Is Affirmative Action the Answer? Shrinking the STEM Gender Gap in Higher Education

Saloni Chopra* Isaac Ahimbisibwe†

January 6, 2025

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Abstract

This paper analyze a gender-based affirmative action policy implemented in 2020 for STEM programs at Uganda's largest public university. Pushing more women in STEM majors by relaxing the admission criterion may lead to a potential mismatch. Improved gender balance, on the other hand, can generate positive peer effects for the entire cohort, especially women. Linking different administrative datasets on student's applications, admissions and college academic performance, we empirically assess the effects of the policy induced changes in gender composition, on students' higher education outcomes. We first establish that the policy successfully increased women's access to STEM majors, resulting in a 9-percentage-point rise in female enrollment in traditionally male-dominated fields. We document that women (men) entering treated majors after the policy have, on average, lower (higher) high school test scores than their counterparts in untreated majors. Despite this, the policy led to improved college GPA and reduced the likelihood of failing courses in the first year for both men and women in the treated majors. Even among the top high school applicants whose admission status were not affected by the policy, we find that both men and women in treated majors experienced significant GPA improvements. Women's GPA rose by 8%, compared to a 4% increase for men. Our results suggest that increased gender diversity, brought by the policy, had positive spillover effects beyond its direct impact on enrollment.

*Agricultural & Resource Economics department at University of California, Davis. I thank Makerere Academic Registrar for their data and assistance. I would also like to thank the participants at Development Tea and Development Seminars at University of California, Davis for their feedback and comments. You may reach out at salchopra@ucdavis.edu

†Baylor University, Isaac_Ahimbisibwe@baylor.edu

1 Introduction

The gender gap in science, technology, engineering, and mathematics (STEM) fields remains a central topic in discussions of educational equity. Recent statistics paint a concerning picture: worldwide, the proportion of women among STEM graduates has stagnated at 35% over the past decade.[1] This continued under-representation in STEM fields, coupled with rapid technological advancement, risks widening technical skill and wage gaps, thereby limiting upward mobility for women (Goldin, 2014; Kirkeboen, Leuven, and Mogstad, 2016). Researchers have made considerable progress in understanding why these disparities persist. Key determinants include gender stereotypes, cultural and social influences (Cvencek, Meltzoff, and Greenwald, 2011; Kahn and Ginther, 2017), gendered preferences (Shi, 2018; Ngo and Dustan, 2024; Zafar, 2013), and exposure and preparation during middle and secondary education (Card and Payne, 2021). While most policy recommendations focus on addressing these gaps during early education (middle and high school), relatively less research has assessed strategies implemented at the higher education level. Affirmative action (AA) is a commonly used tool to address under-representation of minorities in higher education. AA policies have traditionally targeted racial, ethnic, and socioeconomic minorities, with empirical evidence demonstrating increased participation of these groups at selective institutions (Arcidiacono and Lovenheim, 2016). Given this documented success in improving access for targeted populations, a critical question emerges: Could gender-based AA policies, particularly in the form of quotas, effectively address persistent gender disparities in STEM fields at the tertiary level?

This paper examines the impact of a unique gender-based AA policy implemented at a leading university in Uganda on women's access to and educational outcomes in STEM programs. Specifically, we investigate how gender diversity, promoted through gender-based AA, influences higher education outcomes in STEM fields by addressing two key questions: Does the gender-based AA policy effectively reduce gender gaps in STEM, and how does it alter cohort composition? Additionally, how do policy-driven changes in cohort composition—in terms of both gender and academic quality—affect students' academic performance in university STEM programs?

[1] Global Education Monitoring Report Team (2024) reports these statistics using the latest data on STEM gender participation across 122 countries in higher education. Their analysis reveals significant variations in women's representation not just across countries but also across STEM disciplines, with particularly pronounced under-representation in engineering and computer science fields compared to other STEM subjects.

The policy's impact on students' educational outcomes is ambiguous, a priori. On the one hand, if binding, gender quotas in STEM majors would admit more women at lower cutoffs, potentially resulting in academic mismatch and lowering cohort quality — which could negatively impact students' educational outcomes (Sander, 2004; Rothstein and Yoon, 2008; Oliveira, Santos, and Severnini, 2024). On the other hand, research on gender peer effects suggests that both genders can benefit from improved gender balance and increased exposure to same-sex peers, with stronger effects for women (Ramirez-Espinoza, 2023; Han and Li, 2009; Mouganie and Wang, 2020; Busso and Frisancho, 2021). These opposing mechanisms make the net impact of the AA policy's compositional changes (in both gender and quality) on student educational outcomes unclear.

In 2020, Makerere University Kampala (MUK), Uganda's largest public university, implemented a gender quota policy stipulating that neither gender could exceed 60% of admissions in STEM majors. Since STEM majors at the university have been disproportionately male-dominant, this policy effectively reserved 40% of admission spots for women in most STEM majors.[2] We acquired data from various sources at MUK and constructed a comprehensive dataset incorporating students' admission records, high school performance, and university outcomes. The Ugandan higher education system has two distinctive features relevant to our analysis. First, students select their major during the admission process and cannot switch majors once enrolled. Second, admission decisions primarily rely on students' standardized test scores in national exams (A-level exam), with placements determined by program capacity, A-level scores, and students' major preferences.

Our empirical strategy uses a difference-in-differences framework, leveraging pre-policy gender distributions to categorize STEM majors into treatment and comparison groups. The treatment group consists of STEM majors with less than 40% female admitted before the policy implementation, while STEM majors that already exceeded 40% female admissions serve as our comparison group. Our approach's causal identification relies on the assumption that, absent the gender quota, the gap in potential outcomes between treated and non-treated STEM majors would have remained constant. We validate this parallel trends assumption using pre-policy data.

[2]Detailed information about the policy and gender composition across majors is provided in later sections.

Our findings demonstrate that the policy significantly increased women's access to STEM programs at MUK. The treated majors experienced a 9 percentage point increase in women's admission share compared to non-treated majors. This increase in admissions translated into a corresponding 25% rise (from the mean) in women's enrollment in treated STEM majors following the policy implementation.

The policy achieved greater gender diversity by simultaneously adjusting admission standards across genders in treated majors—tightening requirements for men while relaxing them for women. Analysis of high school A-level test scores reveals these differential effects: men enrolled to treated majors post-policy demonstrated higher average scores in physics, chemistry, and economics, while women enrolled to these majors showed significantly lower average scores in mathematics, chemistry, and economics. Next, we evaluate the policy's impact on university educational outcomes using three key metrics: grade point average (GPA), likelihood of course failure (one or more courses) and probability of first-semester dropout.

Despite the notable differences in incoming students' academic preparation, our results indicate that, on average, academic performance improved in treated majors. Specifically, we found: a 20% reduction in the likelihood of first-year course failure and a 0.2-point increase in GPA (equivalent to a 6% rise in mean GPA). The positive effects were more pronounced in majors that had been furthest below the 40% threshold, suggesting that programs experiencing larger increases in female enrollment saw stronger improvements in overall student performance.

Analysis for heterogeneity in treatment effects reveals that academic outcomes improved for both men and women in treated majors. When examining the effects separately by gender, both groups showed higher GPAs and lower failure rates, with men experiencing stronger effects for GPA. These improvements extended across both scholarship and self-funded students, suggesting the policy's benefits transcended funding status.

The positive impacts on treated cohorts could stem from two distinct mechanisms: changes in the composition of enrolled students and increased gender diversity. To isolate the effect of improved gender balance, we analyzed outcomes for students who would have been admitted even without the policy ('always admitted' students). We defined this group using two approaches: first, we use post-policy major-specific cutoffs to restrict the sample. Post policy period have two separate major-specific cutoffs for each gender. Women's cutoffs were consistently lower than or equal to men's cutoffs across all STEM majors. Hence, we use the

men's cutoff for the year 2020-21 (first year post-policy), restricting the sample of 'always admitted' to students who scored greater than or equal to these cutoffs across all years. In the second approach, we define always admitted students as the sample of top 10% students in each major based on their high school test scores. We do observe that within these restricted samples, post-policy students in treated majors demonstrated higher high school test scores compared to the comparison group. To account for this difference in our analysis of university performance of these students we control for individual high school test scores.

Results for the 'always admitted' sample show stronger GPA improvements in treated majors compared to comparison groups, with notably larger effects for women. The estimates for women (0.3 point increase in GPA) are twice as big as those of men (0.15 point). These findings suggest that increasing women's representation in male-dominated STEM majors generates positive spillover effects, benefiting even top-performing scholarship students of both genders. The stronger impact on women's GPAs (double that of men's) particularly highlights the value of improved gender balance in these programs.

Our paper contributes to several strands of literature. First, we advance the limited research on gender quotas in tertiary education. Only two other studies—Bagde, Epple, and Taylor (2016) and Najam (2024)—have evaluated gender quotas, examining cases in India and Afghanistan respectively. Najam (2024) found that gender quotas in public universities in Afghanistan increased women's access, particularly benefiting those from low socioeconomic backgrounds. Bagde, Epple, and Taylor (2016), studying caste-based reservations with one-third seats reserved for women in Indian engineering colleges, documented improved access to higher-quality institutions and increased college attendance without affecting graduation timing. Our study differs by exclusively focusing on gender quotas in STEM programs, analyzing not only increased access but also the effects of enhanced gender diversity on educational outcomes for both genders. To our knowledge, this represents the first comprehensive evaluation of such a targeted policy for STEM education.

Second, most research on AA in tertiary education have focused on access to universities, catch-up effects, and evidence on mismatch (Oliveira, Santos, and Severnini, 2024; Otero, Barahona, and Dobbin, 2021; Londoño-Vélez, Rodríguez, and Sánchez, 2020; Ribeiro and Estevan, 2021). This is because these policies target students from low-income families, under-resourced schools, or disadvantaged backgrounds. Our setting is unique: admitted women don't necessarily differ in socioeconomic status or school quality.

Since the policy led to increased admissions for women at lower cutoffs than men, there could be concerns about women's preparedness (based on their high school test scores) for the degrees they are pursuing. Despite significant differences in high school exam scores, our results for university academic performance for women suggests that high school scores (that are used as cutoffs for admissions) may be a noisy proxy of ability. Similar to Schaede and Mankki (2022)'s findings that male teacher quotas in Finland improved allocations by addressing selection biases, we argue that gender-based AA in STEM at MUK may correct for the quantitative differences in high school test scores of men and women on which the admission process relies.

Third, our paper contributes to the growing body of literature on gender gaps in STEM fields and potential solutions to address these disparities. Studies such as Ngo and Dustan (2024), Breda et al. (2020), Card and Payne (2021) and Buser, Niederle, and Oosterbeek (2014), have suggested or explored various interventions, including nudges, role model effects, information campaigns, and early education interventions, to reduce gender gaps. In Uganda, Ministry of Education and Sports acknowledges that sociocultural differences disadvantage women compared to men at all levels of education. Additionally, negative attitudes towards science (Musiimenta et al., 2019) and prevailing gender stereotypes (Lubaale, 2021) also contribute to the challenges faced by women at higher levels of education. Our findings demonstrate that gender quotas in higher education can significantly reduce the gender gaps, increasing access and lowering barriers for women while addressing these stereotypes and cultural bottlenecks.

Finally, we extend the literature on gender peer effects specifically in higher education (Ramirez-Espinoza, 2023; Mouganie and Wang, 2020). Our results highlight that gender of the peer plays a crucial role in a student's educational outcomes at tertiary level. These effects are strong and significant even for the high-ability students. Multiple mechanisms may drive these effects, including behavioral changes, peer interactions, and classroom environment shifts. Studies across various contexts (Rao, 2019; Londoño-Vélez, 2022; Dahl, Kotsadam, and Rooth, 2021) have documented similar positive impacts of cohort diversification through these channels.

The remainder of the paper is structured as follows: Section 2 provides institutional background and details on the policy. Section 3 describes the data. Sections 4 discuss the first stage effects on admissions,

enrollment and high school test scores. Section 5 presents the results for students' educational outcomes at the university and heterogeneity in treatment effects. We discuss the effects of gender composition in section 6. We provide further evidence for our results in Section 7. Section 8 offers discussion and conclusion.

2 Institutional Background

2.1 Secondary School in Uganda

Uganda's pre-collegiate high school education consists of two levels: O-level, which spans four years, and A-level, a two-year program[3]. The process of choosing a college major or specialization begins midway through the O-level stage. Between the second and third years, students reduce their subject load from over ten subjects to a maximum of ten, with a national exam requiring a minimum of eight. Out of the 8-10 subjects a student takes for national exams (O-level), seven are compulsory: mathematics, biology, chemistry, physics, English, geography, and history. As a result, students have the potential to choose a career in STEM, social sciences, humanities, or business when they move on to university. Students who wish to study languages or art, for example, must select related subjects as their additional 1-3 subjects beyond the seven compulsory ones. This system ensures that students are exposed to a wide range of subjects during the first two years of O-level [4].

At the end of middle school students take the national exams at O-level. When transitioning from middle to high school or O to A-level education students decide on their area of specialization. This decision is based on their results in the O-level exams and their preferences. When entering the A-level, the students must choose three subjects, locally known as a 'combination'. This combination aligns with either a science or arts track, ensuring coherence with university choices. For example, a combination cannot mix humanities subjects like history with science subjects like biology or medicine. The subject combinations offered at admission are flexible, allowing students to modify their combination after they have enrolled at an A-level school.

The A-level subject combination plays a crucial role in shaping a student's undergraduate options, as

[3]This is equivalent to middle school and high school in the schooling system in the US

[4]While the number of subjects offered may vary across schools, all schools are required to provide the compulsory subjects as a minimum.

the student must take national exams in that combination when graduating high school.[5] For instance, a student with a HEG (History, Economics, and Geography) combination cannot pursue a bachelor's in electrical engineering, as that would require Math and Physics at minimum. Instead, they can apply to majors in business, humanities, and social sciences where their chosen subjects are more aligned with the course requirements. On the other hand, a student graduating high school from a science track, such as PEM (Physics, Economics, and Math), can apply to engineering, some physical sciences, humanities, business, and social sciences, giving them a larger pool of options.

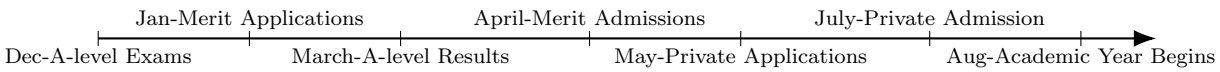
2.2 University Applications and Admissions

Among the 227 higher education institutes (HEIs) (2019-20) in Uganda, 9 are public universities, 44 private and rest are other tertiary institutes.[6] Despite various efforts by the government the country still struggles with retaining students at higher and tertiary levels of education. Statistics presented by Ministry of Education & Sports (MoES) suggests two-thirds students drop out when transitioning from O-level to A-level schools. Every year approximately 100,000 students sit for A-level exams (60% boys and 40% girls). Out of these, 60% or less apply for private and public universities for higher studies. For the academic year 2019-20, 194700 students were enrolled at universities. 54% of these enrollments are at nine public universities. Makerere University (MUK) founded in 1922 is the oldest and largest public university in Uganda. It holds approximately 33% of the students attending public universities in the country.

Students apply and are admitted to the universities under two schemes: (I) a National Merit Scholarship (merit) and (II) a Self-Funding Scheme (private). There are other categories of admissions like district quota, disabled quota, sports, international students, mature age, diploma or degree holder. These form a small part (15%) of the total admissions and are mostly self funded apart from district and disabled quota. Irrespective of these different categories of admissions all applicants follow the same application procedures and timeline across the universities. During the application process, a student lists up to six majors in order of preference. Each scheme requires a separate application, and the preference lists may differ even for students applying under both schemes.

[5] These national exams are similar to the SATs offered by the College Board in the US.
[6] The 10th public university was opened recently in 2023.

Fig 1: Timeline: Applications & Admissions



In Figure 1 above we present the timeline for a student in the final year of high school preparing for A level exams and university admissions. Applications for the Merit Scholarship are submitted before students know their national exam scores in January, with many submitting their applications before taking the national exams in early December. Offers for the National Merit Scholarship are announced in April, one month after the national exam scores are published. Students who do not qualify for the Merit Scholarship can apply for the private admissions about three weeks later, with the advantage of knowing their national exam scores. The university announces offers for private self funded applications in July, one month before the school year begins.

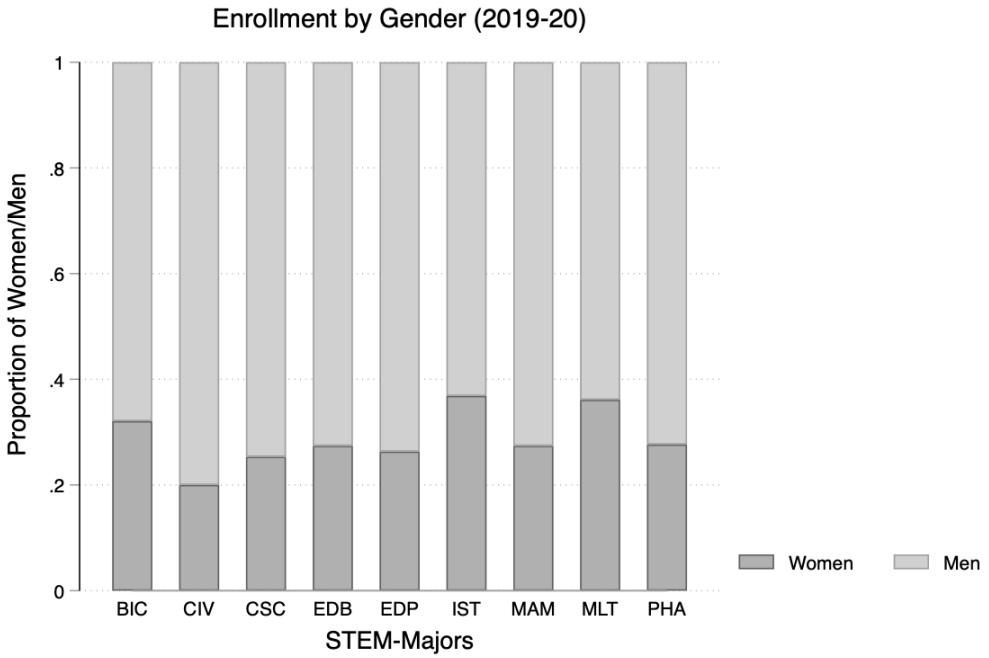
Admission to a major depends on the student's preference set, performance in national exams, and the university's capacity. Importantly, students do not know the scheme-major cutoffs before applying, as these vary by year, leading to a plausibly exogenous admission list.[7] Students cannot choose different sections within the same major because sections do not exist in this setting. As a result, most students' course sequences are pre-determined before they report to campus. The university offers evening and day classes/sections as 'different' majors for high-demand degrees, such as business administration. However, the day class is considered a 'different' major from the evening class, requiring students to apply and be admitted to either the day or evening cohort separately. [8]

2.3 Policy: Affirmative Action for Undergraduate Girls in Uganda

Uganda has one of the lowest university enrollment rates. According to the National Council for Higher Education (NCHE), only 5.3% of college-age students were enrolled in higher education institutions during

[7]Some universities provide previous year's cutoffs for majors on their websites.

[8]For example, students seeking a Bachelor of Business Administration (BBAE) degree can apply and be admitted to either the day cohort (ADM) or the evening cohort (ADN). Students admitted to ADM are not allowed to take classes or sit for exams with students in the ADN cohort



the 2019-2020 academic year, which is much lower than the global average of 38% but much more comparable to the significantly below the Sub-Saharan Africa rate of 9.4% (Uganda-NCHE, 2023).The enrollments are skewed towards non STEM majors with 40% of the students enrolled in STEM degrees. Although the overall ratio of women to men enrolled in higher education is nearly even at 1:1.2 the same cannot be said for the distribution by discipline (Uganda-NCHE, 2023).

The gender gap in various STEM fields is stark. For example, the MOeS in Uganda reports that more than 70% of students enrolled in agriculture, forestry, veterinary, and science programs are male. In comparison, only 30% of university professors are female (Ministry of Education and Sports, 2016). At MUK, the ratio of male to female students in some science majors is as high as 3:1. The STEM majors as defined by the MUK include majors under College of Engineering, Design, Art & Technology, College of Health Sciences, College of Computing & Information Sciences, College of Natural Sciences, College of Veterinary Medicine, Animal Resources & Biosecurity among others. In the figure below we present the number of men and women enrolled in top STEM majors at these colleges in the academic year of 2019-2020 (the year before the policy got implemented).

These majors include Bachelors degree in civil engineering, pharmacy, medicine, industrial chemistry,

physics, information and computer sciences. They comprise of some of the most competitive majors with larger average class size than other STEM majors at MUK. Moreover, gender differences are also pronounced in applications. For example, only 30% of over 1,300 students who applied for veterinary medicine on a merit scholarship were girls, and only 17% of those who listed veterinary medicine as their first choice were female.

In 2019, the Central Management Council (CMC) of MUK passed a resolution to ensure that no gender exceeded 60% of the students enrolled in STEM (Science, Technology, Engineering, and Mathematics) programs in the main Makerere campus. However, recognizing that they could not directly mandate enrollment, the policy was to be implemented through the admissions process. [9] That is, MUK only tracks enrollment once the school year has started, so the gender quota is binding at admissions but should increase the number of girls enrolled in STEM as enrollment is primarily a function of admission.

The admission process under the policy follows the pre-policy process, which is a form of deferred mechanism where each student's profile (set of preferences and their high school scores) is compared to other applicants in the pool, along with the capacities of each major applied to. Students are admitted to a major if their scores exceed the cutoffs for that particular year. However, to ensure 60-40 gender quotas in STEM fields, the admission algorithm includes a gender-balancing step. After the initial gender-blind round, where students are admitted based purely on their scores, the algorithm checks the gender distribution within each major against the 60-40 requirement. If one gender is significantly over-represented, the algorithm replaces the lowest-ranked students of the majority gender with the top-ranked applicants of the minority gender who didn't initially make it initially. For example, suppose the capacity for Civil Engineering is 100 students, and the first round of admissions, which is blind to gender, results in 75 men and 25 women being admitted. In that case, the algorithm will then replace the lowest 15 ranked men with the next 15 qualified women who were not initially admitted. This process results in different cutoff scores for each gender, aiming to achieve a more balanced gender representation in each major.

Moreover, MUK enacted the 60-40 policy to address gender disparities in education that stem from larger societal challenges, particularly at the pre-university level (Makerere University, 2019). Additionally, the

[9] Prior to this resolution, MOeS has been actively working to increase female representation in HEIs. For instance, a longstanding "bonus point policy" awarded an additional 1.5 free points to each female applicant's university admission score, provided they met the minimum requirements. Additionally, MUK had established a gender studies program as early as the 1990s, reflecting its commitment to gender equality.

gender quota policy was enacted to account for sociocultural differences that disadvantage women compared to men. The MoES reports that challenges, such as early marriage, child labor, and female genital mutilation, negatively affect girls, leading to high dropout rates and lower enrollment rates at all levels of education. Furthermore, negative attitudes towards science (Musiimenta et al., 2019) and prevailing gender stereotypes (Lubaale, 2021) also contribute to the challenges faced by girls in education.

3 Data

The MUK Currently ranked number 1 in the country holds the largest share of university going students in Uganda. For this study, we secured access to three different data sets from the university for the period of 2015-2023. The policy, passed in 2019 was implemented in the academic year of 2020-21. First, we have the applications data for students applying to both merit scholarship and private admissions at the university in that academic year. In this data, along with applicant's choices of majors and their ranks, the data also includes some basic information on their demographics.

Second, we have admissions data for all applicants to the university. The admissions data provides the major the students were finally admitted to along with the unique identification numbers that help us track these students for the duration of their degree. Finally, we have the performance data the tracks each of the enrolled students, their coursework within a major and their performance in those courses for every semester these students are registered. Although the university website provides the final cut-offs for all the majors each year, we do not have access to the capacity constraints for each of them. We use the admissions data to get to the capacity constraints for each major every year.[10]

We complement the applications data with the Uganda National Examination Board (UNEB) data on student's performance in A-level exams. As mentioned in previous section, we will be using each student's subject level scores to generate their weighted scores for the choice of their major. Along with the A-level scores the data also provides information on an individual's last school attended.

[10]We did secure data on seats allotted to different majors under merit scholarship as well as private seat distribution for two of the eight academic years which helps us match our numbers to the official numbers by the university.

3.1 Applications

Students applying for undergraduate degrees in Uganda have to specify their majors at the time of applications. Once admitted and enrolled in a major at a university the student cannot change their major during the course of obtaining their degree. As per the timeline, most students applying for college and higher studies do so twice in their final year of schooling. The merit scholarship is a Government of Uganda scheme which covers the tuition fees and accommodation costs of the awardee for the entire duration of their degree. The 4000 merit seats are split 70-30 in favor of STEM majors. 60% of these 4000 spots belong to MUK and its business campus. The rest are spilt among the other nine public universities of the country. We have access to applications submitted for merit scholarship to any university and private application to MUK only. Merit application which are filled in December/January are usually an offline process and cost SHS.52,000 per applications.[11] For private application to MUK students can use both online/offline mode and the application fee is SHS.50,000 for Ugandan and East African students and 75 USD for other international students.

Our data comes from de-identified student administrative records sourced from the Joint Public University Admissions Board (PUJAB) and the MUK Academic Registrar (AR) admissions office. PUJAB lists a major-university combination since students can apply to all public universities under the merit scheme, while the AR application forms list majors for MUK and its affiliate campuses. Therefore the students' choices becomes a combination of major and university under merit. For example, a students can choose Nursing from MUK as one of their choices and Nursing from Busitema University as their other choice and so on. Under private applications to MUK, students can reapply or freshly apply for majors offered at MUK (and its affiliates) only. All our datasets expanse eight academic years, from 2015-16 to 2023-24, excluding the COVID year (2022-23). Thus, our study period covers five pre-policy years and three post-policy years.[12]

Additionally, the application forms include demographic information such as gender, district of origin, and national exam details. The national exam details include the high school from which the student graduated, the subject combination they took during A-level, and their performance in each subject.

[11] This is approximately 14 USD. Commonly, students' high-school help them access and complete the offline forms before the due date.

[12] In 2021-22 due to COVID there were no A-level exams held in Uganda. The only students that could apply for HEIs during that year were students that sat for A-level exams prior to 2021. For this paper we drop the cohort of 2022-23 from our analysis.

We use the national exam performance to compute the weighted scores for the majors a student is applying to. It is important to note that the weighted score varies by major, as subject requirements differ for each major. For example, a student with a subject combination of PEM (Physics, Economics, and Math) applying to civil engineering will have a different score than if they were applying to commerce because the former weights Math and Physics scores more than Economics, while the latter weights Economics and Math more than Physics. We follow the weighting system used by MUK and other public universities to compute each student-major combination.

3.2 Admission

We observe a student's admitted major from de-identified administrative records obtained from AR's office or public records posted on the AR website or in local newspapers.[13] In addition to the major, we observe the scheme of admission: scholarship or self-financing and deduce each major's capacity from these admission lists. As mentioned before, private seats can be further divided into various other scheme like a-levels, diploma or degree entry, mature age entry and international students. The selection criterion does not differ under these schemes. A-level consists of approximately 85% of the total private admissions in our data. For this study, we focus on merit and only A-level entries under private admissions. We also obtain major-academic year cutoffs from public sources, as they are posted on university websites or in admission requirement booklets for the following year's applicants. Thus, a student's major is predetermined during admission, 3-4 months before enrolling.

Each non-extension major is housed within a department, which is a smaller administrative unit within a college. Students admitted to each major follow the same course sequence, as majors do not have separate sections. Consequently, students in the same major take most of their first-year classes together, although they may interact with students from other majors in shared introductory courses.

[13]For example, admission lists are usually posted here: https://www.mak.ac.ug/study-mak/admission-announcements, link accessed on 8/30/2024.

3.3 Academic Performance and Progress

For students enrolled and registered at MUK, we observe course performance reported as percentages (0-100%) from transcripts, which we use to compute GPA by year and semester. This data includes course units and exam scores in percentages by program, department, semester, and year of study. The calendar year of the exam is also listed. We convert the exam scores from the percentage scale to letter grades using information on the percentage range corresponding to each letter grade, printed on the back of transcripts and available in the codebook. These percentage-to-letter grade conversions do not vary across majors. Unlike in U.S. universities, professors in this setting do not curve grades.

Moreover, the transcripts indicate if a student has taken a course more than once. A student has to re-take if they score less than 50%. When a course is re-taken, it is indicated as "RT" on the course, and the new grade replaces the old grade on the printed transcript, although the old one remains in the backup database. We use the "RT" indicator to count the number of course failed per student. Lastly, we deduce drop-out from the transcripts. When a student is enrolled and is observed in the performance in the first year but not in the second year when he is expected to be present. We assume that students dropped out after the first year.

4 Impact of affirmative action on access and composition

In this section we present estimates for the first part of our question which tests the impact of the policy on access and composition of the cohorts. We do so by employing the standard difference-in-differences (DID) regression framework. As mentioned in the previous section, the policy was implemented to the admission seats for all STEM majors offered at main campus of the university. To empirically estimate the impact of the policy on proportion of women admitted and enrolled in these majors we define our treatment and control groups using pre-policy admissions lists. Based on the assumption that in the absence of the policy, the pre policy trends in admissions would have continue, we have about 65% of the STEM major for which the policy is binding. This implies that there were approximately 15 majors which used to have more than 40% women admitted even prior to the policy.[14] Rest of the majors consistently admitted less than 40%

[14] For example, bachelors in statistics, quantitative economics, health sciences, dental and nursing to name a few.

women in pre-policy years. Thus, throughout this paper, we define a STEM major as treated if on average, it admitted less than 40% women in two years prior to the policy.[15] [16] We also use the non-STEM majors as a control group to test the change in proportion of women admitted and enrolled in the STEM group as a whole.

4.1 Admissions

We run the following regression at the major year level:

$$Y_{mt} = \alpha_m + \alpha_t + \beta \times treated_m \times post_t + \epsilon_{mt} \tag{1}$$

where Y_{mt} is the proportion of women admitted in major m in year t. α_m and α_t are major and time fixed effects. The standard errors are clustered at the major level. Treated is the dummy for majors that belong to the treatment group. Post is a variable that takes value 1 for the three years post policy. β is our coefficient of interest.

Table 1: Impact of the Policy on Women's Admissions

	Proportion Women (1)	Proportion Women (2)
(1 if women < 40% in 18-19)*post	0.092***	
	(0.021)	
(STEM majors)*post		0.075***
		(0.017)
N	328	512
R-Squared	0.644	0.806
Dep. Var. Mean	0.355	0.430
major	yes	yes
years	yes	yes

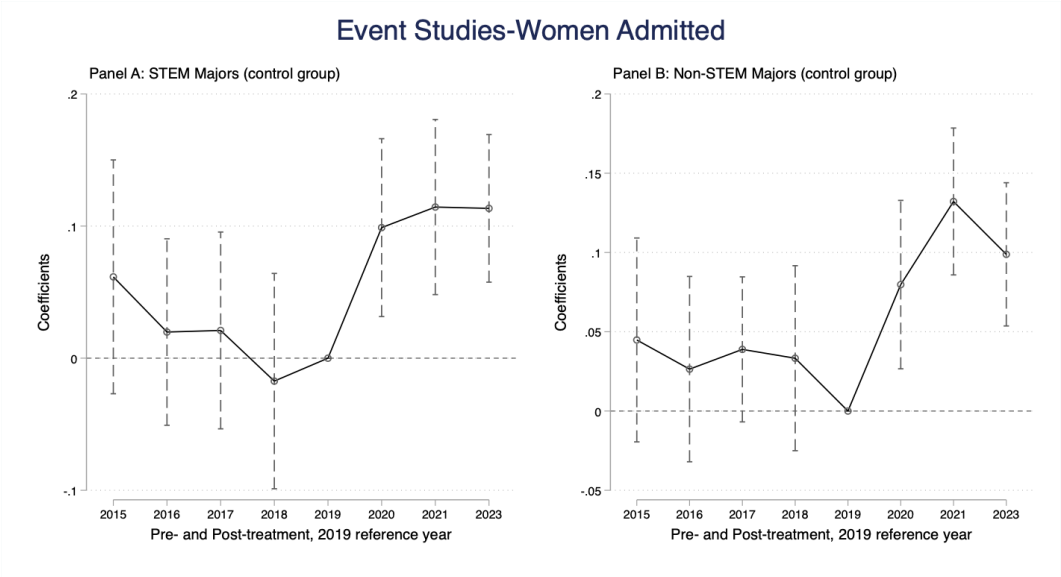
Notes: Standard errors are in parenthesis. Standard errors are clustered at major level.
* denotes significance at 0.10; ** at 0.05; and *** at 0.01.

[15] We test different definitions of the treatment groups. For example, instead of using average proportion of women admitted in the last two years, we use all five years prior to the policy, or just one year prior to the policy. We also used a more strict definition for the treatment group where if a major recorded more than or equal to 40% women in any one year prior to the policy then that major is treated as part of comparison group. Our results, with different definitions of the treatment groups remained qualitatively and quantitatively the same.

[16] The admissions also depend on the application pool. If there is a major where not enough students of a gender applied, the university admits students based on their weighted high school scores and choice of major, irrespective of the gender.

The β coefficients in the table 1 below provides the estimates for change in proportion of girls admitted in STEM majors when compared to the control group within STEM majors and the non-STEM majors. Our results suggest that there was a 9 percentage point (pp) increase in proportion of women in treated STEM majors post policy. Compared to non-STEM majors, STEM majors admitted 7 pp more women post policy. We confirm for parallel trends by using pre-policy periods and running the event studies version of our standard DID regression as below:

$$Y_{mt} = \alpha_m + \alpha_t + \Sigma_{t=-4}^{3} \beta_t \mathbf{1}(year - 2019 = t) \times treated_m + \mu_{mt} \tag{2}$$



The event-study graphs provide suggestive evidence in favor of parallel trends assumption and corroborates our results for standard DID regressions. One cause of concern here could be if the university responds to the policy by changing the capacity or the number of students admitted to a major. Scholarship slots by major are fixed by PUJAB a government's office at central level. The number of seats allocated to MUK under scholarship for different majors has remained exactly the same for the entire period of our study. However, the university may respond to the policy by adjusting the seats for different STEM majors under self-funded admissions. We do not possess the capacity by major data for each year. Probing further at the management and planning unit of MUK we found each department evaluate the programs they offered every 3-5 years to make an assessment on capacity and demand for their majors. Hence, we assume any changes

in the capacity of a particular major is independent of the policy.

We next test if the increase in admissions also corresponds to increase in enrollment in the treated STEM majors.

4.2 Enrollment

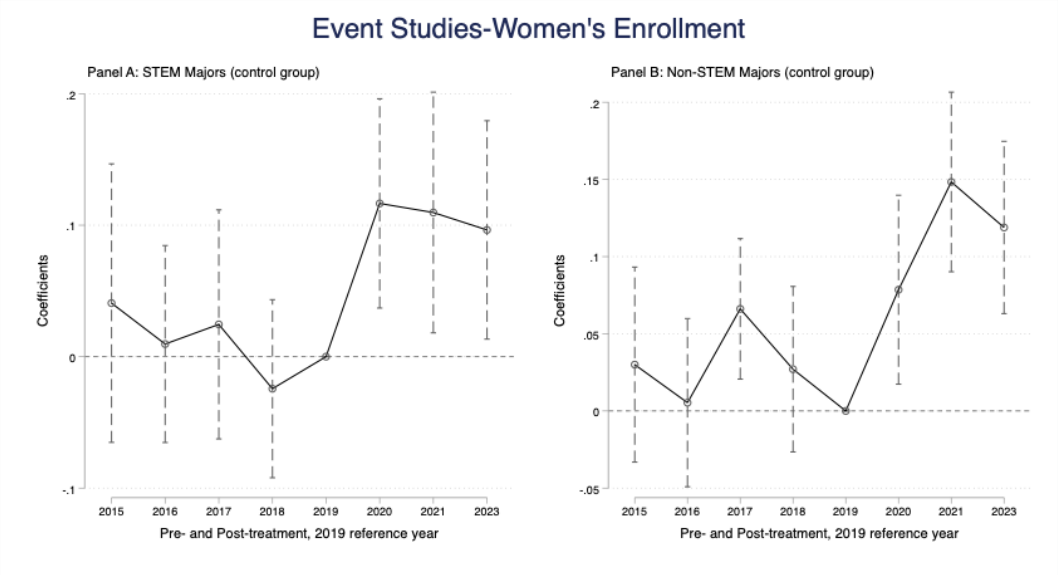
The policy was implemented with the aim of bringing more women into STEM classrooms. However, that may not be achievable if students who got admitted to different STEM majors specifically women, do not end up enrolling into them. In this section we assess if the policy helped increase the enrollment of women in STEM majors. All students admitted have one or more of the outside options (not to enroll for higher education, choosing to go to another major or university, vocational studies, employment). In our data we can only observe the decisions of the students to enroll or not enroll in the major they got admitted to. Hence using the regression equation (1) we test if the policy had an impact on proportion of women enrolled in treated STEM Majors. The β coefficients presented in Table 2 below suggests that treated majors on average saw a 9.7 pp increase in proportion of women in post policy cohorts.

Table 2: Impact of the Policy on Women's Enrollment

	Proportion Women (1)	Proportion Women (2)
(1 if women $< 40\%$)*post	0.097***	
	(0.021)	
(STEM majors)*post		0.090***
		(0.016)
N	328	504
R-Squared	0.660	0.801
Dep. Var. Mean	0.351	0.430
major	yes	yes
years	yes	yes

Notes: Standard errors are in parenthesis. Standard errors are clustered at major level. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Tables 1 and 2 confirm that the policy succeeded in pushing more women in treated STEM majors. We next test for how the policy impact the qualitative composition of the incoming cohort using students' high school test scores.



Using the regression equation (2) we present the event study graphs for enrollment below. The event-study graphs provide suggestive evidence in favor of parallel trends assumption and corroborates our results for standard DID regressions.

4.3 High School Test Scores

Major-specific cutoffs are based on A-level exam scores for a combination of subjects relevant for that major. To qualify for a STEM field at MUK, a student should have taken atleast 3 of the following subjects: math, physics, chemistry, biology and economics in the A-level exams.[17] In our data we can observe a student's chosen A level subjects and grades received. [18]

To push more women in the treated STEM majors the university relaxed the cut-offs for women and raised the cutoffs for men. We test if these changes in the admission standards led to changes in the qualitative composition of the enrolled cohort. We look at the differences in the total scores for science track subjects in the A-level exams for each gender. We run the following DID regression at student level:

$$Y_{imst} = \alpha_m + \alpha_t + \alpha_s + \beta treated_m \times post_t + \mu_{imst} \tag{3}$$

[17] For a few specific STEM majors economics can be replaced with agriculture, geography or entrepreneurship.

[18] We use the official numeric value of the letter grade used by the universities in Uganda to calculate the weighted scores of students which form the cutoffs.

where Y_{imst} is the total score based on grades received in each subject for student i, enrolled in major m from high school s in year t. α_m, α_t, and α_s are fixed effects for major, year and high school respectively. We also control for if a student is a scholarship awardee or not. Tables 3 below provides the coefficients for β.

Table 3: Total Scores High-School A-level Exams – by Gender

	All		**Merit**		**Private**	
	Women	Men	Women	Men	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.207**	0.497***	-0.204**	0.313***	-0.074	0.675***
	(0.086)	(0.074)	(0.095)	(0.071)	(0.112)	(0.099)
N	5174	9532	1608	3262	3240	5591
R-Squared	0.784	0.796	0.759	0.780	0.689	0.730
Dep. Var. Mean	14.544	15.250	17.277	17.922	13.190	13.787
major	yes	yes	yes	yes	yes	yes
years	yes	yes	yes	yes	yes	yes
school	yes	yes	yes	yes	yes	yes
controls	yes	yes	no	no	no	no

Notes: Total Scores in a standardized A-level exams is a score out of 20 for a combination of subjects chosen by a student in high school. The regressions are run on data of all students enrolled in STEM majors at MUK between 2015-2023. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

We document that the changed admission standards also affected the composition of the enrolled cohort post policy. As expected, the men enrolled in the treated majors post policy on average have higher A-level test scores. They scored 0.5 grade points higher than men in untreated group. For women, the results are in the opposite direction. The women enrolling in treated cohort on average scored lesser on average compared to women in untreated majors. It could be that some students put differential efforts in the subjects based on how relevant they are for the major they want to pursue at the university. In Table A2 in appendix we present similar analysis for all students by subjects. The estimations for men and women by subject grades corroborates our results for total scores. Overall, the women in treated majors present lower grades and men higher.

End of high school, A-level exam results does indicate the preparedness of the students at the time of entering college. More women entered the treated majors but at the cost of lowered admission standards.

In the next section we test if these differences in preparedness also affects students academic performance at the university.

5 Impact of affirmative action on tertiary education outcomes

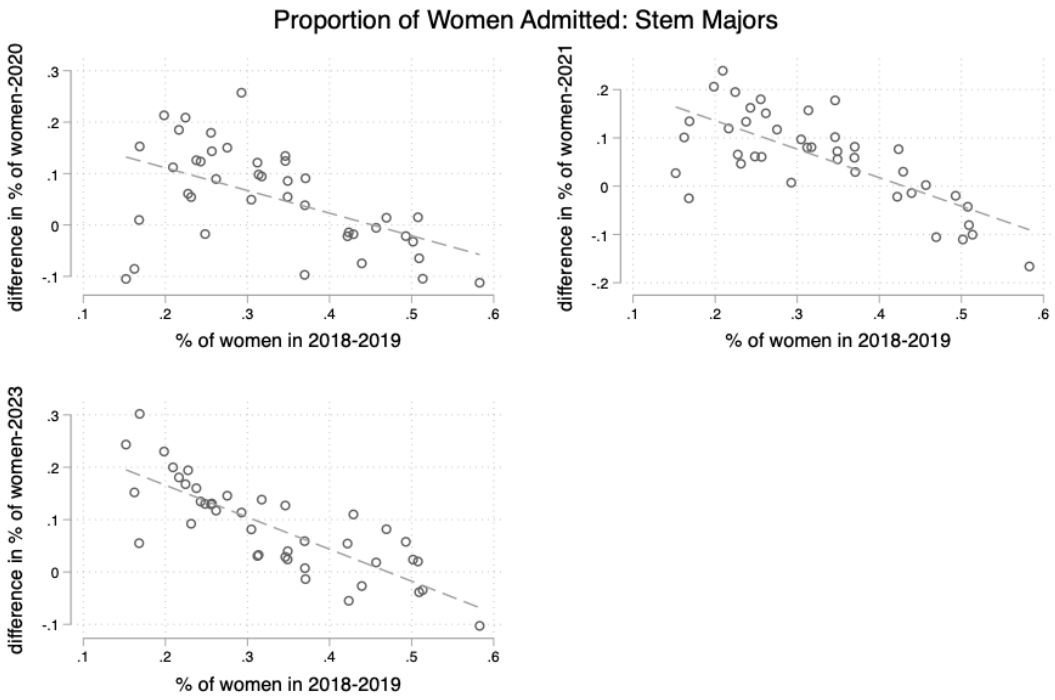
5.1 Empirical Strategy and Outcomes of Interest

In the previous section we document results for the access and composition effects of the policy. The policy, by lowering the cutoffs brought more women into male dominated STEM majors at MUK. Constraining the admissions spots that would have otherwise be filled by men, the policy raised men's cutoffs which also pushed up the average high school scores of men enrolled in treated majors post policy. In this section, we study the impact of these changes on the university-academic performance of the enrolled students. We test whether relaxing admission standards for women to improve gender balance affect the cohorts performance or not. We do so by constructing three outcomes to measure student's academic performance in the first year of their college enrollment. These include the grade point average (GPA) at the end of the first year, the likelihood of failing one or more courses, and the probability of dropping out after the first semester.

All students in their first year of the major have to do the preset coursework designed by the department over the three semesters. We use students scores and course units to calculate the weighted GPA for the first year. The weights used are the course-units allotted by the department to each course based on the workload and difficulty.[19] Second, a student has to re-take a course if they score less than 50%. The indicator fail takes value 1 if a student failed in even one course during their first year. Lastly, we deduce drop-out if a student is enrolled and is observed and sits through the first year exams but not in the second year when he is expected to be present. When using all three years post-policy we cannot use this definition for dropouts as the cohort of 2023-24 are yet to begin their second year. Hence, to include all three years post policy, we construct another dummy which indicates a student as dropout if they were present and passed their first semester and are missing in the next two.[20]

We use the binary DID regressions to analyze the effects of the policy on university education outcomes.

[19] Unlike in U.S. universities, professors in this setting do not curve grades.
[20] We present results based on the former measure in later section.



Notes: The figure above represents the scatter plots for admission for proportion of women in STEM major post policy. The x-axis represents the proportion of girls admitted on average in 2018-2019 (two years prior to policy). The y-axis represents the difference in proportion of women admitted each year (2020, 2021, and 2023) minus the women admitted pre-policy in 2018-2019. The negative relation between the two suggests that the majors that had lower proportion of women admitted pre-policy, experienced higher influx of women post policy.

As mentioned before, STEM majors with strictly less than 40% women admitted prior to the policy are part of the treatment group. Whereas, majors that had 40-60% women admitted prior to policy are our comparison group. Below we present a scatter for the treated and untreated STEM majors based on our definition above. On the x-axis we plot the average proportion of women admitted prior to the policy and on the y-axis we have change in the proportion of women admitted since 2019 for each of the three years post policy. The negative relation here suggests that the majors that had lower proportions prior to policy experienced a larger influx of women in their cohorts in all three years post policy.

To test for the academic achievements of the cohort enrolled we run the following regression at student level:

$$Y_{imst} = \alpha_m + \alpha_t + \alpha_s + \beta treated_m \times post_m + \delta X'_{imst} + \mu_{imst} \tag{4}$$

where Y_{imst} is the outcome of interest for student i in major m from high school s in year t. α_m, α_t, and α_s are fixed effects for major, year and high school respectively. Where ever necessary we also control for gender, if a student is a scholarship awardee or self funded, as well as the enrolled class size.

We expect β to provide causal estimates if there are no time-varying major specific variables that are correlated with our dependent variables, pre-treatment gender composition and the policy. Our major fixed effects control for any time invariant factors and we also control for class size, gender and proportion of merit students. The identification of average level treatment effects hinges on the parallel trends assumption. In our case this would imply that in the absence of the policy the trends in the potential outcomes for the treated majors would have been similar to the trends in the outcomes of the majors that are untreated. One way to test for this assumption is to run an event-study version of our DID regression. This provides evidence on parallel trends using pre-policy period. We interact the treatment indicator with the individual years dummies. Our reference year is an year prior to the policy i.e., 2019. The regression is as follows:

$$Y_{imst} = \alpha_m + \alpha_t + \alpha_s + \Sigma_{t=-4}^{3} \beta_t \mathbf{1}(year - 2019 = t) \times treated_m + \delta X_{imts}^{'} + \mu_{imst} \tag{5}$$

We next present the reduce form effects of the policy on academic performance of student's enrolled at MUK.

5.2 Main Results

In this section we present our main results which show, first, that despite changing the admission standards for men and women enrolled in treated STEM majors, we estimate a significant positive effect of the policy on students enrolled in these majors, with stronger results for majors which were further below the 40% threshold. Second, we find both men and women in treated majors registered improved academic performance in the first year of college. Third, both students enrolled under self-funded and scholarship category experience a significant improvement in their outcomes post policy. Below, we present these results in turn.

5.2.1 Overall Effects

Table 4 below presents the β coefficients from equation (4) for each of the three outcomes. The estimates presented in the first three columns only include fixed effects. Columns 4-6, present the results for our preferred specification which apart from fixed effects also include individual level controls (gender and category of admission) as well as class size.

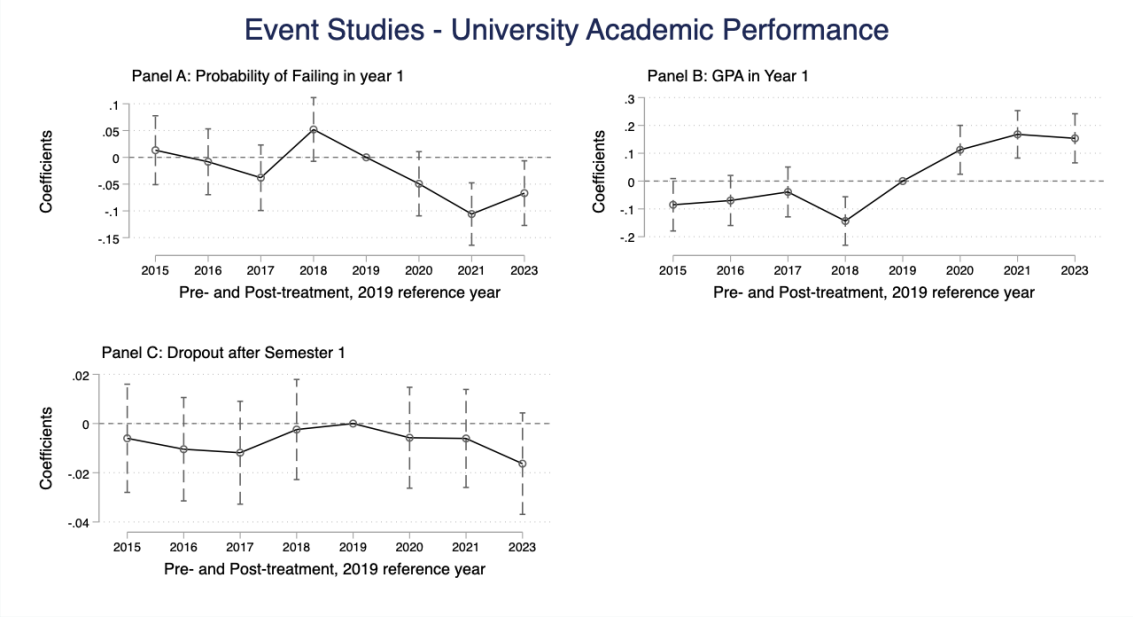
Table 4: Effects of the policy on Students' Educational Outcomes in STEM-Majors

	Dropout	Fails	GPA	Dropout	Fails	GPA
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.005	-0.096***	0.244***	-0.004	-0.080***	0.210***
	(0.006)	(0.017)	(0.025)	(0.006)	(0.017)	(0.024)
N	15669	15669	15669	15669	15669	15669
R-Squared	0.085	0.151	0.211	0.089	0.186	0.294
Dep. Var. Mean	0.025	0.378	3.268	0.025	0.378	3.268
Fixed Effects	yes	yes	yes	yes	yes	yes
controls	no	no	no	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Controls include gender, class size and scholarship status. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

The point estimates for likelihood of failing suggests that on average a student enrolled in treated major had 20% less probability of failing courses taken over the first three semesters, post policy. Similarly, on average they also experienced a 6% (0.2 point) rise in the first year GPA. We find no significant differences in probability of dropping out after first semester. The figures for event study version of the regression presents the dynamic treatment effects. The graphs below illustrates the differences in treated and comparison groups with respect to 2019, a year before the policy. Absence of significant differences in the two groups prior to the policy lends us the confidence in our causal estimates.

We further break up our treated majors into two groups: majors that prior to the policy had 30-40% women admitted and majors that were further below (less than 30%) that threshold. We present the results for these two groups with respect to the comparison group in the table 5 below.



Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All coefficients are with respect to year 2019 (which is a year before the policy was implemented. All regressions include major, year and high school fixed effects.

Table 5: Effects of the policy on Educational Outcomes in STEM-Majors

	Dropout	Fails	GPA
	(1)	(2)	(3)
(1 if 30% < women < 40%)*post	0.003	-0.070***	0.183***
	(0.007)	(0.020)	(0.030)
(1 if women < 30%)*post	-0.008	-0.086***	0.227***
	(0.006)	(0.018)	(0.027)
N	15669	15669	15669
R-Squared	0.089	0.186	0.294
Dep. Var. Mean	0.025	0.378	3.268
Fixed Effects	yes	yes	yes
controls	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Controls include gender, class size and scholarship status. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

The estimates in table 5 corroborates with our previous results that the policy overall had positive effects on treated majors. The coefficients for both treatment groups are positive (negative) and significant for the

GPA (failing). These results are stronger for majors further below the 40% threshold. As previously shown the majors that were the relatively more male-dominating received more women post policy. These are the majors that experienced stronger positive impact of the policy compared to untreated group. We next turn to test for heterogeneity in the treatment effects.

5.2.2 Displaced Men and Replacing Women

The overall positive improvement in the educational outcomes of the treated cohort may mask the performance of directly affected by the policy. It could be that women that could enrolled in their desired STEM majors with the help of the policy may not necessarily be better off than the men they displaced in these majors. In other words, it could be that despite improvement in average GPA of the treated cohort the women pushed in may still be under-performing compared to men whom they replaced.

In order to test this hypothesis, we create a treatment group of men and women within the treated STEM majors that got directly affected by the policy. We use pre-policy 2019 and 2020 cutoffs (one year prior and one year post policy) for each major to restrict our sample to students that were potentially directly affected by the policy. We define displaced men as the men pre policy that score above the 2019 cutoffs but less than the 2020 men's cutoff for their respective major. These men if had applied to their respective majors post policy would not have got admissions in their current majors. Similarly the for women we restrict the sample to post-policy women that were above the women's cutoff in 2020 but less than the cutoffs of 2019 for their respective majors. Again, the assumption is that these women would not have been admitted to their desired majors in the absence of the policy.

Our control group consists of men that would have been admitted to the majors irrespective of the policy. In order to define a comparable control group pre and post policy, we use the men's cutoff in 2020 and restrict the sample of control group to those men whose high school scores were equal to 5% above the men's 2020 cutoffs for their respective majors.

Within the treated majors creating these potentially treated and control students we test whether the women who arguably replaced the men in these majors are performing significantly worse than the men who would have been admitted irrespective of the policy.

Table 6: Educational Outcomes for Women (In) and Men (Out)

	Fails	GPA
	(1)	(2)
treated*post	-0.088	-0.046
	(0.056)	(0.085)
treated (men (out) & women (in))	0.080***	-0.159***
	(0.026)	(0.039)
post=1	-0.065*	0.095*
	(0.034)	(0.051)
N	1970	1970
R-Squared	0.101	0.138
Dep. Var. Mean	0.461	3.099

Notes: treatment group includes pre-policy men that would be displaced post-policy and women that would not have got admitted pre-policy. Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Regression includes major fixed effects. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Our results in table 6 report the coefficients for the student level DID regression for the likelihood of failing and GPA in the first year. The coefficients for the interaction term suggests that there is no significant differences in the scores of the treated men and women compared to the men in the control group, post-policy. In other words, our results in the above table suggests that women that potentially replaced men due to the policy does not perform significantly different from these men when compared to the ones that would have been admitted with or without the policy.

5.2.3 Heterogeneity in Effects By Gender and Scheme

In section 4.3 we show that the policy by restricting spots for male resulted in significantly higher average high school scores (A-level) form men in treated majors. Therefore we test if the average improvement in academic achievement of the treated cohort post policy, could have been led by more selective men in this group. We split the sample of students enrolled by gender and present the results for regression (4) for men and women separately below.

Table 7: Heterogeneous Effects of the Policy by Gender

	Women			Men		
	Dropout	Fail	GPA	Dropout	Fail	GPA
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.009	-0.071***	0.101***	0.003	-0.073***	0.263***
	(0.007)	(0.027)	(0.036)	(0.008)	(0.022)	(0.034)
N	5323	5323	5323	10115	10115	10115
R-Squared	0.113	0.198	0.318	0.111	0.201	0.306
Dep. Var. Mean	0.016	0.335	3.330	0.030	0.400	3.238
Fixed Effects	yes	yes	yes	yes	yes	yes
controls	yes	yes	yes	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Controls include class size and scholarship status. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 8: Heterogeneous Effects of the Policy by Scheme

	Merit			Private		
	Dropout	Fail	GPA	Dropout	Fail	GPA
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.014*	-0.006	0.155***	-0.007	-0.129***	0.298***
	(0.007)	(0.028)	(0.040)	(0.009)	(0.023)	(0.033)
N	5076	5076	5076	8886	8886	8886
R-Squared	0.096	0.118	0.227	0.108	0.187	0.256
Dep. Var. Mean	0.012	0.221	3.611	0.032	0.457	3.096
major	yes	yes	yes	yes	yes	yes
years	yes	yes	yes	yes	yes	yes
school	yes	yes	yes	yes	yes	yes
controls	yes	yes	yes	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Controls include gender and class size. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 7 presents the β coefficients for the treatment effects for men and women separately. Our results illustrate that both men and women in treated majors experience positive impact of the policy. We find despite relaxing the admission criterion, women in treated majors on average have significantly lower probability of failing courses and the change in GPA is also positive and significant compared to untreated group

post policy. The men also have less likelihood of failing with a similar magnitude as that of women. The change in GPA for men is positive and significant with stronger point estimates than women. In Table 8 we show that the policy affected the educational outcomes of all students, irrespective of the their mode of entry. Both students that were admitted under scholarship and those under self funded schemes have on average an improved GPA. There is less likelihood of dropping out if you are a scholarship student in a treated major post policy. For self funded students we also find the significant drop in likelihood of failing coursework.

5.2.4 Second Year of the University

We next test if the policy effects persist beyond first year of course work at the university. Since our latest cohort of 2023-24 have only finished the first year of their college, we drop them from this analysis. The outcomes of interest now include probability of dropping out after first year, probability of failing the coursework in second year and the second year GPA. The results for student-level regressions are presented in Table 9 below.

Table 9: Effects of the policy on Students' Second Year Educational Outcomes

	Dropout	Fails	GPA	Dropout	Fails	GPA	Dropout	Fails	GPA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1 if women $< 40\%$)*post	-0.002	-0.056***	0.215***	-0.001	-0.046	0.106**	-0.006	-0.063**	0.282***
	(0.010)	(0.020)	(0.030)	(0.013)	(0.030)	(0.043)	(0.014)	(0.027)	(0.042)
N	13707	12931	12931	4492	4340	4340	9001	8390	8390
R-Squared	0.109	0.196	0.264	0.135	0.243	0.321	0.121	0.191	0.253
Dep. Var. Mean	0.059	0.398	3.284	0.037	0.337	3.410	0.070	0.430	3.217
Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: Failed in year 2 is a dummy that takes value 1 if a student fails one or more courses in the second year. GPA for year 2 is the grade point average for the second year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first year. All regressions include major, year and high school fixed effects. Controls include gender, class size and scholarship status. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

The positive impact of the compositional change on the treated cohorts post policy persists beyond the first year of classes. The first three columns presents for all students entering the second year of their degrees. Although we find no significant impact on the dropout rates, probability of failing and second year GPA suggests continued higher academic achievements for the treated cohort post policy. Again, the results are

stronger for men but the women in treated majors also have higher GPAs a compared to women in treated majors post policy.

To summarize, even though we record significantly lower high school scores for women enrolled in treated majors post policy, the overall quality of the graduating cohort in the treated group registered improvement in their academic outcomes at the university.

6 Role of Gender Composition

Our results in the previous section informs us of the mean effects of the policy on students' educational outcomes at MUK. In this section we provide evidence that improved gender balance brought by the policy in treated majors had a positive effect on students performance at the university. The positive impact on university outcomes documented in the previous section could be driven by both gender and compositional changes. In an attempt to isolate the impact of gender diversity we restrict our analysis to 'always admitted' students – those who would have been admitted to the majors even in the absence of the policy.

We create this category of 'always-admitted' students two ways. First, we use the cutoffs for scholarship awardees post policy. Pre policy both men and women applying to MUK through scholarship faced a single cutoff. Post policy there are two different cutoffs for men and women, where cutoffs for men is equal to or greater than the cutoffs for women for all STEM majors. We use men's cutoff for the first year post policy and keep all students that have weighted high school scores above this cutoff for all eight years of data. Keeping women which scored above the cutoff for men, we eliminate women that entered the majors using AA post policy. Using the same cutoff for years before policy, we ensure that we do not include men that could not get admitted if policy was in place, and women who would have been included if the policy was implemented. Second, we use the combined A-level test scores for all students enrolled and choose the top performing students based on their high school test scores. We keep men and women belonging to 90th percentile and above in each major-year to assess the effects of the gender composition on these high-ability students.

Table 10: A-Level Grades Always Admitted Men and Women in STEM-Majors

	Cutoff Based		**Top 10%**	
	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
(1 if women < 40%)*post	0.286**	0.401***	0.262	0.246***
	(0.122)	(0.071)	(0.174)	(0.077)
N	632	1654	519	2421
R-Squared	0.797	0.796	0.830	0.827
Dep. Var. Mean	18.299	18.721	17.977	18.003
Fixed Effects	yes	yes	yes	yes

Notes: A-level grades are the total scores received in the combination of five subjects that a student chose in high school (maximum total grade score is 20). All regressions include major, year and high school fixed effects. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

We first test for differences in the high school test scores of always admitted students. The estimates in the table 10 above suggests that our always-admitted men and women differ in their A-level scores across majors, pre and post policy. For always admitted men we have a 0.2 to 0.4 higher average test scores for the ones enrolled in treated majors. For women we record a significant but smaller difference in test scores post policy. To account for these significant differences, we control for individual test scores when we test for the university academic performance for always-admitted students across majors, post policy.

Table 11: Effects on Always Admitted Women in STEM-Majors

	Cutoff Based			**Top 10%**		
	Dropout	Fail	GPA	Dropout	Fail	GPA
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.030	-0.027	0.275***	-0.016	-0.114	0.216*
	(0.020)	(0.073)	(0.102)	(0.020)	(0.086)	(0.127)
N	626	626	626	511	511	511
R-Squared	0.163	0.221	0.375	0.316	0.300	0.405
Dep. Var. Mean	0.011	0.203	3.656	0.010	0.211	3.633
Fixed Effects	yes	yes	yes	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 12: Effects on Always Admitted Men in STEM-Majors

	Cutoff Based			Top 10%		
	Dropout	Fail	GPA	Dropout	Fail	GPA
	(1)	(2)	(3)	(4)	(5)	(6)
(1 if women < 40%)*post	-0.022	-0.023	0.161**	-0.020	0.038	0.086
	(0.015)	(0.050)	(0.074)	(0.014)	(0.043)	(0.066)
N	1632	1632	1632	2383	2383	2383
R-Squared	0.159	0.154	0.275	0.162	0.179	0.295
Dep. Var. Mean	0.015	0.195	3.663	0.021	0.245	3.567
Fixed Effects	yes	yes	yes	yes	yes	yes

Notes: Failed in year 1 is a dummy that takes value 1 if a student fails one or more courses in the first year. GPA for year 1 is the grade point average for the first year of coursework which can take values between 0-5. Dropout is a dummy which takes value 1 if a student decides to drop after the first semester. All regressions include major, year and high school fixed effects. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 11 and 12 provides the estimates for top performing men and women separately. The results suggests both men and women in treated majors experience an increase in their GPAs. Defining students based on merit cutoffs we find always admitted men and women in treated majors score 4% and 8% higher than the baseline GPAs respectively. We find no significant differences in probability of failing and probability of dropout after first semester. When restricting the sample to top 10% of the students in each major, the estimates for men become insignificant. However, for women we still see significant increase in GPA. The magnitude of the estimates are comparable under both definitions and are significantly bigger than men's estimates.

These results corroborate with the existing literature on gender peer effects which suggests that increase in gender balance in a cohort, apart from benefiting both genders positively often have stronger effects on women (Ramirez-Espinoza, 2023; Han and Li, 2009; Mouganie and Wang, 2020). Our evidence suggests the gendered AA policy by increasing gender diversity, had positive effects on even those students whose admissions and enrollment would not have been directly affected by the policy.

7 Course level effects

In this section we present further evidence on for our existing results and their mechanisms. We found positive effects of the policy on students' university academic outcomes. We also show that the policy through increased gender balance also improved the outcomes for students otherwise unaffected by the changes in the admissions. However, one cause of concern in attributing these improvements to the compositional change brought by policy could be the changes in the grading scheme of the teachers teaching the treated majors. These positive impacts could be explained by if the teachers in treated majors changed the course material or relaxed the grading rubric for the cohorts post policy. To provide further evidence that the is not driving our results, we use data on student's course level scores in the first year at university.

We leverage the fact that some courses in the first year of college are shared among students coming from different majors. Therefore we can divide the courses into two broad categories: shared among majors and exclusive to the major. For the courses that are shared by students from different majors, we restrict our sample to the ones that had students from both treated and untreated majors. As mentioned in section 5 the courses are predetermined and students cannot choose to take certain courses chosen and leave others. All students must complete the assigned courses in the given semester. To give an example of a shared course we have computer literacy and application which is shared among majors from engineering, management and environmental science departments. Since, in such setting its hard for teachers to distinguish students coming from different majors, we assume that all students with the course are treated with the same grading standards.

We run the following student-level regression to test the differences in scores received by students across treated and untreated majors over the years:

$$Y_{ict} = \alpha_c + \alpha_t + \beta \times treated_m \times post_t + \epsilon_{ict} \tag{6}$$

where Y_{ict} is the score received by the student i in course c in year t.[21] Scores here are out of 100 which is a sum of midterm and final exam scores (each weighing 50%). α_c and α_t are course and year fixed

[21] We use the scores in the first attempt of the exams. Students who fail can retake the exam next year to improve their scores and grades.

effects respectively and treated is the dummy that takes value 1 for treated STEM majors. The tables below provides the estimates for β, our coefficient of interest.

Table 13: Estimates for Final Scores at Student-Course Level

	Course Scores	Course Scores
	(1)	(2)
(1 if women < 40%)*post	1.726***	1.893***
	(0.120)	(0.122)
N	177992	177975
R-Squared	0.158	0.203
Dep. Var. Mean	65.194	65.194
course-code	yes	yes
years	yes	yes
school	no	yes

Notes: The dependent variable final-score is the sum of scores a student gets in midterm and final exams for a given course (maximum for final-score is 100). Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table 14: Estimates for Final Scores at Student-Course Level by Gender

	Women	**Men**
	Course Scores	Course Scores
(1 if women < 40%)*post	1.471***	2.063***
	(0.185)	(0.167)
N	65316	112624
R-Squared	0.254	0.198
Dep. Var. Mean	65.457	65.043
Fixed Effects	yes	yes

Notes: The dependent variable final-score is the sum of scores a student gets in midterm and final exams for a given course (maximum for final-score is 100). All regressions include course, year and high school attended fixed effects. Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Our coefficients in tables above suggests that students in treated majors score higher than the students in untreated majors, post policy. These differences again are significant and persists for both men and women in treated majors when compared to their counterparts in non-treated majors. Assuming same grading rubric for all these students in a given course our results provide additional evidence which suggests that students in treated majors did experience improved education outcomes post policy and these impact could not all be

driven by a few teachers in treated majors systematically changing grading schemes for students post policy.

8 Discussion and Conclusion

This paper evaluates a unique gender-based affirmative action policy implemented at Makerere University Kampala, Uganda's leading university, aimed at addressing gender imbalance in STEM fields. Our analysis reveals several significant findings with important policy implications for higher education. First, the policy successfully increased women's access to STEM programs, demonstrating that targeted interventions can effectively address gender disparities in traditionally male-dominated fields. Second, contrary to concerns about potential negative effects on academic standards, we find that students in treated majors showed improved academic performance on average. This improvement stems from both changes in cohort composition and enhanced gender balance in the classroom.

Notably, our analysis reveals that the benefits of increased gender diversity extended beyond the directly affected students. Even high-ability, top-performing students experienced positive impacts from the more balanced gender composition. This finding suggests that the benefits of gender diversity in STEM education transcend individual ability levels and affect the broader learning environment.

Our results also highlight an important insight about admission criteria: when these criteria rely on potentially noisy estimates of ability, such as high school test scores, affirmative action policies can serve as a correction mechanism. The policy's success in improving academic outcomes suggests that traditional admission metrics may underestimate women's potential for success in STEM fields.

While our study focuses on immediate academic impacts, several important questions remain for future research. First, tracking the labor market outcomes of these cohorts will be crucial for understanding the policy's longer-term economic implications. Second, investigating whether this policy creates positive spillover effects on girls' educational choices in middle and high school could reveal its potential to influence earlier pipeline decisions. Such research could help determine if university-level interventions can motivate younger female students to pursue science streams, thereby addressing STEM gender gaps at their root.

In conclusion, our findings provide compelling evidence that well-designed affirmative action policies can successfully promote gender diversity in STEM fields while maintaining or improving academic standards.

This suggests that similar interventions could be effective in other contexts where gender disparities in STEM education persist.

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9 Appendix

9.1 Additional Tables & Figures

Table A1: High-School A-Level Grades by Subjects- Women

	Math	Physics	Chemistry	Biology	Economics
	(1)	(2)	(3)	(4)	(5)
(1 if women < 40%)*post	-0.157***	0.046	-0.221***	0.106	-0.149*
	(0.054)	(0.086)	(0.074)	(0.076)	(0.082)
N	4425	2054	2462	1835	2255
R-Squared	0.554	0.709	0.652	0.739	0.511
Dep. Var. Mean	4.813	3.730	4.333	3.324	4.274
major	yes	yes	yes	yes	yes
years	yes	yes	yes	yes	yes
school	yes	yes	yes	yes	yes
controls	yes	yes	yes	yes	yes

Notes: Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table A2: High-School A-Level Grades by Subjects- Men

	Math	Physics	Chemistry	Biology	Economics
	(1)	(2)	(3)	(4)	(5)
(1 if women < 40%)*post	-0.016	0.288***	0.229***	0.119*	0.176**
	(0.042)	(0.064)	(0.059)	(0.067)	(0.073)
N	7843	4798	5344	3489	3146
R-Squared	0.528	0.690	0.651	0.726	0.547
Dep. Var. Mean	5.112	4.312	4.612	3.651	4.289
major	yes	yes	yes	yes	yes
years	yes	yes	yes	yes	yes
school	yes	yes	yes	yes	yes
controls	yes	yes	yes	yes	yes

Notes: Standard errors are in parenthesis. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.