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

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Abstract

Although the gender gap in mathematics and sciences in OECD countries is negligible, female students are less likely to major in STEM fields in college, which can lead to suboptimal talent allocation. One explanation that has received less attention in the literature is that STEM programs are predominantly male-dominated, which makes female students a minority. We study whether the gender ratio at colleges affects high school students' college choices and the extent to which it contributes to the gender gap in STEM programs. Using administrative data, we show that the gender ratio has become more balanced in both STEM and non-STEM programs over the last 15 years, especially in programs where students face fewer trade-offs among attributes. We then conduct an incentivized discrete choice experiment and show that the gender ratio at colleges does affect both female and male students' college choices: both prefer gender-balanced programs over those with a male or female majority. Students avoid programs where they would be a minority mainly because they expect it to be difficult to fit in. A counterfactual analysis suggests that the low female student share in STEM programs decreases the likelihood of female students choosing STEM by 6.0 percentage points or 15.7%, and they incur a utility cost equivalent to 0.58 standard deviations of program selectivity. Removing this constraint would lead to female students with high mathematics ability replacing male students with low mathematics but high reading ability in STEM. Thus, the gender ratio at colleges is an important factor for high school students' college choices, and making STEM programs more gender-balanced can help narrow the STEM gender gap and improve the allocation of talent.

JEL Classification: J16, J24, I24

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

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1 Introduction

Although female and male students perform equally well in mathematics and sciences at age 15 in OECD countries (OECD 2019), female students remain 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 not received much attention in the literature is that STEM programs are predominantly male-dominated and make female students a gender minority in the programs.[1] Indeed, several studies show disadvantages of being a gender minority in the workplace and schools (Bostwick and Weinberg 2022; Cullen and Perez-Truglia 2023; Folke and Rickne 2022; Hampole, Truffa, and Wong 2024). Thus, female students may anticipate these disadvantages and avoid male-dominated programs.

This paper studies whether the gender ratio at colleges affects high school students' college choices and the extent to which it contributes to the gender gap in STEM programs. We first establish empirical patterns about the gender ratios across college programs over the years using administrative data that covers 16 years of the universe of college programs in Japan. We then conduct an incentivized discrete choice experiment with students from selective academic 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. In the experiment, students see 15 hypothetical college program pairs one by one, each with randomly assigned attributes, and choose one of them that they want to attend. After that, they see four statements that many students care about when choosing college programs, and choose the program that best matches each statement for each pair.[2] We incentivize these choices using the incentivized resume rating method (Kessler, Low, and Sullivan 2019) by providing students career advice tailored based on their choices.

We first document using the administrative data that the gender ratio has become more balanced in both STEM and non-STEM programs from 2008 to 2023. However, the change is more pronounced in programs where students are supposed to have greater flexibility in choosing program attributes, and thus the trade-off between gender ratios and other attributes is less binding. We then use the experimental data and show that the gender ratio at colleges does affect 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. Decomposition of their choices shows that both female and male students avoid being a minority in a program mainly because they expect it to be difficult to fit into such an environment. On the other hand, students avoid being a majority for

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.

2. These four statements are selected from the open-ended questions in the pre-test.

various reasons. We do not find that the preference for gender balance differs whether the program is STEM or non-STEM, whether a student excels in academic abilities or not, or whether students are from households with high or low socio-economic status (SES). Thus, the preference for balance is present in both STEM and non-STEM programs, regardless of students' academic abilities or SES backgrounds.

We then perform a counterfactual analysis to quantify the extent to which preferences for gender balance contribute to the gender gap in STEM programs, where female student share is currently low. By extracting individual-level student preference parameters using mixed logit (Train 2009), we show that while 38% of female students prefer STEM over non-STEM programs, the low female student share in STEM reduces their STEM choice probability by 6.0 percentage points or 15.7%, and they face a utility cost equivalent to 0.58 standard deviations in program selectivity. The gender gap in STEM shrinks by 18.5% if this constraint were removed. We also show that removing the constraint does not reduce applicant quality; on the contrary, it can improve talent allocation by increasing the share of female students with high mathematics abilities choosing STEM and decreasing the share of male students with low mathematics but high reading abilities choosing STEM.

Taken together, our findings suggest that the gender ratio at colleges is an important determinant for high school students' college choices, and making STEM programs more gender-balanced can help close the STEM gender gap and improve talent allocation.

Related Literature Our paper contributes to several strands of research. First, it 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 it lowers female employment in male-dominated occupations. 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. 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 low own-gender share.

Second, our paper 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.

Third, our study contributes to recent research on the college major choices, with a particular focus on the differential effect of non-monetary factors on female and male students' choices. Previous research shows that women tend to prefer majors that lead to flexible and stable jobs, while men often choose majors associated with higher earnings (Wiswall and Zafar 2018). Women are also more likely than men to consider future family formation when selecting majors (Wiswall and Zafar 2021). Additionally, Ersoy and Speer (2025) is especially relevant to our study, showing that providing information about majors to students in the US, including student gender composition and other non-job-related factors, affects 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 adds 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).[3] 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).[4] Our findings suggest that a college gender quota can be an effective policy as well, ensuring a certain fraction of students in STEM programs are women, which lessens the concerns about the difficulty of fitting into such programs.

The remainder of the paper is structured as follows. Section 2 explains the Japanese high school and college application system, as well as the job market that follows. Section 3 details the experimental design. Section 4 describes the summary statistics of the experimental data. Section 5 presents the main results. Section 6 provides the results of the counterfactual analysis. Section 7 discusses policy implications of the results. Section 8 concludes.

2 Institutional Background

2.1 Japanese Education System

High School In the Japanese educational system, 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

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

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

rates are also high, at nearly 60%.[5] However, similar to the US, many colleges are similar to vocational schools in Europe, with only a few top colleges being academically oriented. We refer to the former as non-selective and the latter as selective in this paper. Additionally, because Science, Technology, Engineering, and Mathematics (STEM) fields require strong mathematical skills, most STEM programs are offered at selective colleges. As such, not all high schools can prepare students for admission to selective colleges or STEM programs; only academic high schools are equipped for that.

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 focus on reading (Japanese), English, sciences (biology, chemistry, and/or physics), and advanced mathematics. As discussed later, the track choice limits students' college majors.

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).

For the exam-based nature of college admission discussed later, students in these academic high schools regularly take mock exams to prepare for college entrance exams. On the score sheets of these mock exams, students are informed of their likelihood of admission to their preferred program, calculated based on their exam scores and the program selectivity. Each program is assigned a single number called the "selectivity index," which represents the score required to have a good chance of admission to that program. This index is normalized with a mean of 50 and a standard deviation of 10.

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 (Obunsha 2024).

Most programs employ an exam-based, meritocratic admissions system. They rank applicants based on their exam scores and make offers starting from the top of the list. However, each program requires exams in different subjects. Humanities and social sciences programs usually require

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

exams in advanced reading, English, history/social studies, and mathematics. In contrast, 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 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.

Job Search Colleges serve as very important signaling devices in the Japanese job market, and 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).

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).[6] Therefore, attending a college program with a higher selectivity index is very important for high school students, as it determines their career prospects.

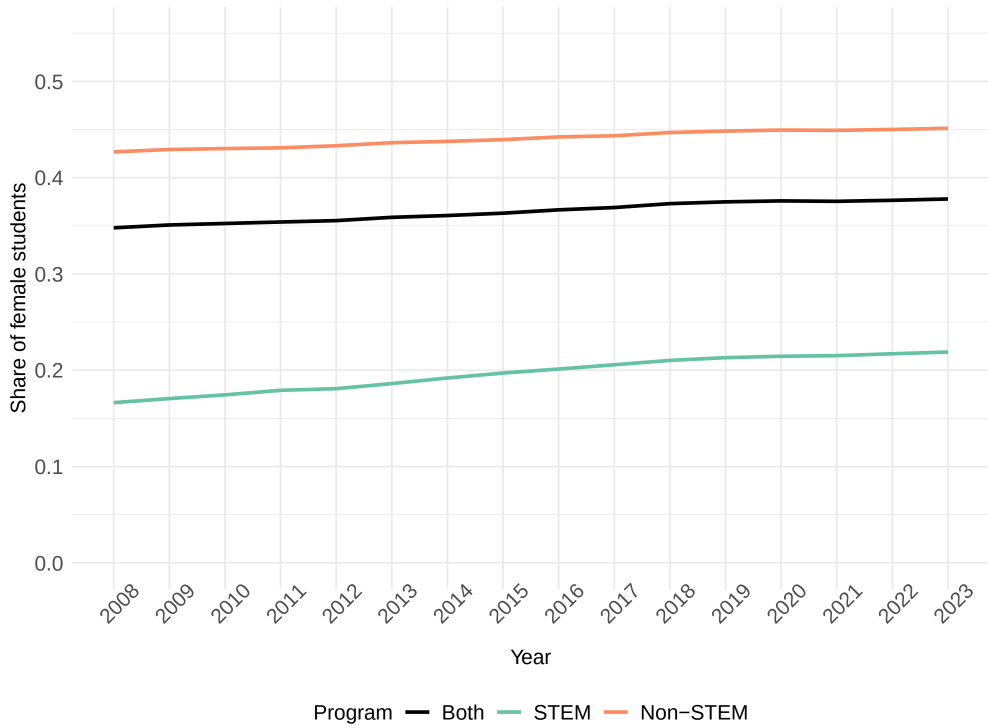
2.2 Descriptive Evidence: Changes in the Gender Ratio at Colleges over 15 Years

We provide some descriptive evidence that the gender ratio at college programs affects high school students' college choices, using the School Basic Survey conducted by the Ministry of Education, Culture, Sports, Science and Technology, which covers all college programs in Japan from 2008 to 2023. Appendix Table A1 provides classification of STEM and non-STEM programs. As of 2023, there are 2718 programs with 10 or more students, of which 448 are defined as STEM and 1040 as non-STEM; see Appendix Figure A1.

Figure 1 shows the trend in the share of female students among college students from 2008 to 2023. Although the female share in STEM programs rose from 16.6% to 21.9% during this period, male students consistently remained the majority in STEM fields. In contrast, the gender ratio in

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

Figure 1: Aggregate Female Student Share across College Programs from 2008 to 2023



Notes: This figure plots female student share among both STEM and non-STEM programs (black), STEM programs (green), and non-STEM programs (orange).
Source: School Basic Survey of the Ministry of Education, Culture, Sports, Science and Technology.

non-STEM programs has been more balanced.

If students prefer gender-balanced programs and their choices are not constrained by factors such as admission likelihood or the availability of programs in their region of residence, we would expect programs with greater gender balance to attract more students.

Figure 2 shows changes in the female student share across programs over the 15 years. We define programs with a selectivity index of 55 or above – that is, 0.5 standard deviations above the mean or higher – as selective. Programs with an index below 55 are classified as non-selective.[7,8] As the selectivity index is available only for 2023, we assign selectivity to 2008 programs based on the selectivity index in 2023. We exclude programs whose selectivity index is missing.[9] Programs observed in 2008 but do not have corresponding programs in 2023 are also excluded, as selectivity scores are unavailable for these programs.[10]

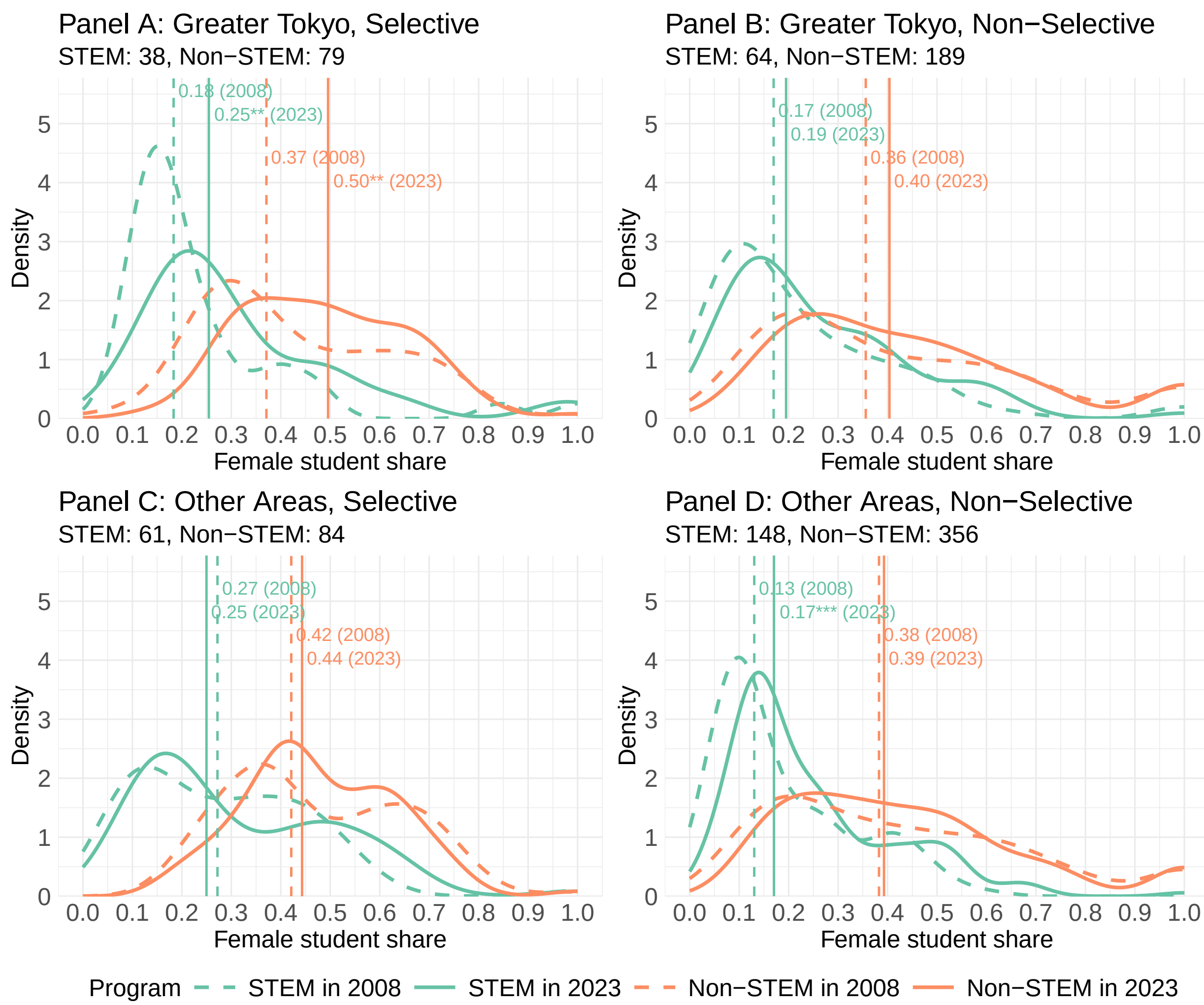
7. The selectivity index of each program is defined based on 2024 data obtained from a list prepared by Kawaijuku, one of the most popular commercial college entrance exam preparation companies in Japan: https://www.keinet.ne.jp/exam/ranking/index.html (accessed December 18, 2024). Since public colleges require a larger number of subjects for entrance exams, we follow Araki, Kawaguchi, and Onozuka (2016) and add 5 to the index of public colleges.

8. Programs with a selectivity index of 55 or higher are classified as rank B or above in Goodman and Oka (2021)'s classification, which aligns with what Japanese people consider a selective program.

9. This happens when, for example, a program primarily admits students without entrance exam or when the program no longer exists in 2024.

10. We hand-matched programs that changed their names or underwent organizational changes between 2008 and

Figure 2: Female Student Share across College Programs in 2008 and 2023



Notes: This figure illustrates changes in the distribution of female student share across programs from 2008 to 2023 for STEM (green) and non-STEM (orange) programs. Selectivity of 2008 programs is based on the selectivity in 2023. Programs that exist only in 2008 or only in 2023 are excluded; corresponding programs across the two years may not be identical, as some may have undergone renaming or organizational reform. Panel A shows the distribution for selective programs in the Greater Tokyo area; Panel B for non-selective programs in the Greater Tokyo area; Panel C for selective programs in other areas; and Panel D for non-selective programs in the other areas. Dashed lines correspond to 2008, and solid lines to 2023.
Source: School Basic Survey of the Ministry of Education, Culture, Sports, Science and Technology.

Panel A shows the distribution for selective programs in the Greater Tokyo area; Panel B for non-selective programs in the Greater Tokyo area; Panel C for selective programs in other areas; and Panel D for non-selective programs in other areas. STEM and non-STEM programs are shown in green and orange, with dashed lines for 2008 and solid lines for 2023. In 2008, compared to the relatively flat and diverse distribution of female student shares in non-STEM programs, STEM programs not only had lower female representation on average, but were also concentrated at the

2023.

lower end of the female share distribution at the program level.

From 2008 to 2023, with the exception of selective STEM programs in other areas, the distribution of gender ratios shifted to the right across all categories as the female student share increased over this period. However, selective STEM programs in the Greater Tokyo area experienced not only a larger shift toward gender balance, but also a flatter distribution of female student shares, with a thicker right tail. One possible explanation is that high-performing students in the Greater Tokyo area have greater flexibility in choosing program attributes than students in other areas or lower-performing students, making the trade-off between gender ratios and other attributes less binding. If more gender-balanced programs attract more female students than less gender-balanced programs do not, the distribution of female shares across programs will become more dispersed.

We examine whether this change in the distribution of program gender ratios is driven by high school students' preferences using a discrete choice experiment.

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.

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 3 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 received a participation gift (a set of cute, functional pens) equivalent to 500 JPY (approx. 5.27 USD in 2022 PPP) for their participation.[11]

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

11. 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).

Figure 3: Hypothetical Program Pair

Pair 4/15

AB College Dept. of Literature		AX College 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.

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. These were unrelated to the actual college names. The department was drawn from a list of 12 popular departments, 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 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%.[12] These attribute values were drawn with replacement for each program. Appendix Table A2 shows the possible values for each attribute.

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 few STEM programs had male students as the minority, and using actual college names would lead students to infer attributes not displayed.

One concern with 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 issue 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. Specifically, because the students were from academic high schools interested in attending

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

selective colleges, we assume most believed the experimenters had valuable academic and career information.[13].

Specifically, we provided the following information in the information letter and at the beginning of the experimental instructions, which closely followed the information Kessler, Low, and Sullivan (2019) and Low (2024) provided in their experiments:

> *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.*

Several studies employed the incentivized resume rating method to elicit preferences for attributes that are hard to elicit from revealed preferences. For example, 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, one of the most popular commercial college exam preparation companies in Japan.[14] As public colleges require more subjects in the entrance exam, we follow Araki, Kawaguchi, and Onozuka (2016) and add 0.5 to the index of public colleges (which is 5 in the raw index).

13. 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

14. The link to the list: https://www.keinet.ne.jp/exam/ranking/index.html (accessed December 18, 2024).

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 as neutral.[15] 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: 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%.

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.[16] 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,

15. 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).

16. Appendix Figure A2 shows the distribution of abilities for female and male students.

consistent with existing literature on gender differences in preferences (Croson and Gneezy 2009). Although not statistically significant, the gender difference in competitiveness aligns with prior research, indicating that male students tend to be more competitive than female students.

5 Effect of the Gender Ratio at Colleges on 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. However, we present the results with logit as a robustness check.[17]

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 decompose the treatment effects of the female student share 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:

$$C^r_{ij} = \alpha^{g,base} + \zeta^{g,base}(FShare_{jr} - FShare_{jl} = k) + (W_{jr} - W_{jl})'\omega^{g,base} + \epsilon^{base}_{ij} \tag{3}$$

Where C^r_{ij} 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^r_{ij} with the four reasons:

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

where M^m_{ij} (for $m = 1, 2, 3, 4$) is an indicator variable equal to 1 if student i indicated that reason

17. Equation 2 is equivalent to equation 7. See Train (2009), Section 3.1, for references.

m better applies to the right program in the choice pair j.

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

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

Gelbach (2016) shows that:

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

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.

As explained later, we discretize the female student share. Thus, we perform this decomposition for each bin of the share.

5.2 Preferences for Gender Ratio

Table 2: Preferences for Program Attributes

Sample:	Female			Male		
Estimation:	OLS		Logit (AME)	OLS		Logit (AME)
Outcome:	Choose the program (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
STEM	-0.079***	-0.079***	-0.078***	0.038**	0.038**	0.038**
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
Female student share	0.090***	0.821***	0.819***	-0.036	0.818***	0.815***
	(0.022)	(0.088)	(0.097)	(0.024)	(0.089)	(0.097)
Female student share squared		-0.745***	-0.742***		-0.875***	-0.872***
		(0.088)	(0.095)		(0.090)	(0.099)
Selectivity index (population SD)	0.046***	0.047***	0.046***	0.075***	0.075***	0.074***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Cohort size/100	0.003	0.003	0.003	0.006**	0.006**	0.006**
	(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**
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Club participation rate	0.193***	0.196***	0.196***	0.122***	0.130***	0.130***
	(0.042)	(0.042)	(0.043)	(0.041)	(0.040)	(0.041)
Constant	0.503***	0.503***		0.488***	0.487***	
	(0.007)	(0.007)		(0.008)	(0.008)	
Adj. R-squared	0.036	0.054		0.021	0.045	
No. observations	4649	4649	4649	4451	4451	4451
No. students	310	310	310	297	297	297

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, and columns 4 to 6 present estimates for male students. Standard errors are clustered at the student level. Significance levels: * 10%, ** 5%, and *** 1%.

Table 2 presents the coefficient estimates for program attributes, with choice as the dependent variable.[18] Columns 1 to 3 present estimates for female students, and columns 4 to 6 present estimates for male students. 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. Second, both female and male students prefer programs with higher selectivity indices, but male students show a 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.

Third, students also favor the social aspects of the programs. Both female and male students prefer programs that include an international exchange program, but female students prefer it more: having an international exchange program increases female students' choice probability by 5.9 to 6.0 percentage points, while it increases male students' choice probability by 3.3 to 3.4 percentage points. Club participation rates also affect students' choices: a 10% 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. Additionally, male students slightly favor larger programs, whereas female students do not: an increase of a program size by 100 students increases male students' choice probability by 0.6 percentage points. Logit (average marginal effects or AME) estimates in columns 3 and 6 show results essentially the same as those from OLS.

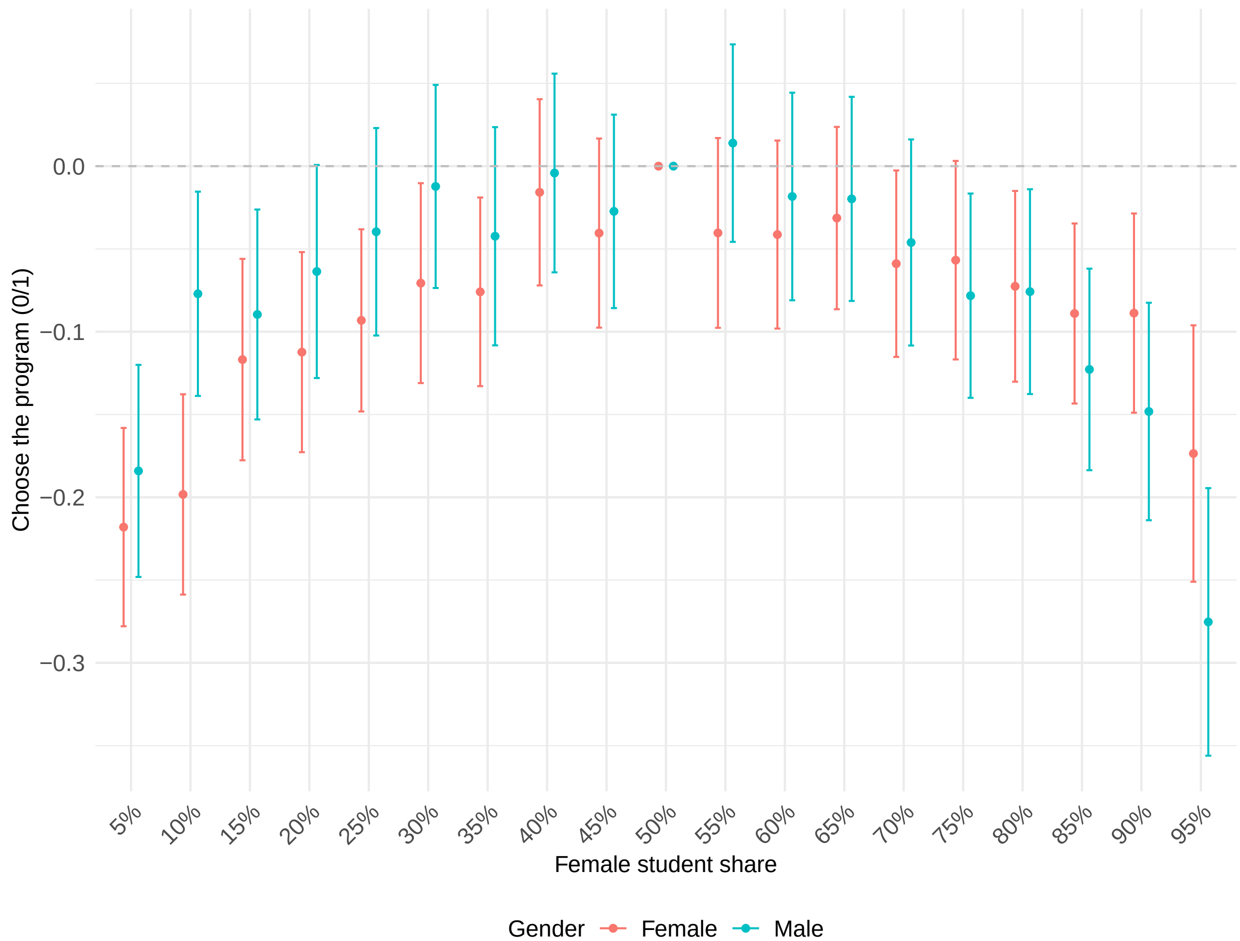
However, our main variable of interest, female student share, is highly non-linear for both female and male students: the coefficient estimates on the squared female student share are statistically and quantitatively significant for both groups, as shown in columns 2 and 4. Therefore, we discretize the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

Figure 4 plots the coefficient estimates and the 95% confidence intervals for female student share discretized into 19 equally spaced bins with 50% as the baseline, separately for female students (red) and male students (blue). 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 with fewer students of their own gender: compared to a program where 50% of students are female, female students are about 22-20 percentage points less likely to choose a program with only 5- 10% of female students, while male students are about 27-15 percentage points less likely to choose a program with only 5- 10% of male students (and 90- 95% female students).

Interestingly, both female and male students also prefer programs with a balanced gender ratio over those with a majority 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 (with 10-5% of students being female). However, both female and male students generally prefer a program where most students are their own gender rather than one with only a small proportion of students of their gender.

18. Appendix Table A4 presents the same specifications but with indicator variables for the four reasons instead of choice as the outcome variables.

Figure 4: Preferences for Gender Ratio



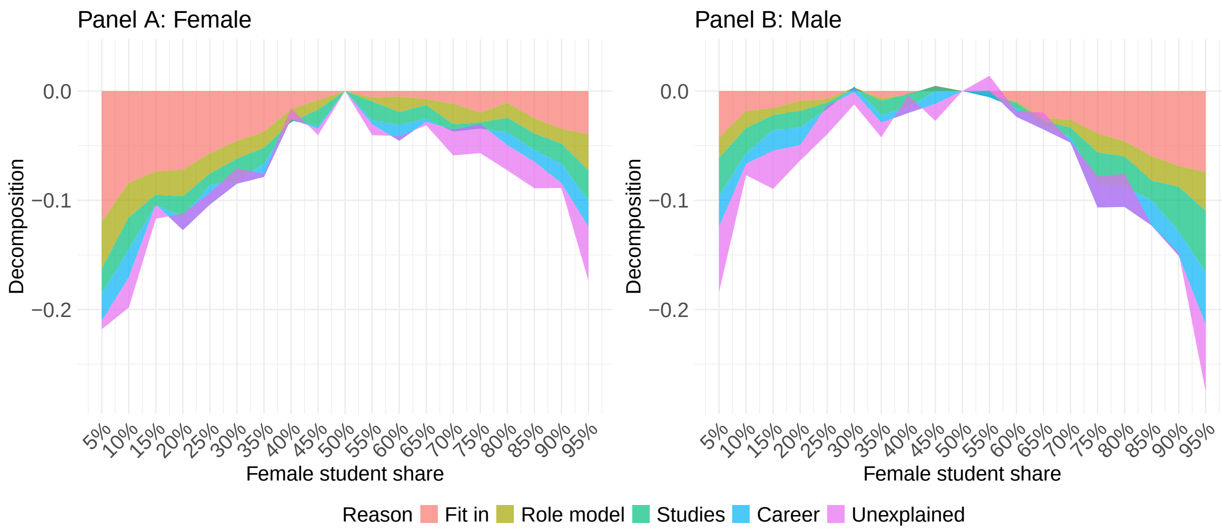
Notes: This figure plots the coefficient estimates and the 95% confidence intervals of female student share discretized into 19 equally spaced bins, with 50% as the baseline, separately for female students (red) and male students (blue). Standard errors are clustered at the student level.

5.3 Reasons for the Preferences

To investigate why the gender ratio affects students' college choices and why they tend to avoid being a minority and a majority, Figure 5 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. Specifically, when the majority of students are male, the gender ratio affects female students' program choices primarily due to concerns about fitting in. Conversely, when most students are female, multiple factors – such as concerns about fitting in, finding a role model, doing well in studies, and

Figure 5: Decomposition of Preferences for 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.

finding a career, as well as unexplained reasons – all contribute to how the gender ratio affects their decisions.

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 why.

5.4 Heterogeneity of the Preferences

STEM vs. Non-STEM Programs Appendix Figure A3 plots coefficient estimates and their 95% confidence intervals on discretized female student shares separately for STEM program (orange) and non-STEM program (green) for female (Panel A) and male (Panel B) students. The F statistic on the top left of each panel shows the differences in the estimates between STEM and non-STEM programs. The figure shows no significant heterogeneity between STEM and non-STEM programs for female or male students. This figure suggests that the gender ratio affects students' program choices regardless of whether it is STEM or non-STEM.

Top 50% vs. Bottom 50% Academic Abilities Appendix Figure A4 plots coefficient estimates and their 95% confidence intervals for discretized female student shares, shown separately for students in the top 50% (orange) and the bottom 50% (orange) of mathematics abilities. The F statistic on the top left of each panel shows the differences in estimates between the two groups. Panel A plots the estimates for female students, while Panel B plots the estimates for male students. The figure shows no significant heterogeneity between the two groups of students, both female and male.

Figure A5 plots the estimated differences in reading abilities and shows a marginally statistically significant difference (10%) between the top 50% and bottom 50% of male students in reading ability, but not among female students. Specifically, male students in the top 50% of reading abilities are more likely to choose male-majority programs than those in the bottom 50%. However, male students with top 50% reading abilities are less likely to choose programs where the majority of students are female. Overall, these figures suggest that the gender ratio affects students' program choices regardless of their academic ability.

High vs. Low SES Households Appendix Figure A6 plots coefficient estimates and their 95% confidence intervals for discretized female student shares, separately for students from households with high socioeconomic status (SES) (orange) and low SES (green). The F statistic in the top left corner of each panel shows the difference in estimates between the two groups of students. We measure SES by parents' education level: we classify students whose mother and father have at least bachelor's degree as high SES and students whose mother or father does not have bachelor's degree as low SES.[19] The figure shows no significant heterogeneity by household SES, suggesting that the gender ratio affects students' program choices regardless of their household SES.

To summarize, there is surprisingly little heterogeneity for preferences for the gender ratio across program types, students' academic ability levels, and household SES status. Preferences for gender balance are present among both STEM and non-STEM programs and students from diverse backgrounds.

6 Contribution to the Gender Gap in STEM Programs

To estimate the extent to which the preferences for the gender ratio and the low female student share in STEM programs contribute to the gender gap in these programs, we conduct a counterfactual analysis. First, we estimate individual-level preferences for each program attribute. Then, we use these individual-level preferences to predict STEM choice probabilities under two scenarios: the actual scenario where the gender ratio in STEM and non-STEM programs is set to the students' median belief level, and the counterfactual scenario where the gender ratio is balanced. We then analyze the STEM choice probabilities in these two scenarios.

A caveat with this counterfactual exercise is that we do not consider other constraints and assume that students are free to choose their programs solely based on their preferences. In reality, students' actual choices can be constrained by other factors such as financial considerations, parents' and teachers' suggestions, and other factors that we do not include in the program attributes in the experiments. Nonetheless, the comparison between the actual and the counterfactual scenarios can still be valid since those factors are held constant between the two scenarios.

19. There are 266 students classified as high SES and 278 students as low SES. Additionally, 65 students are unclassified because they responded that they did not know either their mother's or father's education (or both).

6.1 Econometric Framework

Estimation of Individual-Level Preferences To estimate individual students' preferences for program attributes, we use mixed logit. Rewrite equation 2 as follows:

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

where P^g_{ijd} is student i of gender g's choice probability of program $d \in \{r, l\}$ with attributes X in pair j.

Now, assume β^g_i 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:

$$P^g_{ijd}|\theta^g = \int \frac{\exp(X'_{jd}\beta^g_i)}{\sum_{k\in\{r,l\}}\exp(X'_{jk}\beta^g_i)} f(\beta^g|\theta^g)d\beta^g \tag{8}$$

where we allow arbitrary correlations among elements in β^g_i.

We draw individual-specific parameters β^g_i from the estimates as a weighted average of the conditional distribution of β^g_i, $h(\beta^g|y, X, g, \theta^g)$, 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). However, a normal distribution gives essentially the same results. We use a quadratic functional form for female student share to keep the number of model parameters adequate for the sample size.[20]

Prediction of Actual and Counterfactual STEM Choice Probabilities We predict the actual STEM choice probability with logit using individual-specific parameters $\hat{\beta}_i$:

$$\hat{P}^{STEM,Actual}_i = \frac{\exp(\bar{X}'_{STEM}\hat{\beta}_i)}{\sum_{k\in\{STEM,non\text{-}STEM\}}\exp(\bar{X}'_k\hat{\beta}_i)} \tag{9}$$

Where $\bar{X}_d$ is a vector of the average values of attributes a program can take, except the female student share, which is set to students' median belief (25% for STEM, 55% for non-STEM; see Appendix Table A3).

Now, we predict the STEM choice probability with $\tilde{X}_d$, where we set the female student share in STEM and non-STEM in $\bar{X}_d$ to 50%, so that i's choice is not constrained by the female student share:

$$\hat{P}^{STEM,CF}_i = \frac{\exp(\tilde{X}'_{STEM}\hat{\beta}_i)}{\sum_{k\in\{STEM,non\text{-}STEM\}}\exp(\tilde{X}'_k\hat{\beta}_i)} \tag{10}$$

Calculating Actual and Counterfactual Gender Balances in STEM We calculate the share of female and male students in STEM programs in both actual and counterfactual scenarios

20. The tipping point of female student share is 0.55 for female students and 0.47 for male students with quadratic female student share, which are not very different from the tipping points in Figure 4.

by averaging the STEM choice probabilities for each scenario. A capacity constraint is incorporated into the calculation of student shares because, in reality, not everyone can be admitted to their preferred program. This capacity constraint is applied to both actual and counterfactual scenarios by including a shadow price term in equations 9 and 10. We define the shadow price as follows and subtract it from the indirect utility of choosing STEM but excluding the error term, $X'_{STEM}\beta_i$:

$$\text{Shadow price}_i = \lambda(\overline{Selectivity} - \text{math score}_i) \tag{11}$$

where math score$_i$ is student i's math score and $\overline{Selectivity}$ is the average selectivity index a hypothetical program can take (63.75). The shadow price λ increases as more students place higher value on the STEM option. When λ is positive, it implies that entering a STEM program is more costly for students with lower mathematics ability and less costly for students with higher mathematics 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.[21]

We have the graduates' program-level placement record for one high school that participated in the experiment, and about 1/3 of the students enrolled in STEM programs. Therefore, we calibrate the λ so that the average probability of choosing STEM programs across all students in the sample is 1/3. 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 mathematics ability.

6.2 STEM Choice Probabilities

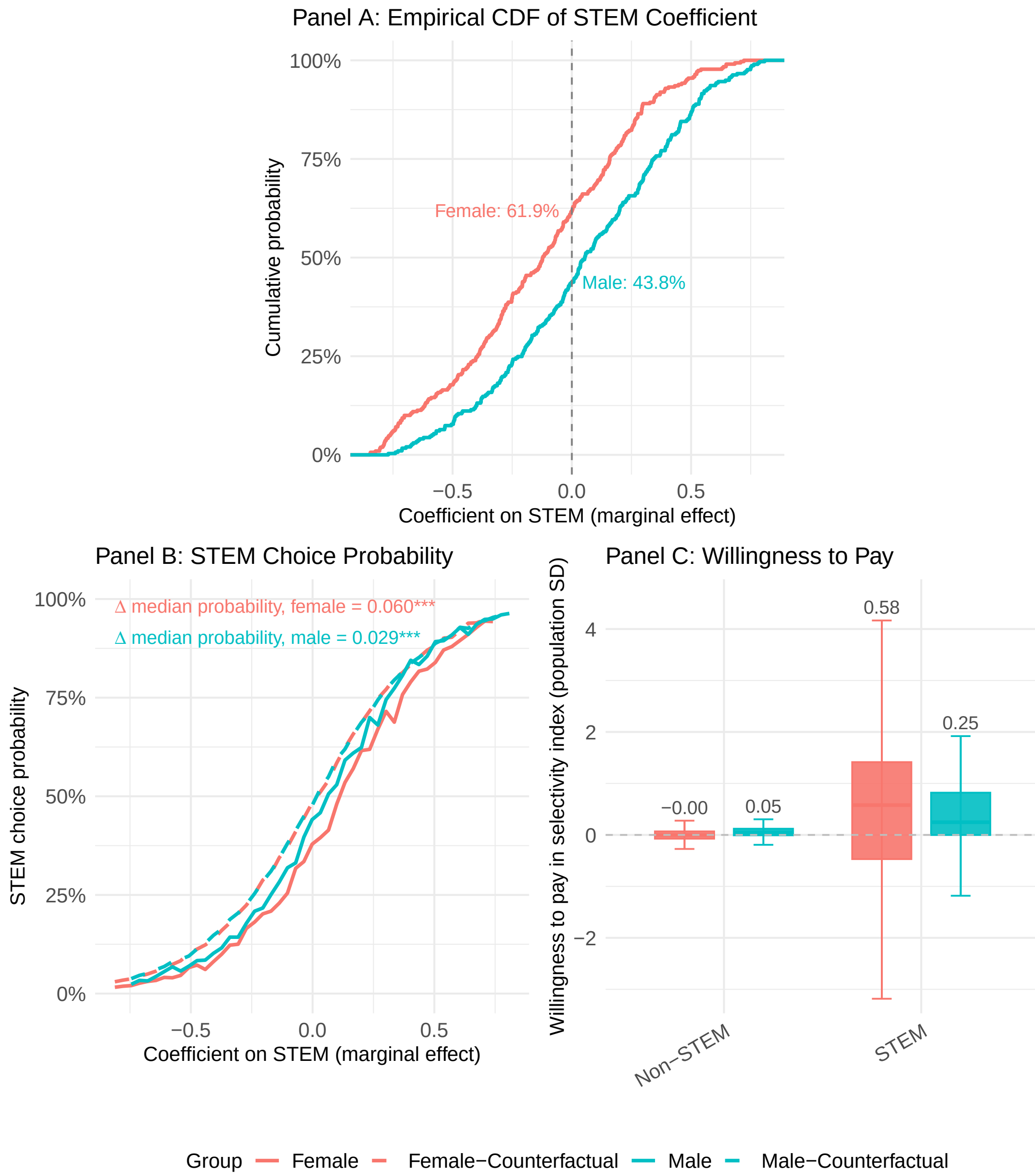
Panel A of Figure 6 plots empirical cumulative distribution functions (CDFs) of STEM coefficients for female (red) and male (blue) students. The figure shows that 38% of female students and 56% of male students have positive STEM coefficients. This suggests that in the absence of any constraints, 38% of female students and 56% of male students prefer STEM over non-STEM programs.[22]

However, the low female student share in STEM programs constrains their choices, especially female students' choices. Panel B of Figure 6 plots the actual (solid line) and counterfactual (dashed line) STEM choice probabilities for female (red) and male (blue) students. The texts at the top left show the median differences in choice probabilities under the two scenarios. In the counterfactual scenario where the student gender ratio is balanced, female and male students with an estimated coefficient on the STEM indicator indifferent between STEM and non-STEM programs consistent

21. Using the total score instead of the mathematics score does not change the results qualitatively; Appendix Figure A8 presents the results corresponding to Figure 7 and Appendix Figure A9 presents the results corresponding to Figure 8 but using the total score instead of the mathematics score in the shadow price.

22. Appendix Table A5 compares students who prefer STEM (with positive STEM coefficients) to those who prefer non-STEM (with non-positive STEM coefficients), separately for females and males. Panel A confirms that both female and male students who prefer STEM tend to have higher mathematics abilities than those who prefer non-STEM. However, Panel B shows that female students who prefer STEM are less confident in their reading abilities and more confident in their mathematics abilities, while male students do not exhibit differences in confidence.

Figure 6: STEM Choice Probabilities Under Actual and Counterfactual Scenarios



Notes: Panel A plots empirical cumulative distribution functions (CDFs) of STEM coefficient for female (red) and male (blue) students. Panel B plots the actual (solid line) and counterfactual (dashed line) STEM choice probabilities for female (red) and male (blue) students. The texts on the top left show the median differences in the choice probabilities under the two scenarios. The significance level is based on the Wilcoxon rank-sum test. Panel C plots the willingness to pay for moving from actual to the counterfactual scenarios measured by the selectivity index (in population standard deviation). The whisker indicates the range between the 5th and the 95th percentiles, and the number on the top indicates the median. Significance levels: * 10%, ** 5%, and *** 1%.

with expected choices in the absence of constraints. In the actual scenario, however, female students are 6 percentage points or 15.7% less likely to choose STEM at the median. The low female student share also reduces male students' choice probability by 2.9 percentage points or 5.2% at the median relative to the counterfactual scenario.

To quantify the utility cost associated with a low female student share in STEM programs, Panel C of Figure 6 plots the individual willingness to pay for moving from the actual to counterfactual scenarios, measured in units of the selectivity index (in population standard deviations). The whisker indicates the range between the 5th and 95th percentiles, and the number on top shows the median. The willingness to pay is calculated based on the indirect utility function in equation 1. Specifically, it is the additional selectivity index required to make individual i's indirect utilities equal when the female student share decreased from 50% to 25% (corresponding to the actual share in STEM) or increases from 50% to 55% (corresponding to the actual share in non-STEM). While the selectivity index is not a monetary measure, it is related to career success, which many students care about.[23]

Although it is a noisy measure, neither female nor male students are willing to significantly sacrifice the selectivity index in non-STEM programs to achieve a 50% female student share as expected, given that the share in non-STEM programs is already close to parity. In contrast, in STEM programs where female student share is far below 50%, a median female student is willing to sacrifice 0.58 standard deviations or more of the selectivity index. Male students are also willing to sacrifice, by 0.25 standard deviations at the median, though less than female students. These results suggest that the current low female student share in STEM programs imposes utility costs on students, particularly on female students.

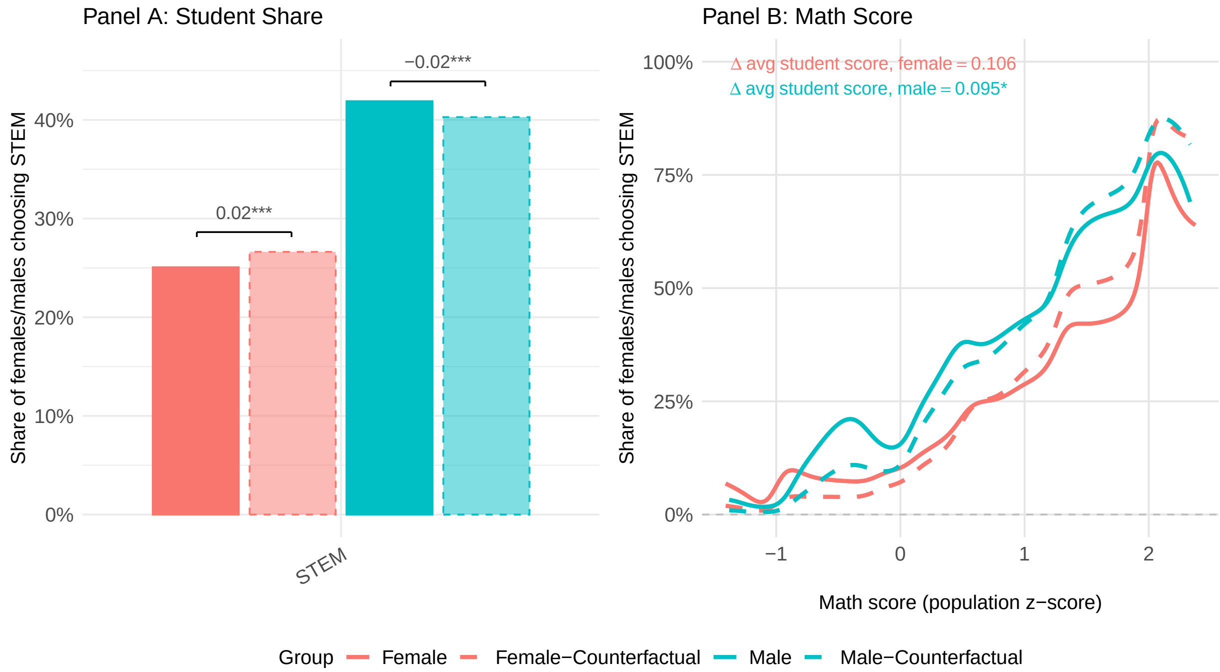
6.3 Student Shares in STEM

Panel A of Figure 7 plots the share of female (red) and male (blue) students who choose STEM programs under actual (solid) and counterfactual (dashed) scenarios. It shows that in the actual scenario, 25.1% of female students and 41.9% of male students choose STEM over non-STEM programs, resulting in a gender gap of 16.8 percentage points. However, when the gender ratio is balanced, the share of female students increases by 1.5 percentage points while the share of male students decreases by 1.6 percentage points. Thus, when the gender ratio is balanced, we achieve higher gender balance: 26.6% of female students and 40.3% of male students choose STEM over non-STEM programs, reducing the gender gap to 13.7 percentage points or narrowing it by 18.5% compared to the actual scenario. While female students are replacing male students who would have chosen STEM in the actual scenario, this substitution can actually improve the average student quality, as we show in the next subsection.

Note that the realized gender ratio does not reach 50:50 even under the counterfactual scenario. This is because the underlying preference for STEM is lower among female students than among male students, as shown in Panel B of Figure 6. Various factors may contribute to these gender differences in underlying preferences: the lack of STEM role models and the gender stereotypes

23. We are not the first to use a non-monetary measure to estimate willingness to pay. For example, Gallen and Wasserman (2023) measures willingness to pay for having a same-gender mentor by the probability that someone wants to be mentored by a person in their preferred occupation.

Figure 7: Student Share and Abilities in STEM Under Actual and Counterfactual Scenarios



Notes: Panel A plots share of female (red) and male (blue) students who choose STEM programs under actual (solid) and counterfactual (dashed) scenarios, and the significance level for gender share differences is based on a t-test. Panel B plots the mathematics ability of female (red) and male (blue) students who choose STEM under the actual (solid line) and the counterfactual (dashed line) scenarios, and the texts on the top left show the mean differences in the average student quality under the two scenarios where the statistical significance is obtained with the Horvitz-Thompson estimator using STEM choice probability as the selection probabilities (Horvitz and Thompson 1952). Significance levels: * 10%, ** 5%, and *** 1%.

associated with STEM, as discussed in the introduction.[24] Nonetheless, the low female student share in STEM is a factor that has a sizable effect on female students' choices, among other factors that prevents them from choosing STEM programs.[25]

6.4 Student Abilities in STEM

One concern policymakers would have is that increasing the female student share may attract students less prepared for STEM, which may deteriorate the quality of students. To address this concern, Panel B plots STEM choice probabilities of female (red) and male (blue) students under the actual (solid line) and the counterfactual (dashed line) scenarios against the mathematics ability on the x-axis. The texts on the top left show the mean differences in the average student quality under the two scenarios.[26]

24. It is also possible that female students have comparative advantage in readings and thus more likely to choose non-STEM (Dekhtyar et al. 2018). However, it is likely due to misconception of STEM programs as verbal skills are necessary both in STEM and non-STEM.

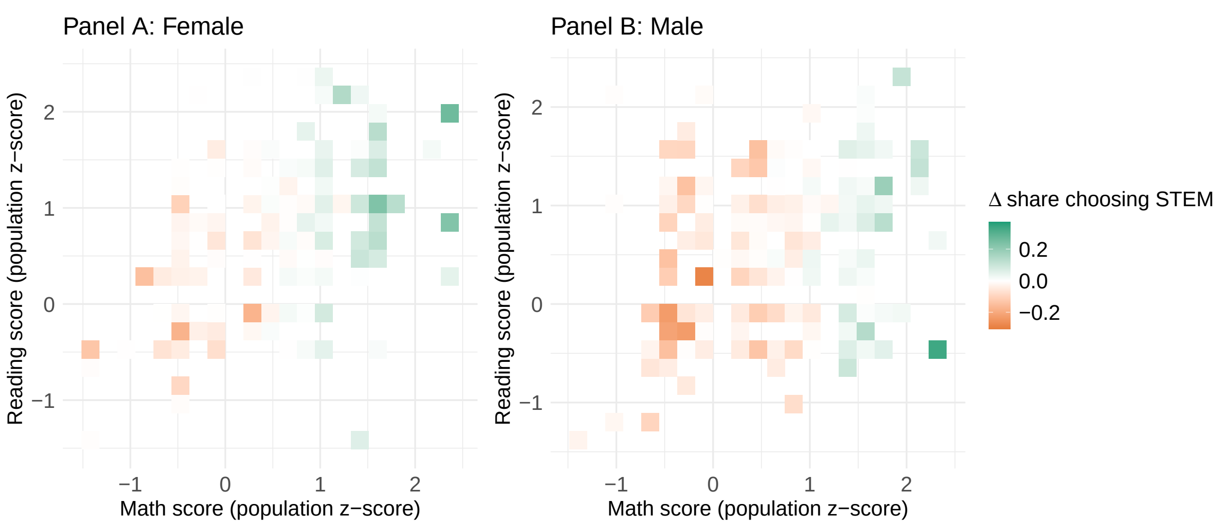
25. Appendix Figure A7 presents the same plots as Figure 7 but without capacity constraint.

26. The statistical significance is obtained with the Horvitz-Thompson estimator using STEM choice probability as the selection probabilities (Horvitz and Thompson 1952).

The Panel B of Figure 7 shows that under the actual scenario, about 7% of female students with mathematics ability 1 standard deviation below the population mean choose STEM programs. The share increases roughly with mathematics ability, reaching approximately 75% among female students whose mathematics ability is 2 standard deviations above the population mean. Under the counterfactual scenario, the share of female students who choose STEM programs drops further among those with mathematics ability 1 standard deviation below the population mean and increases slightly among those with mathematics ability 2 standard deviations above the population mean. More generally, balancing gender ratio attracts higher-performing students and replace lower-performing ones, resulting in a stronger association between the mathematics abilities and the likelihood of choosing STEM under the counterfactual scenario than under the actual scenario.

We see a similar pattern for male students who choose STEM programs between actual and counterfactual scenarios; however, the drop in the share of students with low mathematics abilities is more pronounced for male students. As a result, the change in the average student quality is marginally positive and statistically significant at 10% level.

Figure 8: Changes in Students' Abilities in Counterfactual Scenario



Notes: This figure plots a cross tabulation of mathematics (x-axis) and reading abilities (y-axis) of students who switch to STEM programs under the counterfactual scenario for females (Panel A) and males (Panel B).

While these results suggest an improvement in student quality in STEM programs, this may come at the cost of lowering student quality in non-STEM programs, given that STEM and non-STEM abilities are likely to be correlated. To elaborate this point, Figure 8 plots a cross tabulation of mathematics (x-axis) and reading abilities (y-axis) of students who switch to STEM programs under the counterfactual scenario for females (Panel A) and males (Panel B).[27] The figure shows that under the counterfactual scenario, male students who excel in reading but do not do well in

27. We see more changes along the 45 degree line because students who excel in mathematics also tend to excel in readings, especially female students. The correlation between mathematics and reading score is 0.481 for female students and 0.270 for male students.

mathematics are more likely to choose non-STEM than under the actual scenario, leading to an improved talent allocation. These results suggest that the current low female student share may be attracting male students who are less well-prepared for STEM, whereas making STEM programs more gender-balanced can attract students more prepared for STEM. On the other hand, we do not see this pattern for female students. Instead, the substitution seen in Panel A of Figure 7 involve female students with high mathematics abilities replacing male students with low mathematics but high reading abilities.

To summarize, the current low female student share in STEM programs constrains students' STEM choices, especially female students' choices. Removing this constraint can make STEM programs more gender balanced and can improve the allocation of talent – contrary to a potential policy concern that increasing the female student share may attract students less prepared for STEM and thereby deteriorate student quality.

7 Policy Implications

Although our results are based on a small fraction of high school students in Japan, we can still derive some policy implications for affirmative action for women in STEM in higher education.

First, a common criticism of affirmative action concerns individual merit: it does not benefit underrepresented students. For example, Arcidiacono, Aucejo, and Hotz (2016) find that at the University of California campuses, affirmative action for underrepresented minority (URM) students—which essentially lowers the admission standards—can actually have adverse effects on those students in STEM programs. They are more likely to drop out and take longer to graduate because they are less academically prepared.[28] Building on this, Arcidiacono and Lovenheim (2016) argue that while affirmative action can improve the quality of education that URM students receive, it can also reduce the fit between those students' academic readiness and the colleges' academic standards. Our findings suggest that this concern does not apply to policies aimed at female students, as female students affected by these policies are as academically prepared for STEM as currently enrolled male students.[29]

Another criticism of affirmative action concerns its potential negative spillover effects at the aggregate level: it can be discriminatory against non-minority groups. This is likely the reason behind the ban on affirmative action at colleges by the US Supreme Court in 2023 (see, for example, Mangan 2023) and the sentiments of some US high school students (The Learning Network 2023). In our context, we remain cautious that potential negative effects on male students could offset the welfare gains from improved overall student quality in STEM programs from a more balanced gender ratio.

Nevertheless, our findings indicate that some form of affirmative action may be justified due to a market failure: although women's underrepresentation in STEM could be associated with the

28. URM groups in this context refer to African Americans, Hispanics, and Native Americans.

29. There is also evidence that an affirmative action—specifically, a gender quota for candidates in a Swedish political party—improved the competence of politicians (Besley et al. 2017).

social losses such as talent misallocation, as discussed in the introduction, individual students are unlikely to internalize these societal costs when making decisions on their human capital investments. Specifically, although gender quotas are banned in the US, implementing a policy that ensures a certain percentage of incoming students are female could potentially benefits that outweigh the costs. Such a quota can generate short-run and medium-run effects. First, because a gender quota would alter the female student share – a component of X in students' indirect utility (equation 1) – and thereby directly affect the probability that female students choose STEM in the short term. Second, increasing the number of women in STEM programs and careers could shift societal perceptions in the medium term – for example, by creating more role models or reducing gender-based stereotypes about STEM aptitude – which, in turn, may influence the formation of underlying preference, represented by β in students' indirect utility in equation 1.

However, given the second criticism, such policies must be carefully designed to minimize negative spillover effects. Additionally, each program must implement measures to reduce stigma that students admitted through quotas may face – namely, the perception of being less capable than those admitted outside the quota (Yokoyama et al. 2024). Since the primary reason female students avoid being in the minority is the difficulty fitting in the environment, policies that lead potential applicants to worry about their ability to integrate socially or academically would likely be ineffective.

8 Conclusion

Female students are less likely to pursue STEM fields at colleges, despite negligible gender differences in mathematics and sciences. Having fewer women in STEM programs at colleges leads to several social issues. One potential reason that has received less 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 to what extent it contributes to the gender gap in STEM programs.

We first show, using administrative data that covers the entire universe of college programs in Japan, that colleges have become more gender balanced in both STEM and non-STEM programs, especially in programs where students face a weaker trade-off between gender ratios and other attributes. We then use an incentivized discrete choice experiment to demonstrate that the gender ratio at colleges does affect female but also male students' college choices. In particular, both female and male students dislike being a minority or a majority, and their main reason for disliking being a minority is the expected difficulty of fitting into the program.

A counterfactual analysis indicates that low female student share in STEM programs decreases the likelihood that a female student chooses a STEM program by 6 percentage points or 15.7%, and they incur the utility cost equivalent to 0.58 standard deviations of program selectivity. Removing this constraint would increase the gender balance in STEM programs and replace male students with low mathematics but high reading abilities with female students with high mathematics abilities.

Overall, the gender ratio at colleges is indeed an important determinant for students' college choices, and making STEM programs more gender-balanced can help close the gender gap in STEM, address social issues that come from it, and improve talent allocation.

A natural next question is how to make STEM programs more gender balanced. As discussed in Section 7, a gender quota would likely bring net benefits, and exploring the effects of the quota or its optimal design would be promising. While answering these questions would be difficult with our data, future research could implement some interventions or exploit the introduction of gender quotas in certain college programs. Although we should be cautious not to overgeneralize our findings, our paper highlights the importance of student gender ratios at colleges in closing the gender gap in STEM.

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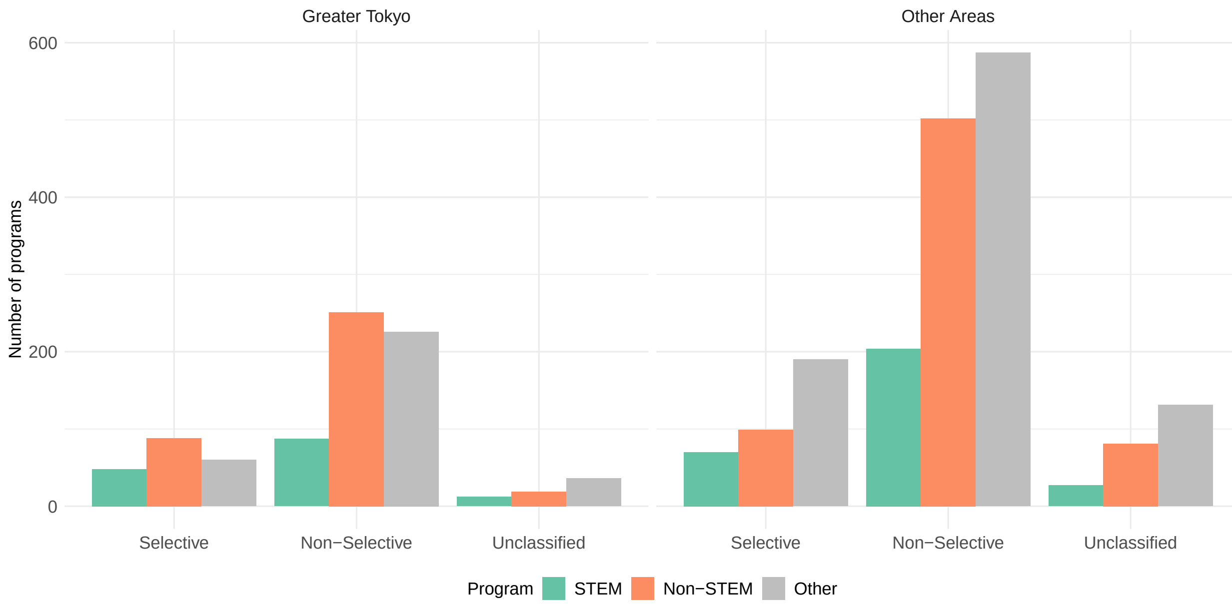
Online Appendix

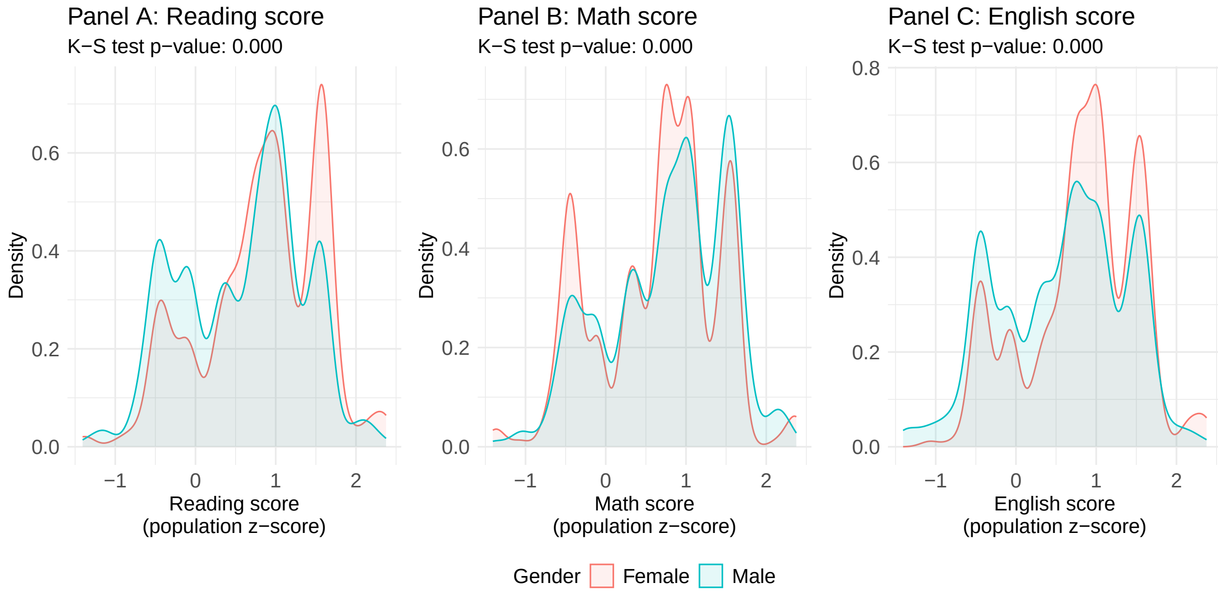
A Additional Figures and Tables

Figure A1: Number of College Programs in 2023



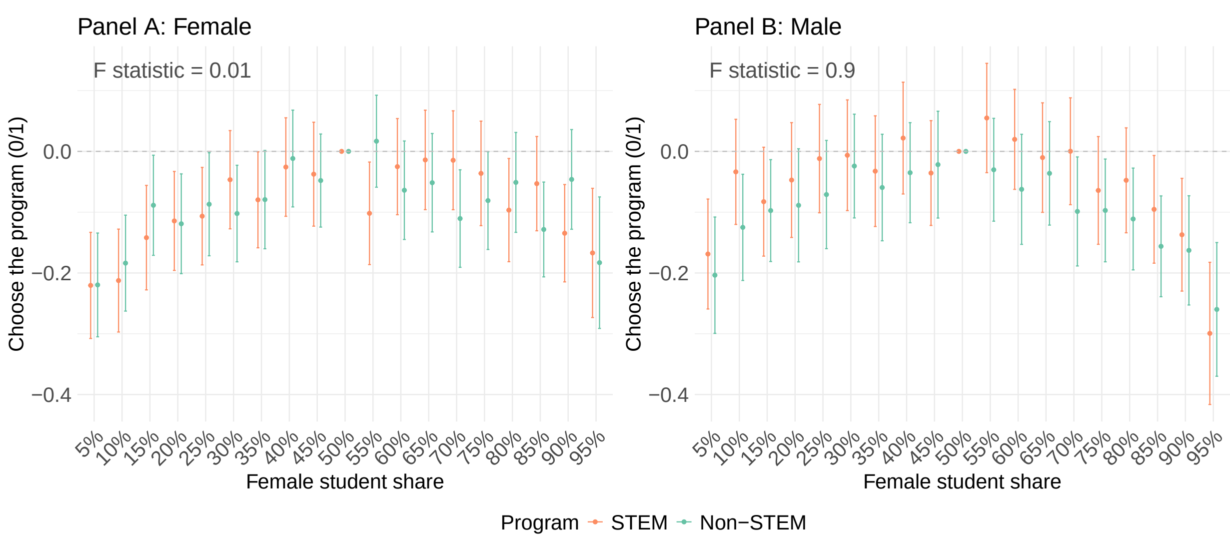
Notes: This figure presents the number of college programs in 2023 by program type, selectivity, and region.
Source: School Basic Survey of the Ministry of Education, Culture, Sports, Science and Technology.

Figure A2: Distribution of Abilities



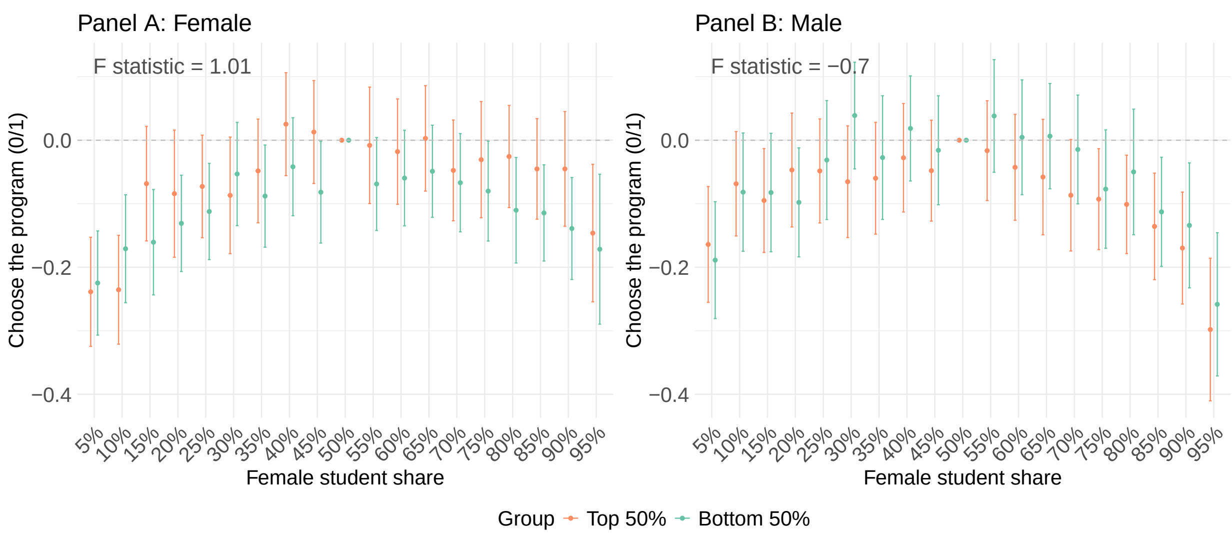
Notes: This figure presents the distribution of abilities of female and male students in reading (Panel A), mathematics (Panel B), and English (Panel C). K-S test p-value shows the Kolmogorov-Smirnov test p-value for differences in the distribution between female and male students.

Figure A3: Preferences for Gender Ratio by STEM vs. Non-STEM Programs



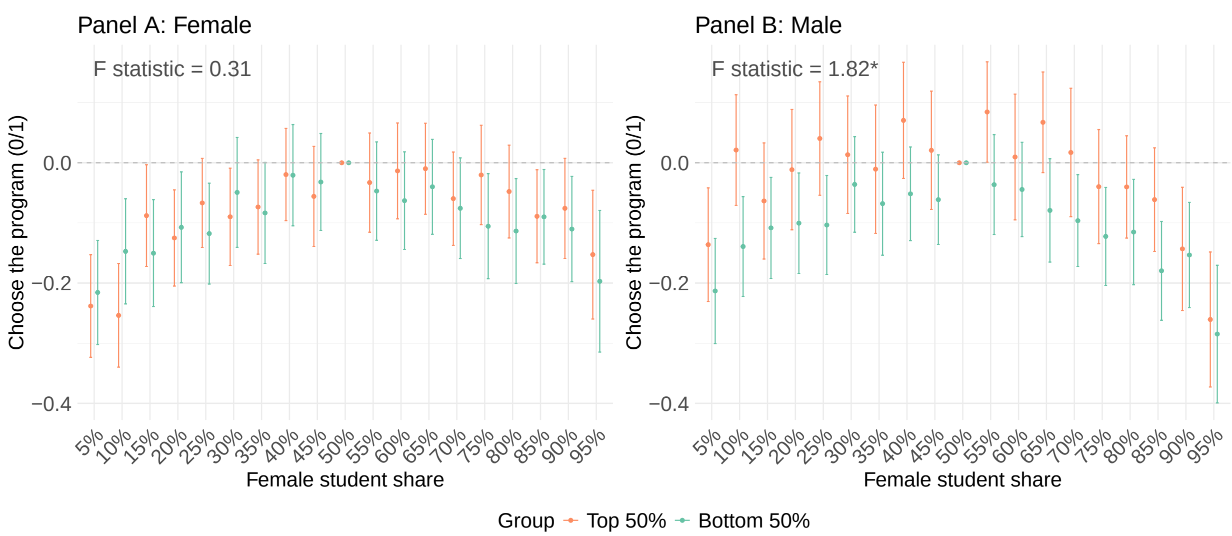
Notes: This figure plots coefficient estimates and their 95% confidence intervals on discretized female student shares separately for STEM program (orange) and non-STEM program (green) for female (Panel A) and male (Panel B) students. The F statistic on the top left of each panel shows the differences in the estimates between STEM and non-STEM programs. Significance levels: * 10%, ** 5%, and *** 1%.

Figure A4: Preferences for Gender Ratio by Top 50% vs. Bottom 50% Mathematics Abilities



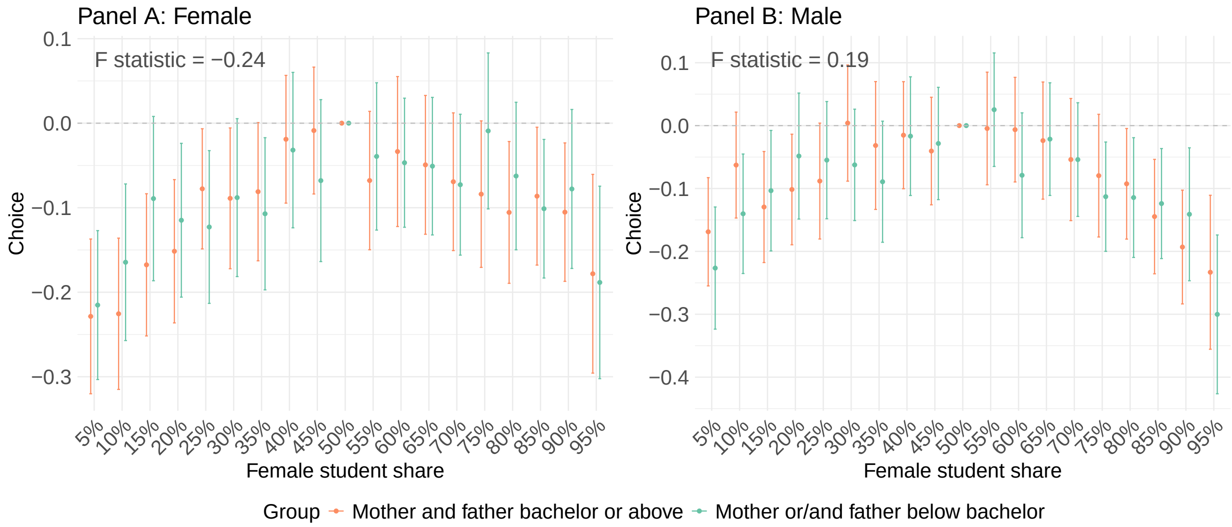
Notes: This figure plots coefficient estimates and their 95% confidence intervals on discretized female student shares separately for students in the top 50% (orange) and the bottom 50% (orange) of mathematics abilities. The F statistic on the top left of each panel shows the differences in the estimates between two groups of students. Significance levels: * 10%, ** 5%, and *** 1%.

Figure A5: Preferences for Gender Ratio by Top 50% vs. Bottom 50% Reading Abilities



Notes: This figure plots coefficient estimates and their 95% confidence intervals on discretized female student shares separately for students in the top 50% (orange) and the bottom 50% (orange) of reading abilities. The F statistic on the top left of each panel shows the differences in the estimates between two groups of students. Significance levels: * 10%, ** 5%, and *** 1%.

Figure A6: Preferences for Gender Ratio by Household Socioeconomic Status



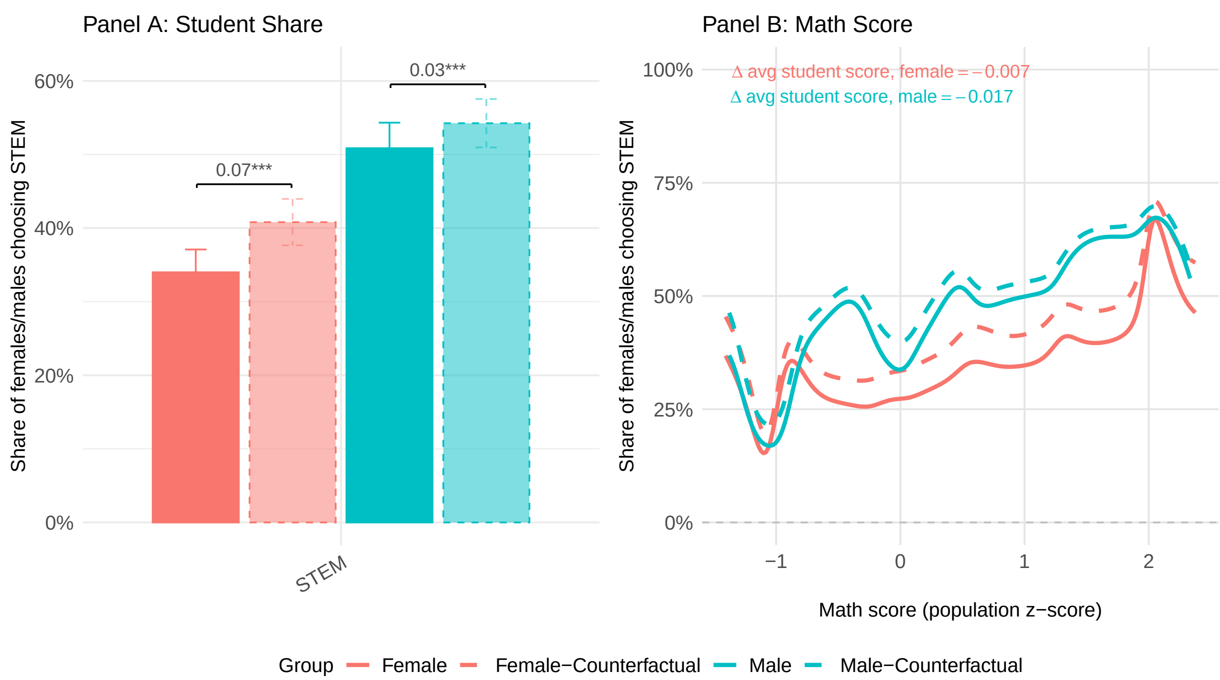
Notes: This figure plots coefficient estimates and their 95% confidence intervals on discretized female student shares separately for students from households with high socioeconomic status (SES) (orange) and with low socioeconomic status (green). The F statistic on the top left of each panel shows the differences in the estimates between two groups of students. Significance levels: * 10%, ** 5%, and *** 1%.

Table A1: Program Classification

Category and code	**Classification**	**Examples of majors**
Humanities (A, B)	Non-STEM	Literature, History, Philosophy, Foreign Language
Social Sciences (C, D)	Non-STEM	Law, Political Science Economics, Business Administration, Sociology
Natural Sciences (E, F)	STEM	Mathematics, Physics Chemistry, Biology
Engineering (G, H, I, J)	STEM	Mechanical Engineering, Electrical Engineering Civil Engineering, Textile Engineering
Agriculture (K, L)	STEM	Agriculture, Agricultural Chemistry Forestry, Fisheries
Health Sciences (M, N, O)	Other	Medicine, Dentistry Pharmacy, Nursing
Maritime (P)	STEM	Navigation, Marine Engineering Maritime Systems, Maritime Logistics
Home Economics (Q, R)	Other	Home Economics, Nutrition Clothing and Apparel, Housing Studies
Education (S, T, U)	Other	Education, Teacher Training Educational Psychology, Special Needs Education
Arts (V, W)	Other	Fine Arts, Music Design, Performing Arts
Others (X, Y, Z)	Other	Liberal Arts, Integrated Sciences, Global Studies, Human Relations Sciences

Notes: This table presents the classification of fields of study as defined by the School Basic Survey conducted by the Ministry of Education, Culture, Sports, Science and Technology.

Figure A7: Student Share and Abilities in STEM Under Actual and Counterfactual Scenarios – No Capacity Constraint



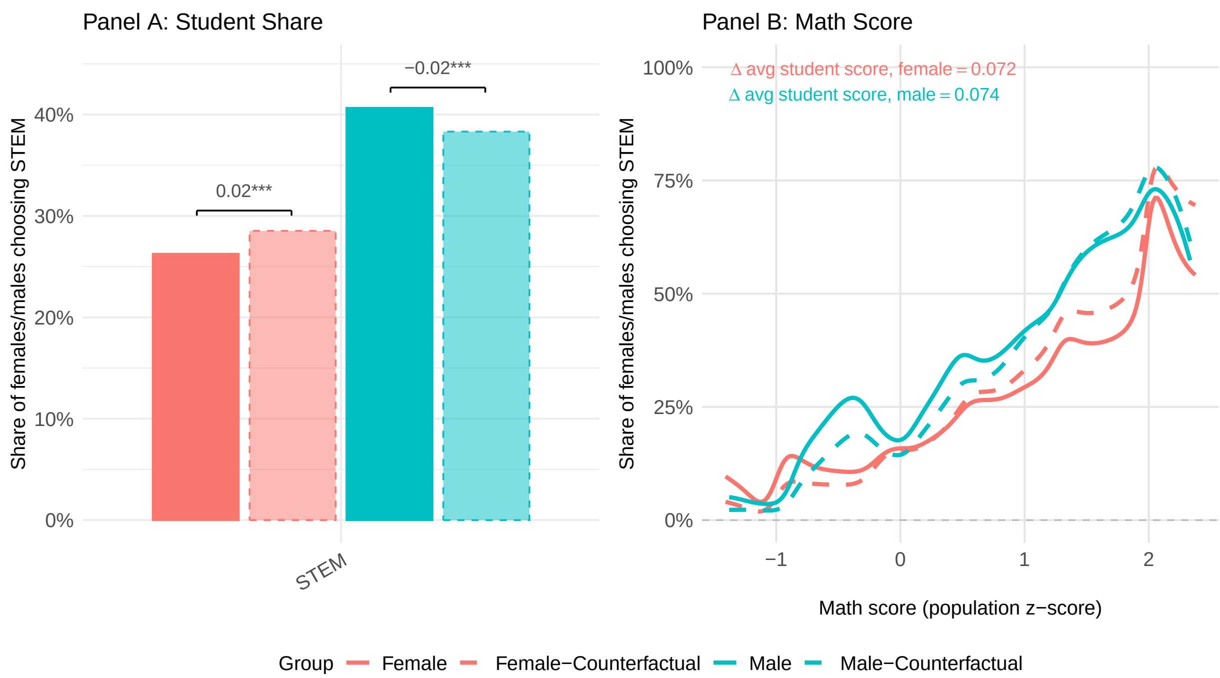
Notes: Panel A plots share of female (red) and male (blue) students who choose STEM programs under actual (solid) and counterfactual (dashed) scenarios without capacity constraint, and the significance level for gender share differences is based on a t-test. Panel B plots the mathematics ability of female (red) and male (blue) students who choose STEM under the actual (solid line) and the counterfactual (dashed line) scenarios without capacity constraint, and the texts on the top left show the mean differences in the average student quality under the two scenarios where the statistical significance is obtained with the Horvitz-Thompson estimator using STEM choice probability as the selection probabilities (Horvitz and Thompson 1952). Significance levels: * 10%, ** 5%, and *** 1%.

Table A2: 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 A8: Student Share and Abilities in STEM Under Actual and Counterfactual Scenarios – Using Total Score in the Shadow Price



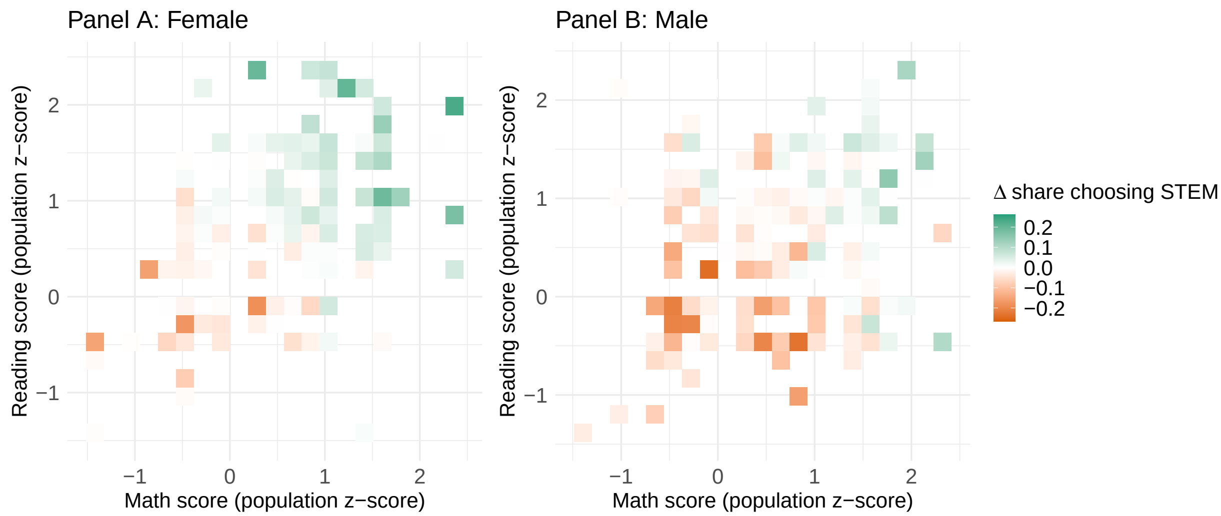
Notes: Panel A plots share of female (red) and male (blue) students who choose STEM programs under actual (solid) and counterfactual (dashed) scenarios, and the significance level for gender share differences is based on a t-test. Panel B plots the mathematics ability of female (red) and male (blue) students who choose STEM under the actual (solid line) and the counterfactual (dashed line) scenarios, and the texts on the top left show the mean differences in the average student quality under the two scenarios where the statistical significance is obtained with the Horvitz-Thompson estimator using STEM choice probability as the selection probabilities (Horvitz and Thompson 1952). Unlike Figure 7, we use total score in the shadow price. Significance levels: * 10%, ** 5%, and *** 1%.

Table A3: Median Belief about Female Student Share in Each Program

	Females' belief (N=311)	Males' belief (N=298)	Actual
Non-STEM	55.0%	50.0%	45.2%
STEM	25.0%	25.0%	22.8%

Notes: This table presents female and male students' median beliefs about female student share in each program.

Figure A9: Changes in Students' Abilities in Counterfactual Scenario – Using Total Score in the Shadow Price



Notes: This figure plots a cross tabulation of mathematics (x-axis) and reading abilities (y-axis) of students who switch to STEM programs under the counterfactual scenario for females (Panel A) and males (Panel B). Unlike Figure 8, we use total score in the shadow price.

Table A4: 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 A5: Comparison of Students Who Prefer STEM and Non-STEM

	Females (N=310)						Males (N=297)					
	Prefer non-STEM (N=192)		Prefer STEM (N=118)		Difference (STEM – non-STEM)		Prefer non-STEM (N=130)		Prefer STEM (N=167)		Difference (STEM – non-STEM)	
	Mean	SD	Mean	SD	Mean	SE	Mean	SD	Mean	SD	Mean	SE
Panel A: Demographics												
Mother bachelor or above	0.61	0.49	0.56	0.50	-0.06	0.06	0.57	0.50	0.55	0.50	-0.02	0.06
Father bachelor or above	0.77	0.42	0.84	0.37	0.07	0.05	0.73	0.44	0.80	0.40	0.06	0.05
Both bachelor or above	0.49	0.50	0.52	0.50	0.03	0.06	0.47	0.50	0.49	0.50	0.01	0.06
Extra schooling (no. days/week)	1.03	1.05	0.80	1.07	-0.23*	0.12	0.95	1.11	0.90	1.00	-0.06	0.12
Panel B: Academic abilities (population z-score)												
Reading score	0.85	0.76	0.79	0.70	-0.06	0.09	0.67	0.71	0.52	0.77	-0.15*	0.09
Math score	0.55	0.75	0.80	0.72	0.25***	0.09	0.60	0.72	0.90	0.74	0.29***	0.09
English score	0.79	0.68	0.88	0.71	0.09	0.08	0.49	0.81	0.64	0.75	0.14	0.09
Total score	0.67	0.74	0.79	0.74	0.11	0.09	0.52	0.72	0.67	0.78	0.15*	0.09
Panel C: Behavioral traits												
Reading confidence [-1,1]	0.03	0.41	-0.06	0.34	-0.09**	0.04	0.10	0.52	0.01	0.46	-0.09	0.06
Math confidence [-1,1]	-0.05	0.39	0.05	0.36	0.10**	0.04	0.14	0.51	0.22	0.49	0.09	0.06
English confidence [-1,1]	0.02	0.40	-0.02	0.38	-0.04	0.05	0.13	0.47	0.07	0.43	-0.06	0.05
Competitiveness [-1,1]	0.04	0.66	0.03	0.69	-0.01	0.08	0.09	0.69	0.13	0.68	0.04	0.08
Risk-taking [-1,1]	-0.35	0.60	-0.36	0.62	-0.01	0.07	-0.13	0.72	-0.21	0.69	-0.08	0.08

Notes: This table compares students who prefer STEM (who have a positive STEM coefficient) and students who prefer non-STEM (who have a non-positive STEM coefficient), separately for females and males. 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.

——————————— Page break ———————————

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]