleges affects high school students' college choices and whether the low female share in STEM contributes to talent misallocation. We show that the gender ratio at colleges affects both female and male students' college choices: they prefer gender-balanced programs over those with a male or female majority, and prefer being a majority over a minority. Students avoid being a minority mainly because they expect it to be difficult to fit into such environments. Because of these preferences, the low female share in STEM decreases female students' STEM choice probabilities, especially among those with high mathematics ability, and leads to male students with low mathematics ability crowding out female students with high mathematics ability. These preferences and the resulting talent misallocation provide an additional rationale for policies to close the gender gap in STEM.

JEL Classification: J16, J24, I24

Keywords: STEM Gender Gap, College Choice, Gender Ratio, Preference Elicitation, Discrete Choice Experiment

1 Introduction

Although female and male students perform equally well in mathematics and sciences at age 15 in OECD countries (OECD 2019), female students are less likely to major in Science, Technology, Engineering, and Mathematics (STEM) at colleges (OECD 2018). This situation causes several social issues, such as suboptimal allocation of talent, gender-biased research topics (Truffa and Wong 2025), and gender-biased product innovation (Einiö, Feng, and Jaravel 2025; Koning, Samila, and Ferguson 2021). It can also lead to the so-called "gender data gap," where men's data is primarily used to establish medical and industry safety standards, making medical treatments and industry tools less suitable for women (Perez 2019).

One potential reason that has received little attention in the literature is that STEM programs are predominantly male-dominated and thus make female students a gender minority.[1] As a result, female students may avoid such programs in anticipation of the disadvantages of being a minority. While several studies show the disadvantages of being a gender minority in the workplace and in graduate programs (Bostwick and Weinberg 2022; Cullen and Perez-Truglia 2023; Folke and Rickne 2022; Hampole, Truffa, and Wong 2024), few studies examine whether high school students anticipate these disadvantages and adjust their choices accordingly when choosing a college.

This paper studies whether the gender ratio at colleges affects high school students' college choices and whether the low female share in STEM contributes to talent misallocation. To answer these questions, we conduct an incentivized discrete choice experiment with students from high schools in Japan to elicit their preference over independently varied college program attributes, including the gender ratio, STEM or non-STEM, and program selectivity. We incentivize these choices using the incentivized resume rating method (Kessler, Low, and Sullivan 2019) by providing students with career advice tailored based on their choices.

We find that the gender ratio at colleges affects the college choices of both female and male students. Specifically, both female and male students prefer gender-balanced programs over male- or female-majority programs, and prefer programs where they will be a majority rather than a minority, especially female students. A decomposition of their choices reveals that both female and male students avoid being a minority mainly because they expect it to be difficult to fit into such environments. We also find that students' preferences for the gender ratio differ between STEM and non-STEM programs. In particular, female students in the top 50% of mathematics ability in the sample exhibit stronger avoidance of being a minority in STEM programs than in non-STEM programs. We do not find such heterogeneity for other female students. We also find that male students are generally less sensitive to the gender ratio in STEM programs than in non-STEM programs.

We then quantify the degree of talent misallocation due to the low female share in STEM programs by turning on and off students' preferences for the gender ratio. We find that the low female share reduces female students' STEM choice probabilities by 7.1 percentage points or 17.0%

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1. A notable exception is Ersoy and Speer (2025), who show that students consider non-job-related factors when choosing their college major, including student gender balance.

relative to the scenario where we turn off their gender preferences. For male students, the drop is 5.2 percentage points or 9.6%. The drop in STEM choice probabilities is especially pronounced among female students in the top 50% of mathematics ability – they reduce STEM choice probabilities by 8.8 percentage points, or 18.7%, due to their stronger avoidance of being a gender minority. For male students, the drop is more modest: 3.5 percentage points or 5.9%. As inferred from the larger drop in the STEM choice probabilities among female students, especially those among the top 50% in mathematics ability, we show that the low female share in STEM indeed leads to talent misallocation: it results in male students with an average mathematics score of 0.463 standard deviations below the median replacing female students with an average mathematics score of 0.544 standard deviations above median.

Taken together, our findings suggest that the gender ratio at colleges is an important determinant of high school students' college choices, and that the low female share in STEM programs contributes to the misallocation of talent.

Related Literature   Our paper contributes to several strands of literature. First, it contributes to the literature on the disadvantages of being a gender minority. Folke and Rickne (2022) find that women receive more sexual harassment in male-dominated jobs, which contributes to gender differences in occupational sorting. Interestingly, they find that men also receive more sexual harassment in female-dominated jobs. Similarly, Cullen and Perez-Truglia (2023) find that workers assigned to a manager of the opposite gender are less likely to get promoted due to less frequent social interactions. In educational settings, Bostwick and Weinberg (2022) find that female STEM PhD students are more likely to drop out of the program when assigned to a male-majority cohort. Hampole, Truffa, and Wong (2024) show that female MBA graduates are less likely to advance to senior management positions than their male counterparts when there are fewer female peers. Additionally, Karpowitz et al. (2024) show that female students in male-majority work teams in a college course have less influence in the team than male students. Shan (2024), on the other hand, finds that female students in introductory economics courses achieve lower grades when placed in female-only study groups. We add to this literature by showing that anticipation of these disadvantages is consequential for women's and men's college choices, constraining their choices for male- or female-dominated fields.

Second, our paper enriches and extends the emerging literature on preferences for gender balance in the workplace. Schuh (2024) finds that US workers, both women and men, but especially women, prefer gender diversity in the workplace, and such a preference leads to low female employment in male-dominated occupations that typically pay higher salaries. Similarly, Högn et al. (2025) find that German university students are willing to pay about 5% of their expected salary for a gender-diverse future workplace, and female students have a higher willingness to pay than male students. Further, Funk, Iriberri, and Savio (2024) show that MTurk workers prefer learning from gender diverse instructors. We add to these studies by showing that high school students also prefer gender balance at colleges and that the reason for avoiding being a gender minority is concern about

the difficulty of fitting into programs with a high opposite gender share.

Third, our study contributes to the literature on the differential effect of non-monetary factors on female and male students' major choices. Wiswall and Zafar (2018) show that women tend to prefer majors that lead to flexible and stable jobs, while men often choose majors associated with higher earnings. Corroborating this, Wiswall and Zafar (2021) show that women are more likely than men to consider future family formation when choosing their majors. Further, Ersoy and Speer (2025) show that providing non-job-related major information to students, including student gender composition, changes their major choices. We build on these studies and show that the student gender ratio is indeed an important determinant of students' major choice, and avoiding a major dominated by the opposite gender can explain female students' low probability of choosing STEM majors.

Finally, our paper speaks to the literature on policies aimed at closing the gender gap in STEM. The most prominent policy so far is role model intervention, where we expose students to successful female STEM professionals (Breda et al. 2023; Carrell, Page, and West 2010; Riise, Willage, and Willén 2022; Riley 2024).[2] Another policy involves changing pedagogical practices, either by making the learning process more interactive (Di Tommaso et al. 2024) or by teaching the societal relevance of the discipline (Long and Takahashi 2025).[3] Our findings suggest that we can justify these policies solely on the efficiency basis, without resorting to diversity, equity, and inclusion (DEI) arguments. In particular, while affirmative action is often criticized for not benefiting the underrepresented minority students because they are less academically prepared than majority students (e.g., Arcidiacono and Lovenheim 2016; Arcidiacono, Aucejo, and Hotz 2016), this is not the case for female students in STEM; rather, it is quite the opposite.[4]

The remainder of the paper is structured as follows. Section 2 explains the institutional background. Section 3 details the experimental design. Section 4 describes the summary statistics of the experimental data. Section 5 presents the main results. Section 6 quantifies the degree of talent misallocation. Section 7 concludes.

2 Institutional Background

High School In Japan, high school runs from grades 10 to 12, typically from age 15 to 18. Although it is not compulsory, nearly 99% of junior high school graduates attend it (Ministry of Education, Culture, Sports, Science and Technology 2021). College enrollment rates are also high, at nearly 60%.[5] However, just like in the US, many colleges are essentially vocational schools in Europe, and only a handful of top colleges are academically oriented. We call the former non-selective colleges and the latter selective colleges. Also, because the Science, Technology, Engineering, and

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2. Porter and Serra (2020) show the effectiveness of female role models in inspiring female college students to pursue an economics major.

3. Avery et al. (2024) and Owen and Hagstrom (2021) also find similar results in economics curricula.

4. While not in education, Besley et al. (2017) show that a gender quota for candidates in a Swedish political party improved the politicians' competences. We expect the same for women in STEM in higher education.

5. As of 2023: https://www.ipss.go.jp/syoushika/tohkei/Data/Popular2024/T11-03.htm (accessed June 9, 2025).

Mathematics (STEM) fields require strong mathematical skills, most STEM programs are offered at selective colleges. As such, only academic high schools can prepare students for selective colleges or STEM programs.

Students at academic high schools choose a track at the end of grade 10, which determines the subjects they study in grades 11 and 12. There are two tracks: humanities and sciences. In the humanities track, students study advanced reading (advanced Japanese), English, history/social studies, and mathematics. In the sciences track, students study reading (Japanese), English, sciences (biology, chemistry, and/or physics), and advanced mathematics.

A similar track system exists in other countries as well, such as Italy, where students choose their track between humanities and sciences at the end of grade 9 (see, for example, Carlana and Corno 2022), France, where students choose their track between humanities, social sciences, and sciences at the end of grade 10 (see, for example, Breda et al. 2023), and the Netherlands, where students in academic secondary schools (VMBO) choose their track between science, health, social sciences, and humanities at the end of grade 9 (see, for example, Buser, Niederle, and Oosterbeek 2014).

Students in these academic high schools regularly take mock exams to prepare for college entrance exams. On the score reports for these mock exams, students can see the likelihood of admission to their preferred programs, calculated based on their exam scores and the program's selectivity, which they use to make and adjust their study plan. To help students select their preferred programs, almost all academic high schools have a school counselor room where students can read information about each program, including selectivity, gender ratio, and other attributes used in this paper's experiment.

College Application   Like in Europe but unlike in the US (Bordon and Fu 2015), students apply to specific college programs and cannot change their majors later. Programs differ in their attributes, such as major, selectivity, tuition, whether they are public or private, and location, among others. Since living alone can be costly and some parents prefer their children not to live alone, many college students live with their parents. Among various locations in Japan, the greater Tokyo area offers the greatest variety of college attributes: nearly 29% of all colleges are located there, where about 41% of all college students study.[6]

Most programs employ an exam-based, meritocratic admissions system. They rank applicants by exam score and make offers from the top of the list. However, each program requires exams in different subjects. Humanities and social sciences programs usually require exams in advanced reading, English, history/social studies, and mathematics. On the other hand, science, engineering, and medicine programs typically require exams in advanced mathematics, English, sciences, and reading. Since students who choose the science track in high school do not study advanced readings and history/social studies, they cannot apply to humanities and social sciences programs. Similarly, students who choose the humanities track in high school do not study advanced mathematics and

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6. From an article by an educational materials and news publishing company Obunsha: https://eic.obunsha.co.jp/file/educational_info/2024/1022.pdf (accessed July 31, 2025).

sciences, so they cannot apply to science, engineering, and medicine programs. In this way, high school track choice determines the set of college majors students can realistically pursue.

Each college program is assigned a single number called the "selectivity index" by commercial college entrance exam preparation companies. The index represents the difficulty of entering and the selectivity of the program and is calculated based on admitted students' mock exam performance. The index is expressed as a z-score modified to have a mean of 50 and a standard deviation of 10.

Job Search The Japanese labor market is known for its rigidity and very limited job mobility (Moriguchi 2014). On-the-job training is common, and workers accumulate non-transferable skills, often remaining with the same company throughout their careers. Although the labor market has been gradually evolving and the job separation rate has been rising, especially among young workers (Kambayashi and Kato 2017), it is still typical for individuals, particularly graduates from selective colleges considered in this study, to stay with one company for their entire career. Consequently, most students tend to stay in their first job after graduation and seldom switch jobs. As a result, the quality of the first job significantly affects their career prospects (Genda, Kondo, and Ohta 2010).[7]

Because of the rigidity and widespread norm of on-the-job training in the labor market, companies tend to place more emphasis on job seekers' potential rather than their college achievements, and the potential is measured by the selectivity index of the program they attended. In fact, the selectivity of a program from which a student graduates significantly affects their job search, both on the extensive and intensive margins. On the extensive margin, it is highly associated with the quality of jobs a student can get (Nakajima 2018). On the intensive margins, it is associated with the promotions in the first few years after starting the job (Araki, Kawaguchi, and Onozuka 2016). Therefore, entering a college program with a higher selectivity index is very important for high school students, as it determines their career prospects.

3   Experimental Design

To investigate whether the gender ratios at colleges affect high school students' college choices, we conducted an incentivized discrete choice experiment at four selective academic high schools in the greater Tokyo area in Japan. We integrated this experiment as a "career planning module" within the 10th-grade curriculum of the participating high schools from December 2023 to July 2024. The experiment was conducted in person at three high schools and asynchronously online at one high school.

The experiment lasted about 40 minutes on average, including distributing the participation gifts. A total of 628 students took part, with 619 providing valid responses (311 females, 298 males, 10 non-binaries). Since this study focuses on binary gender, we excluded responses from non-binary students, resulting in 609 responses with 15 observations each, for a total of 9135 observations.

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7. Genda, Kondo, and Ohta (2010) find that those who entered the labor market during the recession suffer worse employment conditions in terms of unemployment rate and earnings in Japan than in the US.

3.1 Sample Selection

Schools We contacted teachers at academic high schools in the greater Tokyo area through our network and obtained their consent to conduct the experiment as part of their school curriculum. We restricted our potential sample to academic high schools in the greater Tokyo area for three reasons. First, we wanted to ensure the experimental content was relevant to students: the experiment focused on college choices, and students needed to be planning to attend college. Based on the schools' placement records, over 95% of recent graduates attended college. Second, we wanted to include students whose mathematics skills did not constrain their major choices: as discussed in Section 2, most STEM programs require good mathematics abilities, and only students from academic high schools are prepared for STEM. Third, we wanted to prevent students from implicitly considering potential location and financial constraints when making their choices: as discussed in Section 2, the greater Tokyo area offers the widest variety of college programs, making such constraints less relevant there. We also wanted the attributes of the hypothetical college programs to appear natural to students, and the greater Tokyo area was suitable for this purpose as well.

Students The teachers at the participating high schools distributed the information letter and consent form to guardians of all 10th-grade students, except at one school where only one class participated. We restricted the sample to 10th-grade students before their track choice because the track choice restricted the college programs they could apply for, as discussed in Section 2. The information letter did not mention that the experiment was about gender ratios or STEM to minimize the experimenter demand. Instead, we explained that students would evaluate 15 hypothetical college programs, answer a short questionnaire, and receive a tailored career advice sheet based on their evaluations. We also clarified that the data from the experiment would be used for academic research to improve education policy. Nearly 90% of the guardians and students provided consent and participated.

3.2 Flow of the Experiment

Students were first told that they would receive a career advice sheet based on their choices in the experiment. We promised them that their responses and the career advice sheet would not be shared with anyone, including guardians, teachers, or peers, to minimize their potential influence, as previous studies suggest they can affect students' study choices (Carlana 2019; Carlana and Corno 2022; Giustinelli 2016; Müller 2024). Students then saw 15 program pairs one by one and chose one they wanted to attend; see Figure 1 for an example of a hypothetical program pair. Additionally, they saw four statements that many students consider important when choosing college programs, selected from open-ended questions in the pre-test. For each pair, students indicated which program each statement applied to better.

After making choices for the 15 program pairs, students completed a questionnaire about their demographics, academic abilities, behavioral traits, and beliefs about the gender ratios in average college programs in Japan. Appendix Section B presents the questionnaire. Afterward, students

Figure 1: Hypothetical Program Pair

Pair 4/15

	AB College	AX College
	Dept. of Literature	Dept. of Engineering
	Dept. Characteristics	
57.5	Selectivity index	62.5
700	Cohort size	600
35% male, 65% female	Student gender ratio	55% male, 45% female
	College Characteristics	
Yes	Intl exchange program	No
65%	Club participation rate	45%

Which program would you like to attend?

AB College, Dept. of Literature	AX College, Dept. of Engineering

Which program do you feel these statements apply to more?

	AB College, Dept. of Literature	AX College, Dept. of Engineering
I can do well in my studies	○	○
I can find a career I want to pursue	○	○
I can fit in	○	○
I can meet inspiring seniors	○	○

Notes: This figure shows an example of a hypothetical program pair students would see during the experiment.

received a participation gift (a set of cute, functional pens) equivalent to 500 JPY (approx. 5.27 USD in 2022 PPP) for their participation.[8]

Several weeks later, each student received a career advice sheet we created. The sheet had two

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8. USD to JPY PPP was 94.93 in 2022: https://www.oecd.org/en/data/indicators/purchasing-power-parities-ppp.html (accessed November 18, 2024).

parts: a tailored part and a non-tailored part. The tailored part included the top three attributes that students cared about most, along with the top reason they prioritized when choosing a college program, based on their choices in the hypothetical programs. The non-tailored part contained non-individualized information useful for most high school students, such as tips for choosing college programs, college admissions, financing, studying abroad, attending graduate school, and finding jobs.

3.3 Attributes

We randomly assigned attributes to each program, including college name, department, department selectivity index, department cohort size, department student gender ratio, whether the college has an international exchange program, and college club activity participation rate. Our main interests are (i) student gender ratio and (ii) department, which indicates whether the program is STEM or non-STEM. We included other attributes to make the programs appear more realistic to students and selected attribute value ranges that are plausible for students in our sample to reduce hypothetical bias (List and Shogren 1998; List, Sinha, and Taylor 2006). We asked them to assume that attributes not shown were identical between the programs.

College names consist of two alphabets and we draw them without replacement for each program in a pair from a list ranging from AA to BD to make sure they were unrelated to the actual college names. The department was drawn from a list of 12 popular departments among college students, where 6 being STEM and 6 non-STEM. First, we randomly assigned either STEM or non-STEM to one program in the pair. If STEM was selected, then the other program was assigned non-STEM with 75% probability and STEM with 25% probability to reduce the chances that both programs are in the same category. Next, we selected a specific department within the relevant list. STEM departments included Physics, Chemistry, Biology, Engineering, Information Technology, and Agriculture. Non-STEM departments included Literature, Law, Business, Economics, Sociology, and Foreign Language. We excluded Medicine and Education, as both are popular but lead to specialized careers such as doctors, nurses, pharmacists, and teachers, which differ from most student career paths, and the attributes used may not be very relevant for these programs.

Other attributes include selectivity index, which ranges from 55 to 72.5 with an increment of 2.5; cohort size, which varies from 200 to 900 with an increment of 50; student gender ratio, which spans from 5% to 95% for females and males but sums to 100%; whether the college has an international exchange program, which has an 80% chance of being "Yes" and a 20% chance of being "No"; and club participation rate, which ranges from 40% to 85% with an increment of 5%.[9] These attribute values were drawn with replacement for each program. Appendix Table A1 shows the possible values for each attribute.

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9. We set the probability that a program has an international exchange program to 80% because most colleges in Japan have one.

3.4 Incentives

We used a hypothetical choice experiment because it allowed us to elicit students' preferences over attributes that were varied independently. This was crucial for our study, as there are only a few STEM programs where female students are the minority, and using actual college names would lead students to infer attributes not shown to them.

One concern with hypothetical choice experiments is that students may lack incentives to state their true preferences without real consequences. Although Hainmueller, Hangartner, and Yamamoto (2015) shows that choices in hypothetical vignettes and actual behaviors are highly correlated, we addressed this concern by incentivizing the choices using the incentivized resume rating method (Kessler, Low, and Sullivan 2019), which involves providing career advice based on their choices. Assuming students believed that we experimenters had new information potentially valuable to them, it is incentive compatible: the expected value of the advice increases with the truthfulness of their choices. Because the students were from academic high schools interested in attending selective colleges, we assume most believed the experimenters had valuable academic and career information.[10] Several studies employed the incentivized resume rating method to elicit preferences for attributes that are hard to elicit from revealed preferences (Chan 2024; Gallen and Wasserman 2023; Macchi 2023).[11]

Specifically, we provided the following information in the information letter and at the beginning of the experimental instructions, which closely followed the original incentivized resume rating studies (Kessler, Low, and Sullivan 2019; Low 2024):

> *Through this module we will give you information relevant for your career choice. You will complete it on the internet using a laptop or a tablet. It is expected to last for 25 minutes and consists of two parts:*
>
> - *Evaluation of the hypothetical 15 program pairs*
> - *A short questionnaire*
>
> *We will send you a career advice sheet created based on your evaluation.*

As an additional check, we also compare predictions from the experimental data and students' actual track choices in Figure 2, and the data predicts 78.5% of the choices correctly. Note that because the predictions do not take into accounts for the constraints students face when they make choices, such as parents' and teachers' suggestions, they do not need to perfectly coincide with the actual choices. See Section 4 for further discussion on this point.

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10. At the time of the experiment, Inoue obtained a PhD from one of Japan's most prestigious colleges, Saito earned a master's degree in the US and has industry experience, and Takahashi earned a PhD from a European university

11. Low (2024) elicited heterosexual adults' preferences for dating partners by providing dating advice from a dating coach based on their ratings of hypothetical opposite-gender partner profiles. Macchi (2023) elicited loan officers' preferences for borrowers by offering referrals to loan clients based on their ratings of hypothetical borrower profiles. Gallen and Wasserman (2023) elicited college students' mentor preferences by providing mentor characteristics that students care most about. Chan (2024) elicited patients' preferences for doctors by offering booking options based on patients' choices.

4 Data

4.1 Variable Constructions

Academic Abilities We convert students' academic abilities, obtained through a post-experimental questionnaire, into population z-scores to make them comparable across schools and interpretable within the entire student pool. To do this, we use the latest placement records of graduates from each participating high school, assign the selectivity index to each college in the records, rank the placements by the selectivity index, and then assign the selectivity index to each student within a given high school based on their academic abilities in specific subjects (reading, mathematics, English, and total). The selectivity index for each program was obtained from the list prepared by Kawaijuku in 2024, one of the most popular commercial college exam preparation companies in Japan.[12] Since public colleges require a larger number of subjects in the entrance exam, we add 0.5 to the index of public colleges (which is 5 in the raw index), following Araki, Kawaguchi, and Onozuka (2016).

Behavioral Traits We elicited students' behavioral traits through a post-experimental questionnaire: confidence in reading, mathematics, and English, competitiveness, and risk-taking, all rated on a 5-point Likert scale with 3 being neutral.[13] For confidence questions, we asked how accurately their recent exam scores, entered on the previous page, reflected their ability. We convert these 5-point scales to the range [-1, 1] for better interpretability, with 0 being neutral.

4.2 Summary Statistics

Table 1 presents summary statistics for 311 female and 298 male students in the final sample (totaling 609 students), along with their differences. Panel A presents students' demographics and indicates no differences in parents' education levels or parental investments (proxied by extra schooling days per week) between female and male students. Panel B presents students' academic abilities and shows that female students outperform males in reading and English, while males excel in mathematics, and females have a slight edge in overall scores.[14] However, as expected, our sample students perform approximately 0.6 to 0.7 standard deviations above the average Japanese high school student. Panel C presents students' behavioral traits, showing that male students are more confident in their mathematics and English abilities and are less risk-averse than female students, consistent with existing literature on gender differences in preferences (Croson and Gneezy 2009). Although statistically insignificant, the gender difference in competitiveness is also consistent with existing literature, with male students more competitive than female students.

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12. https://www.keinet.ne.jp/exam/ranking/index.html (accessed December 18, 2024)

13. The questionnaire-based competitiveness measure was adapted from Buser, Niederle, and Oosterbeek (2024), and the risk-taking measure was adapted from Dohmen et al. (2011).

14. Appendix Figure A1 shows the distribution of abilities for female and male students.

Table 1: Summary Statistics of Students in the Final Sample

|	Female (N=311)		Male (N=298)		Difference (M − F)	
	Mean	SD	Mean	SD	Mean	SE
Panel A: Demographics						
Mother bachelor or above	0.59	0.49	0.56	0.50	-0.03	0.04
Father bachelor or above	0.80	0.40	0.77	0.42	-0.03	0.04
Both bachelor or above	0.50	0.50	0.48	0.50	-0.02	0.04
Extra schooling (no. days/week)	0.94	1.06	0.92	1.04	-0.02	0.09
Panel B: Academic abilities (population z-score)						
Reading score	0.82	0.74	0.59	0.75	-0.23***	0.06
Math score	0.65	0.75	0.77	0.75	0.12**	0.06
English score	0.82	0.69	0.58	0.78	-0.25***	0.06
Total score	0.71	0.74	0.61	0.76	-0.11*	0.06
Panel C: Behavioral traits						
Reading confidence [-1,1]	-0.01	0.39	0.05	0.49	0.06	0.04
Math confidence [-1,1]	-0.02	0.39	0.18	0.50	0.20***	0.04
English confidence [-1,1]	-0.00	0.40	0.10	0.45	0.10***	0.03
Competitiveness [-1,1]	0.03	0.67	0.11	0.68	0.08	0.05
Risk-taking [-1,1]	-0.36	0.61	-0.18	0.70	0.18***	0.05

Notes: This table presents summary statistics of 311 female and 298 male students in the final sample (609 students in total) as well as their differences. Significance levels: * 10%, ** 5%, and *** 1%.

4.3 Consistency with the Track Choice Data

Figure 2 compares the predicted STEM choices obtained from the mixed logit estimate in Section 6 and the actual track choices obtained from the schools.[15] We denote sciences track as STEM and humanities track as non-STEM. First, for students whose track choice data is available, the experimental data correctly predict 78.5% of the actual choices. Second, the data predict male students' choices more accurately (81.2%) than female students (75.6%), primarily due to predictions for STEM choices. Because the predictions do not take into accounts for the constraints students face when they make choices, such as parents' and teachers' suggestions and peers' influences, they do not need to perfectly coincide with the actual choices. Still, the fact that the data predict female students' STEM choices less accurately than track male students' STEM choices as well as female and male students' non-STEM choices seems to be consistent with that female students face stronger obstacles when choosing STEM as suggested by the literature (Carlana 2019; Carlana and Corno 2022; Giustinelli 2016).

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15. We requested schools for students' track choice data, and they provided the data for 446 students (73.5% of students for whom we have mixed logit estimates). The data is obtained either directly from the schools or through a follow up survey to students. The predicted STEM choice is defined as $\mathbb{1}[\hat{\beta}_i^{STEM} > 0]$ where $\hat{\beta}_i^{STEM}$ is mixed logit estimate for STEM dummy of student i.

Figure 2: Mixed Logit Prediction vs. Actual Track Choices
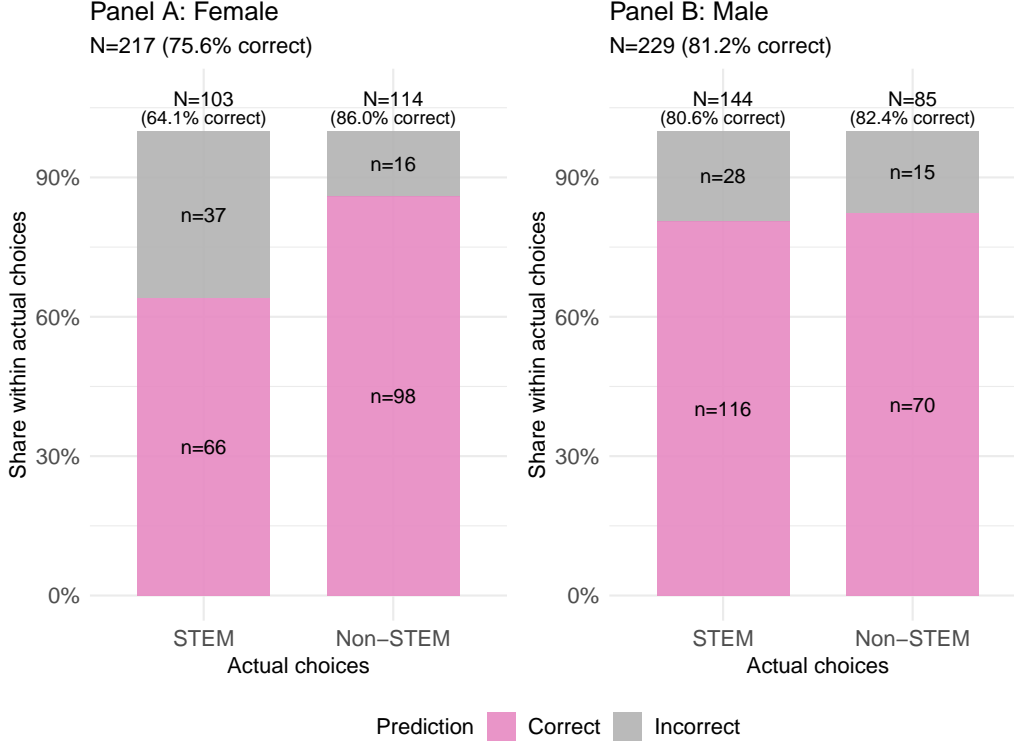
Notes: This figure compares the predicted STEM choices obtained from the mixed logit estimate in Section 6 and the actual track choices obtained from the schools. We denote sciences track as STEM and humanities track as non-STEM. Overall, the experimental data correctly predict 78.5% of the actual choices.

5 Results 1: The Gender Ratio at Colleges Affects High School Students' College Choices

5.1 Econometric Framework

Estimation of Preferences To estimate students' preferences for program attributes, we assume that student i of gender g's preferences over program d with attributes X in pair j are represented by a linear indirect utility function:

$$V_{ijd} = X'_{jd}\beta^g + \varepsilon_{ijd} \tag{1}$$

The probability that student i chooses the right program r over left l in choice pair j is then:

$$P(V_{ijr} > V_{ijl}|X, g) = F((X_{jr} - X_{jl})'\beta^g) \tag{2}$$

where F is the cumulative distribution function (CDF) of $\varepsilon_{ijr} - \varepsilon_{ijl}$. We assume an identity function for the CDF, $F(x) = I(x) = x$, and estimate the model using OLS for ease of interpretation and decomposition. Yet, we present the results with logit (assume $F(x) = \Lambda(x)$) as a robustness check.

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Decomposition of the Choices   To investigate the underlying reasons for students' program choices, we treat the four reasons we elicited in the experiment as mediators: fit in, role model, studies, and career. We then decompose the treatment effects of the female student share on the choices into these four reasons, following Gelbach (2016) and Gong, Lu, and Song (2021).

Denote the reduced form of equation 2 that we estimate using OLS as follows:

$$C_{ij}^r = \alpha^{g,base} + \zeta^{g,base}(FShare_{jr} - FShare_{jl} = k) + (W_{jr} - W_{jl})'\omega^{g,base} + \epsilon_{ij}^{base} \tag{3}$$

Where C_{ij}^r is an indicator variable equal to 1 if student i chooses the right program in choice pair j, $FShare_{jd}$ is the share of female students in program d within pair j, $W_{jd} \equiv X_{jd} \setminus \{FShare_{jd}\}$ is a vector of program d's attributes in pair j excluding the female student share, and α^g is the intercept for the right program.

Now, replace C_{ij}^r with the four reasons:

$$M_{ij}^m = \kappa^{m,g} + \xi_{m,g}(FShare_{jr} - FShare_{jl}) + (W_{jr} - W_{jl})'\psi^{m,g} + \nu_{ij}^m \tag{4}$$

where M_{ij}^m (for $m = 1, 2, 3, 4$) is an indicator variable equal to 1 if student i indicated that reason m better applies to the right program in the choice pair j.

Finally, include all the M_{ij}^ms in equation 3:

$$C_{ij}^r = \alpha^{g,full} + \zeta^{g,full}(FShare_{jr} - FShare_{jl}) + (W_{jr} - W_{jl})'\omega^{g,full} + \sum_{m=1}^{4} \eta^{m,g}M_{ij}^m + \epsilon_{ij}^{full} \tag{5}$$

Gelbach (2016) shows that:

$$\hat{\zeta}^{g,base} = \hat{\zeta}^{g,full} + \sum_{m=1}^{4} \hat{\eta}^{m,g}\hat{\xi}^{m,g} \quad \forall g \tag{6}$$

where $\hat{\eta}^{m,g}\hat{\xi}^{m,g}$ is the part of the treatment effects $\hat{\zeta}^{g,base}$ explained by reason M_{ij}^m, and $\hat{\zeta}^{g,full}$ is the part of the treatment effects $\hat{\zeta}^{g,base}$ unexplained by any of the four reasons.

We discretize the female student share as discussed later, so we perform this decomposition for each bin of the share.

5.2   Preferences for the Gender Ratio

Table 2 presents the coefficient estimates for program attributes with choice as the dependent variable. Columns 1 to 3 present estimates for female students, columns 4 to 6 present estimates for male students, and columns 7 to 8 present estimates for differences between female and male students.[16] First, female students are 7.9 percentage points less likely to choose STEM programs, while male students are 3.8 percentage points more likely to do so, consistent with the literature.

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16. Appendix Table A2 presents the same specifications but with indicator variables for the four reasons instead of choice as the outcome variables.

Table 2: Preferences for Program Attributes

| Sample:	Female			Male			All	
Estimation:	OLS		Logit (AME)	OLS		Logit (AME)	OLS	Logit (AME)
Outcome:	Choose the program (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STEM	-0.079***	-0.079***	-0.078***	0.038**	0.038**	0.038**	0.038**	0.038**
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Female student share	0.090***	0.821***	0.819***	-0.036	0.818***	0.815***	0.818***	0.811***
	(0.022)	(0.088)	(0.097)	(0.024)	(0.089)	(0.097)	(0.089)	(0.094)
Female student share squared		-0.745***	-0.742***		-0.875***	-0.872***	-0.875***	-0.868***
		(0.088)	(0.095)		(0.090)	(0.099)	(0.090)	(0.096)
Selectivity index (population SD)	0.046***	0.047***	0.046***	0.075***	0.075***	0.074***	0.075***	0.074***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Cohort size/100	0.003	0.003	0.003	0.006**	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Intl exchange program	0.059***	0.060***	0.060***	0.033**	0.034**	0.034**	0.034**	0.034**
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Club participation rate	0.193***	0.196***	0.196***	0.122***	0.130***	0.130***	0.130***	0.130***
	(0.042)	(0.042)	(0.043)	(0.041)	(0.040)	(0.041)	(0.040)	(0.041)
Female							0.015	0.015
							(0.011)	(0.011)
STEM x Female							-0.116***	-0.116***
							(0.024)	(0.025)
Female student share x Female							0.003	0.011
							(0.126)	(0.131)
Female student share squared x Female							0.131	0.123
							(0.126)	(0.131)
Selectivity index (population SD) x Female							-0.028*	-0.027*
							(0.016)	(0.016)
Cohort size/100 x Female							-0.003	-0.003
							(0.004)	(0.004)
Intl exchange program x Female							0.026	0.026
							(0.019)	(0.019)
Club participation rate x Female							0.066	0.067
							(0.058)	(0.059)
Constant	0.503***	0.503***		0.488***	0.487***		0.487***	
	(0.007)	(0.007)		(0.008)	(0.008)		(0.008)	
Adj. R-squared	0.036	0.054		0.021	0.045		0.050	
No. observations	4649	4649	4649	4451	4451	4451	9100	9100
No. students	310	310	310	297	297	297	607	607

Notes: This table presents the coefficient estimates on the program attributes with choice as the dependent variable. Columns 1 to 3 present estimates for female students, columns 4 to 6 present estimates for male students, and columns 7 to 8 present estimates for differences between female and male students. The average marginal effects for constant term of logit estimates are undefined and thus are not shown. Standard errors are clustered at the student level. Significance levels: * 10%, ** 5%, and *** 1%.

Second, both female and male students prefer programs with higher selectivity indices, but male students show a slightly stronger preference: a 1 standard deviation increase in the selectivity index increases female students' choice probability by 4.6 to 4.7 percentage points, while it increases male students' choice probability by 7.5 percentage points, which is 2.8 percentage points larger than female students.

Third, students also favor the social aspects of the programs. Both female and male students prefer programs that have an international exchange program: having an international exchange program increases female students' choice probability by 5.9 to 6.0 percentage points and male students' choice probability by 3.3 to 3.4 percentage points. Club participation rates also affect students' choices: a 10 percentage point increase in club participation rate increases female students' choice probability by 19.3 to 19.6 percentage points and male students' choice probability by 12.2 to 13.0 percentage points. The effect of the cohort size is quantitatively minimal: an increase of a

program size by 100 students increases male students' choice probability by 0.6 percentage points and no statistically significant effects on female students. Logit estimates in columns 3, 6, and 8 where we converted the coefficient estimates into average marginal effects (AME) show essentially the same results as those with OLS.

Figure 3: Preferences for the Gender Ratio
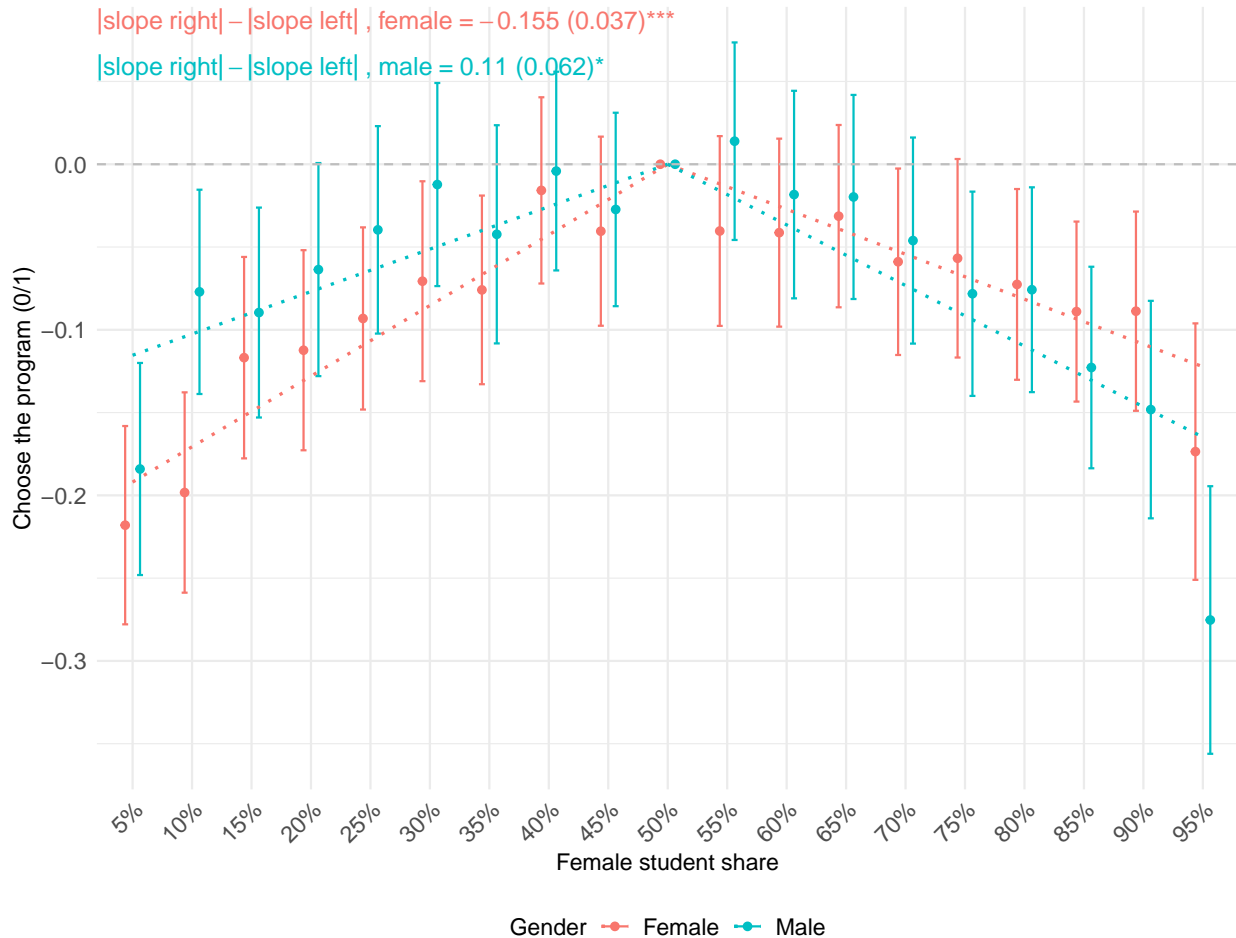
Notes: This figure plots the coefficient estimates and the 95% confidence intervals of female student share discretized into 19 equally spaced bins, with 50% as the baseline, separately for female students (red) and male students (blue). Standard errors are clustered at the student level. The dotted lines are weighted least squares linear fits of each point, weighted by the inverse of its standard error, for female and male students on both sides (below 50% and above 50%). We imposed the constraint that the lines pass through the 50% point.

However, our main variable of interest, female student share, is highly non-linear for both female and male students: the coefficient estimates on the squared female student share are statistically and quantitatively highly significant for both groups, as shown in columns 2 and 4. Therefore, we discretize the female student share into 19 equally spaced bins with a 5 percentage point increment and re-estimate equation 2 with 50% as the baseline, separately for female and male students.

Figure 3 plots the coefficient estimates and the 95% confidence intervals for female students (red) and male students (blue). The dotted lines are fitted lines that account for estimation precision:

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they are weighted least squares linear fits of each point, weighted by the inverse of its standard error, for female and male students on both sides (below 50% and above 50%). We imposed the constraint that the lines pass through the 50% point.

The figure shows that the gender ratio does affect both female and male students' college choices. Specifically, both female and male students prefer programs with balanced gender ratios over those where only a small fraction of students are of their own gender: compared to a program where 50% of students are female, female students are about 20 to 22 percentage points less likely to choose a program where only 5-10% of students are female, while male students are about 15 to 27 percentage points less likely to choose a program where only 5-10% of students are male (90-95% of students are female).

Interestingly, both female and male students also prefer programs with a balanced gender ratio over those where a majority of students are of their own gender: compared to a program where 50% of students are female, female students are about 17 to 9 percentage points less likely to choose a program where 90-95% of students are female, and male students are about 18 to 7.5 percentage points less likely to choose a program where 90-95% of students are male (10-5% of students are female).

Still, female students prefer a program where the majority of students are female over one where only a small fraction are female. Looking at the weighted linear fit, the slope on the left side of the 50% is 0.16, steeper than the slope on the right side of the 50%. We see a similar pattern for male students, albeit only marginally statistically significant and quantitatively less significant than for female students.

5.3 Underlying Reasons

To investigate the underlying reasons the gender ratio affects students' college choices, Figure 4 plots $\hat{\theta}^{m,g}\hat{\xi}^{m,g}$ ($m = 1, 2, 3, 4$) and $\hat{\zeta}^{g,full}$ from equation 6 estimated for each of the 19 bins separately for female (Panel A) and male (Panel B) students. The red area shows fitting in, the yellow shows finding a role model, the green shows doing well in studies, the blue shows finding a career to pursue, and the purple shows reasons other than these four.

Panel A shows that the main reason the gender ratio affects female students' program choices varies significantly depending on whether most students in the program are male or female. When the majority of students are male, the gender ratio affects female students' program choices primarily due to their concerns about fitting in. On the other hand, when the majority of students are female, multiple factors – not only concerns about fitting in, but also concerns about finding a role model, doing well in studies, finding a career, and unexplained reasons – all contribute to how the gender ratio affects their choices.

Interestingly, Panel B shows that the patterns are very similar for male students: when most students are female, the gender ratio affects male students' program choices primarily through the expected difficulty in fitting in. When most students are male, however, all four reasons, along with other reasons beyond these four, explain their choices.

Figure 4: Decomposition of Preferences for the Gender Ratio
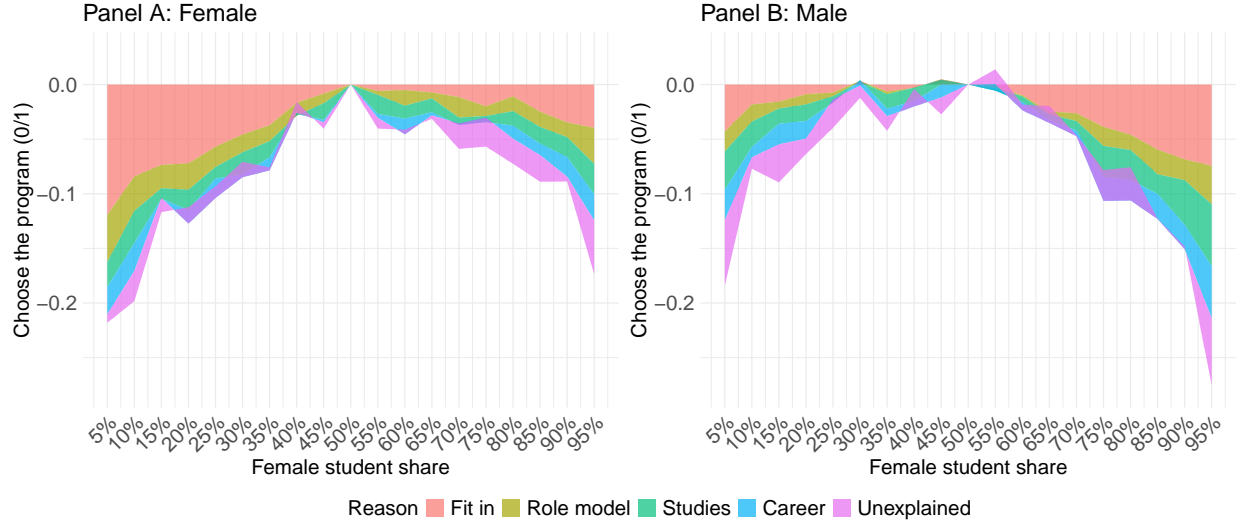
Notes: This figure plots $\hat{\theta}^{m,g}\hat{\xi}^{m,g}$ ($m = 1, 2, 3, 4$) and $\hat{\zeta}^{g,full}$ from equation 6 estimated for each of the 19 bins separately for female (Panel A) and male (Panel B) students. The red area shows fitting in, the yellow area shows finding a role model, the green area shows doing well in studies, the blue area shows finding a career to pursue, and the purple area shows reasons other than these four.
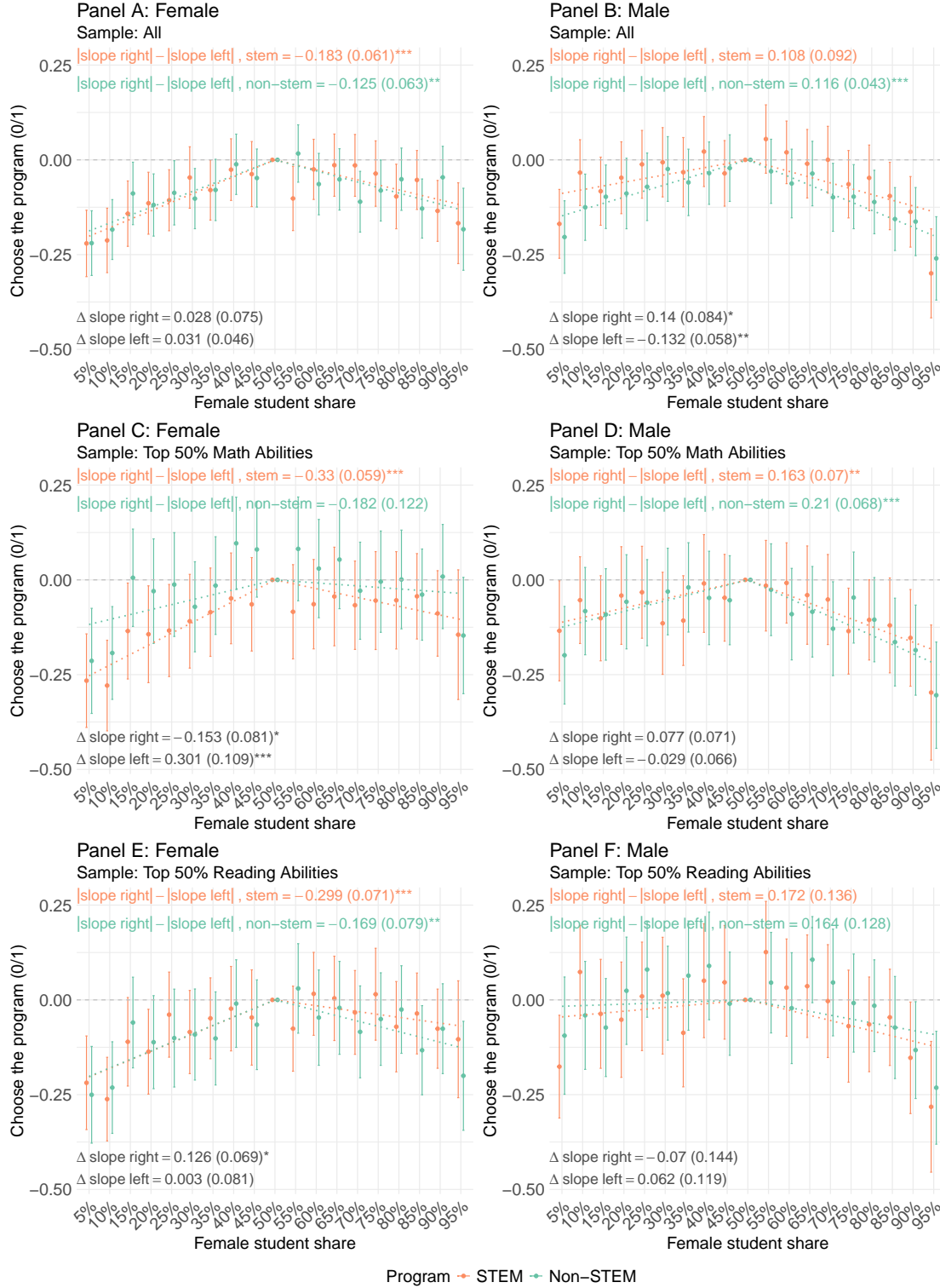
5.4 Heterogeneity of Preferences

Figure 5 plots coefficient estimates and the 95% confidence intervals for female and male students, where we interact the attributes with the STEM dummy. Panels A and B shows all students, Panels C and D restrict the sample to students among the top 50% in mathematics abilities in the sample, and Panels E and F restrict the sample to students among the top 50% in reading abilities in the sample.

Panel A shows that the preferences for the gender ratio are quantitatively very similar for STEM (orange) and non-STEM (green) programs among female students. Panel B shows the same plot for male students, and while the general pattern is the same as female students, there is some heterogeneity. In particular, male students are less sensitive to the gender ratio in STEM programs, and care less about being a gender minority than in non-STEM programs.

Female students in the top 50% of mathematics ability also exhibit heterogeneity in their preferences. Panel C shows that female students in the top 50% of mathematics ability avoid being a gender minority in STEM programs more than in non-STEM programs. More generally, they are more sensitive to the gender ratio in STEM programs than in non-STEM programs. On the other hand, Panel D shows that male students in the top 50% of mathematics ability do not exhibit significant heterogeneity. Neither female nor male students in the top 50% of reading ability do not exhibit significant heterogeneity in their preference, as shown in Panels E and F, albeit that male students in the top 50% of reading ability are overall less sensitive to the gender ratio. Regarding their preferences for other attributes, neither female nor male students exhibit significant heterogeneity by STEM/non-STEM program, as shown in Figure 6.

Figure 5: Heterogeneity of Preferences for the Gender Ratio – STEM vs. Non-STEM

Notes: This figure plots coefficient estimates and the 95% confidence intervals for female and male students, where we interact the attributes with the STEM dummy. Panels A and B plot all female and male students' preferences, Panels C and D female and male students in the top 50% of mathematics ability in the sample, and Panels E and F female and male students in the top 50% of reading ability in the sample. Standard errors are clustered at the student level. The dotted lines are weighted least square linear fits of each point weighted by the inverse of its standard error for each side (below 50% and above 50%) for two groups. We imposed the constraint that the lines pass through the 50% point. The differences in the slopes between STEM and Non-STEM are calculated using the weighted least squares standard errors. Significance levels: * 10%, ** 5%, and *** 1%.

Figure 6: Heterogeneity of Preferences for Other Attributes – STEM vs. Non-STEM
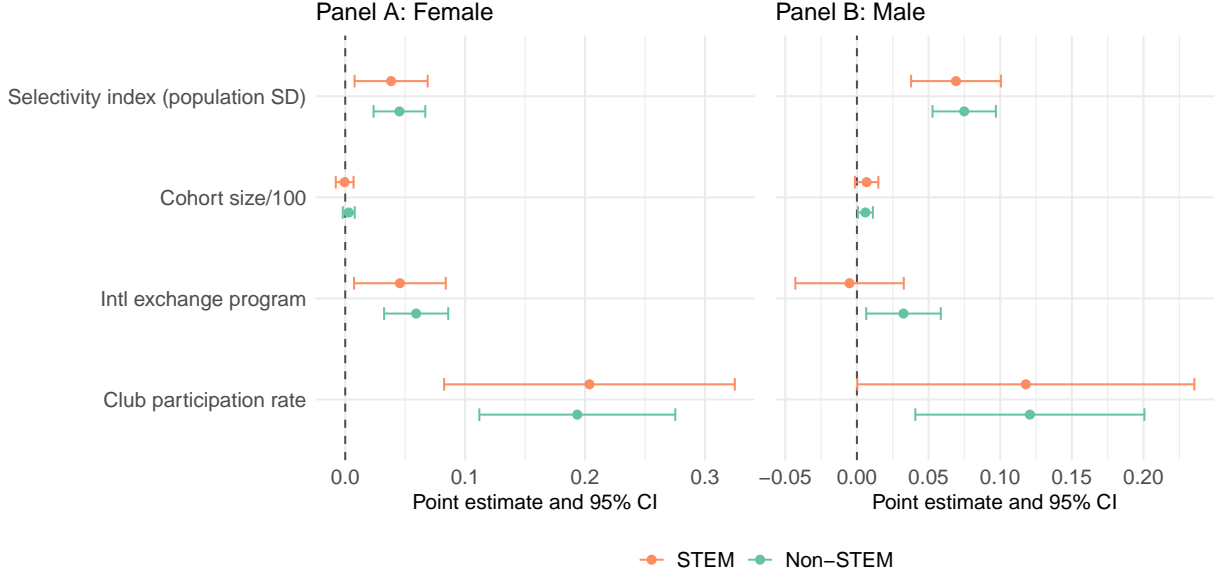
Notes: This figure plots coefficient estimates and the 95% confidence intervals of program attributes for female (Panel A) and male students (Panel B) for STEM and non-STEM programs. Female student share is included in the estimation but omitted from this figure for brevity. Standard errors are clustered at the student level.

Thus, while both female and male students prefer gender balanced programs over their own gender majority or own gender minority programs, and prefer their own gender majority programs over their own gender minority programs, there is heterogeneity in how sensitive they are to the female share by STEM vs. non-STEM programs. Specifically, female students who excel in mathematics are more sensitive to being a gender minority in STEM programs than in non-STEM programs, and male students are, in general, less sensitive to the gender ratio in STEM programs than in non-STEM programs. It may be because students perceive STEM as a male domain, and male students do not need to have enough students of their own gender to fit in. On the other hand, female students, especially those who are used to competing with male peers in a male-dominated domain, know it is difficult to fit in without having enough students of their own gender to fit in. Yet, although we cannot pin down the reasons, this heterogeneity is likely causing talent misallocation, which we discuss in Section 6.

Figure 7 plots coefficient estimates and the 95% confidence intervals for female and male students where we interact the attributes with an indicator variable for academic abilities. Panels A and B interact with an indicator variable for top 50% mathematics abilities students and Panels C and D interact with an indicator variable for top 50% reading abilities students.

Panel A shows that female students in the top 50% of mathematics ability avoid being a gender majority less compared to female students among the bottom 50% in mathematics abilities. As shown in Panel C, we see the same pattern for female students in the top 50% of reading ability compared to female students among the bottom 50% in reading abilities. Thus, as with Figure 6,

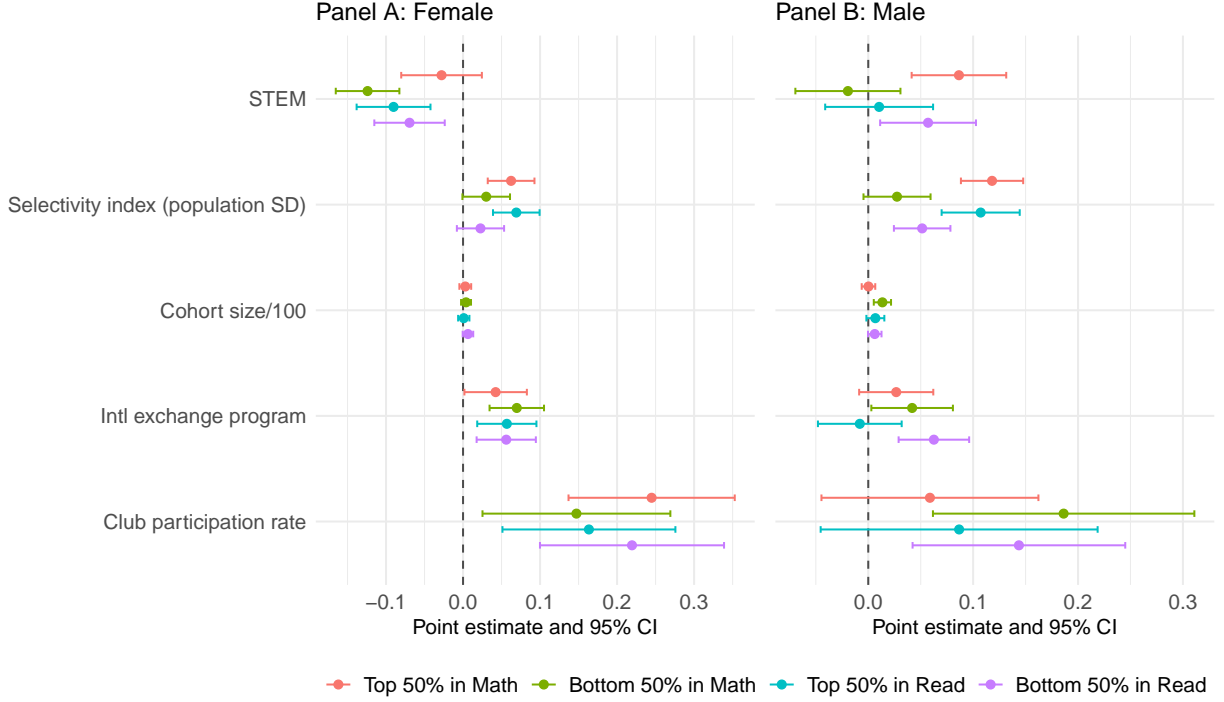Figure 7: Heterogeneity of Preferences for the Gender Ratio by Abilities
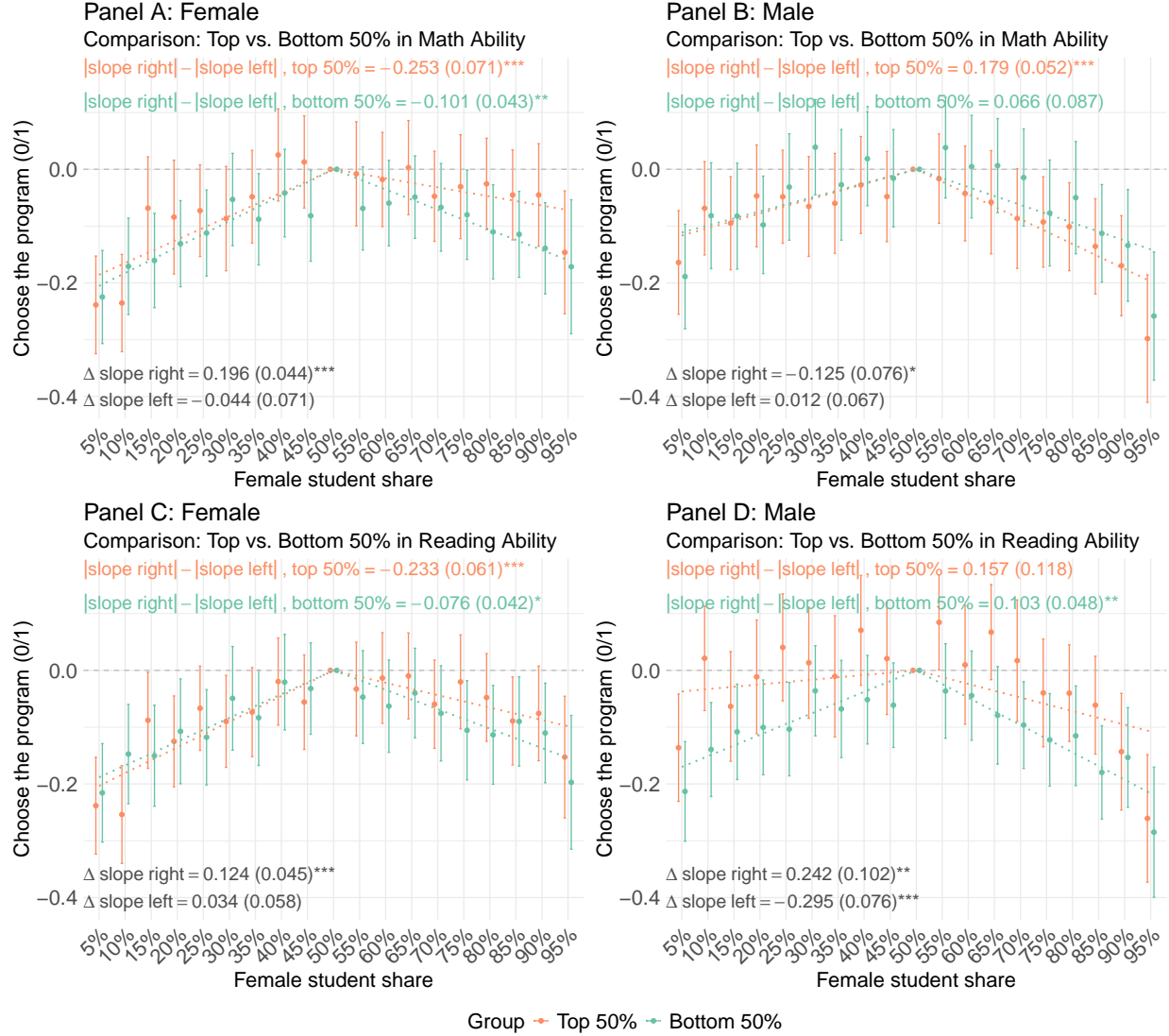
Notes: This figure plots coefficient estimates and the 95% confidence intervals for female and male students where we interact the attributes with an indicator variable for academic abilities. Panels A and B interact with an indicator variable for top 50% mathematics abilities students and Panels C and D interact with an indicator variable for top 50% reading abilities students. Standard errors are clustered at the student level. The dotted lines are weighted least square linear fits of each point weighted by the inverse of its standard error for each side (below 50% and above 50%) for two groups. We imposed the constraint that the lines pass through the 50% point. The differences in the slopes between the two groups are calculated using the weighted least squares standard errors. Significance levels: * 10%, ** 5%, and *** 1%.

while both female and male students prefer gender balanced programs over own gender majority or own gender minority programs, and prefer own gender majority programs over own gender minority programs, there is heterogeneity in how sensitive they are to the female share by their academic abilities.[17]

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[17]. Appendix Figure A2 presents similar plots for parental education level, and we do not see significant heterogeneity either. The sample size between the two groups is roughly the same: there are 266 students whose parents both

Figure 8: Heterogeneity of Preferences for Other Attributes by Ability

For other attributes, students among the top 50% and the bottom 50% of mathematics and reading abilities differ in their preferences. Figure 8 plots coefficient estimates and the 95% confidence intervals of program attributes for female (Panel A) and male students (Panel B) with different academic abilities. Panel A shows that female students who excel in mathematics are indifferent between STEM and non-STEM programs and have a stronger preference for selective programs compared to female students who do not excel in either mathematics or reading. Female students who excel in reading, on the other hand, still prefer non-STEM but also have stronger preferences for selective programs compared to female students who do not excel in either mathematics or reading. Looking at Panel B, we see similar patterns for male students albeit stronger preferences for selective programs and weaker preferences for social aspects of colleges such as the presence of international exchange programs and club participation rate among top 50% in mathematics and reading ability students compared to bottom 50% in mathematics and reading ability students.

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have bachelor's degrees or above and 278 students whose either or both parent does not have bachelor's degree. The parental education status is unknown for 65 students who responded that they did not know their mother's or/and father's education level.

6 Results 2: The Low Female Share in STEM Contributes to Talent Misallocation

In the previous section, we find that female and male students prefer programs with a balanced gender ratio, followed by programs where the majority of students are of their own gender and programs where the majority of students are of the opposite gender. However, it is unclear whether such preferences together with the low female share in STEM programs lead to talent misallocation.

To investigate whether the low female share in STEM leads to talent misallocation, we conduct counterfactual exercises comparing an actual scenario in which students care about the gender ratio in college programs with a counterfactual scenario in which we turn off students' preferences for the gender ratio. Because we do not know the constraints students face when they make choices, we hold factors other than preferences for the gender ratio constant across the two scenarios and focus on the differences.

6.1 Econometric Framework

STEM Choice Probabilities By Gender To estimate the STEM choice probabilities for female and male students, we consider two hypothetical college programs. The two programs are identical except that one is STEM and the other is non-STEM, and their female student shares are the actual shares of respective programs in Japan in 2024 – 22.7% in STEM and 45.2% in non-STEM.[18] Other attributes are set to the median values that a hypothetical college program in the experiment can take and are the same for both programs.[19] We then apply the logit parameter estimates from equation 2 on the two programs to obtain the average STEM choice probability for female and male students under the two scenarios using logit. We use a quadratic functional form for the female student share to define the choice probability over the continuous female share.

STEM Choice Probabilities Over the Whole Ability Distribution To assess talent misallocation, we estimate each student's choice probability and compare their STEM choice probability across the two scenarios. To do so, we first need to estimate individual students' preferences for program attributes. Rewrite equation 2 as follows:

$$P_{ijd}^g = \frac{\exp(X'_{jd}\beta^g)}{\sum_{k \in \{r,l\}} \exp(X'_{jk}\beta^g)} \tag{7}$$

where P_{ijd}^g is student i of gender g's choice probability of program $d \in \{r, l\}$ with attributes X in pair j. Note that this expression is equivalent to equation 2 in Section 5 (see, for example, Train 2009, Section 3.1).

Now, assume β_i^g is a random variable with density $f(\beta^g|\theta^g)$, where θ^g are parameters of this distribution for gender g. Then the choice probability can be written in a mixed logit form:

$$P_{ijd}^g|\theta^g = \int \frac{\exp(X_{jd}'\beta_i^g)}{\sum_{k\in\{r,l\}} \exp(X_{jk}'\beta_i^g)} f(\beta^g|\theta^g)d\beta^g \tag{8}$$

where we allow arbitrary correlations among elements in β_i^g.[20]

We draw individual-specific parameters β_i^g from the estimates as a weighted average of the conditional distribution of β_i^g, $h(\beta^g|y, X, g, \theta^g)$, following Train (2009), where y is a vector of choices across the 15 pairs. We assume f to be a triangular distribution to prevent outliers from affecting the estimates, following Kremer et al. (2011) and León and Miguel (2017).[21] Again, we use a quadratic functional form for the female student share to keep the number of model parameters adequate for the sample size as well as to define the choice probability over the continuous female share. We then apply the individual parameter estimates to the two hypothetical college programs discussed above using logit. Appendix Table A3 presents the mixed logit parameter estimates. While the scales are different, the sign and the relative magnitude of the coefficients between female and male students are quantitatively the same as in Table 2.

To examine the substitution patterns among students with different abilities under the two scenarios, we need to apply a capacity constraint to the STEM program. To do so, we subtract the following shadow price from the STEM indirect utility:

$$\text{Shadow price}_i = \lambda(\max_{k\in I}(\text{ability}_k) - \text{ability}_i), \quad i \in I \tag{9}$$

where ability_i is student i's academic ability and I is set of all students in the sample. The shadow price λ increases as more students place a higher value on the STEM program. When λ is positive, it implies that entering a STEM program is more costly for students with lower ability and less costly for students with higher ability. This shadow price can be interpreted as reflecting the effort required to prepare for the entrance exam, the effort needed to catch up to the class after entering, or the risk of not being admitted into the program.

We calibrate the λ so that the average probability of choosing STEM programs across all students in the sample is equal to 31.7%, the actual fraction of students in STEM programs in Japan in 2024.[22]

Figure 9: STEM Choice Probabilities by Gender
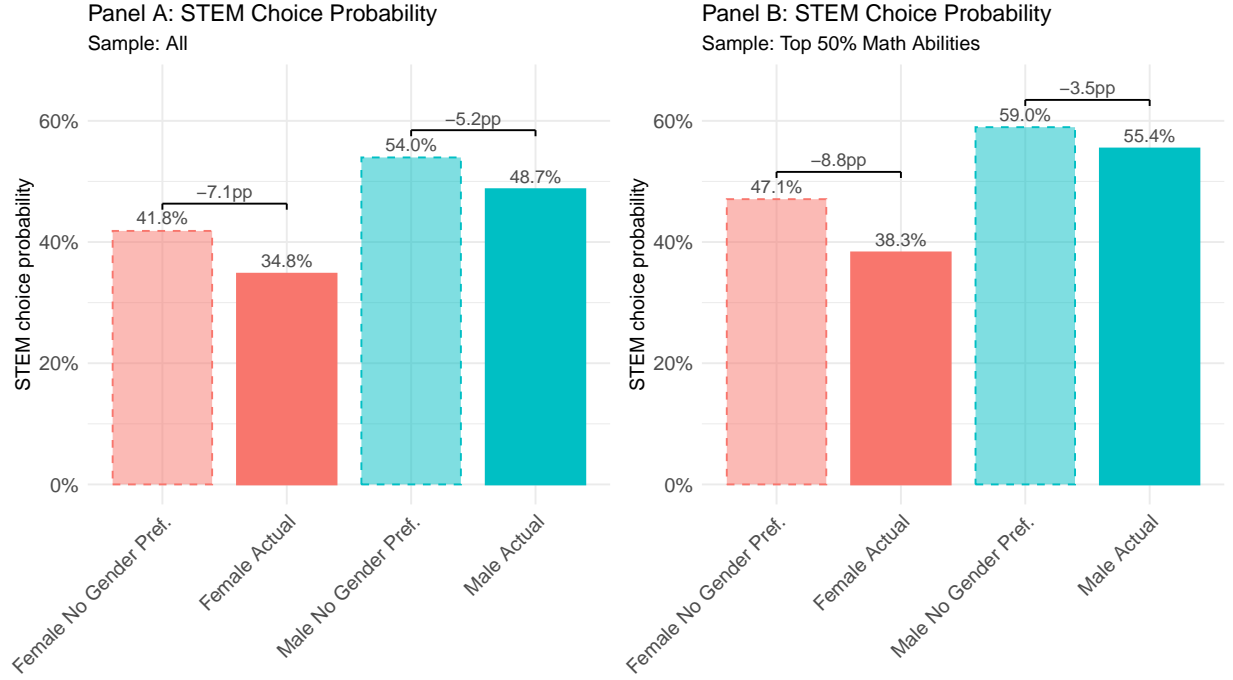
Notes: This figure plots the STEM choice probability predicted by logit under the actual (solid) and no gender preferences scenarios (dashed) for female (red) and male (blue) students. Panel A plots all students and Panel B plots students among the top 50% in their mathematics ability.

6.2 STEM Choice Probabilities by Gender

Figure 9 plots the STEM choice probability predicted by logit under the actual (solid) and no gender preferences scenarios (dashed) for female (red) and male (blue) students. Looking at Panel A, the low female share in STEM decreases both female and male students' STEM choice probability, but more for female students: female students reduce their STEM choice probability by 7.1 percentage points (17.0% relative to the no gender preference scenario) while male students reduce by 5.2 percentage points (9.6% relative to the no gender preference scenario). The smaller reduction by male students is likely due to their weaker sensitivity to the STEM programs relative to non-STEM programs, as we saw in Panel B of Figure 6.

Looking at Panel B, the low female share in STEM decreases female students among the top 50% in their mathematics ability more. It reduces their STEM choice probability by 8.8 percentage points (18.7% relative to the no gender preference scenario). On the other hand, the low female

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20. Mixed logit relaxes the following standard logit assumptions: (i) no random preference variation among individuals, (ii) independence of irrelevant alternatives, and (iii) no correlation in unobserved factors over time (Train 2009, Section 6). Our logit results in Table 2 are still valid as there are only two alternatives in each pair and no notable time-varying unobserved factors exist in the experiment. We use mixed logit to relax the first assumption to estimate individual-level preference parameters.

21. However, a normal distribution gives essentially the same results.

22. This is similar to adjusting the STEM-alternative constant term (see, for example, Train 2009, Section 2.8). However, unlike the alternative-specific constant, our adjustment varies with individual ability.

share in STEM has weaker effects on the STEM choice probability of male students among the top 50% in their mathematics ability, with the drop in 3.5 percentage points (5.9% relative to the no gender preference scenario). The first point likely comes from the stronger aversion to being a gender minority among female students who excel in mathematics, as we saw in Panel C of Figure 6, which is somewhat mitigated by their stronger preferences for STEM programs, as we saw in Panel A of Figure 8. The second point likely comes from the stronger preferences for STEM programs among male students who excel in mathematics, as we saw in Panel B of Figure 8.

We next examine the implications of these differences in the STEM choice probabilities among female and male students with different mathematics abilities for talent misallocation.

6.3 STEM Choice Probabilities Over the Whole Ability Distribution

Figure 10 plots STEM choice probabilities predicted by mixed logit (equation 8) over the whole ability distributions under the actual (solid) and no gender preferences scenarios (dashed) for female (red) and male (blue) students. Panels A and B use the mathematics score as the ability measure in the shadow price (equation 9) and Panels C and D the total score.

Panel A shows that the higher the mathematics ability, the more likely a student is to choose a STEM program regardless of gender in both scenarios. However, compared to the no gender preferences scenario, the actual scenario has 4% fewer female students in STEM. Those 4% of students' mathematics ability is 0.544 standard deviations above the sample median on average. On the other hand, the actual scenario has 2.7% more male students in STEM relative to the no gender preferences scenario, and those male students' mathematics ability is 0.463 standard deviations below the sample median on average.

We also see that the positive association between students' mathematics ability and their STEM choice probability is less pronounced in the actual scenario than in the no gender preferences scenario. Panel B shows similar crowding out patterns for reading abilities, too, although there is a weak to no association between the students' reading score and their STEM choice probability. The similar crowding out patterns exist for reading ability too, likely because there is a positive correlation between mathematics and reading abilities.[23] Panel C shows qualitatively very similar patterns when we use the total score in the shadow price calculation.

Thus, the low female share in STEM leads to talent misallocation, substituting male students with lower mathematics ability for female students with higher mathematics ability.

7 Conclusion

Female students are less likely to pursue STEM fields at colleges in OECD countries, despite negligible gender differences in mathematics and sciences at age 15. Having fewer women in STEM programs at colleges leads to several social issues, including suboptimal allocation of talent. One

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23. The correlation coefficient is 0.36 overall, with female students exhibiting a stronger correlation (0.48) than male students (0.27).

Figure 10: STEM Choice Probabilities Over the Whole Ability Distribution

Panel A: Math Score
Ability Measure in the Shadow Price: Math Score
Δ avg score, female $(\Delta N/N = -4\%) = -0.544\ (0.053)^{***}$
Δ avg score, male $(\Delta N/N = 2.7\%) = -0.463\ (0.057)^{***}$

Panel B: Reading Score
Ability Measure in the Shadow Price: Math Score
Δ avg score, female $(\Delta N/N = -4\%) = -0.27\ (0.052)^{***}$
Δ avg score, male $(\Delta N/N = 2.8\%) = -0.32\ (0.069)^{***}$

Panel C: Math Score
Ability Measure in the Shadow Price: Total Score
Δ avg score, female $(\Delta N/N = -5.1\%) = -0.41\ (0.055)^{***}$
Δ avg score, male $(\Delta N/N = 3.7\%) = -0.283\ (0.061)^{***}$

Panel D: Reading Score
Ability Measure in the Shadow Price: Total Score
Δ avg score, female $(\Delta N/N = -5.1\%) = -0.378\ (0.05)^{***}$
Δ avg score, male $(\Delta N/N = 3.7\%) = -0.549\ (0.06)^{***}$

Group — Female No Gender Pref. — Female Actual — Male No Gender Pref. — Male Actual

Notes: This figure plots STEM choice probabilities over the whole ability distributions under the actual (solid) and no gender preferences scenarios (dashed) for female (red) and male (blue) students. Panels A and B use the mathematics score as the ability measure in the shadow price (equation 9) and Panels C and D the total score. The change in the average scores are calculated as an expected marginal change in average student's test score s_i within each gender between the two scenarios: $\sum_i (p_i^{\text{actual}} - p_i^{\text{no gender pref.}}) s_i / \sum_i |p_i^{\text{actual}} - p_i^{\text{no gender pref.}}|$. The statistical significance is based on the bootstrapped standard error with 2000 draws. The expected change in the number of students between the two scenarios is in parentheses. Significance levels: * 10%, ** 5%, and *** 1%.

potential reason that has received little attention in the literature is that STEM programs are predominantly male-dominated, which may discourage women from pursuing STEM. In this paper, we examine whether the gender ratio affects students' college choices and whether the low female share in STEM contributes to talent misallocation.

Using an incentivized discrete choice experiment with students at selective academic high schools in Japan, we show that the gender ratio at colleges affects both female and male students' college choices. Specifically, both genders prefer college programs with a balanced gender ratio over those dominated by one gender. However, they, especially female students, prefer their own gender majority programs over the opposite gender majority programs. The main reason for avoiding being a gender minority is the anticipated difficulty of fitting into the program. There is heterogeneity in their preferences: female students who excel in mathematics are particularly averse to being a minority in STEM programs compared to non-STEM programs. Additionally, male students are less sensitive to the gender ratio in STEM programs than in non-STEM programs. A counterfactual exercise comparing the actual scenario—where students have the same preferences as in the experiment—and a hypothetical scenario—where we turn off students' preferences for the gender ratio—shows that the low female share in STEM programs reduces female students' probability of choosing STEM, especially among those excelling in mathematics. As inferred from the larger drop in STEM choice probability among female students who excel in mathematics, the low female share in STEM does indeed lead to talent misallocation: male students who do not perform well in mathematics crowd out female students who excel in mathematics. These findings suggest that the gender ratio at colleges is an important factor for students' college choices, and increasing gender balance in STEM programs can improve talent allocation.

Although our results are based on students from a few selective academic high schools in Japan, we can infer the external validity in other settings. First, these students care much more about getting into selective college programs than students at less selective high schools, and the effect of the gender ratio would likely be stronger for them. Second, while Japan's STEM gender gap is worse than that of other OECD countries, the results are not necessarily weaker in those other countries. For instance, Japanese people tend to be more reserved than people in Europe or the US, and their social interactions are less intense in public. Therefore, although the low female share in STEM is more pronounced in Japan, social dynamics in the public sphere are more important in other countries, where concerns about the gender ratio kick in.

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Online Appendix

A   Additional Figures and Tables

Figure A1: Distribution of Abilities
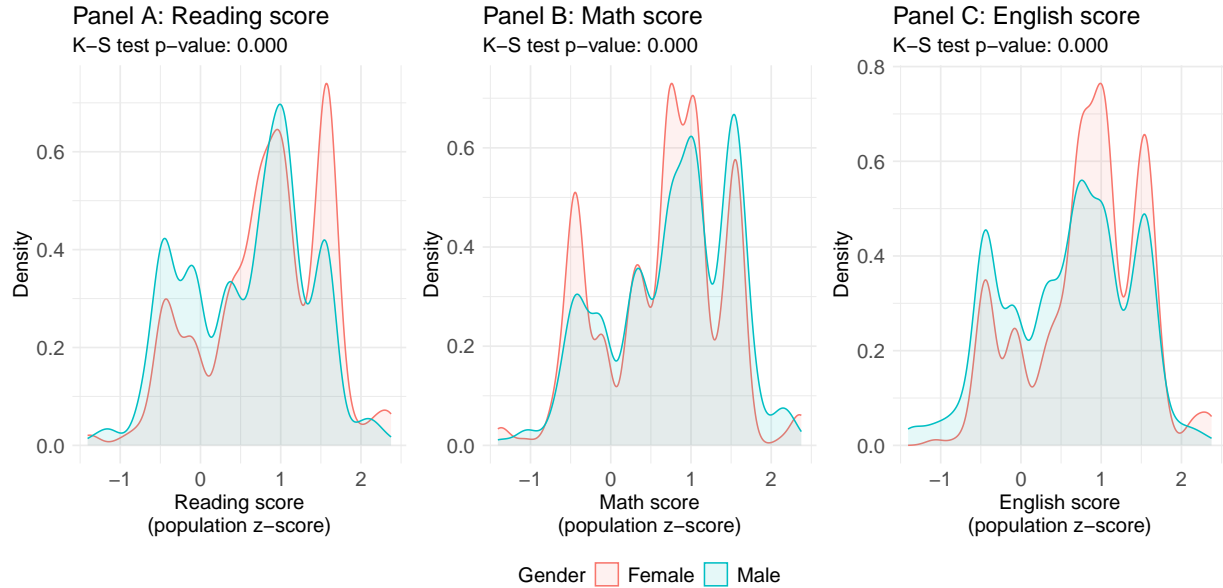
Notes: This figure presents the distribution of abilities of female and male students in reading (Panel A), mathematics (Panel B), and English (Panel C). K-S test p-value shows the Kolmogorov-Smirnov test p-value for differences in the distribution between female and male students.

Table A1: Attribute Values

General attributes	
College name:	AA, AB, AC, AD, AE, AF, AG, AH, AI, AJ, AK, AL, AM, AN, AO, AP, AQ, AR, AS, AT, AU, AV, AW, AX, AY, AZ, BA, BB, BC, BD
Department:	
Non-STEM:	Literature, Law, Business, Economics, Sociology, Foreign Language
STEM:	Physics, Chemistry, Biology, Engineering, Information Technology, Agriculture
Department attributes	
Selectivity index:	55, 57.5, 60, 62.5, 65, 67.5, 70, 72.5
Cohort size:	200, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 800, 850, 900
Female student share:	5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%
College attributes	
International exchange program:	Yes, Yes, Yes, Yes, No
Club participation rate:	40%, 45%, 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%

Notes: This table presents the values each attribute can take in a given program.

Figure A2: Heterogeneity of the Preferences by Parental Education Levels
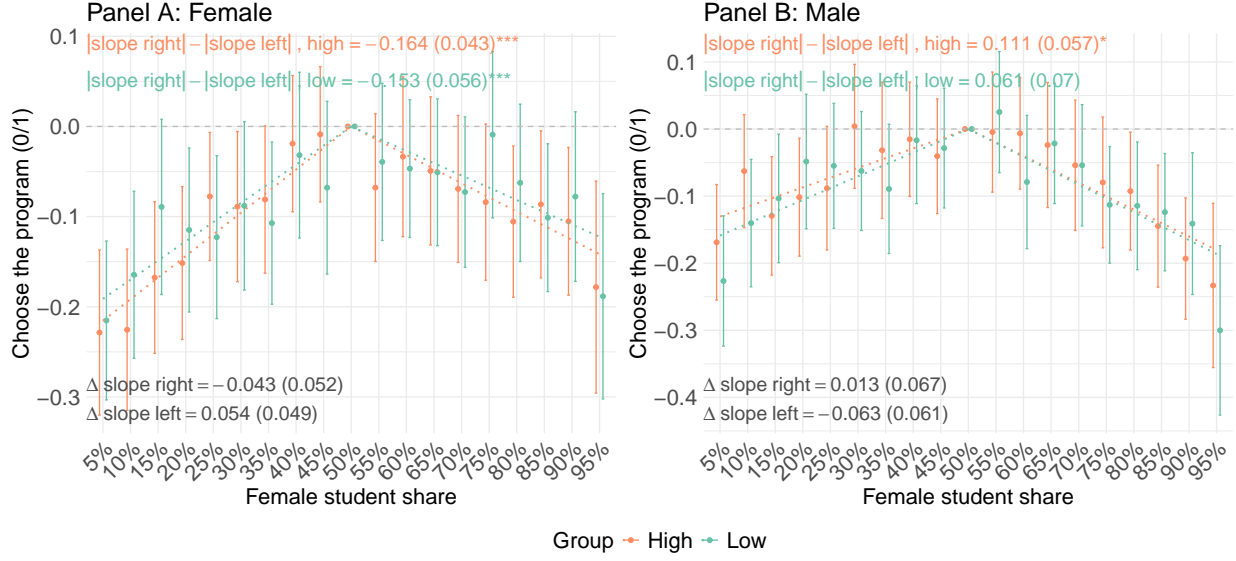
Notes: This figure plots plots coefficient estimates and the 95% confidence intervals for female and male students, just like Figure 3, but interact the attributes with an indicator variable for whether both parents have bachelor's degrees or above (High if 1, Low if 0). Standard errors are clustered at the student level. The dotted lines are weighted least square linear fits of each point weighted by the inverse of its standard error for each side (below 50% and above 50%) for two groups. We imposed the constraint that the lines pass through the 50% point. The differences in the slopes between STEM and non-STEM are calculated using the weighted least squares standard errors. Significance levels: * 10%, ** 5%, and *** 1%.

Table A2: Preferences for Program Attributes – Reasons as Dependent Variables

Sample:	Female	Male	Female	Male	Female	Male	Female	Male
Outcome:	Fit in		Role model		Studies		Career	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
STEM	-0.037***	0.007	-0.047***	0.011	-0.061***	0.041***	-0.062***	0.021
	(0.012)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.016)	(0.017)
Female student share	1.819***	1.099***	0.708***	0.605***	0.239***	0.453***	0.336***	0.407***
	(0.089)	(0.092)	(0.085)	(0.089)	(0.086)	(0.084)	(0.087)	(0.085)
Female student share squared	-1.477***	-1.384***	-0.621***	-0.685***	-0.225***	-0.503***	-0.320***	-0.450***
	(0.094)	(0.093)	(0.084)	(0.089)	(0.084)	(0.086)	(0.086)	(0.086)
Selectivity index (population SD)	-0.014	0.015	0.088***	0.080***	0.084***	0.094***	0.075***	0.080***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.015)	(0.014)	(0.010)	(0.011)
Cohort size/100	0.002	0.005*	0.012***	0.013***	-0.002	0.000	0.004*	0.006**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Intl exchange program	0.021	0.020	0.049***	0.040***	0.034***	0.047***	0.053***	0.051***
	(0.014)	(0.013)	(0.014)	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)
Club participation rate	0.282***	0.200***	0.651***	0.443***	0.086**	0.070*	0.165***	0.158***
	(0.042)	(0.043)	(0.054)	(0.050)	(0.039)	(0.041)	(0.040)	(0.043)
Constant	0.504***	0.479***	0.518***	0.490***	0.483***	0.480***	0.494***	0.495***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Adj. R-squared	0.159	0.100	0.104	0.062	0.032	0.037	0.035	0.029
No. observations	4649	4451	4649	4451	4649	4451	4649	4451
No. students	310	297	310	297	310	297	310	297

Notes: This table presents the same specifications as Table 2 but with indicator variables for the four reasons in place of choice as the outcome variables. Significance levels: * 10%, ** 5%, and *** 1%.

Table A3: Mixed Logit Parameter Estimates

Sample:	Female	Male
Outcome:	Choose the program (0/1)	
	(1)	(2)
STEM	-0.556***	0.240***
	(0.054)	(0.051)
Female student share	5.394***	4.916***
	(0.524)	(0.512)
Female student share squared	-4.823***	-5.313***
	(0.514)	(0.518)
Selectivity index (population SD)	0.290***	0.522***
	(0.052)	(0.056)
Cohort size/100	0.025*	0.028*
	(0.014)	(0.014)
Intl exchange program	0.392***	0.179**
	(0.075)	(0.075)
Club participation rate	1.311***	0.819***
	(0.231)	(0.237)
Intercept for right	-0.005	-0.049
	(0.040)	(0.040)
Log Likelihood	-2708.980	-2606.917
No. observations	9298	8902
No. students	310	297

Notes: This table presents mixed logit parameter estimates for female students (column 1) and male students (column 2). We assume the density for β_i^g is triangular distribution and allow arbitrary correlations among elements in β_i^g. We make 1000 Halton quasi-Monte Carlo draws to evaluate the integral instead of pure Monte Carlo draws for stability and faster convergence as suggested by (Train 2009, Section 9). Significance levels: * 10%, ** 5%, and *** 1%.

B Post-Experimental Questionnaire

Post-Experimental Questionnaire (English translation)

Questionnaire 1/4

Please tell us about yourself and your family.

- Your gender: [Male, Female, Non-binary or Other]
- Your father's academic background: [Below high school, High school, Vocational school, Associate degree, Bachelor's degree, Master's degree or above, I do not know]
- Your mother's academic background: [Below high school, High school, Vocational school, Associate degree, Bachelor's degree, Master's degree or above, I do not know]
- Extra schooling per week: [No extra schooling, one day a week, two days a week, three days a week, four days a week, five days a week or more]

Please recall the exam held on [Month Day]. What was your score in the following subjects?

- Reading: [Integer]
- Mathematics: [Integer]
- English: [Integer]

Please click "→" to proceed.

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Questionnaire 2/4

Do you think **your scores in the exam held on [Month Day] accurately reflect your abilities?** Please answer for each of the subjects below.

	My abilities are lower than the score	My abilities are slightly lower than the score	It reflects my ability accurately	My abilities are slightly higher than the score	My abilities are higher than the score
Reading	○	○	○	○	○
Mathematics	○	○	○	○	○
English	○	○	○	○	○

- Do you consider yourself someone who is **willing to compete with others**, or someone who **avoids competing with others**? [Avoid competing with others, Slightly avoid competing with others, Neither avoid nor willing to compete with others, Slightly willing to compete with others, Willing to compete with others]

- Do you consider yourself someone who is generally **willing to take risks**, or someone who **avoids taking risks**? [Avoid taking risks, Slightly avoid taking risks, Neither avoid nor willing to take risks, Slightly willing to take risks, Willing to take risks]

Please click "→" to proceed.

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Questionnaire 3/4

What do you think is **the average female-student ratio** in the following departments across the colleges in Japan?

	Below 10%	11-20%	21-30%	31-40%	41-50%	51-60%	61-70%	71-80%	81-90%	91% or above
Humanities Departments (Literature, history, philosophy, etc.)	○	○	○	○	○	○	○	○	○	○
Social Sciences Departments (Law, Economics, Sociology, etc.)	○	○	○	○	○	○	○	○	○	○
Sciences and Engineering Departments (Physics, Biology, Mechanical Engineering, Information Technology, etc.)	○	○	○	○	○	○	○	○	○	○
Medicine and Nursing Departments (Medicine, Dentistry, Pharmacy, Nursing, etc.)	○	○	○	○	○	○	○	○	○	○

Please click "→" to proceed.

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Questionnaire 4/4

Please tell us your opinion about this survey.

- Was it easy to follow? [Difficult to follow, Slightly difficult to follow, Neither difficult nor easy to follow, Slightly easy to follow, Easy to follow]
- Which parts did you find it difficult to answer? [Text]
- What do you think is the purpose of this survey? [Text]
- Other comments? (optional) [Text]