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Unpacking the STEM Gender Gap: Evidence From Taiwan[*]

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Abstract

Across many countries, women enroll in science, technology, engineering, and math (STEM) fields less often than men. Using Taiwanese data from 2011–2018, we unpack the drivers of this gap. We find the gap in STEM enrollment largely reflects a gap in STEM applications. Conditional on applying to a STEM program, a female applicant is as or more likely to be admitted as a similar male applicant. We then turn to the gap in STEM applications and find one-third can be explained by math and science scores. We also find important differences between men and women in how test scores predict whether they apply to any STEM programs and how many they apply to. Finally, we find the gender gap in STEM applications differs widely across high schools, suggesting that educational institutions and social factors play a role in determining the number of women who pursue degrees in STEM.

Keywords: STEM gender gap, College major choice, Higher education, Blinder-Oaxaca decomposition

JEL Codes: I23, I26, J16

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1 Introduction

In Taiwan, women are far less likely than men to enroll in science, technology, engineering, and math (STEM) programs. Although half of Taiwanese college students are women, they only account for one-quarter of STEM enrollment. Between 2011 and 2018, only 17 percent of female applicants enrolled in a STEM program compared with 42 percent of male applicants. The gender gap in STEM enrollment is not unique to Taiwan; it arises across a wide variety of countries (Mostafa, 2019). Large gender gaps in STEM fields raise concerns that social factors might be preventing promising students from pursuing STEM degrees, a particular concern given the importance of STEM in technological innovation and economic growth (Beede et al., 2011).

How concerned we should be about the STEM gender gap depends on where it comes from. Some researchers argue these gaps reflect direct discrimination against women (Moss-Racusin et al., 2012) while others worry STEM gaps come from more subtle forms of social pressure that discourage girls from pursuing STEM fields (Kugler et al., 2021). Still others have pointed out that women may be discouraged by a lack of female role models (Carrell et al., 2010; Porter and Serra, 2020). Whatever their cause, it appears that men and women diverge in their math and science preparation well before college (Fryer and Levitt, 2010; Card and Payne, 2021). If these gaps were driven by direct discrimination, social pressure, or lack of role models, then this raises a concern that we are misallocating talent to these crucial fields. On the other hand, if gender differences in major choice largely reflect the underlying preferences of men and women (Zafar, 2013; Kahn and Ginther, 2018), then the gender gap in STEM enrollment looks far less worrisome.

Several features of Taiwan's college admissions system allow us to unpack the sources of the gender gap in STEM enrollment. Unlike in the United States, students in Taiwan apply directly to individual departments or programs. For example, rather than apply to National Taiwan University itself, a student would apply to specific programs within the university like economics or biology or mechanical engineering. Students are free to apply to any mix of programs either at the same university or at different universities. A student might apply to the same program at six different universities, six different programs at the same university, or anything in between. We use administrative data from Taiwan's centralized college application system on all students who applied to college between 2011 and 2018. The data include information on each student's high school, her entrance exam scores, the list of up to six programs she applied to, the programs to which she was admitted, and the one she ultimately chose. We also observe each program's admissions criteria and how it ranked each of its applicants.

We find a substantial gap in rates of applying to STEM programs for men and women. Nearly double the number of men than women apply to at least one STEM program, and five times as many men than women apply exclusively to STEM programs. Among math-intensive STEM programs, the differences are even starker. Nearly two and a half times as many men apply to math-intensive STEM programs, and more than six times as many apply exclusively to math-intensive STEM programs. A Blinder-Oaxaca decomposition confirms that nearly all of the gap in STEM enrollment can be explained by the gap in STEM applications. Therefore, the key to understanding the gender gap in STEM enrollment lies in understanding why men and women apply to STEM programs at such different rates.

Perhaps women avoid applying to STEM programs because they foresee facing discrimination from admissions committees. In our data we observe many applicants to the same program along with the ranking each program awards to each of its applicants. These rankings are based on exam scores, which we observe, and a subjective score, which we do not observe. To test for gender discrimination in the admissions process, we go program by program regressing each applicant's ranking on a gender dummy, controlling for entrance exam scores. The gender dummy coefficient tells us the extent to which the program prefers men or women with the same exam scores. If STEM programs discriminate against women, we would expect them to rank women lower than men with the same exam scores. But we find that, on average, programs actually exhibit a pro-female bias. That is, conditional on exam scores, programs tend to rank women higher than men. This pro-female bias is largest at programs with the fewest women faculty and applicants (which tend to be math-intensive STEM programs) but disappears at programs with more women faculty and applicants (which tend to be non-STEM programs). Thus, we find no evidence that admissions committees are biased against women. If anything, the bias runs in their favor, which only deepens the mystery of why women are so reluctant to apply to these programs.[1]

We find that about one-third of the gap in STEM applications can be explained by gender differences in exam scores. All students in Taiwan take exams in five areas: Chinese, English, math, science, and social science. Many programs only consider a subset of the five scores in their admissions. For example, non-math-intensive programs like history or literature will often consider only a student's Chinese and English scores

[1] It's possible that, despite receiving favorable treatment at the admissions stage, women nevertheless are discriminated against later on in either coursework or the labor market. Our data do not allow us to explore this possibility.

while ignoring her math scores completely. On the other hand, STEM programs tend to place more weight on the math and science scores. Although we find essentially no difference between men and women in Chinese, English, and social science scores, men do tend to score higher than women in math and science. Thus it is not surprising that math and science scores can explain some of the gender gap in STEM applications. We also find that men and women differ in subtle but important ways on the extensive margin (whether to apply to any STEM programs) and intensive margin (how many STEM programs to apply to). For example, while men are far more likely than women to apply to math-intensive STEM programs, women are more likely to apply to non-math-intensive STEM programs among high scoring students, especially those who are strong in math and science.

To summarize, STEM enrollment gaps are almost entirely explained by STEM application gaps. After ruling out discrimination at the admissions stage, we find that one-third of the application gap can be explained by the fact that men tend to have higher math and science exam scores. Or put differently, two-thirds of the gap in STEM applications cannot be explained by exam scores. This evidence is consistent with the theory that gender gaps in STEM applications (and by extension enrollment) are driven to a large extent by less interest in STEM among women *at the college application stage*.

This immediately raises the question of when and how women become less interested in STEM, and we find suggestive evidence that social or cultural influences are at least partly responsible. Going high school by high school, we regress the number of STEM applications submitted by each graduate on a gender dummy, controlling for exam scores. The coefficient on the gender dummy reflects the degree to which girls from that high school apply to fewer STEM programs than equally qualified boys. We find that the gender gap in STEM applications varies across high schools, which we would not expect if the entire gender gap were due to innate differences between men and women. Indeed, at some high schools there is no difference in STEM applications between boys and girls. We find that the gap in applications is larger at high schools with better test scores and those with more female faculty but smaller if the principal is female. We also find a smaller gap at high schools located in communities with higher income, more colleges nearby, and a higher female-to-male earnings ratio.

2 Institutional Background

In January or February of each year, high school seniors in Taiwan who are applying for college take the General Scholastic Aptitude Test (GSAT), which consists of five subject exams in Chinese, English, math, social science, and science. After receiving their scores, students can apply to up to six programs at one or more universities through the Personal Application. If their scores clear a program-specific threshold, they are invited to submit a detailed application portfolio which may include an in-person interview. Then, each program accepts some applicants, wait-lists others, and rejects the rest. They also rank all the applicants who were either accepted or wait-listed based on both objective and subjective criteria. Students likewise submit a rank order list of the programs to which they have been either accepted or wait-listed. Finally, the central mechanism uses a deferred acceptance algorithm to assign students to programs using the rank order lists submitted by each applicant and each program.

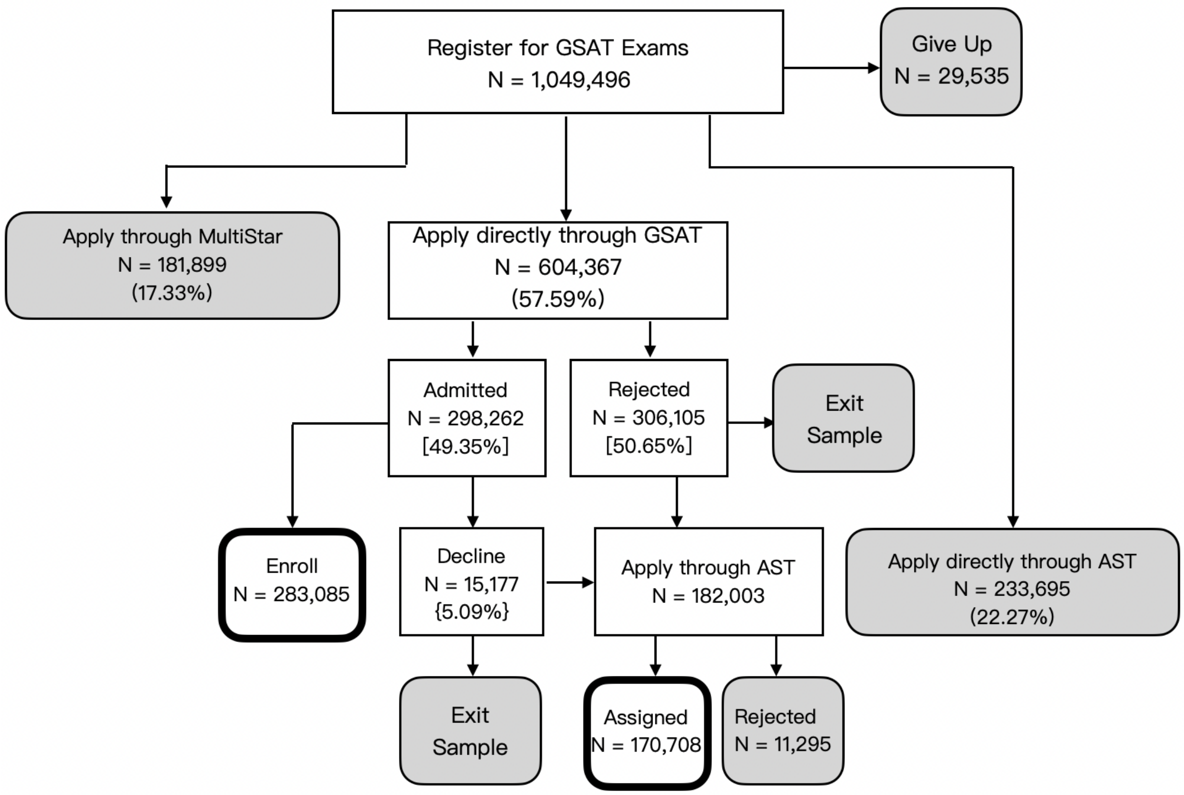
At the conclusion of the deferred acceptance algorithm, many students remain unassigned and a small number reject their assignments. They then have the option to take a new set of exams called the Advanced Subjects Test (AST) during the summer. After receiving their AST scores, they submit a (potentially long) rank order list of programs and are assigned through a second deferred acceptance algorithm.[2]

Figure 1 illustrates the entire application process. Among the more than one million students who registered for the GSAT exams between 2011–2018, just over 600,000 of them applied through the Personal Application. About half of those received an assignment, with 95 percent accepting their assignment and enrolling. The other half of Personal Application students who did not receive an assignment either gave up and exited the sample or took the AST. The vast majority of those taking the AST received an assignment. Figure 1 also illustrates two alternative channels a student can take to apply for college. She can apply through the Stars Program which uses a very different application process to help disadvantaged students access higher ranked universities.[3] Or she can skip the Personal Application completely and go straight to taking the AST in the summer. For this paper, we focus on students who applied through the Personal Application and ultimately enrolled, either by accepting a Personal Application assignment or an AST assignment.

[2]In this case, each program's ranking of students is based on a fixed, program-specific weighted average of AST scores.

[3]The Stars Program is similar to the Texas Top Ten Percent Rule for admission to the University of Texas.

Figure 1: Structure of the Taiwanese College Admission System



Note: The figure illustrates the overall structure of the exam system in Taiwan from 2011 to 2018. The registration for GSAT exams can be divided into three groups: (1) applying through MultiStar; (2) applying directly through GSAT (Personal Application); (3) skipping the Personal Application and applying through the AST. Our sample consists of applicants who end the process in either of the two nodes outlined in bold. These are applicants who applied through the GSAT and ultimately enrolled, either through the GSAT or through the AST. Applicants who end at any of the gray nodes are excluded from our sample.

3 Data

We obtain data from the National Academy for Educational Research (NAER) on all takers of the GSAT and AST exams between 2011–2018. The datasets for the GSAT and AST takers are separate. For the GSAT, the data contains the following information on each student: gender, high school, exam scores, the programs she applied to, where she was admitted and waitlisted, her assignment, and whether she accepted that assignment. We also observe the rankings each program gave to its applicants in each year. For the AST data, we observe the following: gender, high school, GSAT exam scores, AST exam scores, and the ultimate AST assignment. Unfortunately, the GSAT and AST data does not contain a student id variable to link a student across the two datasets. However, we are able to link almost all AST students back to the GSAT data by matching on the student's gender, high school, and five GSAT exam scores. This is because it is very rare for two students from the same high school with the same gender to receive exactly the same GSAT scores on all five exams. After linking, our dataset consists of all students who applied through the GSAT and ultimately enrolled, whether through the GSAT or through the AST.

Table 1 reports descriptive statistics for applicants in our sample. Column 1 includes those who applied and enrolled through the Personal Application channel (GSAT) while column 2 includes those who applied through the Personal Application but ultimately enrolled through the AST channel (GSAT+AST). Panel A in Table 1 reports the gender composition of applicants, Panel B reports descriptive statistics for the applicant's high school, and Panel C reports neighborhood characteristics of the applicant's high school. Applicants in both channels are evenly split between males and females. Those in the GSAT+AST channel are more likely to have attended a public high school and to be coming from a large city.[4]. Aside from that, high school and neighborhood characteristics do not differ much between the two channels.

[4]The 6 big cities includes Taipei, New Taipei, Taoyuan, Taichung, Tainan, and Kaoshiung.

Table 1: Descriptive Statistics

	(1) **GSAT**	(2) **GSAT+AST**	(3) **Total**
Panel A: Applicants			
Male	51.85%	50.63%	51.49%
	(219,005)	(92,157)	(311,162)
Female	48.15%	49.37%	48.51%
	(203,359)	(89,846)	(293,205)
Panel B: High School Characteristics			
Public high school	63.19%	76.63%	67.24%
	(266,887)	(139,464)	(406,351)
Female faculty	59.46%	60.36%	59.69%
Female students	50.01%	50.01%	50.01%
Big Cities	31.56%	35.85%	32.85%
	(133,306)	(65,248)	(198,554)
Panel C: Neighborhood Characteristics			
Average income (in thousands of NTD)	1,037	1,068	1,045
Number of colleges	1.40	1.50	1.43
Male graduated from college	44.61%	45.84%	44.92%
Female graduated from college	40.57%	41.68%	40.85%
Total applicants	422,364	182,003	604,367

Note: This table reports summary statistics for all applicants who enrolled through the GSAT and GSAT+AST channels. Public high school indicates whether an applicant graduated from a public high school. Female faculty represents the percent of female faculty at the applicant's high school. Female students represents the percent of female students at the applicant's high school. Big cities indicates whether the applicant graduated from a high school in one of the six main cities: Taipei, New Taipei, Taoyuan, Taichung, Tainan, and Kaoshiung city. Neighborhood income is denominated in thousands of New Taiwan dollars (NTD) per year (1 USD $\approx$ 30 NTD). The numbers in parentheses are raw counts of applicants.

Table 2 reports STEM and non-STEM enrollments by application channel and gender. Total enrollments are split fairly evenly between males and females. However, males make up 73 percent of STEM enrollments while females make up 61 percent of non-STEM enrollments. Male applicants also apply to 2.7 STEM programs while females apply to only 1.02.

Table 2: Enrollment in STEM Programs

	(1)	(2) **GSAT**	(3)	(4)	(5) **GSAT+AST**	(6)	(7)	(8) **Total**	(9)
	All	Male	Female	All	Male	Female	All	Male	Female
STEM Enrollment	100% (118,267)	74.12% (87,660)	25.88% (30,607)	100% (60,542)	69.58% (42,127)	30.42% (18,415)	100% (178,791)	72.59% (129,787)	27.41% (49,022)
Non-STEM Enrollment	100% (176,694)	38.82% (68,585)	61.18% (108,109)	100% (110,166)	39.50% (43,512)	60.50% (66,654)	100% (286,860)	39.08% (112,097)	60.92% (174,764)
Total Enrollment	100% (294,961)	52.97% (156,245)	47.03% (138,716)	100% (170,708)	50.17% (85,639)	49.83% (85,069)	100% (465,669)	51.94% (241,884)	48.06% (223,785)
Total Applicants	422,364	219,005	203,359	182,003	92,157	89,846	604,367	311,162	293,205
# STEM application	1.94	2.77	1.04	1.76	2.53	0.96	1.88	2.70	1.02
# Non-STEM application	3.38	2.60	4.21	3.13	2.46	3.81	3.30	2.56	4.09

Note: This table reports enrollment rates in STEM and non-STEM programs. Columns (1) - (3) report enrollment for those who enrolled through the GSAT channel. Columns (4) - (6) reports enrollment for those who applied through the GSAT channel but ultimately enrolled through the AST. Columns (7) - (9) combine both groups. Raw counts are reported in parentheses. The final two rows report the average number of STEM and non-STEM applications.

4 Empirical strategy

4.1 Ordinary least squares and multinomial logit

We begin by estimating the following regression specification

$$\mathbb{E}[D_i|M_i, X_i] = M_i\beta + X_i \cdot \gamma \tag{1}$$

where D_i is a dummy variable equal to one if student i enrolls in a STEM program and M_i is a dummy equal to one if i is male. X_i are other student characteristics, like exam scores or the number of STEM programs applied to, that could explain whether student i enrolls in a STEM program.[5] When X_i is omitted, β will correspond to the raw gender gap in STEM enrollment.

In addition to using OLS to estimate the gender gap in STEM enrollment, we also use a multinomial logit model where the outcome contains five groups of majors: math-intensive STEM, non-math-intensive STEM, social sciences, arts and humanities, and medical and nursing programs. Doing so allows us to estimate raw gender gaps in math-intensive and non-math-intensive STEM enrollment as well as how those gaps change when controlling for applicant characteristics.

4.2 Blinder-Oaxaca decomposition

To quantify the role of student characteristics in explaining the gender gap in STEM enrollment, we perform a Oaxaca decomposition. The raw gender gap in STEM enrollment is

$$\Delta^{RAW} = \mathbb{P}[D_i = 1|M_i = 1] - \mathbb{P}[D_i = 1|M_i = 0] = \mathbb{E}[D_i|M_i = 1] - \mathbb{E}[D_i|M_i = 0]$$

We might naturally wonder to what extent other covariates X explain this raw gender gap. If we assume a linear specification for the conditional expectations

$$\mathbb{E}[D_i|M_i = 1, X_i] = X_i \cdot \gamma^M$$
$$\mathbb{E}[D_i|M_i = 0, X_i] = X_i \cdot \gamma^F$$

[5] X_i also includes an intercept term.

then the raw gender gap can be written as[6]

$$\begin{aligned}\Delta^{RAW} &= \overline{X}_M \cdot \gamma^M - \overline{X}_F \cdot \gamma^F \\ &= \underbrace{(\overline{X}_M - \overline{X}_F) \cdot \gamma^F}_{\text{Endowment}} + \underbrace{\overline{X}_F \cdot (\gamma^M - \gamma^F)}_{\text{Coefficient}} + \underbrace{(\overline{X}_M - \overline{X}_F) \cdot (\gamma^M - \gamma^F)}_{\text{Interaction}} \end{aligned} \tag{2}$$

where $\overline{X}_M$ and $\overline{X}_F$ are the mean values of the covariates for men and women. That is, the raw gap can be decomposed into three components: differences due to different endowments of X, differences due to different coefficients γ, and the interaction of the two.

4.3 Zero-inflated Poisson regression

As mentioned in the introduction, we find that the number of STEM applications is a key driver of the gender gap in STEM enrollment. To better understand how men and women differ in their application choices, we estimate a zero-inflated Poisson regression (Lambert, 1992). For each student i, the number of STEM applications takes on values with probabilities

$$Y_i = \begin{cases} 0 & \text{with probability } (1 - p_i) + p_i \mathrm{e}^{-\lambda_i} \\ k & \text{with probability } p_i \frac{\mathrm{e}^{-\lambda_i} \lambda_i^k}{k!} \end{cases}$$

where

$$p_i = \frac{\exp\{X_i \cdot \beta\}}{1 + \exp\{X_i \cdot \beta\}} \tag{3}$$

$$\lambda_i = \exp\{X_i \cdot \gamma\}. \tag{4}$$

As before, X_i are student covariates including a gender dummy. The zero-inflated Poisson model assumes the number of STEM applications follows a Poisson distribution with mean governed by the parameter vector γ, while the probability of zero applications is inflated by a logistic term governed by the vector β. In the limit when $p_i = 1$, the model reduces to a standard Poisson regression model. It is not necessary for the same covariates to enter into the expressions for both p_i and λ_i, but, lacking a reason to exclude a covariate from one or the other, we include all covariates in both. The zero-inflated Poisson regression model allows us to distinguish gender differences on the extensive margin of STEM applications—*did the student apply to any STEM programs?*—from the intensive margin—*how many STEM programs did she apply to?* More precisely, the expected

[6] See Jann (2008) for a derivation of this decomposition. Relative to equation (1), the only difference here is that we are allowing for the coefficient vector γ to differ for men and women.

number of STEM applications can be written as $\mathbb{E}[Y] = \mathbb{P}[Y > 0] \times \mathbb{E}[Y|Y > 0]$, and we can separately calculate the marginal effects $\frac{\partial \mathbb{P}[Y>0]}{\partial x_j}$ and $\frac{\partial \mathbb{E}[Y|Y>0]}{\partial x_j}$ for a given covariate x_j (see Table 8). Moreover, a bit of algebra allows us to decompose the overall gap in expected applications into two pieces

$$\frac{\mathbb{E}[Y|M]}{\mathbb{E}[Y|F]} = \frac{\mathbb{P}[Y > 0|M]}{\mathbb{P}[Y > 0|F]} \times \frac{\mathbb{E}[Y|Y > 0, M]}{\mathbb{E}[Y|Y > 0, F]} \tag{5}$$

with the first term capturing the gender gap in the extensive margin and the second the gap in the intensive margin.

5 Empirical Results

In this section, we estimate the sensitivity of the gender gap in STEM enrollment to including various controls. We then perform a Blinder-Oaxaca decomposition to identify differences between males and females that explain the STEM enrollment gap. After concluding that the number of STEM applications is the primary driver of the enrollment gap, we dive deeper into understanding the gender gap in STEM applications. After ruling out discrimination from admissions committees, we again use a Blinder-Oaxaca decomposition to decompose the application gap. We also estimate a zero-inflated Poisson model to distinguish between the extensive and intensive margins of STEM applications. Finally, we present evidence from high schools suggesting a role for environment factors in shaping the application decisions of males and females.

5.1 Gender gap in STEM enrollment

5.1.1 Estimates of the gender gap in STEM enrollment

Table 3 reports estimated coefficients from regressing a dummy for enrolling in a STEM program on student covariates. Panel A contains estimates from the subsample of students who enrolled through the GSAT, while panel B contains those who were rejected in the GSAT but ultimately enrolled through the AST. Panel C contains estimates using the full sample of students who applied through the GSAT. Column 1 reports estimates from a simple regression of STEM enrollment on the variable $Male_i$. Males are 30.8 percentage points more likely than females to enroll in STEM programs, but once we control for the number of STEM programs applied to, the gap falls to 2.9 percentage points. In other words, the number of STEM applications alone can explain 90 percent of the raw gender gap in STEM enrollment. In contrast, exam scores alone can explain only half of the raw gap (see column 3). Adding additional controls does little to further close the gap (see columns 4–7).

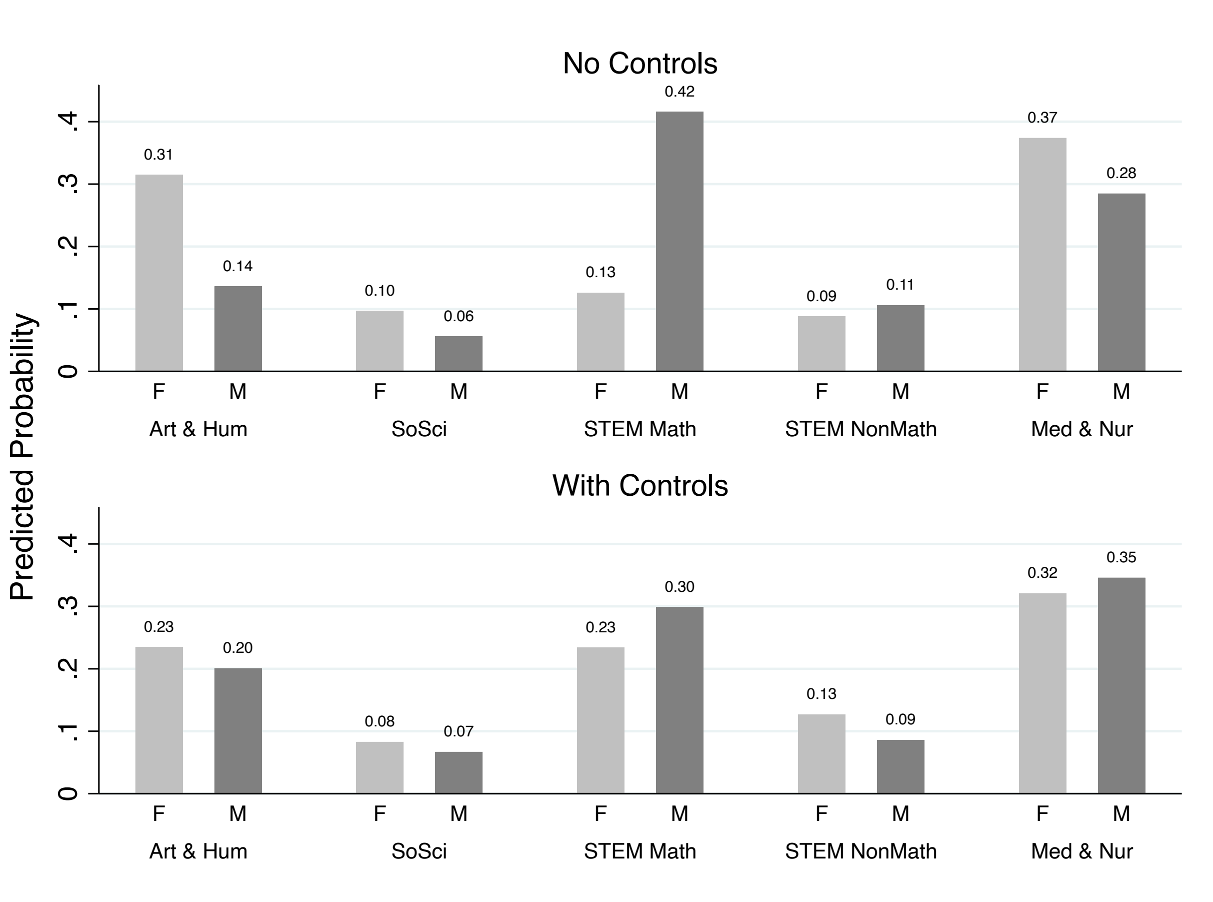
Table 3: The Gender Gap in STEM Enrollment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Enrolled through GSAT channel							
Male	0.3404***	0.0103***	0.1798***	0.0073***	0.0070***	0.0133***	0.0118***
	[0.0017]	[0.0011]	[0.0017]	[0.0011]	[0.0011]	[0.0011]	[0.0011]
Total				294,961			
Panel B: Enrolled through GSAT+AST channel							
Male	0.2522***	0.0586***	0.1247***	0.0368***	0.0373***	0.0373***	0.0372***
	[0.0021]	[0.0019]	[0.0021]	[0.0020]	[0.0020]	[0.0020]	[0.0020]
Total				182,003			
Panel C: Full Sample							
Male	0.3080***	0.0293***	0.1601***	0.0203***	0.0202***	0.0250***	0.0236***
	[0.0013]	[0.0010]	[0.0013]	[0.0010]	[0.0010]	[0.0010]	[0.0010]
Total				476,964			
# STEM Applied		√		√	√	√	√
Exam Scores			√	√	√	√	√
# Medical Applied					√	√	√
# STEM Admitted						√	√
# Medical Admitted							√

Note: This table reports coefficients of Male based on OLS equation (1) from 2011 to 2018. The outcome for each regression is a dummy variable indicating whether a student enrolled in a STEM program. Panel A only includes students who enrolled through GSAT route. Panel B only includes students who applied through the GSAT route but ultimately enrolled through the AST route. Panel C combines students from panels A and B. Standard errors are reported in brackets. *** p<0.01, ** p<0.05, and *p<0.1

Of course, applicants face more options than simply STEM or non-STEM, so we estimate a multinomial logistic regression with five categories of programs: arts & humanities, social science, math-intensive STEM, and non-math-intensive STEM, and medical & nursing. We divide STEM programs into math-intensive and non-math-intensive programs based on Douglas and Salzman (2020)'s study of college mathematics coursework. Math-intensive STEM programs include the physical sciences, math and statistics, engineering, and computer sciences. Non-math-intensive programs include life sciences, architecture, agriculture, and natural resources. Figure 2 reports predicted probabilities of enrolling in each major group, separately for men and women. Without controls, we find large gender gaps in arts & humanities, math-intensive STEM, and medical &

Figure 2: Predicted Probabilities of Major Enrollment



Note: The figure reports predicted probabilities of enrolling in each of five groups of majors using a multinomial logistic regression. The top figure reports predicted probabilities with no controls included. The bottom figure reports predicted probabilities after controlling for the number of STEM applications, the number of medical applications, the numbers of STEM and medical admissions, and exam scores (controls were set to their means when calculating predicted probabilities).

nursing. But after including controls, these gaps shrink considerably.

5.1.2 Blinder-Oaxaca decomposition of STEM enrollment

In this section, we employ a Blinder-Oaxaca decomposition to break the gender gap into three components: endowment effects, coefficient effects, and an interaction term. We include the same covariates as before: STEM applications, exam scores, and medical and STEM admissions. The method initially estimates coefficients for Equation (2) and then provides the estimated difference between males and females in Panel A of Table 4. We find that males have a 30.80 percentage point higher probability of enrolling in a STEM program than females (see Columns (1) and (2)). 28.22 percentage points (accounting for 91.63 percent of the raw gap) can be attributed to endowment effects, 1.99 (accounting for

6.47 percent) to coefficient effects, and the remaining 0.58 (accounting for 1.89 percent) to the interaction term. In other words, the raw gender gap can be largely explained by mean differences between males and females in the explanatory variables. Panel B of Table 4 breaks the endowment effect down into the three variables providing the largest contribution. By far, the primary driver of the raw gap between males and females is the number of STEM programs applied to, accounting for 87 percent of the endowment effect and 80 percent of the raw gap.

Table 4: Blinder-Oaxaca Decomposition

	(1)	(2)
	Effect	%
Panel A. Decomposition of the gender gap in STEM enrollment		
Difference	0.3080	100%
Endowments	0.2822	91.63%
Coefficients	0.0199	6.47%
Interaction	0.0058	1.89%
Panel B. Decomposition of the endowment effect: top 3 contributors		
Endowment Effect	0.2822	100%
# STEM Program Applied	0.2460	87.17%
# STEM Program Admitted	0.0247	8.76%
Science Scores	0.0138	4.89%
Total	476,964	

Note: This table reports the Blinder-Oaxaca decomposition based on equation (2). Panel A gives decomposition of three components: differences due to different endowments of X, differences due to different coefficients γ, and the interaction of the two. Panel B states top three contributions of endowment that possess differences most for the gender gap.

To explore the specific group driving the gender gap, we split the sample into quintiles of applicants' total scores (the sum of the five GSAT scores). Table 5 presents the same analysis as Table 4, but separately for each quintile. We find that the raw gender gap is largest in the middle quintiles of the distribution, those falling between the 40th and 80th percentiles. Across quintiles, endowment effects account for the vast majority of the gender gap, ranging from 88.8 to 99.5 percent. And the vast majority of the endowment effect is explained by the number of STEM applications. The one exception is the bottom quintile where STEM admissions become relevant.

Table 5: Blinder-Oaxaca Decomposition: By Total Score Quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Top 20		**60-80**		**40-60**		**20-40**		**Bottom 20**	
	Effect	%	Effect	%	Effect	%	Effect	%	Effect	%
Panel A. Decomposition of the gender gap in STEM enrollment										
Difference	0.3240	100%	0.3708	100%	0.3744	100%	0.3048	100%	0.2091	100%
Endowments	0.3029	93.49%	0.3670	98.97%	0.3726	99.50%	0.2823	92.61%	0.1856	88.77%
Coefficients	0.0033	1.02%	0.0077	2.09%	0.0085	2.26%	0.0103	3.37%	0.0088	4.21%
Interaction	0.0178	5.50%	-0.0039	-1.06%	-0.0066	-1.77%	0.0122	4.02%	0.0147	7.03%
Panel B. Decomposition of the endowment effect: top 3 contributors										
Raw Gap	0.3029	100%	0.3670	100%	0.3726	100%	0.2823	100%	0.1856	100%
# STEM Program Applied	0.2831	93.45%	0.3270	89.10%	0.3330	89.38%	0.2278	80.72%	0.1148	61.87%
# STEM Program Admitted	0.0187	6.16%	0.0330	8.99%	0.0323	8.68%	0.0504	17.84%	0.0684	36.85%
Science Scores	0.0007	0.25%	-0.0001	-0.04%	0.0036	0.97%	0.0033	1.17%	0.0006	0.34%
Total	65,029		68,062		63,283		64,107		37,177	

Note: This table reports the Blinder-Oaxaca decomposition based on equation (2). Panel A gives decomposition of three components: differences due to different endowments of X, differences due to different coefficients γ, and the interaction of the two. Panel B states top three of endowment that have differences most for the gender gap. Columns (1) - (2) display the results of applicants whose total scores are above 20 percentile across all applicants. Columns (3) - (4) display the results of applicants whose total scores between 60 to 80 percentile across all applicants. Columns (5) - (6) display the results of applicants whose total scores between 40 to 60 percentile across all applicants. Columns (7) - (8) display the results of applicants whose total scores between 20 to 40 percentile across all applicants. Columns (9) - (10) display the results of applicants whose total scores below 20 percentile across all applicants.

5.2 Gender gap in number of STEM applications

So far we have found that the number of STEM applications is the key factor driving the gender gap in STEM enrollment. Table 6 reports rates of applying to STEM programs separately for men and women. Roughly double the number of men than women apply to at least one STEM program: 68 versus 38 percent. But five times as many men than women apply exclusively to STEM programs: 23 versus 5 percent. Among math-intensive STEM programs, the differences are even starker. More than six times as many men than women apply exclusively to math-intensive STEM programs. In this section, we explore several explanations for why females apply to fewer STEM programs than males. First, we test for discrimination against female applicants by admissions committees. Second, we perform a Blinder-Oaxaca decomposition of the gender gap in STEM applications. Third, we use a zero-inflated Poisson regression to estimate gender differences in both the extensive and intensive margins of STEM applications. Finally, we estimate high school–specific gaps in STEM applications and show that these are persistent over time and correlate with several characteristics of high schools.

Table 6: Number of Application in STEM Programs by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
	STEM		**STEM Math**		**STEM Non-Math**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
At least one STEM application	68.20%	38.14%	59.32%	24.63%	28.48%	22.34%
Six STEM applications	23.34%	4.66%	14.90%	2.34%	0.70%	0.48%
Mean # STEM applications	2.71	1.05	2.16	0.62	0.54	0.42

Note: This table reports the number of applications to STEM programs. The first and second row report the percent of total applicants who applied at least one STEM program and who applied six STEM programs, respectively (applicants can submit maximum of six applications). The third row reports the mean number of STEM applications. Columns (1) - (2) represent all STEM applications. Columns (3) - (4) separate out math-intensive STEM applications while columns (5) - (6) separate out non-math-intensive STEM applications.

5.2.1 Gender gaps in program admissions

Perhaps women apply to fewer STEM programs because they anticipate being discriminated against in the admissions process. Recall that after students take the five exams, they apply to up to six programs. Each program ranks its applicants based on objective criteria like exam scores and subjective criteria based on essays and/or interviews. To test for discrimination against female applicants, we estimate the following regression specification

$$\text{rank}_{ijt} = \beta_j \text{male}_i + \text{ExamScores}_i \cdot \gamma_j + \delta_{jt} + \epsilon_{ijt}$$

where rank_{ijt} is the rank program j awards student i (a lower number is better), male_i is a dummy equal to one if student i is male, ExamScores_i is a vector of student i's five exam scores, and δ_{jt} are program-year fixed effects. We run the regression separately for each program and estimate program-specific β_j's, which quantify how much higher or lower program j ranks male applicants compared to female applicants. A positive β_j means that program j ranks male applicants lower than females with the same exam scores.

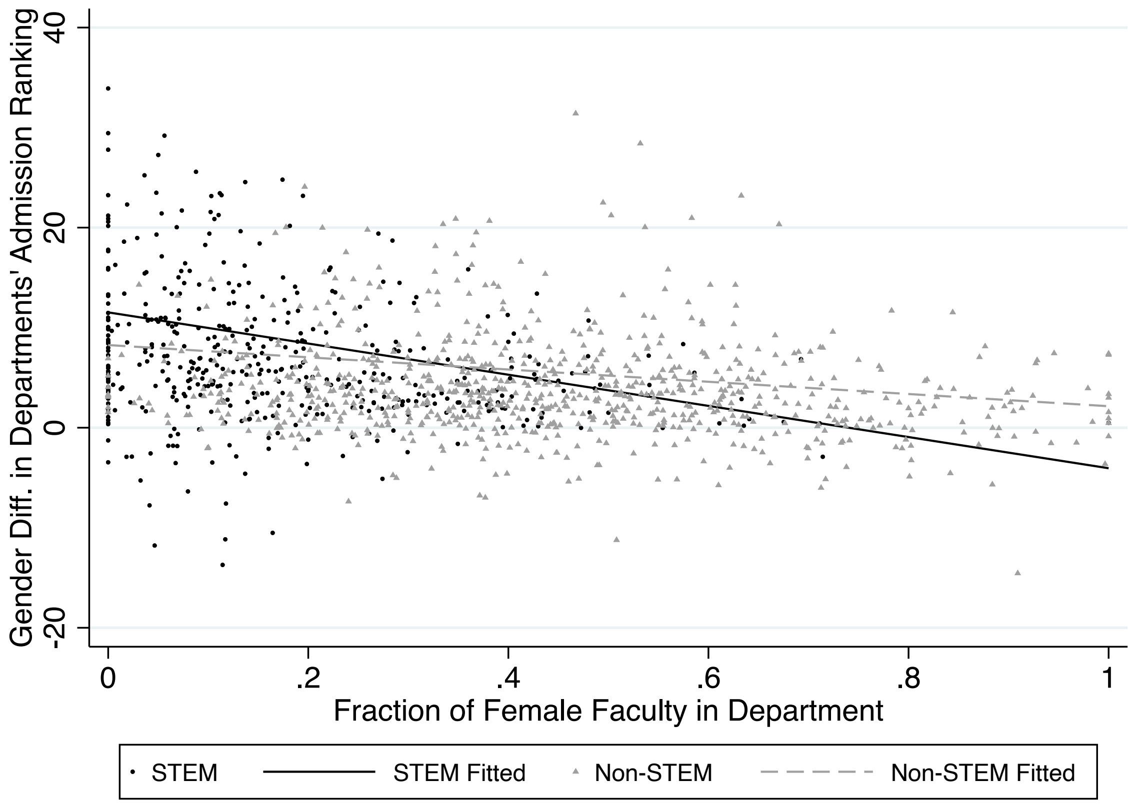
Figure 3 plots the β_j for each program on the vertical axis. On the horizontal axis, we plot the percent of the program's faculty who are female, and we differentiate STEM and non-STEM programs. The vast majority of programs have positive estimated β_j's. This is especially true of programs with fewer female faculty, which also tend to be STEM programs. STEM programs with no female faculty on average rank female applicants ten spots higher than their male peers with the same exam scores. This difference largely disappears at programs with many female faculty, which also tend to be non-STEM programs. Figure 4 is similar, except the horizontal axis is the percent of applicants who are female. Both Figures 3 and 4 provide little evidence for discrimination against female applicants at the admissions stage. If anything, we find that programs with few female faculty and few female applicants tend to give their female applicants a boost relative to comparable male applicants.

5.2.2 Blinder-Oaxaca decomposition of STEM applications

Figure 5 plots the empirical cumulative distribution functions (CDF) of scores for the five exams (scores range from zero to fifteen). Males and females generally perform similarly in Chinese and English, but males tend to perform better in Math and Science. They also appear to have a small edge in Social Science. Might these score differences help explain the gender gap in STEM applications? Table 7 reports estimates of a Blinder-Oaxaca decomposition where the dependent variable is the number of STEM applications a student submits. We estimate a raw gender gap of 1.56 more STEM applications for males than females. Using equation (2), we decompose this raw gap into 43.32 percent due to endowment effects, 56.21 percent due to coefficient effects, and a remaining 1.47 percent due to interaction effects.

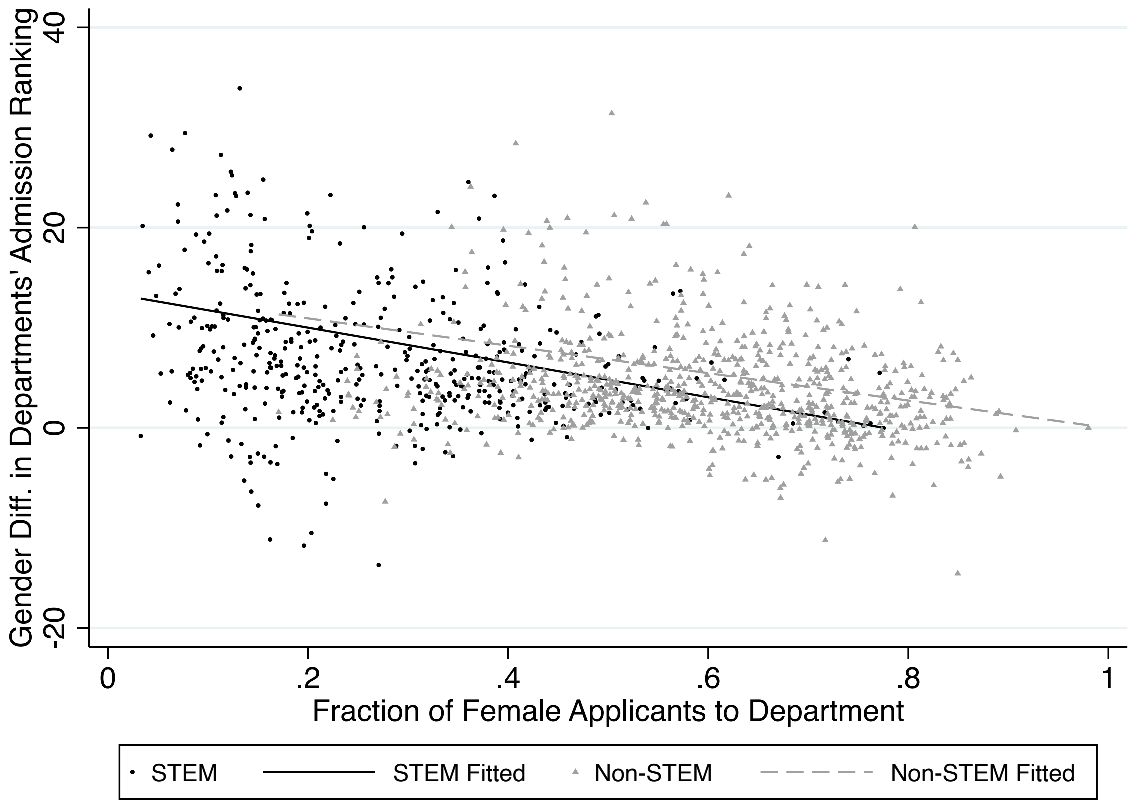
Male students have higher math and science scores on average, and exam scores alone can account for about one-third of the raw gap in STEM applications. But the

Figure 3: Gender Gap in Program Rankings and Percent of Female Faculty in Program



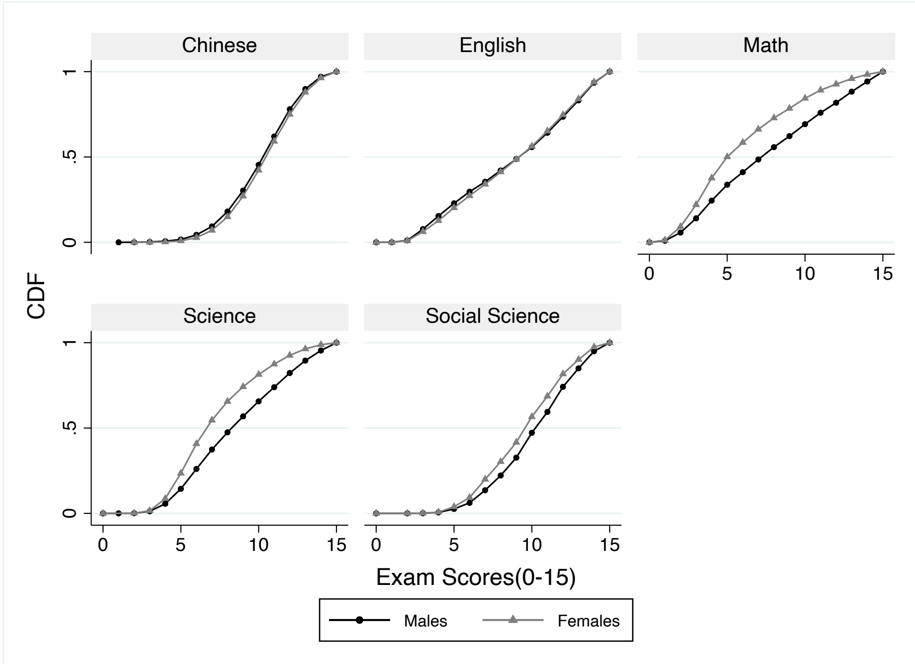
Note: This figure displays the relationship between the estimated gender gap in a program's ranking of its applicants and the percent of female faculty in the program. The horizontal axis plots the percent of female faculty in the program, while the vertical axis plots the estimated gender gap in the program's rank of its applicants. The circle (black) and triangle (gray) symbols represent STEM and non-STEM programs, respectively. The solid (black) and dashed (gray) lines represent regression lines (programs were weighted by their numbers of applicants).

Figure 4: Gender Gap in Program Rankings and Percent of Female Applicants in Program



Note: This figure displays the relationship between the estimated gender gap in a program's ranking of its applicants and the percent of female applicants to the program. The horizontal axis plots the percent of female applicants to the program, while the vertical axis plots the estimated gender gap in the program's rank of its applicants. The circle (black) and triangle (gray) symbols represent STEM and non-STEM programs, respectively. The solid (black) and dashed (gray) lines represent regression lines (programs were weighted by their numbers of applicants).

Figure 5: Distribution of Exam Scores by Gender



Note: The figure plots the empirical CDF of exams scores in each subject. Exam scores range from 0 to 15. Male and female applicants are represented by circle and square symbols, respectively. The darker line (black) and lighter line (gray) correspond to males and females, respectively.

gap in STEM applications is also explained by differences in how exam scores translate into STEM applications. Higher math and science scores increase STEM applications for males much more than they do for females, whereas the reverse is true for Chinese, English, and social science scores. In other words, male applicants are more sensitive to their exam scores when choosing how many STEM programs to apply to. Aside from exam scores, we also find that males and females respond differently to having more high school female faculty and peers so that having more female faculty and peers tends to widen the gap in STEM applications. Characteristics of the student's neighborhood, such as education or income, do not appear to explain much of the gap.[7]

5.2.3 Extensive and intensive margins of STEM applications

The Blinder-Oaxaca decomposition highlights exam scores as an important explanation for why males apply to more STEM programs than females. In this section, we use a zero-inflated Poisson regression to disentangle the extensive margin (whether to apply to any STEM programs) and the intensive margin (how many STEM programs to apply

[7] We actually observe the neighborhood of the student's high school.

Table 7: Blinder-Oaxaca Decomposition of the Number of STEM Applications

	(1)	(2)	(3)	(4)	(5)	(6)
Raw Gap is 1.6643	**Endowment (32.72%)**		**Coefficient (60.48%)**		**Interaction (6.80%)**	
	Effect	%	Effect	%	Effect	%
Overall Effect	**0.5446**	**100%**	**1.0066**	**100%**	**0.1132**	**100%**
Science scores	0.3676	67.51%	1.2295	122.15%	0.1893	167.29%
Math scores	0.1982	36.40%	0.4762	47.30%	0.1164	102.86%
Social science scores	-0.0738	-13.54%	-0.6500	-64.57%	-0.0322	-28.44%
Percent of high school female faculty	-0.0392	-7.20%	0.3755	37.30%	-0.0269	-23.79%
Chinese scores	0.0361	6.63%	-0.5209	-51.74%	0.0209	18.48%
English scores	0.0273	5.02%	-0.5999	-59.60%	0.0173	15.29%
Percent of high school female students	0.0249	4.58%	0.4588	45.58%	-0.1646	-145.46%
Percent of female graduated from college	0.0050	0.92%	-0.1735	-17.23%	0.0026	2.27%
Percent of male graduated from college	-0.0032	-0.59%	0.0536	5.33%	-0.0010	-0.88%
Average income	0.0008	0.15%	-0.0228	-2.27%	0.0002	0.15%
Public high school	0.0004	0.07%	-0.0741	-7.36%	-0.0029	-2.52%
Number of colleges in town	0.0003	0.05%	-0.0829	-8.24%	-0.0060	-5.27%
Constant			0.5371	53.35%		
Total			278,543			

Note: This table reports the Blinder-Oaxaca decomposition based on equation (2). The outcome of interest is the number of STEM programs a student applied to. The raw gap between males and females is 1.6643. The percent in parentheses is how much of each component accounts for the difference. The table reports each variable's contribution to the gender gap. Columns (1) - (2) decompose endowment effect, columns (3) - (4) decompose the coefficient effect, and columns (5) - (6) decompose the interaction. Since neighborhood information is only available after 2015, the sample is restricted to the years 2015–2018.

to). Table 8 reports estimates from a zero-inflated Poisson regression of the number of STEM applications on a gender dummy, exam scores, and interactions between gender and scores.[8] Rather than include each of the five subject scores, we include the average of a student's five exams along with deviations from this average for English, Math, Social Science, and Science.[9]. Thus, the coefficient on the average score represents the effect of scoring higher overall. The coefficient on English represents the effect of raising an applicant's English score by one point while lowering her omitted score (Chinese) by one point, thereby holding her average score constant. The same is true for the coefficients on Math, Social Science, and Science. Columns 1–3 report estimates for all STEM applications. Column one reports marginal effects on the total number of STEM applications. Column two reports marginal effects on the extensive margin only

[8] We also include the total number of applications as a covariate.

[9] We exclude the Chinese score due to collinearity.

(i.e. the probability of applying to at least one STEM program). Column 3 reports marginal effects on the intensive margin (i.e. the expected number of STEM applications conditional on applying to at least one). Columns 4–6 and 7–9 estimate the same model, but with the number of math-intensive and non-math-intensive STEM applications as the outcomes. Controlling for exam scores, males apply to 0.88 more STEM programs than females. This is due to the fact that they are 18.4 percentage points more likely to apply to at least one STEM program and, conditional on applying to at least one, apply to 0.74 more programs on average. These differences are driven by math-intensive STEM programs—little if any gap exists in applications to non-math-intensive programs.

Table 8: Zero-Inflated Poisson Regression: Marginal Effects

	STEM			STEM Math			STEM Non-Math		
	Overall	Extensive Margin	Intensive Margin	Overall	Extensive Margin	Intensive Margin	Overall	Extensive Margin	Intensive Margin
Gender									
Female		(Base)			(Base)			(Base)	
Male	0.8766***	0.1842***	0.7357***	0.8465***	0.2454***	0.7265***	0.0038	-0.0003	0.0171**
	(0.0094)	(0.0035)	(0.0089)	(0.0078)	(0.0022)	(0.0158)	(0.0079)	(0.0041)	(0.0074)
Gender*Avg. Score									
Female	0.0107***	0.0019***	0.0142***	0.0072***	0.0019***	0.0128***	0.0032***	0.0010***	0.0060***
	(0.0007)	(0.0002)	(0.0005)	(0.0004)	(0.0001)	(0.0005)	(0.0003)	(0.0002)	(0.0003)
Male	0.0157***	0.0018***	0.0159***	0.0139***	0.0024***	0.0143***	0.0017***	0.0003***	0.0044***
	(0.0006)	(0.0001)	(0.0005)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0001)	(0.0002)
Gender*English									
Female	-0.0065***	-0.0018***	-0.0057***	-0.0042***	-0.0018***	-0.0027***	-0.0023***	-0.0010***	-0.0029***
	(0.0008)	(0.0002)	(0.0007)	(0.0005)	(0.0002)	(0.0006)	(0.0004)	(0.0002)	(0.0005)
Male	-0.0069***	-0.0017***	-0.0029***	-0.0049***	-0.0020***	0.0005	-0.0026***	-0.0013***	-0.0017***
	(0.0011)	(0.0003)	(0.0005)	(0.0009)	(0.0003)	(0.0005)	(0.0003)	(0.0002)	(0.0002)
Gender*Math									
Female	0.0279***	0.0096***	0.0157***	0.0248***	0.0104***	0.0181***	0.0025***	0.0019***	-0.0024***
	(0.0010)	(0.0003)	(0.0006)	(0.0006)	(0.0003)	(0.0005)	(0.0003)	(0.0002)	(0.0005)
Male	0.0430***	0.0106***	0.0191***	0.0472***	0.0135***	0.0223***	-0.0044***	-0.0016***	-0.0063***
	(0.0012)	(0.0003)	(0.0005)	(0.0014)	(0.0004)	(0.0007)	(0.0004)	(0.0002)	(0.0007)
Gender*Social Science									
Female	-0.0017*	-0.0002	-0.0029***	-0.0011**	-0.0002	-0.0022***	-0.0007	-0.0001	-0.0022***
	(0.0009)	(0.0003)	(0.0007)	(0.0005)	(0.0002)	(0.0005)	(0.0005)	(0.0002)	(0.0004)
Male	-0.0008	0.0003	-0.0027***	-0.0012	-0.0001	-0.0017***	-0.0004	0.0000	-0.0018***
	(0.0011)	(0.0003)	(0.0006)	(0.0009)	(0.0003)	(0.0005)	(0.0003)	(0.0001)	(0.0003)
Gender*Science									
Female	0.0501***	0.0163***	0.0322***	0.0252***	0.0106***	0.0186***	0.0235***	0.0116***	0.0165***
	(0.0010)	(0.0004)	(0.0005)	(0.0007)	(0.0003)	(0.0006)	(0.0007)	(0.0004)	(0.0005)
Male	0.0685***	0.0160***	0.0342***	0.0523***	0.0151***	0.0241***	0.0144***	0.0069***	0.0109***
	(0.0010)	(0.0003)	(0.0006)	(0.0008)	(0.0002)	(0.0005)	(0.0002)	(0.0002)	(0.0004)
# Applications	0.4724***	0.0765***	0.4988***	0.3312***	0.0775***	0.3992***	0.1190***	0.0483***	0.1494***
	(0.0037)	(0.0016)	(0.0053)	(0.0056)	(0.0020)	(0.0065)	(0.0023)	(0.0010)	(0.0045)

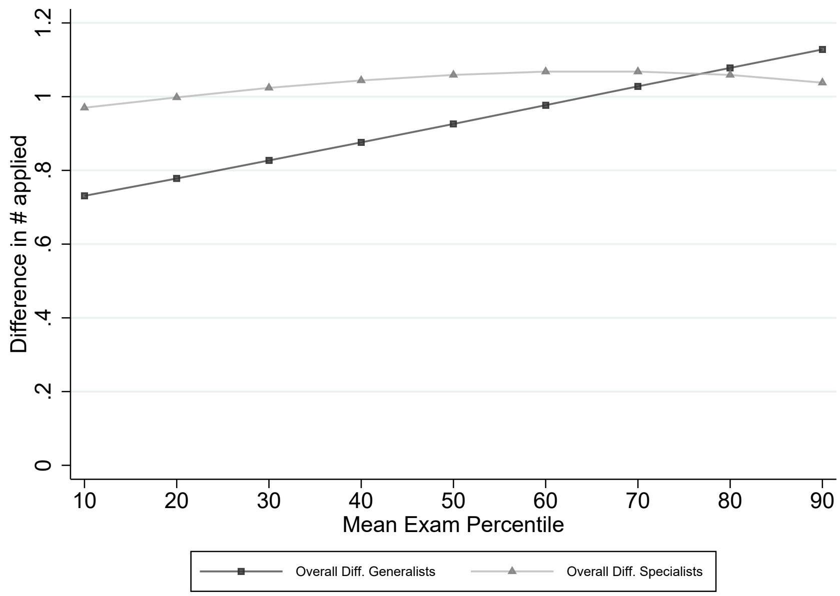
Note: This table reports estimated marginal effects from three zero-inflated Poisson regression models. The dependent variables are the total number of STEM applications and the number of math-intensive and non-math-intensive STEM applications. The first column for each model reports the marginal effect of each variable on the expected number of applications. The second and third columns separate out the marginal effect of the variable on the extensive margin $\mathbb{P}[Y > 0]$ and the intensive margin $\mathbb{E}[Y|Y > 0]$. The explanatory variables in all three regressions include gender, a student's average percentile score across all five subjects, and the deviation of each subject's percentile from that average. The marginal effects of each subject exam represent the marginal effect of increasing the subject score holding constant the student's average score. Since the Chinese language score is omitted, an increase in any subject must be offset by a decrease in the student's Chinese score to hold the average score constant. The total number of applications and year dummies (unreported) were also included as covariates.

Figure 6 plots the gender gap in applications separately for two types of students: "generalists" and "specialists." We define a generalist to be a student who is equally strong in all areas, so that her average percentile score equals her percentile score in each of the five subjects. For example, if her average score percentile is 70, her test score in each subject would also be at the 70th percentile. In terms of Table 8, this means that we would set the value of the average score to 70 and the values of the subjects scores to zero. We define a specialist to be a student who scores 10 percentage points above her average in math and science. For example, if a specialist's average test score is at the 70th percentile, she would score at the 80th percentile in math and science and at the 63.3 percentile in each of Chinese, English, and Social Science (thereby keeping her average percentile score at 70). Figure 6 plots the differences in levels. Among low scoring students, the gap in STEM applications is larger for specialists, but this reverses at the top end of the score distribution. When breaking math-intensive and non-math-intensive applications out separately, specialists have larger gaps for math-intensive applications while generalists have higher gaps for non-math-intensive applications. Indeed, among higher-scoring generalists, and especially among higher scoring specialists, females actually apply to more non-math-intensive programs than males.

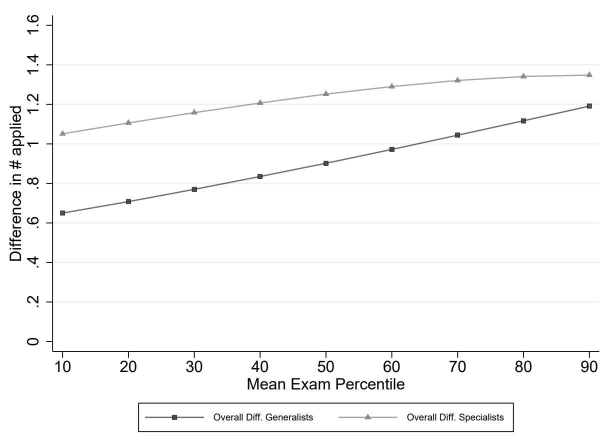
Figure 7 plots the log of the ratio of male and female STEM applications. Unlike in Figure 6 when we plotted the STEM application gap in levels, when we calculate it in logs the largest gaps occur at the bottom of the score distribution and generalists now have the largest application gaps. One advantage of calculating the gap in logs is that we can use equation (5) to decompose the gap into an intensive and extensive margin. Females are less likely to apply to any STEM program and also apply to fewer when they do, although this is less true among the highest scoring students. Generally speaking, both margins contribute to the overall gender gap although the intensive margin is somewhat larger among generalists while the extensive margin is a bit larger among specialists.

Figure 6: Gender Gap in STEM Applications (Difference)

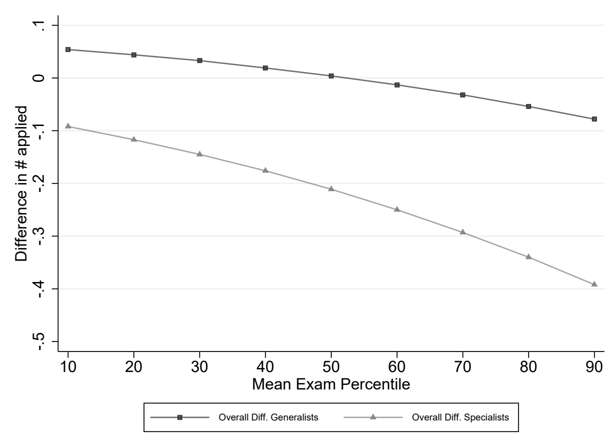
(a) All STEM Applications



(b) Math-Intensive Applications



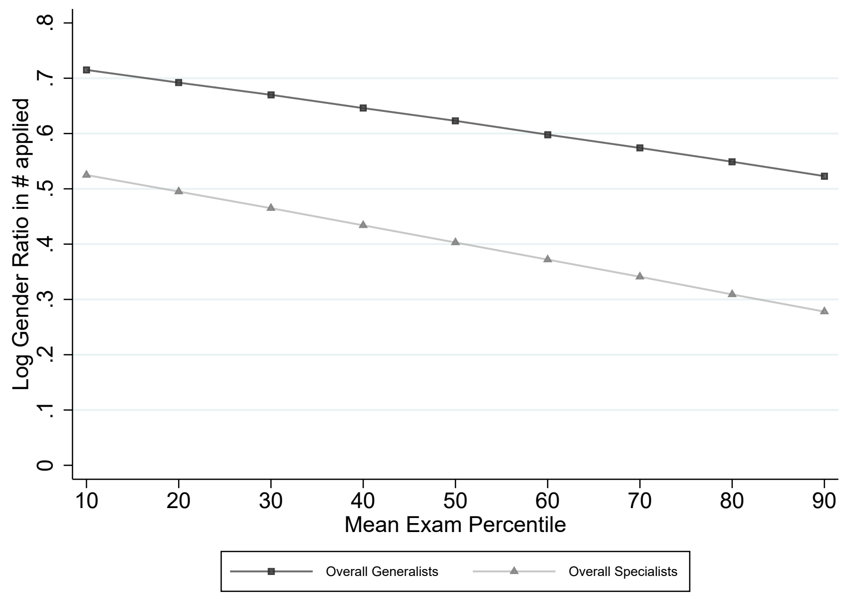
(c) Non-Math-Intensive Applications



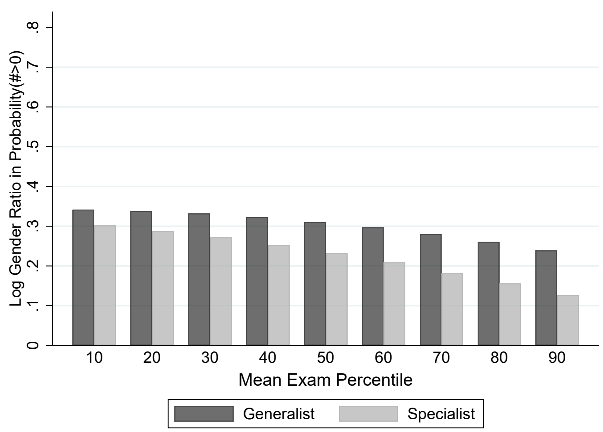
Notes:

Figure 7: Decomposing Application Gap into Extensive and Intensive Margins

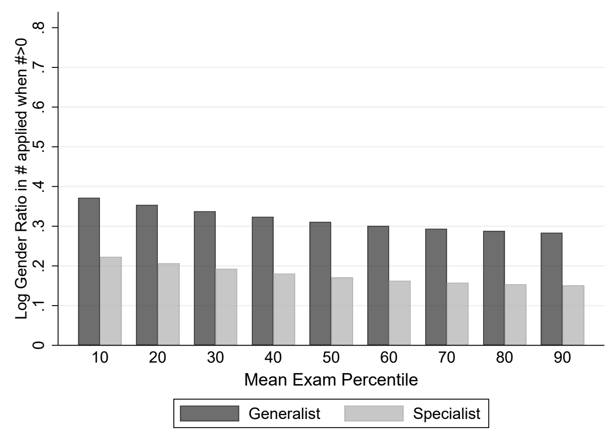
(a) Male to Female Ratio in STEM Applications



(b) Extensive Margin



(c) Intensive Margin

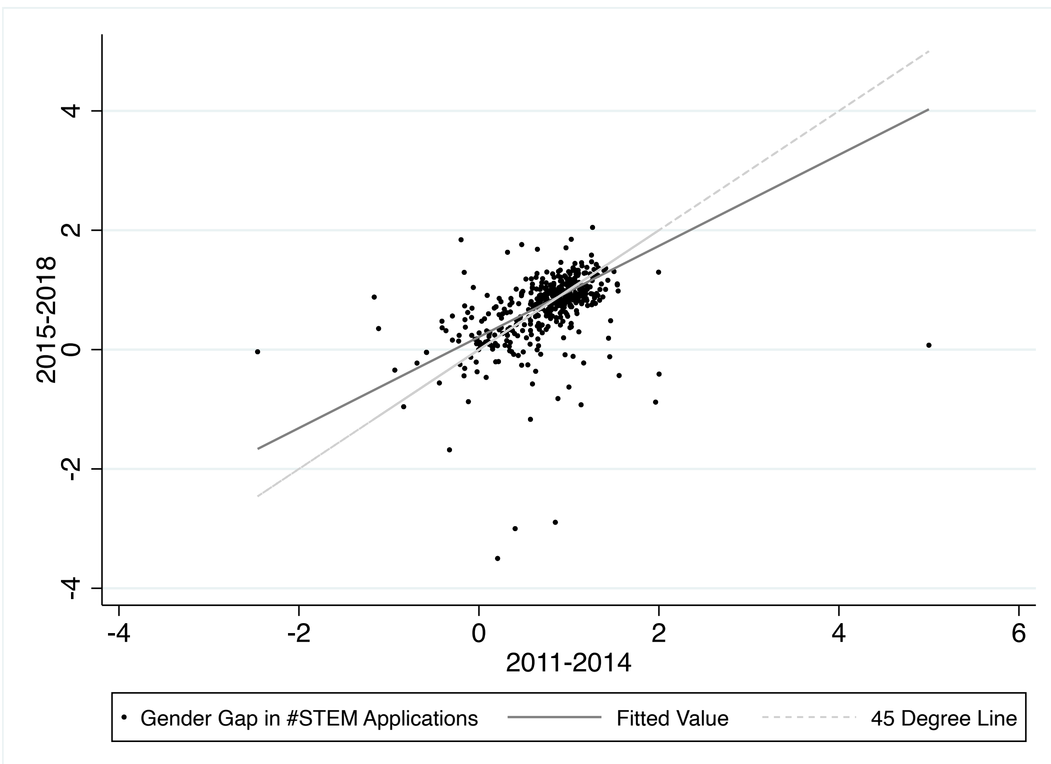


Notes:

5.2.4 STEM application gaps differ by high school

Finally, in this section we explore how STEM application gaps differ across high schools. We begin by estimating a high school–specific application gap by regressing, separately for students from each high school, the number of STEM programs a student applies to on a gender dummy, her exam scores, and year dummies. This gap tells us how many more, or fewer, STEM applications are submitted by males than females who graduate from a given high school with the same exam scores. Figure 8 plots these high school–specific gaps from 2011-2014 and 2015–2018. High school–specific application gaps are strongly correlated over time, suggesting there is something relatively stable about high schools which causes some to generate large gender gaps in STEM applications and others to generate small or even zero gaps.

Figure 8: High School-specific Gender Gap in STEM Applications



Notes: The figure displays the relationship between the estimated gender gap of number of STEM programs applied from 2011 to 2014 and from 2015 to 2018. The estimated gender gap is weighted by number of each high school applied. The horizontal axis shows the estimated gender gap from 2011 to 2014. The vertical axis shows the estimated gender gap from 2015 to 2018. Each circle symbol represents a single high school. The solid line is the fitted value for the estimated gender gap between 2011-2014 and 2015-2018. The dotted line is 45 degree line.

To better understand what might be generating these high school–specific gaps in STEM applications, we regress them on a set of high school and neighborhood characteristics. Table 9 reports OLS estimates of the relationship between high school and neighborhood characteristics on the high school's gender gap in STEM applications. For this regression, we pool all the years from 2011–2018 and weight the regression by the number of graduates we observe from each high school. The high school characteristics we observe are the average GSAT scores at the school, the percent of students and faculty who are female, the percent of years from 2011–2018 when the school had a female principal, and whether the high school is public or not. The neighborhood characteristics we observe are the (log) average income of the neighborhood, the number of colleges in the neighborhood, the female-male earnings and employment ratios, the vote share of the DPP (one of Taiwan's two major political parties), and region. We find that the gender gap in STEM applications is larger at schools with better test scores. Having more female faculty exacerbates the gap while having a female principal mitigates it. High schools in higher income communities have smaller gaps as do those with more colleges nearby and a higher female-to-male earnings ratio.

Table 9: Predicting High School–Specific Gaps in Applications

	(1)	(2)	(3)
HS SAT percentile	0.0409***		0.0335***
HS SAT percentile squared	-0.0003***		-0.0002***
% Female students	0.0018		0.0008
% Female faculty	0.0021		0.0035*
% Years with female principal	-0.0016***		-0.0009**
Public HS	-0.1503***		-0.1655***
ln(neighborhood average income)		-0.1118**	-0.1134**
Number of colleges in neighborhood		-0.0138	-0.0226**
Female-male earnings ratio		-0.0155***	-0.0094***
Female-male employment ratio		-0.0014	-0.0042
Vote share of DPP		0.0054	0.0003
Region: Central		0.1238*	0.0784
Region: South		0.0138	0.0102
Region: East & Islands		0.0190	0.0331
R-squared	0.3665	0.1123	0.4430
Number of Observations	417	417	417

Note: Regressions are performed at the high school level (pooled across years 2011–2018). The dependent variable is the estimated high school–specific gap in STEM applications between males and females. All regressions are weighted by the number of graduates from each high school.
*** p<0.01, ** p<0.05, and *p<0.1.

6 Conclusion

We use administrative data from Taiwan to unpack the determinants of the gender gap in STEM enrollment. Because college applicants in Taiwan apply to individual programs, we can see the types of programs a student applies to separately from the programs she is admitted to and the one she ultimately enrolls in. Using data from 2011–2018, we find that nearly all of the gender gap in STEM enrollment can be explained by the gender gap in STEM applications. Women simply apply to far fewer STEM programs than men. We then explore how application choices differ for men and women. Men tend to have higher math and science scores, which can explain one-third of the gender gap in STEM applications. We rule out discrimination by admissions committees—if anything, they give female applicants a boost, especially at programs that have few female faculty or applicants. We fit a zero-inflated Poisson model and find that men are more likely to apply to STEM programs in general and, conditional on applying to one, tend to apply to more than women. This is driven by math-intensive STEM programs like engineering or physics; no substantial gender gap is evident for non-math-intensive programs once we control for exam scores, and for these programs the application gap actually goes the other way among high ability applicants who are strong in math and science. Finally, we show that the gender gap in STEM applications differs widely across high schools. At some high schools, boys and girls apply to the same number of STEM programs while at others there is a large discrepancy. We find that the gap in applications is larger at high schools with better test scores and those with more female faculty but smaller if the principal is female. We also find a smaller gap at high schools located in communities with higher income, more colleges nearby, and a higher female-to-male earnings ratio. Our findings are consistent with the theory that gender gaps in STEM applications (and by extension enrollment) are driven to a large extent by less interest in STEM among women *at the college application stage*. But the evidence on variation across high schools also suggests that educational institutions and social factors play a role in shaping women's interests in STEM.

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Appendix

A Additional Tables

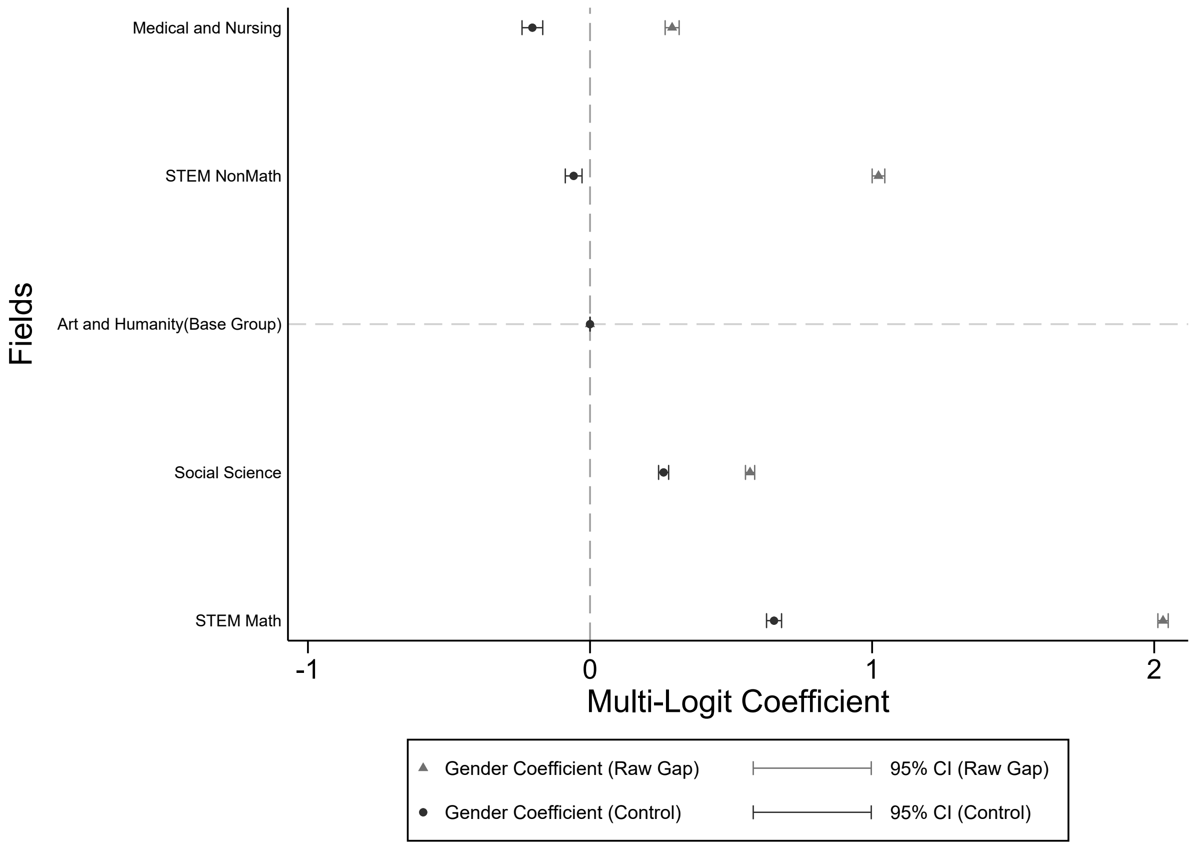
Table A1: Choice Regression: Zero-Inflated Poisson Regression

	(1)	(2)	(3)	(4)	(5)	(6)
	STEM		**STEM Math**		**STEM Non-Math**	
	β (Extensive)	γ (Intensive)	β (Extensive)	γ (Intensive)	β (Extensive)	γ (Intensive)
Gender						
Female	Base		Base		Base	
Male	0.3767***	0.5967***	0.6356***	0.7647***	-0.0838	0.1417***
	(0.0570)	(0.0124)	(0.0494)	(0.0223)	(0.0666)	(0.0110)
Gender*Mean total PR						
Female	0.0008	0.0103***	0.0025***	0.0121***	-0.0002	0.0078***
	(0.0010)	(0.0004)	(0.0009)	(0.0005)	(0.0010)	(0.0003)
Male	0.0049***	0.0069***	0.0069***	0.0072***	-0.0026***	0.0056***
	(0.0006)	(0.0003)	(0.0006)	(0.0003)	(0.0004)	(0.0002)
Gender*English PR(Dmean)						
Female	-0.0053***	-0.0042***	-0.0085***	-0.0026***	-0.0028***	-0.0037***
	(0.0008)	(0.0005)	(0.0010)	(0.0005)	(0.0011)	(0.0006)
Male	-0.0080***	-0.0012***	-0.0090***	0.0002	-0.0063***	-0.0022***
	(0.0014)	(0.0002)	(0.0013)	(0.0002)	(0.0013)	(0.0003)
Gender*Math PR(Dmean)						
Female	0.0374***	0.0114***	0.0468***	0.0171***	0.0144***	-0.0031***
	(0.0014)	(0.0003)	(0.0013)	(0.0006)	(0.0015)	(0.0006)
Male	0.0488***	0.0082***	0.0545***	0.0112***	-0.0035***	-0.0080
	(0.0016)	(0.0002)	(0.0017)	(0.0004)	(0.0013)	(0.0009)
Gender*Social Science PR(Dmean)						
Female	0.0009***	-0.0021***	0.0001	-0.0021***	0.0018***	-0.0028***
	(0.0011)	(0.0005)	(0.0009)	(0.0005)	(0.0011)	(0.0006)
Male	0.0024***	-0.0012***	0.0000	-0.0009***	0.0022***	-0.0022***
	(0.0013)	(0.0003)	(0.0011)	(0.0003)	(0.0009)	(0.0004)
Gender*Science PR(Dmean)						
Female	0.0604***	0.0234***	0.0474***	0.0176***	0.0543***	0.0214***
	(0.0016)	(0.0005)	(0.0016)	(0.0004)	(0.0021)	(0.0007)
Male	0.0722***	0.0148***	0.0613***	0.0121***	0.0316***	0.0138***
	(0.0015)	(0.0003)	(0.0010)	(0.0003)	(0.0015)	(0.0006)
# Applications	-0.1649***	0.2767***	0.1926***	0.2724***	0.1397***	0.1915***
	(0.0077)	(0.0010)	(0.0094)	(0.0014)	(0.0059)	(0.0060)
Constant	-0.3149***	-1.4110***	-1.3492***	-0.17036***	-0.10434***	-1.3635***
	(0.0866)	(0.0268)	(0.0643)	(0.0411)	(0.0776)	(0.0278)

Note: This table reports estimates from three zero-inflated Poisson regression models. Each pair of columns come from a regression of the number of STEM program applications. The first column reports the estimated coefficients governing inflated zeros, and the second column reports the estimated coefficients governing the mean of the Poisson process. Models two and three are similar to model one, except that now the dependent variables are the number of math-intensive STEM applications and non-math-intensive STEM applications. The explanatory variables include the average of each subject's test score percentile (mean PR), the de-meaned percentiles for individual subjects (demeaned PR), the total number of applications, and year dummies (unreported).

B Additional Figures

Figure B1: Multinomial Logistic Regression of Major Enrollment



Note: The figure displays the multinomial logistic regression coefficients on gender. The triangle symbol represents the gender coefficient without any controls. The circle symbol represents the gender coefficient with the same covariates controls as Column (7) of Table 3 in the paper. The horizontal axis is the coefficient of each field relative to the base field: Arts & Humanities. The horizontal lines indicate 95 percent confidence intervals.