Preferences, Access, and the STEM Gender Gap in Centralized High School Assignment

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The gender gap in science, technology, engineering, and mathematics (STEM) widens during high school, due both to differences in student choices and institutional barriers to accessing STEM education. Using rich data from Mexico City's centralized assignment system and a structural model of high school choice, we document strong demand for elite STEM and relatively weak demand for non-elite STEM programs. Decomposition and counterfactual simulations demonstrate that most of the gap is due to gendered choices, with males more strongly preferring STEM. Test-based assignment restricts elite STEM access for females, who have lower placement test scores despite similar low-stakes exam scores.
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Women are underrepresented in science, technology, engineering, and math (STEM) roles throughout the world. In Mexico, the STEM gender gap is large, with women earning fewer than a third of STEM post-secondary degrees (López-Bassols et al., 2018). This STEM gender gap has important welfare consequences. First, fewer females in STEM can result in less innovation (Hong and Page, 2004; Hofstra et al., 2020), less STEM persistence overall (Griffith and Main, 2019), and aggregate productivity losses in Mexico and elsewhere (Ostry et al., 2018; Cuberes, Saravia and Teignier, 2022). Second, STEM occupations have higher pay in many contexts (Kahn and Ginther, 2017), paying 14 to 18 percent more among females in Mexico.[1] The STEM premium is not limited to high-skilled professions; it also exists in occupations that only require technical or vocational education, and such positions compose a substantial fraction of the workforce (Rothwell, 2013). Thus, increasing female participation in STEM can increase incomes throughout the education and skill distribution. Third, STEM fields build fundamental skills like creativity, problem-solving, confidence, and team-

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[1] Authors' calculations. See Section I.

work, that are increasingly important globally (UNICEF, 2020). For these reasons, there is substantial interest in reducing the STEM gender gap in Mexico and Latin America (Bello, 2020; Uribe, 2021), with calls to identify and target obstacles that keep females away from STEM (UNESCO, 2017).

Within education, these obstacles can be classified into two broad categories. First, preferences may be gendered (Rask, 2010; Zafar, 2013), arising from factors like culture, role models, family expectations, and discrimination (Kahn and Ginther, 2017). Second, institutional features may limit access to preferred schools, particularly for females.[2] Specifically, test-based admissions policies give lower priority to low-scoring students, and females often score lower on high-stakes exams (Montolio and Taberner, 2021) despite performing similarly or better on other academic measures. The relative contribution of preferences and access to the STEM gap is an empirical question.

We examine these issues by estimating a rich model of student preferences over STEM and non-STEM options, including both highly-demanded elite STEM programs and non-elite technical STEM programs. We study Mexico City high schools in 2007 and 2008, where females were 11 percentage points (p.p.) less likely to attend STEM programs than males, with the gap arising in both elite and non-elite programs. Mexico City has a centralized high school choice policy in which students submit a ranked list of school programs and receive assignment priorities based on their performance on a placement test. We estimate utilities for different program types by gender, geographic location, and other student characteristics including academic achievement and parental education. Importantly, we identify student ability using performance on a low-stakes exam that is separate and imperfectly correlated with the placement test. This allows us to estimate preferences for all students and program types under relatively weak assumptions, even though low-scoring students are never admitted to highly-demanded schools. We then use the model results to formally decompose the STEM gap, quantifying the contributions of preferences, placement scores, and other characteristics. Finally, we implement various counterfactual exercises to further understand the roles of preferences and access. These counterfactuals fully simulate the assignment process to account for general equilibrium effects arising from competition for limited program capacities.

Several key findings emerge from the model estimates. First, the marginal utility for elite STEM programs (relative to traditional programs) is high for both males and females and is low for non-elite STEM programs. Second, preferences for STEM programs are highly gendered, with stronger male STEM preference, holding constant other factors. The model also shows that high parental education, grade point averages (GPA), and math test scores predict stronger prefer-

[2] "Access" can be understood to encompass a wide range of both institutionalized and de facto contributors. We use the term "access" to more narrowly refer to admissions criteria that are formally considered in granting entry into a field or school. Examples of explicit merit-based tracking into schools include Trinidad and Tobago (Jackson, 2010), Ghana (Ajayi, 2022), Romania (Pop-Eleches and Urquiola, 2013), and the U.S. (Corcoran and Baker-Smith, 2018).

ence for elite STEM schools. However, these differences are small compared to the gender difference, and there are few qualitative gender differences with respect to these dimensions of heterogeneity.

The decomposition exercise shows that these gendered preferences contribute substantially to the STEM gender gap, explaining the majority of both the elite and non-elite STEM gaps. Access constraints are important when considering elite STEM programs, with placement test score differences explaining 33% of the elite STEM gap. This means the test-based admissions policy is a barrier for females, who score 0.2 standard deviations (SD) lower on the placement test despite having similar performance on the low-stakes exam and higher middle school GPAs. Other student characteristics, including place of residence, explain very little of the gap.

The counterfactual simulations confirm the key roles of preferences and placement test scores while accounting for general equilibrium effects. The overall STEM gap would reverse sign if females had the same preferences as observably similar males, and the elite STEM gap would close by over 20% in a scenario where female placement test scores resembled male scores. Finally, we simulate affirmative action policies to benchmark the extent of intervention required to close the STEM gap in the presence of preference and score differences. Closing the STEM gap would require giving females increased priority at STEM programs equivalent to a 0.6 SD higher placement test score. The aggregate welfare effects of such a policy appear small.

Together, these results highlight the critical role of gendered preferences and the question of what shapes these preferences. We provide suggestive evidence on why females have weaker preference for STEM by examining school characteristics by type. STEM schools have fewer female staff and female students, and elite STEM schools have substantially higher failure rates. Thus, consistent with other literature, females may choose STEM less because they lack role models, have fewer female peers, and/or are more averse to challenging tasks and failure.[3] At the same time, many studies examine additional causes of gendered preferences. Explanations include female perceptions that non-STEM work is more pro-social and cooperative (Croson and Gneezy, 2009; Eccles and Wang, 2016; Shi, 2018) and more flexible with respect to work-life balance and child-bearing (Tan-Wilson and Stamp, 2015; Jiang, 2021). Studies also highlight female comparative non-STEM advantage (Delaney and Devereux, 2019; Goulas, Griselda and Megalokonomou, 2022), lower female self-evaluations for math and science performance (Exley and Kessler, 2022), higher female risk aversion (Eckel and Grossman, 2008; Croson and Gneezy, 2009), and higher female dislike for competition (Niederle and Vesterlund,

[3]For studies on role models, see Carrell, Page and West (2010), Bottia et al. (2015), Porter and Serra (2019), and Canaan and Mouganie (2023). For studies on female peers, see Schneeweis and Zweimüller (2012), Griffith and Main (2019), Mouganie and Wang (2020), and Schøne, Simson and Strøm (2020). With respect to aversion to challenge and failure, Niederle and Yestrumskas (2008) find that females are more likely to shy away from challenging tasks, and Owen (2010) and Ahn et al. (2019) show that females are more affected by poor grades in STEM.

2010; Iriberri and Rey-Biel, 2019).

However, these preferences and beliefs are influenced by many factors, including gendered stereotypes about STEM ability (Cvencek, Meltzoff and Greenwald, 2011; Bian, Leslie and Cimpian, 2017), societal beliefs about gender equality (Guiso et al., 2008; Nollenberger, Rodríguez-Planas and Sevilla, 2016), and gendered expectations from parents (Eccles, Jacobs and Harold, 1990; McCoy, Byrne and O'Connor, 2022) and teachers (Lavy and Sand, 2018; Burgess et al., 2022; Rakshit and Sahoo, 2023). Additionally, STEM spaces can be exclusive and discriminatory (Cabay et al., 2018; Astorne-Figari and Speer, 2019; Diele-Viegas et al., 2021). Together, this means that males receive more encouragement to pursue STEM jobs and education (Ceci and Williams, 2007; Lambrecht and Tucker, 2019; Murciano-Goroff, 2022). Several recent studies confirm the importance of these environmental factors in Mexico and Latin America (Bastarrica et al., 2018; Agurto et al., 2021; Del Carpio and Guadalupe, 2022; Del Carpio and Fujiwara, 2023).

At the same time, access issues are important for highly demanded schools. Test-based admissions contribute to gaps elsewhere (Corcoran and Baker-Smith, 2018), and gender gaps are likely with lower female test scores in many contexts (Hyde et al., 2008; Stoet and Geary, 2013). This is a particular concern when there is gender bias in standardized test scores (Saygin, 2020) and when females are negatively affected by high stakes, high pressure settings like testing (Booth and Lee, 2021; Montolio and Taberner, 2021; Arenas and Calsamiglia, 2022).

In our analysis, we examine two less-studied aspects of the STEM gender gap. First, we show how the STEM gender gap starts before entering high school, expanding on studies focused on the university level (Card and Payne, 2021; Lichtenberger and George-Jackson, 2013). Second, we examine the gap in both highly-demanded academic STEM programs and less-selective technical STEM programs, where preferences likely play a greater role than access. While much of the existing literature on STEM gender gaps considers elite education and high-skilled professions, we additionally focus on the technical programs that serve as important labor market entry points for many economies (Rothwell, 2013).

Our counterfactual analyses are similar to Corcoran and Baker-Smith (2018), but we tie the simulations to a model of student preferences, adding to an active literature on structural models of student preferences within centralized assignment mechanisms.[4] We follow Fack, Grenet and He (2019) in assuming that students are assigned to their most-preferred feasible program conditional on their assignment priority. We allow for rich preference heterogeneity with respect to observable characteristics, following Abdulkadiroğlu et al. (2020).

[4]See, for example, Hastings, Kane and Staiger (2009), Glazerman and Dotter (2017), Agarwal and Somaini (2018), Bordón, Canals and Mizala (2020), Calsamiglia, Fu and Güell (2020), Kapor, Neilson and Zimmerman (2020), Pathak and Shi (2021), and Beuermann et al. (2023).

I. Context

A. STEM in Mexico

While the STEM gender gap is common throughout the world, its magnitude depends on the context and definition of STEM (Ceci et al., 2014). We use an inclusive definition of STEM following Rothwell (2013), which classifies STEM occupations as those that require substantial knowledge in any one STEM field. It includes fields with higher female representation like nursing, fields requiring higher education like engineering, and fields with lower education like equipment maintenance. The nonprofessional STEM fields are a large fraction of STEM jobs, particularly in Mexico and other developing countries.

We describe the returns to STEM in Mexico using the 2010 and 2012 Encuesta Nacional de Ocupación y Empleo (INEGI, 2012*b*). Online Appendix Table A1 shows that, among females, STEM jobs pay 14 to 18 percent more than non-STEM jobs after controlling for a set of basic demographics.[5] This premium exists among low education and high education workers, and is the same or larger for females relative to males. The results are consistent with STEM wage premia elsewhere (Even, Yamashita and Cummins, 2023) and with causal studies on the returns to STEM (Kirkeboen, Leuven and Mogstad, 2016; Ng and Riehl, 2023).

We also find that high school STEM education is an important part of the STEM pipeline in Mexico, using the 2010 and 2012 Encuesta Nacional de Inserción Laboral de los Egresados de la Educación Media Superior (INEGI, 2012*a*). Online Appendix Table A2 shows that females who study STEM in high school are 42% more likely to study STEM in college and 140% more likely to work in STEM (186% more likely among the sample who do not proceed to college). Females who study STEM in college are 540% more likely to work in STEM. Together, these results suggest that studying STEM in high school can be an important avenue for raising female wages and increasing the representation of females in STEM jobs.[6] Additional details are included in online Appendix A.

B. School choice in Mexico City

Mexico City has many public high school options, with students choosing from more than 600 academic programs available throughout the area. We delineate

[5]We control for urban residence, age, household size, household headship, and marital status. We also control for parental education when it is observed in the household roster (i.e., for children who are currently living with their parents). Among this selected sample, the STEM premium for females is 11 to 19 percent and remains statistically significant.

[6]Prior research shows that the effectiveness of STEM-specific high school programs is context dependent. Some studies find positive impacts of STEM program attendance on STEM course-taking and interest (Means et al., 2016) and on STEM test scores and rates of STEM test-taking (Wiswall et al., 2014), while others find null (Eisenhart et al., 2015; Bottia et al., 2018) or heterogeneous results (Gnagey and Lavertu, 2016). In Mexico City, Dustan, de Janvry and Sadoulet (2017) show that attending selective STEM programs increases end-of-high-school test scores, and a working paper by Ortega Hesles and Dougherty (2017) discusses the returns to technical schools.

five different types of programs: elite STEM, non-elite STEM (i.e., technical STEM), elite non-STEM, technical non-STEM, and traditional public school programs (which are non-technical, non-elite, and non-STEM).

Two subsystems of programs are considered elite. The elite STEM programs focus on science and engineering and are affiliated with the Instituto Politécnico Nacional (IPN), a prestigious national polytechnic university. IPN also offers a few elite non-STEM programs, focused on social sciences and business administration. The remaining elite non-STEM programs are affiliated with the Universidad Nacional Autónoma de México (UNAM), and offer broader, liberal arts-style curricula. Both elite subsystems are highly demanded and draw students from all areas of Mexico City (Dustan and Ngo, 2018) despite being clustered near the city center (Figure 1, Panel A).[7]

The remaining non-elite programs are less competitive, drawing most of their students from nearby neighborhoods (Figure 1, Panel B). The non-elite STEM programs provide STEM-focused technical training and are primarily operated by the Colegio Nacional de Educación Profesional Técnica (CONALEP) and Dirección General de Educación Tecnológica Industrial (DGETI). The technical non-STEM programs also provide technical training but are specialized in non-STEM areas like business administration.[8] Non-elite STEM and technical non-STEM programs are often present on the same high school campus. Finally, traditional public schools offer general academic curricula. Students from any high school program can go on to higher education, but students in UNAM-affiliated high schools receive favorable consideration in UNAM university admissions.

Participation in a centralized choice process is mandatory for public school enrollment; students who do not submit any choices cannot attend a public school. The choice process is run by Comisión Metropolitana de Instituciones Públicas de Educación Media Superior de la Zona Metropolitana de la Ciudad de México (COMIPEMS) and occurs during and after students' final year of middle school (grade nine). First, students rank their preferred programs, listing up to a maximum of twenty options. Students then take a multi-subject placement test.[9] Finally, students are assigned to programs using a serial dictatorship algorithm, a special case of the student-proposing deferred acceptance algorithm (SPDA) characterized by Gale and Shapley (1962). A computer orders all students according to their placement test scores, and moving from highest scoring to lowest scoring, assigns each student to her highest-ranked program with a remaining seat when her turn arrives. Programs that fill up thus have a "cutoff score" equal to the placement score of the student assigned to the final seat.[10]

[7]See Dustan, de Janvry and Sadoulet (2017) for more on Mexico's elite programs and their returns.

[8]See Avitabile, Bobba and Pariguana (2017) and Ortega Hesles and Dougherty (2017) for additional discussion on the constraints and returns to these educational tracks.

[9]All questions on the exam are equally weighted with no penalty for incorrect answers.

[10]The schools decide in real-time whether to accept or reject the group of students with the same score. In addition, the elite IPN and UNAM programs require that students have a middle school GPA of 7/10 or above, but this standard is low enough that it almost never binds.

Information on program options and the choice process was widely available during this time period. In addition to receiving detailed printed materials, including a full list of programs, students had access to large, well-attended orientation expos. The elite programs regularly receive media attention about the competitiveness of their admissions, suggesting that these choices are salient for most students (Gonzalez, 2003). For all programs, cutoffs from prior years are publicly available and provided in a centralized website. Cutoffs are fairly stable over time, allowing students to anticipate future cutoffs (see online Appendix Figure A1).

There is full compliance with the assignment mechanism; students cannot enroll at a public school to which they were not assigned. Most participating students (85%) are assigned through this algorithm. The remaining unassigned students chose programs with cutoffs higher than their own score. These students can later choose from programs with seats remaining after the computerized assignment. We do not observe this outcome for most years, but show in 2005 that the STEM gender gap is similar before and after this later round of assignment (online Appendix Table A3).

Separately, students also complete a low-stakes multi-subject standardized exam, Evaluación Nacional del Logro Académico en Centros Escolares de Educación Media Superior (ENLACE 9). ENLACE 9 scores have no effects on middle school graduation or any other student outcomes but provide a measure of student ability in a non-pressurized environment.

Most middle school students participate in the choice process (COMIPEMS, 2010), though some apply only to private schools or drop out entirely. Students effectively exercise their choices, with many attending schools that are far away (Dustan and Ngo, 2018). Using data from a 2017 survey on commuting, Encuesta Origen Destino en Hogares de la Zona Metropolitana del Valle de México, EOD, (INEGI, 2017), we find that both male and female students travel an average of 8 kilometers (44 minutes) to school and use a mix of transportation modes (online Appendix Table A4).

II. Data

We use data from the 2007 and 2008 COMIPEMS administrative databases (SEP, 2008*b*). This includes each student's ranked program list, placement score, and final assignment status and program. It also includes gender, middle school GPA, middle school graduation status, self-reported parental education levels, and home postal codes.[11] The database covers all students participating in the COMIPEMS choice process. Since participation is mandatory for attendance, this is the universe of students interested in attending public high schools. The majority of these students are finishing middle school (ninth graders). The remaining

[11] We use the male/female classifications in the data that are extracted from national identification records. We do not have data on students' self-identified genders or on any non-binary gender categories. We follow the literature in referring to this gap as the gender gap.

students graduated previously but are returning because they failed to graduate on time for the previous COMIPEMS cycle, or, more infrequently, were assigned elsewhere in a previous cycle and are attempting to enter a different school. We do not observe students who drop out entirely or only apply to private schools.

We explore selection into the COMIPEMS sample by examining all students in the Mexico City area who take the ENLACE 9, which is administered to ninth grade students in all public and some private schools. Online Appendix Table A5 shows that 80% of ENLACE 9 takers appear in the COMIPEMS data; this is similar to government reports (COMIPEMS, 2010). Females are 1 p.p. more likely to participate. While COMIPEMS students are positively selected with respect to ENLACE 9 score, the degree of selection is quite similar across genders. Below, we find that a large gender gap in placement test scores persists even after controlling for ENLACE 9 scores.

Our analysis restricts the sample to students eligible for assignment and for whom we are able to estimate preferences.[12] We exclude students whose address is either invalid (missing home and middle school) or outside the COMIPEMS area. For students with no home address but with a middle school, we use the location of their middle school as their address. We also exclude adults who are returning to school, as they are substantially different from the majority of the students. Excluded students are 3.2% of all assignable students. Analyses of the gap in assigned programs only include students who were assigned to a program in the computerized assignment process.

We match ninth grade students in our analytical sample to their individual ENLACE 9 exam scores (SEP, 2008*a*), matching 96% of these students successfully.[13] Students who have already graduated middle school do not take the exam, so they are left unmatched.

We supplement school choice data with geographic information system (GIS) data to locate postal codes (SPM, 2014; INEGI, 2014) and schools (SEP, 2008*c*). Postal codes are small (Dustan and Ngo, 2018), and we proxy for students' home locations using postal code centroids. We use the Open Source Routing Machine, OSRM, (OSRM, 2023; Geofabrik, 2018) to calculate the shortest driving distances between schools and home postal codes. OSRM is a free, publicly available application and has been used to accurately measure commute-relevant distances (Luco, 2019; Kutscher, Nath and Urzúa, 2023). In additional models, we use straight-line distance and travel time as alternate measures. We estimate travel time using the relationship between driving distance and commute time from a model based on the 2017 EOD commute survey (online Appendix A). We prefer the OSRM driving distance because it provides a more accurate estimate of travel costs than straight-line measures (Kutscher, Nath and Urzúa, 2023), and is less subject to measurement error and changing traffic patterns than estimated travel

[12]Students are not eligible for assignment if they failed middle school or scored below a minimum score on the placement exam. They are dropped from our analysis.

[13]We restrict our analysis to the 2007 and 2008 cohorts because we do not have ENLACE 9 scores for other cohorts.

time from 2017.

Finally, we classify the high school programs as STEM or non-STEM using the Brookings STEM occupational categories (Rothwell, 2013). Specifically, we identify all possible occupational matches for each program and take the average STEM classification for them. We label programs with average STEM classifications of 0.5 or more as STEM. Each classification was done independently by two people, with discrepancies reconciled by a third individual. The program-level STEM classifications are presented in online Appendix Table A6. Examples of STEM programs include electronics, agro-industrial technician, and nursing, while examples of non-STEM programs include social work, tourism, and business.

Table 1 presents summary statistics for academic outcomes, school choices, demographics, and geography by gender. With respect to academics, males significantly outperform females on the placement test, scoring 3.9 points (0.2 SD) higher than females. The low-stakes ENLACE 9 does not show the same disparity: males score 0.14 SD higher in math, while females score 0.21 SD higher in Spanish, such that overall performance is quite similar. Online Appendix Table A7 presents regression results showing that ENLACE 9 subscores explain about 65% of the variation in placement test scores. Conditional on ENLACE 9 subscores, males have an even larger advantage in placement test results than in the uncontrolled comparison. Females obtain 0.54 SD higher middle school GPAs than males. Figure 2 displays the densities of these four indicators. Panel A shows large differences in placement test scores throughout the distribution, and Panel D shows strikingly different middle school GPA distributions.

Males choose STEM programs more than females. STEM programs are 31.5% of male choice portfolios (10.5% elite STEM and 21.0% non-elite STEM), compared to 21.6% of female choice portfolios (6.6% elite STEM and 15.0% non-elite STEM). Females list slightly more programs than males (9.6 versus 9.4), and are more likely to list elite non-STEM, technical non-STEM, and traditional programs. Males and females both list programs that are 12.1 km away on average.

Males are slightly more likely to have a highly educated parent and are 7 p.p. more likely to be middle school graduates, reflecting their higher rate of failing to graduate from middle school on time and needing to participate in the following admissions cycle. Overall geographical access to schools is quite similar, with students living 11.5 to 11.6 km away from their closest elite STEM school and 2.9 km away from their closest non-elite STEM options.

Table 2, Panel A summarizes program assignment by gender for assigned students. 38.7% of males are assigned to STEM programs compared to 27.6% of females, generating an 11.1 p.p. STEM gender gap (5.6 and 5.5 p.p. for elite STEM and non-elite STEM, respectively).[14] Females are 1.2, 2.9, and 6.9 p.p. more likely to be assigned to elite non-STEM, technical non-STEM, and tra-

[14]The gender gap among public middle school students is similar, at 10.9 p.p. For this group, private high schools are unlikely as an outside option so assignment closely mirrors enrollment.

ditional programs, respectively. Females are also assigned to programs 0.3 km closer than males. Panel B shows that females are 5.7 p.p. more likely to be left unassigned by the algorithm, compared to a male non-assignment rate of 11.7%.

Figure 3 shows the STEM gender gap by placement test score percentile. The total gap is higher for very low scorers and for high scorers, exceeding 15 p.p. at the top of the score distribution. The gap in non-elite STEM assignment dominates for low scores, and the gap in elite STEM assignment grows at higher scores, as assignment to more competitive programs becomes feasible.

III. Methods

This section explains the discrete choice model used to estimate student preferences, the STEM gap decomposition exercise, and the counterfactual simulations.

A. *Student preferences and their estimation*

We model student i as having preferences over programs $j \in \{1, ..., J\}$, which depend on the interaction of program and student characteristics. Students are partitioned into mutually exclusive cells $c(X_i, M_i)$, based on their covariates X_i and gender M_i. Program characteristics Z_{ij} consist of indicators for program type and distance from the student's home. Allowing mean utilities to differ at the program level, assuming linear preferences with additive separability, and fixing one covariate cell as the base group gives the following expression for utility from assignment to program j:

$$U_{ij} = \delta_j - d_{ij} + Z_{ij}\beta_{c(X_i,M_i)} + \eta_{ij} = V_{ij} + \eta_{ij}, \tag{1}$$

where δ_j capture the base group's mean utilities for each program, and $\beta_{c(X_i,M_i)}$ allows each cell to have different utilities from distance and program types. The base group's utility from distance d_{ij} is normalized to -1, and η_{ij} are unobserved idiosyncratic tastes.

We estimate student preferences under the assumption that the COMIPEMS assignment mechanism results in stable matches. This follows Fack, Grenet and He (2019), who show that stability is a weaker assumption than common alternatives. Specifically, "weak truth-telling" assumes that students truthfully rank programs and that all unlisted programs are less-preferred than all listed programs. In Mexico City, students rarely exhaust all elite options in their ranked lists. Instead, they often list a few elite programs and then list less-competitive, neighborhood programs. This is more likely due to students' beliefs about their likelihood of acceptance into the marginal elite school, conditional on scoring too low for assignment to the already listed elite schools, rather than students having lower preferences for unlisted elite options (Ali and Shorrer, 2021).

In contrast, stability assumes that students are assigned to their most-preferred program that was *ex post* feasible given their assignment priority. This is plausible in Mexico City, where information on program feasibility is available and students can list enough programs that they are assigned to their most-preferred feasible program. Program cutoff scores are stable from year to year (online Appendix Figure A1), and these cutoffs are public for applicants to observe. Students apply before knowing their placement scores and imperfectly predict their achievement (Bobba and Frisancho, 2022), but this uncertainty is mitigated by the ability to rank many programs. Only 2.7% of students exhaust all 20 choices, suggesting that students are not constrained by the number of options they can list.

Stability has an additional benefit over truth-telling models with respect to "mistakes," or misordered rankings, in the submitted choice lists. Specifically, stability allows for robust preference estimation under payoff-*irrelevant* mistakes, i.e., omissions or misorderings that do not change final assignments (Rees-Jones and Shorrer, 2023). Payoff-*relevant* mistakes (those that affect assignments) can bias parameter estimates. The data do not permit us to identify mistakes, but we present an exploratory exercise here. We define a potential payoff-relevant "mistake" as a portfolio containing a feasible program whose cutoff is one standard deviation (20 points) higher than the cutoff of the assigned program, such that the student could have been admitted to a more-competitive program but ranked it below a less-competitive one. These could reflect mistakes or true preferences for the lower-cutoff program. Online Appendix Table A8 shows that the overall rate of payoff-relevant "mistakes" is low, at 9.1%,[15] with even lower rates of mistakes affecting STEM assignment. Rates are generally similar for males and females.

These institutional features suggest that estimating preferences under the stability assumption is reasonable. Fack, Grenet and He (2019) show that, asymptotically, stability nests truth-telling—even when students rank programs in order of preference and prefer listed programs to unlisted ones, empirical approaches based on stability alone still consistently recover preference parameters.[16]

Estimating student preference parameters is straightforward under the stability assumption. Here, student i's feasible programs are those whose cutoff scores $\underline{s}_j$ are less than or equal to her placement test score s_i: $\mathcal{J}_i = \left\{j : s_i \geq \underline{s}_j\right\}$.[17] Stability implies that among all programs in this "personalized choice set," her most-preferred is the one to which she was assigned, denoted by A_i:

$$A_i = \underset{j \in \mathcal{J}_i}{\arg\max}\ U_{ij}.$$

We first construct each student's personalized choice set $\mathcal{J}_i$ using her placement

[15]This is consistent with rates reported in other studies. These rates have been interpreted as sufficiently low enough to be minimally consequential (Rees-Jones and Shorrer, 2023).

[16]The drawback of assuming stability alone when truth-telling holds is that empirical approaches based on truth-telling use students' full portfolios for preference estimation, making them more efficient than stability-based approaches that only use the assigned program.

[17]A 7.0 GPA or above is also required to be considered at UNAM and IPN programs, so it is part of assignment priority at those programs. We account for this in the empirical analysis by including the GPA cutoff in the feasibility requirement for these programs.

test score and program-level cutoffs from her COMIPEMS year. Assuming that η_{ij} is i.i.d. extreme value type I, Fack, Grenet and He (2019) show that Equation 1 can be estimated using a conditional logit with the personalized choice sets. We follow this approach while accounting for features specific to the institutional and empirical context. First, we allow for flexible preference heterogeneity across geographical regions r and exam years t by estimating preferences separately by region-year cell. While families may sort spatially with respect to schools, geographical access to STEM schools is similar for males and females (Table 1), suggesting that residential sorting is not gendered. We separate by region to compare among students who have similar geographical access to different program types, dividing into three regions: the Federal District, East State of Mexico, and West State of Mexico. We denote the region-year-specific observable utilities by $V_{ijrt} = \delta_{jrt} - d_{ij} + Z_{ij}\beta_{c(X_i,M_i)rt}$. Second, we aggregate non-elite programs of the same type (non-elite STEM, technical non-STEM, and traditional) outside of the region into region-year-specific alternatives.[18] Finally, because some students remain unassigned by the computerized assignment process, we consider "unassigned" to be the outside option available in every student's choice set and normalize its utility to zero.

The conditional likelihood for student i's assignment outcome is:

$$\mathcal{L}\left(A_i | c(X_i, M_i), \boldsymbol{Z}_i, \boldsymbol{d}_i, \underline{\boldsymbol{s}}_t, s_i\right) = \frac{exp\left(V_{iA_irt}\right)}{\sum_{j \in \mathcal{J}_i} exp\left(V_{ijrt}\right)}, \tag{2}$$

where $\boldsymbol{Z}_i$ and $\boldsymbol{d}_i$ are matrices containing the student-program covariates and distances for all programs $j \in \mathcal{J}_i$, respectively; $\underline{\boldsymbol{s}}_t$ contains all program cutoff scores in year t, and s_i is the student's placement test score. Covariate cells are determined by the interaction of indicators for male gender, above-median middle school GPA, above-median ENLACE 9 math score, above-median ENLACE 9 Spanish score, missing ENLACE 9 score, high parental education, missing parental education, and middle school graduate status. For example, there is one cell for ninth grade females with high middle school GPAs, low ENLACE 9 math scores, high ENLACE 9 Spanish scores, and high parental education.[19] The ENLACE 9 covariates serve as measures of academic ability that do not directly determine the feasible set (as the placement test score does), allowing heterogeneous preferences with respect to ability while maintaining the stability approach.[20] Middle school GPA plays a similar role, while allowing for heterogeneity with respect

[18] These two modeling choices are similar to those taken by Abdulkadiroğlu et al. (2020), who estimate preferences separately by borough and aggregate all schools outside a student's borough into an outside option.

[19] Some cells are empty by definition. For example, no cell has both high and missing parental education. Middle school graduates participated in COMIPEMS later than their ninth grade year, so they are not matched to the ENLACE 9. Covariate cells for middle school graduates are thus always classified as "missing ENLACE 9 score."

[20] Partitioning by placement test score would result in all below-median students lacking elite programs in their feasible sets, precluding estimation of heterogeneous tastes for these program types.

to academic skills beyond those captured by standardized tests. Parental education is a proxy for socioeconomic status, while middle school graduates are sufficiently different from "standard" ninth grade COMIPEMS participants that their educational objectives and preferences are likely quite distinct.[21]

The vector Z_{ij} includes program type indicators, a constant (to allow utility relative to the outside option to vary with student characteristics), and distance from home to school. We estimate the model via maximum likelihood. The set of parameters includes the region-year-specific scale factor applied to η_{ij} due to the normalization of the base category distance parameter.

B. *STEM gender gap decomposition*

We use a nonlinear decomposition procedure to separate the roles of preferences, placement test scores, and other student characteristics in generating the STEM assignment gap. We follow the technique described in Fairlie (1999, 2005, 2017), which extends the Oaxaca-Blinder decomposition (Kitagawa, 1955; Blinder, 1973; Oaxaca, 1973) to nonlinear models. We summarize the decomposition procedure here and provide details in online Appendix B. For simplicity, this discussion relates to the probability of STEM assignment unconditional on assignment, but the appendix shows how we apply the procedure to decompose the gap among assigned students.

The gender difference in the probability of STEM assignment $P(S = 1)$ for males ($M = 1$) and females ($M = 0$) can be decomposed into a component due to differences in all observable student characteristics excluding gender $\tilde{X}_i = \{X_i, \boldsymbol{d}_i, s_i\}$ with gender-specific joint distributions $F(\tilde{X}|M)$ and a component due to differences in preferences:

(3)

$$
\begin{aligned}
P(S=1|M=1) - P(S=1|M=0) = \\
\int P(S=1|M=1,\tilde{X})dF(\tilde{X}|M=1) - \int P(S=1|M=0,\tilde{X})dF(\tilde{X}|M=0) = \\
\underbrace{\int P(S=1|M=1,\tilde{X})dF(\tilde{X}|M=1) - \int P(S=1|M=1,\tilde{X})dF(\tilde{X}|M=0)}_{\text{Characteristic component}} + \\
\underbrace{\int P(S=1|M=1,\tilde{X})dF(\tilde{X}|M=0) - \int P(S=1|M=0,\tilde{X})dF(\tilde{X}|M=0)}_{\text{Preference component}}.
\end{aligned}
$$

We predict assignment probabilities for each feasible student-program using

[21] Assuming stability allows for less flexible parameterization of utility than similar approaches based on truth-telling because it uses assignments rather than the full sequence of choices in the student's portfolio. In particular, we cannot estimate separate program fixed effects by covariate cell as in Abdulkadiroğlu et al. (2020) because most covariate cells have several programs to which no students were assigned.

the conditional logit estimates, and sum over all STEM programs to predict $P\left(S_i = 1|M_i, \tilde{X}_i\right)$. The first and last terms of equation 3 correspond to mean predicted probabilities of male and female STEM assignment, respectively. The middle terms relate to STEM assignment probabilities of female students in the counterfactual setting where they have "male preferences." Given our parameterization of preferences, this simply requires reassigning each female i to covariate cell $c(X_i, M = 1)$ and recomputing the predicted probabilities.

The preference component gives the contribution of preference differences to the STEM gap, holding female observables constant. The characteristic component gives the difference in the STEM gender gap due to gender differences in observables, holding preferences constant.[22] Following the simulation procedure from Fairlie (2017), we also estimate the separate contributions of each student characteristic by matching all females to randomly drawn males from the same region-year, sequentially replacing the elements of $\tilde{X}_i$ with their matched male counterparts, and recomputing the predicted probabilities at each step. Changing s_i affects the student's feasible set $\mathcal{J}_i$, allowing us to estimate how differences in placement test scores contribute to the STEM gap.[23]

As a counterfactual exercise, this decomposition procedure does not account for the fact that program capacities are limited, so shifts in demand due to changes in female preferences or covariates are not permitted to affect program-level cutoff scores and thus assignment probabilities. The counterfactual simulations in the next section will allow for such general equilibrium effects.

C. *Counterfactual simulations*

We use assignment simulations to assess model fit, to obtain counterfactual STEM gaps while accounting for general equilibrium effects on program cutoffs, to understand the welfare implications of gender differences in placement test scores, and to contextualize the magnitude of the STEM gap by illustrating the extent of affirmative action that would be required to close it.

We summarize the procedure here, while online Appendix B gives more detail. First, the estimated preference parameters (actual or counterfactual) and student-program characteristics are used to simulate preference orderings over *all* programs and the outside option of non-assignment, for each student in the sample. We draw unobserved tastes from the appropriately scaled extreme value type I distribution and rank programs by simulated utilities.[24] Second, these preference orderings are submitted to the assignment mechanism, which is implemented

[22] Males are the reference group in this decomposition; we hold preferences constant at male preferences when estimating the characteristic component.

[23] Online Appendix B explains the computation of standard errors and the implementation of this "detailed decomposition," including the use of repeated simulations to eliminate path dependence.

[24] We combine these rankings with the observed portfolios of the small sample of assignable students who were excluded from the estimation sample (i.e., adults and students with addresses that were either invalid or outside of the COMIPEMS boundary). This results in "portfolios" for the universe of assignable students.

using the actual or counterfactual priority structure to obtain simulated program assignments.[25] This simulation differs from the actual COMIPEMS assignment process because it uses students' full preference orderings rather than shorter choice portfolios. This follows the approach of Artemov, Che and He (2021), who note that this is valid under the stability assumption.

Finally, we simulate changes in overall and gender-specific consumer surplus to show how gender differences in placement test scores affect the level and distribution of welfare. Differences in expected consumer surplus between the status quo and a counterfactual result from differences in the feasible sets they generate, $\mathcal{J}_i^0$ and $\mathcal{J}_i^1$ (Small and Rosen, 1981; Williams, 1977):

$$\Delta \mathrm{E}\left(CS_{irt}\right) = \ln\left(\sum_{j \in \mathcal{J}_i^1} \exp(\widehat{V}_{ijrt})\right) - \ln\left(\sum_{j \in \mathcal{J}_i^0} \exp(\widehat{V}_{ijrt})\right). \tag{4}$$

Equation 4 is used to compute student-level changes in expected consumer surplus, which are then averaged in the full or gender-specific sample.

IV. Results

The stability model fits the data well. Simulating preference orderings from the model and implementing the assignment mechanism yields overall and component-specific gender gaps that are nearly identical to the actual gender gaps (online Appendix Table C1). Simulated program-level cutoff scores also correspond closely to those observed in the data (online Appendix Figure C1), with an assignment count-weighted correlation of 0.98. Comparing stability to the weak truth-telling model following the test proposed by Fack, Grenet and He (2019), we overwhelmingly reject the truth-telling model ($\chi^2(3316) = 191618$, $p < 0.00001$).

A. *Student preferences*

Table 3 summarizes female preferences for different program types relative to the base category of traditional programs, obtained by regressing estimated program fixed effects $\hat{\delta}_{jrt}$ on program type indicators. The omitted student covariate cell is females in middle school who have high parental education and above-median middle school GPA, ENLACE 9 math, and Spanish scores. The $\hat{\delta}_{jrt}$ correspond to this cell's program-specific mean utilities, and their utility from distance is -1, so coefficients may be interpreted as marginal willingness to travel (WTT) for this group. Column 1 uses driving distance—our preferred distance measure—and shows that these females value elite STEM schools highly, with a marginal WTT of 18.5 km. WTT for elite non-STEM programs is even higher, at

[25]For this step, the "programs" that aggregate far-away alternatives are replaced with a randomly drawn feasible alternative among those that were aggregated.

27.0 km. Preferences for non-elite programs go in the opposite direction: WTT for non-elite STEM programs is -10.4 km, slightly more negative than the -7.6 km for technical non-STEM programs. Columns 2 and 3 present the models using straight-line distance and travel time, respectively, and show broadly similar patterns. The straight-line distance estimates are smaller in magnitude, as straight-line distances are shorter than driving distances. WTT for elite STEM programs is 14.7 km. In the travel time model, WTT for elite STEM programs is 50.8 minutes.

Table 4 reports gender differences in preferences, obtained by differencing estimated preference parameters between male and female covariate cells that are identical except for gender:

$$\hat{\Delta}_g = \int \left[\hat{\beta}_{c(X,M=1)rt} - \hat{\beta}_{c(X,M=0)rt}\right] dF(X,r,t) \tag{5}$$

Under the assumption of constant $Var(\eta_{ij})$ across covariate cells, $\hat{\Delta}_g$ reflects preference differences weighted by the number of students in the cell-region-year. Because cell-specific utilities from distance deviate very little from -1, we continue to interpret marginal utilities as WTT.

We find significant gender differences in preferences for STEM programs. Column 1 shows our preferred estimates using driving distance. WTT for elite STEM and non-elite STEM programs are 5.0 and 2.6 km higher for males than females, respectively. Preference differences for non-STEM programs are more modest: males have 0.9 km lower WTT for elite non-STEM programs and 0.2 km higher WTT for technical non-STEM programs. Males have lower preferences for remaining unassigned. Differences in preferences over distance are very small, with males expressing 2% lower marginal disutility for distance compared to females. The straight-line distance model in column 2 and travel time model in column 3 show similar patterns in gender differentials for STEM programs, with higher WTT for males for elite STEM and non-elite STEM programs. Gender differences over technical non-STEM preferences are noisier under the travel time model, but all three models show similarly small gender differences in distance preferences. For the remaining results, we use driving distance as our preferred distance measure.

Online Appendix Table C2 shows these gender differences in preferences by region. Small differences in non-STEM estimates exist across regions, but the STEM differentials are largely similar. Specifically, male elite STEM WTT is higher by 4.4 km, 5.7 km, and 5.2 km in the Federal District, East State of Mexico, and West State of Mexico, respectively. Similarly, males more strongly prefer non-elite STEM programs by 2.3 km, 2.7 km, and 3.3 km in the Federal District, East State of Mexico, and West State of Mexico, respectively. The remainder of the paper presents results aggregated across all regions.[26]

[26] An additional concern in identifying preferences is that students do not fully understand the pro-

Figure 4 summarizes differences in STEM preferences with respect to other student demographics. These are estimated as in equation 5 except that we estimate differences separately by gender and the comparisons are between high and low levels of the specified covariate. In Panel A, we find both males and females with high parental education, high ENLACE 9 math scores, and high middle school GPA have stronger preferences for elite STEM schools, with WTT differentials on the order of 1 to 2 km. High ENLACE 9 Spanish scores predict the opposite, with approximately 1 km lower WTT for elite STEM schools. Preference heterogeneity in these dimensions is much smaller than the first-order gender differences. Panel B shows differences for non-elite STEM programs and finds that high ENLACE 9 math scores predict stronger preference for non-elite STEM programs while high parental education and middle school GPA are associated with weaker preferences for non-elite STEM. Here, there are larger gender-by-covariate differentials. In general, males in each group have higher (less negative) marginal WTT for non-elite STEM. Online Appendix Table C3 shows the comparisons for the remaining assignment preference dimensions.

B. STEM gender gap decomposition

Table 5 shows the results of the decomposition analysis, beginning with the overall STEM gap in column 1. Gendered preferences play a very large role, contributing 13.1 p.p. (117.5%) to the overall 11.1 p.p. gap. Overall differences in student characteristics contribute negatively to the gap, driven almost entirely by gender differences in placement test scores (-1.6 p.p. or -14.5%). In other words, the STEM gap would be larger than 11.1 p.p. under similar placement score distributions, since giving females higher priority makes them less likely to be assigned to STEM programs. Thus, preference differences are the predominant driver of the gender gap in the *overall* STEM sector, while lower female placement scores attenuate the gap. Very little of the gap is explained by gender differences in ENLACE 9 scores, parental education, and distance to schools.

The findings are quite different when separately decomposing the elite and non-elite STEM gaps in columns 2 and 3. Preferences explain a smaller proportion (87.5%) of the elite gap. Placement test score differences explain 33.3% of the elite gap, confirming the importance of the access constraints due to lower female placement test scores. Gender differences in middle school GPA contribute negatively to the elite gap by 19.4%. Again, this is because females have higher middle school GPAs and higher-GPA students have higher marginal utilities from elite schools.

The origins of the non-elite STEM gap are somewhat different. Preference differences are the overwhelming determinant of the non-elite gap, explaining

grams available to them (Dynarski et al., 2021), despite the large amount of information available in this context. To address this, we examine the results from the Federal District only, where options are more salient since students reside close to all program types. Here, we continue to find strong gender differentials for STEM programs.

148.4% of it. Placement test score differences attenuate the gap significantly (-63.9%) because low overall demand for non-elite STEM programs makes them less competitive and thus a more likely destination for lower-scoring students. Gender differences in middle school GPA increase the non-elite gap for the same reason that they decrease the elite gap: higher-GPA students have lower preference for non-elite programs, and girls have higher GPAs. Overall, the aggregate STEM gap is almost entirely due to preferences, while access constraints play an important role in widening the elite gap and narrowing the non-elite gap.

C. *Counterfactual simulations*

Table 6 presents the results of the counterfactual simulations. These account for general equilibrium effects that arise from changes to program cutoffs when preferences, placement test scores, or assignment priority structures are altered. Figure 5 illustrates counterfactual impacts on the STEM gap across the placement test score distribution. We first replace female preferences with male preferences using the same procedure from the decomposition exercise, and then implement the simulation procedure described in Section III.C. Similar to the partial equilibrium decomposition, the overall STEM gap reverses (a change of -111.1%). The elite STEM gap decreases substantially (-84.8%) and the non-elite STEM gap reverses (-138.3%). These results suggest that aligning male and female preferences would have large effects on both elite and non-elite STEM gaps, even after accounting for endogenous changes in cutoffs. This preference alignment would not widen the overall elite education gap (inclusive of both STEM and non-STEM elite options): Panel A of online Appendix Figure C2 shows that the overall elite gap is weakly reduced everywhere in the test score distribution. Put differently, gender differences in STEM preferences are currently leading some elite-eligible females to forego an elite education altogether.

In a second scenario, we explore the independent role played by gender differences in placement test scores. In contrast to the decomposition exercise, we leave preferences unchanged but match females to males who scored similarly on their ENLACE 9 exams and draw placement test scores from these matching males.[27] Here, the overall STEM gap grows 16.8% as females are given higher priority and assigned to their more preferred programs, which tend to be non-STEM. However, giving females male placement test scores reduces the elite STEM gap by 22.3%, driven by students with scores near the margin of admission to elite schools. The impacts are similar to the results of the decomposition, but differ in part because the decomposition imposes male preferences while the counterfactual allows preferences to differ. The male advantage in placement test scores conditional on ENLACE 9 scores has welfare implications: males have higher average welfare

[27]Specifically, we partition the students by ENLACE 9 subscore deciles, region, and year. We then match females to males drawn from the same partition, with replacement, maintaining the placement test score ordering among females within the same partition.

under the status quo (0.69 km) and females have lower welfare (-0.64 km), with no aggregate welfare effects.[28]

Finally, we examine two counterfactual policies aimed at closing the STEM gap. They serve as a benchmark for the extent of intervention in the assignment mechanism required to close the STEM gap in the absence of changes in gendered preferences or the gendered nature of placement test scores. A STEM-focused affirmative action (AA) policy would need to award females 11 additional points (0.6 SD) for priority at STEM schools to (approximately) close the STEM gap. This more than closes the elite STEM gap (-132.0%), where access constraints are the most binding, again driven by large effects for students with scores near the margin of elite admission. This policy only reduces the non-elite STEM gap by 55.8% due to the predominant role of gendered preferences. The aggregate welfare effects of this policy are small, with males losing 0.48 km, females gaining 0.35 km, and aggregate losses of 0.05 km. In contrast, a general AA policy giving females 11 points higher priority at *all* programs increases the overall STEM gap by 37.7%, pairing a 121.1% increase in the non-elite STEM gap with a 42.9% reduction in the elite STEM gap.

D. Explaining gendered preferences

While explaining the causal factors behind gender differences in STEM preference is beyond the scope of this paper, we explore a set of possible factors using school census data (SEP, 2012) to describe school characteristics by program type (online Appendix Table C4). The school census provides data for aggregate campuses as opposed to COMIPEMS programs, so we classify non-elite STEM campuses as those that have 50 percent or more students in STEM programs. Compared to elite non-STEM schools, elite STEM schools have fewer female teachers (35.4% versus 47.1%) and fewer female staff. There is a similar but smaller differential among non-elite schools. Consistent with COMIPEMS assignments, STEM schools have fewer females in their entering classes. Thus, gendered preferences could be driven by a lack of female role models and female peers.

Academic outcome measures are similar between non-elite STEM and technical non-STEM schools. However, within elite schools, elite STEM schools have lower graduation rates (59.9% versus 69.2%) and substantially higher failure rates (43.6% versus 7.6% of students failing between one and five courses) than elite non-STEM schools. Thus, female preference for school completion may also contribute to gendered STEM preferences. Finally, within each school type, females have higher graduation rates and lower failure rates than males. In this context, females are more likely to persist in STEM than males, in contrast to lower female STEM completion rates elsewhere (Griffith, 2010; Speer, 2023).[29] However, the

[28]Online Appendix Figure C3 shows welfare effects across the distribution. Welfare effects are largest for students with scores near the margin of elite admission.

[29]Similarly, Dustan, de Janvry and Sadoulet (2013) shows no evidence of a gender differential in the

female graduation advantage is larger in non-STEM schools, indicating that the gender gap in STEM completion may be larger than the assignment gap we study here. At the same time, the labor force transition analysis (online Appendix Table A2) shows that females are as likely or more likely than males to continue into STEM study and occupations after STEM high school, suggesting that the STEM gender gap may be similar at later stages.

V. Discussion

Our findings have implications for reducing the gender gap, especially in centralized admissions systems. The role of access constraints implies that, to the extent that closing the STEM gender gap in elite or otherwise competitive programs is a policy goal, there may be a role for focused affirmative action or admissions policies that deemphasize high stakes test scores.[30] Still, such measures may be insufficient given the importance of gendered preferences, particularly in the case of non-elite STEM programs. In light of the observed wage premium for STEM occupations, including among less-educated workers, and the linkage between STEM studies and later STEM employment, there may be a role for interventions that increase female demand for STEM. A growing body of evidence shows that a variety of interventions can be effective in changing students' choices, suggesting that such efforts may be viable complements to assignment policy reforms.[31]

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impact of marginal admission to elite STEM schools.

[30]For example, some have proposed admissions policies that use levels of student disadvantage (Jaschik, 2019), test scores aligned with problem-solving curriculum (Treschan et al., 2013), prior course-taking and grades (California Community Colleges, 2018), lotteries (Shapiro, 2020), and various combinations of the above (Karp, 2021).

[31]Examples include interventions that focus on information provision (Hastings and Weinstein, 2008; Bobba and Frisancho, 2022; Wiswall and Zafar, 2014), interactive curricula (Polikoff et al., 2018), changing assessment strategies (Owen, 2010; Burgess et al., 2022), and increasing exposure to content (Joensen and Nielsen, 2009; Gottfried and Bozick, 2016), role models (Carrell, Page and West, 2010; Breda et al., 2020; Lim and Meer, 2019; Porter and Serra, 2019), and peers (Schneeweis and Zweimüller, 2012).

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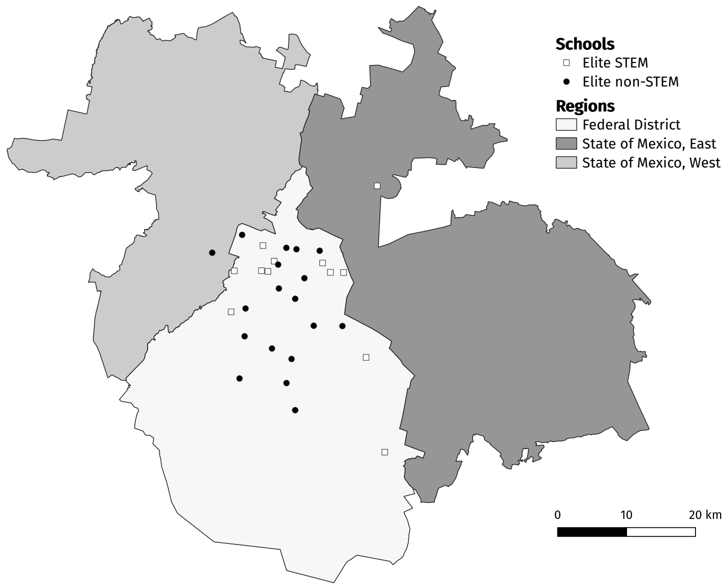
Panel A. Elite schools



Panel B. Non-elite schools

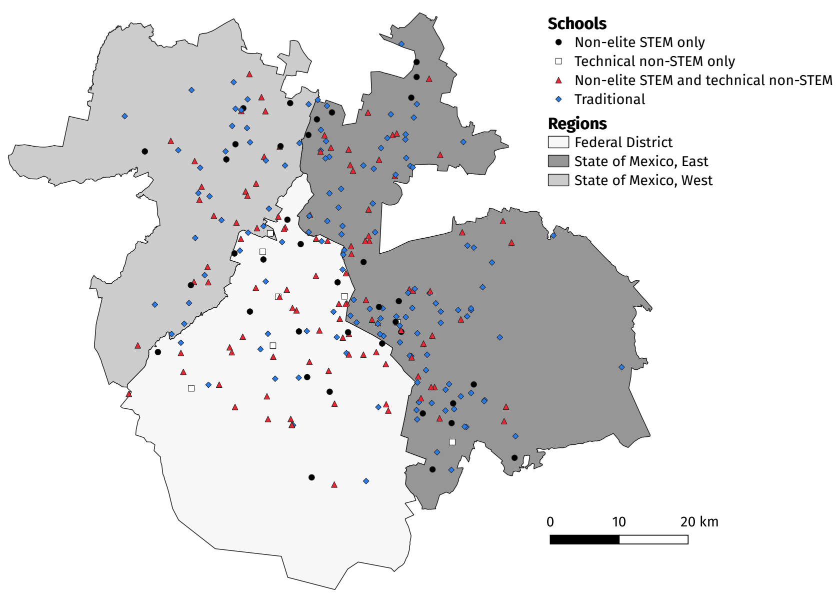


Figure 1. High schools in the COMIPEMS zone

Note: Markers correspond to public high schools in the COMIPEMS zone. School classifications are on the basis of programs available for students to choose in the choice process. Regions are those used to partition the student sample in the preference estimation.

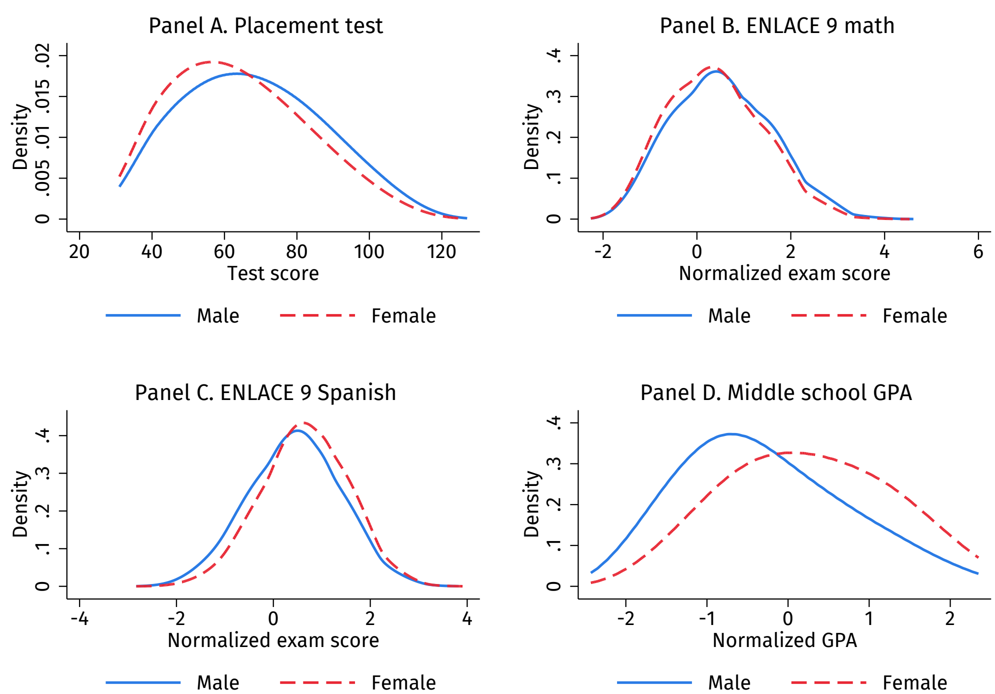


Figure 2. Academic achievement distributions, by gender

Note: Plots are for all students in analysis sample in the 2007 and 2008 COMIPEMS cycles. Placement test score is raw score out of 128. ENLACE 9 subscores are nationally normed. Middle school GPA is normalized by year within the analysis sample.

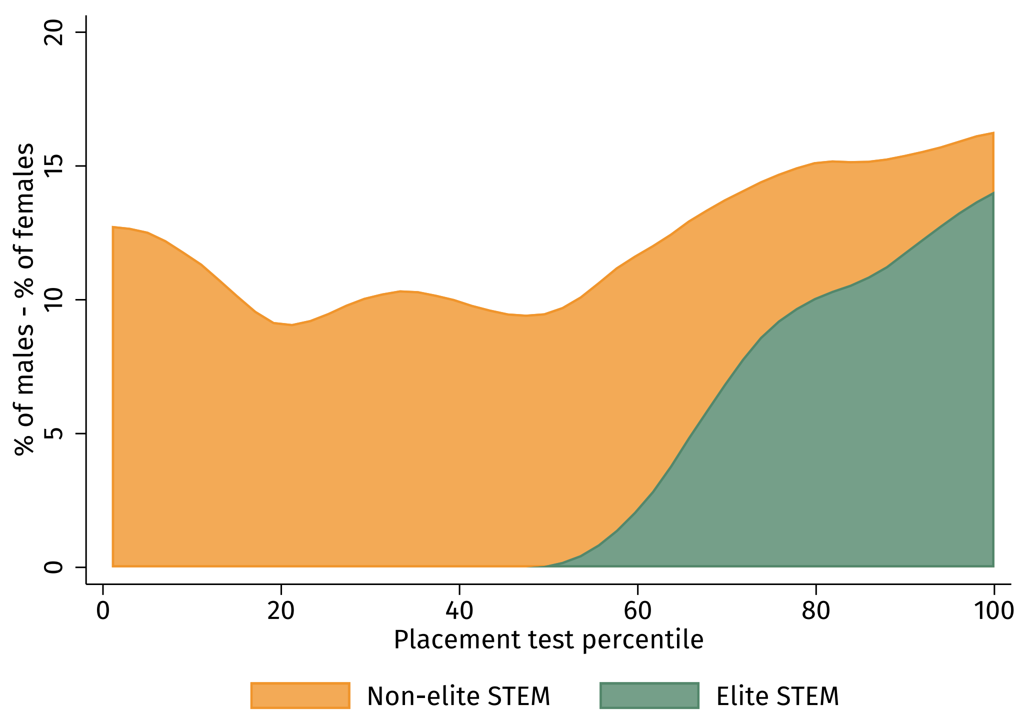


Figure 3. STEM gender gap in program assignment by placement test percentile

Note: The non-elite and elite STEM gap components are stacked, so that the overall STEM gap is represented by the top of the stack. Calculated percentages are for all students in analysis sample assigned to a program by the placement algorithm in the 2007 and 2008 COMIPEMS cycles. Test score percentiles are from the pooled (male and female) distribution of scores within each year.

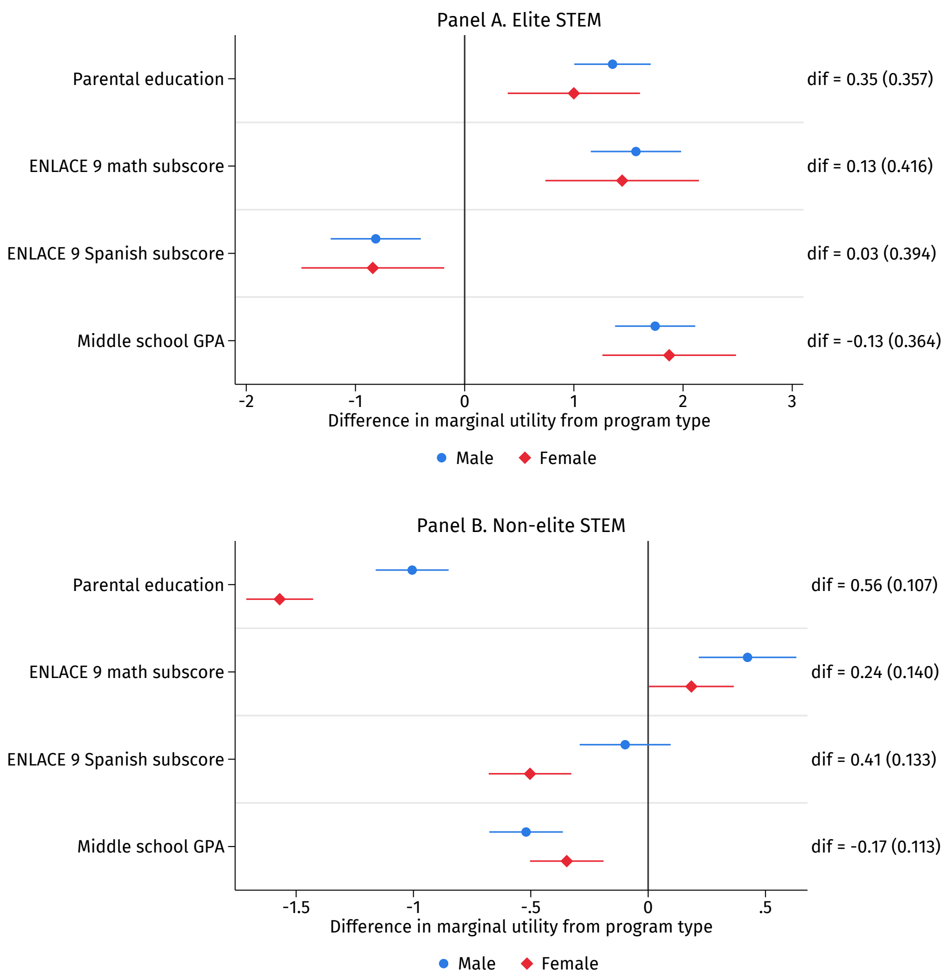


Figure 4. STEM preferences with respect to student characteristics

Note: Points are estimated differences in gender-specific average marginal utilities from the program type indicated in the panel title between students with high and low levels of the indicated characteristic, following Section IV.A. For example, in Panel A, the top "Middle school GPA" entry is the estimated difference in marginal utility from elite STEM programs between males with above-median GPA and males with below-median GPA. Bars correspond to 95% confidence intervals. The "dif" entries in the margin are differences between the gender-specific estimates, with standard errors in parentheses.

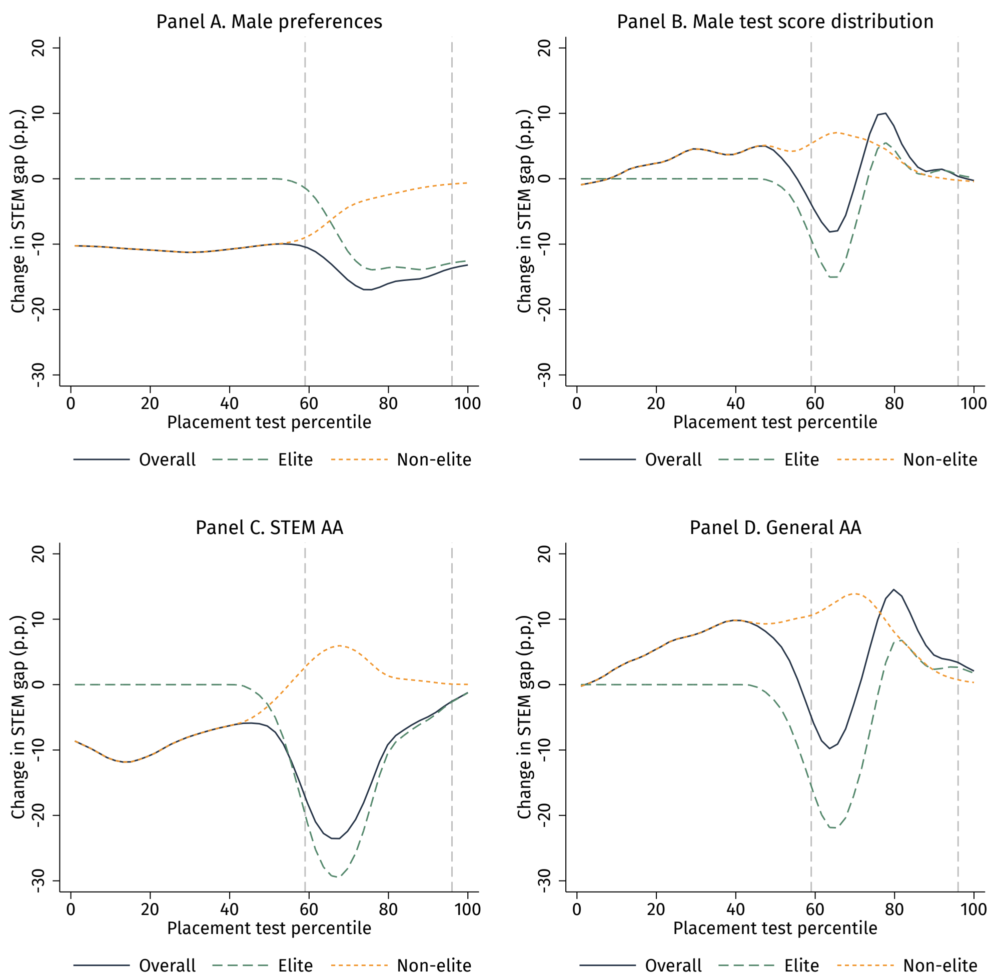


Figure 5. Simulated effects of preference, score distribution, and priority structure changes on STEM gap and its components, by placement test percentile

Note: Lines represent percentage point differences between the simulated STEM gaps under the status quo and the counterfactual indicated in the panel title, conditional on the placement test percentile. Simulated changes are means over 100 independent simulations of the assignment process accounting for uncertainty in student preference parameters, idiosyncratic student preferences, and random tie-breakers in assignment. Simulations are as described in Section III.C and online Appendix B. Dashed vertical lines indicate the percentiles corresponding to the lowest and highest elite program cutoff scores.

Table 1—Academic, choice, and demographic summary statistics, by gender

	(1) Male	(2) Female	(3) Difference
Academic achievement			
Placement test score	67.84	63.93	3.91
	(19.521)	(18.735)	(0.054)
ENLACE 9 math subscore (normalized)	0.54	0.39	0.14
	(1.035)	(0.986)	(0.003)
ENLACE 9 Spanish subscore (normalized)	0.44	0.65	-0.21
	(0.925)	(0.869)	(0.003)
Middle school GPA (normalized)	-0.29	0.24	-0.54
	(0.955)	(0.966)	(0.003)
School choices			
Total number of choices listed	9.36	9.55	-0.19
	(3.734)	(3.747)	(0.011)
Percent of choices that are elite STEM	10.52	6.56	3.96
	(17.991)	(12.998)	(0.045)
Percent of choices that are non-elite STEM	21.00	15.02	5.98
	(24.313)	(20.924)	(0.065)
Percent of choices that are elite non-STEM	30.10	35.21	-5.11
	(30.400)	(31.333)	(0.088)
Percent of choices that are technical non-STEM	9.36	10.46	-1.09
	(15.347)	(16.447)	(0.045)
Percent of choices that are traditional academic	29.01	32.75	-3.74
	(26.878)	(27.831)	(0.078)
Average driving distance to all choices (km)	12.12	12.09	0.03
	(5.987)	(5.875)	(0.017)
Demographics and geography			
High parental education (high school or more)	50.97	48.32	2.65
	(49.991)	(49.972)	(0.152)
Middle school graduate	25.03	17.96	7.07
	(43.317)	(38.382)	(0.116)
Driving distance to closest elite STEM program (km)	11.52	11.57	-0.05
	(6.608)	(6.631)	(0.019)
Driving distance to closest non-elite STEM program (km)	2.87	2.87	-0.00
	(1.919)	(1.951)	(0.005)
Observations	239969	257246	497215

Note: Calculations are for all students in the analysis sample for the the 2007 and 2008 COMIPEMS cycles. Standard deviations are in parentheses in columns 1 and 2; standard errors are in parentheses in column 3. Placement test score is raw score out of 128. ENLACE 9 subscores are nationally normed. Middle school GPA is normalized by year within analysis sample.

Table 2—Student assignment outcomes, by gender

	(1) Male	(2) Female	(3) Difference
Panel A. Program type conditional on assignment			
STEM assigned program (elite or non-elite)	38.7	27.6	11.1
	(48.70)	(44.68)	(0.14)
Elite STEM assigned program	10.2	4.6	5.6
	(30.32)	(20.93)	(0.08)
Non-elite STEM assigned program	28.4	23.0	5.5
	(45.11)	(42.06)	(0.13)
Elite non-STEM assigned program	17.2	18.5	-1.2
	(37.77)	(38.82)	(0.12)
Technical non-STEM assigned program	12.8	15.7	-2.9
	(33.40)	(36.41)	(0.11)
Traditional academic assigned program	31.3	38.2	-6.9
	(46.37)	(48.59)	(0.15)
Driving distance to assigned program (km)	10.1	9.8	0.3
	(7.98)	(7.88)	(0.02)
Observations	211899	212483	424382
Panel B. Assignment			
Unassigned	11.7	17.4	-5.7
	(32.14)	(37.91)	(0.10)
Observations	239969	257246	497215

Note: Calculations in Panel A are for all students in the analysis sample who were assigned to a program by the placement algorithm in the 2007 or 2008 COMIPEMS cycles. Calculations in Panel B do not condition on assignment. Indicator variables are percentages. Standard deviations are in parentheses in columns 1 and 2; standard errors are in parentheses in column 3.

Table 3—Female preferences for program types, by distance measure

	(1)	(2)	(3)
Elite STEM	18.47	14.67	50.76
	(1.295)	(1.035)	(3.320)
Non-elite STEM	-10.35	-8.12	-22.77
	(0.644)	(0.500)	(1.590)
Elite non-STEM	26.97	21.25	72.20
	(1.300)	(1.109)	(3.171)
Technical non-STEM	-7.61	-5.98	-15.93
	(0.712)	(0.551)	(1.816)
Observations	1477	1477	1477
Adjusted R^2	0.786	0.770	0.815
Fixed effects	Region-year	Region-year	Region-year
Distance variable	Driving (km)	Straight-line (km)	Time (min)

Note: Coefficients are from a regression of region-year-specific program fixed effects $\hat{\delta}_{jrt}$ on program type indicators and region-year fixed effects, which allow utility of the outside option to vary by region-year. Regressions weight by number of students in region-year estimation cell. Distance variable is the measure of home to school distance used in estimating the preference model. Base category is traditional academic program (non-elite, non-STEM). Coefficients correspond to average marginal utilities for the base covariate cell: females in middle school who have high parental education and above-median middle school GPA, ENLACE 9 math, and Spanish scores. Standard errors clustered at the program level are in parentheses.

Table 4—Gender differences in preferences, by distance measure

	(1)	(2)	(3)
Elite STEM	5.01	3.91	11.55
	(0.168)	(0.132)	(0.394)
Non-elite STEM	2.61	2.02	5.68
	(0.051)	(0.040)	(0.122)
Elite non-STEM	-0.94	-0.78	-2.41
	(0.217)	(0.175)	(0.457)
Technical non-STEM	0.24	0.19	-0.28
	(0.060)	(0.047)	(0.142)
Unassigned	-0.33	-0.25	-0.37
	(0.070)	(0.054)	(0.183)
Distance	0.02	0.02	0.02
	(0.002)	(0.003)	(0.002)
Distance variable	Driving (km)	Straight-line (km)	Time (min)

Note: Entries are estimated differences between male and female students in mean marginal utilities from the indicated program characteristics, following equation 5 in Section IV.A. Distance variable is the measure of home to school distance used in estimating the preference model. Standard errors are in parentheses.

Table 5—Decomposition of STEM gender gaps into preference and student characteristic components

	(1) Overall gap	(2) Elite gap	(3) Non-elite gap
Male STEM assignment	38.7	10.2	28.4
Female STEM assignment	27.6	4.6	23.0
STEM gender gap	11.1	5.6	5.5
Contribution of preference differences	13.1	4.9	8.1
	(0.06)	(0.03)	(0.06)
	[117.5%]	[87.5%]	[148.4%]
Contributions of differences in student characteristics			
Placement test score	-1.6	1.9	-3.5
	(0.02)	(0.02)	(0.01)
	[-14.5%]	[33.3%]	[-63.9%]
ENLACE 9 math subscore	0.1	0.0	0.0
	(0.01)	(0.01)	(0.01)
	[0.6%]	[0.8%]	[0.4%]
ENLACE 9 Spanish subscore	0.1	0.0	0.0
	(0.02)	(0.01)	(0.01)
	[0.7%]	[0.8%]	[0.6%]
Middle school GPA	-0.1	-1.1	1.0
	(0.05)	(0.03)	(0.04)
	[-1.2%]	[-19.4%]	[17.6%]
Parental education	-0.1	0.0	-0.1
	(0.01)	(0.00)	(0.01)
	[-0.5%]	[0.4%]	[-1.4%]
Middle school graduate	-0.4	-0.2	-0.1
	(0.02)	(0.01)	(0.02)
	[-3.2%]	[-3.9%]	[-2.4%]
Distance	0.1	0.0	0.0
	(0.00)	(0.00)	(0.00)
	[0.7%]	[0.8%]	[0.6%]
Total	-1.9	0.7	-2.6
	(0.06)	(0.03)	(0.06)
	[-17.5%]	[12.5%]	[-48.4%]

Note: Decomposition follows the procedure described in Section III.B and online Appendix B. Column headers give the STEM gap being decomposed. Entries are in percentage points. Standard errors are in parentheses. Percent contributions to the gap are in brackets. Decomposition uses estimates from the model using driving distance as the measure of distance.

Table 6—Simulated effects of preference, score distribution, and priority structure changes on STEM gender gap and welfare

	(1) Total gap	(2) Elite gap	(3) Non-elite gap	(4) Male welfare	(5) Female welfare	(6) Overall welfare
Male preferences	-12.3	-4.8	-7.5			
	(0.17)	(0.09)	(0.16)			
	[-111.1%]	[-84.8%]	[-138.3%]			
Male test score distribution	1.9	-1.3	3.1	-0.69	0.64	-0.00
	(0.10)	(0.07)	(0.08)	(0.01)	(0.01)	(0.01)
	[16.8%]	[-22.3%]	[57.2%]			
STEM AA	-10.5	-7.4	-3.0	-0.48	0.35	-0.05
	(0.08)	(0.05)	(0.08)	(0.01)	(0.00)	(0.00)
	[-94.5%]	[-132.0%]	[-55.8%]			
General AA	4.2	-2.4	6.6	-1.68	1.58	0.01
	(0.10)	(0.05)	(0.10)	(0.02)	(0.02)	(0.01)
	[37.7%]	[-42.9%]	[121.1%]			
Baseline gap	11.1	5.6	5.5			
	(0.18)	(0.09)	(0.17)			

Note: Rows represent counterfactual preferences, test score distributions, or priority structures. "STEM AA" refers to a policy in which female applicants receive 11 additional points (0.6 SD) on their priority score for STEM-designated programs. "General AA" gives female applicants 11 additional points (0.6 SD) on their priority score for all programs. Columns 1 through 3 are simulated changes in the respective STEM gap, compared to the baseline gap, using the procedure described in Section III.C. Simulated changes in STEM gaps are in percentage points. Simulated changes are means over 100 independent simulations of the assignment process accounting for uncertainty in student preference parameters, idiosyncratic student preferences, and random tie-breakers in assignment. Standard deviations of the simulated changes are in parentheses. Percent changes compared to baseline are in brackets. Baseline gap is the simulated level of the respective STEM gap under the status quo priority structure. Simulated welfare changes are in columns 4 through 6, with standard deviations of the simulated changes in parentheses. Simulations use estimates from the model using driving distance as the measure of distance.