The Impact of Advisor Gender on Female Students' STEM Enrollment and Persistence*

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Abstract

To reduce the gender gap in science fields, policymakers often propose providing women with mentoring by female scientists. However, there is no clear evidence on whether one-on-one mentor gender influences women's STEM participation. We exploit a unique setting where students are randomly assigned to academic advisors—who are also faculty members—in their freshman year of college. Advisors help students select courses and decide on a major. We find that having a female rather than a male science advisor substantially increases the likelihood that women enroll and graduate with STEM degrees. A non-science advisor's gender has no impact on students' major choice.

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1 Introduction

Women are still largely underrepresented in the fields of science, technology, engineering and mathematics (STEM) despite the large documented earnings gains from holding STEM versus non-STEM degrees (Hastings, Neilson and Zimmerman, 2013; Kirkbøen, Leuven and Mogstad, 2016; Canaan and Mouganie, 2018). In 2013, women accounted for 31 percent of U.S. postsecondary graduates in the sciences and merely a quarter of all STEM jobs. The first year of college is crucial for the recruitment of science majors but it is also the period when many women shy away from careers in STEM. In 2012, only 7.2 percent of female compared to 26.6 percent of male freshman college students planned on pursuing a degree in mathematics, statistics, computer sciences, physical sciences, and engineering (U.S. Chamber of Commerce Foundation, 2015).

Understanding the factors that influence female STEM choices is essential to inform policy discussions on how to improve the status of women in the sciences. In this paper, we examine an important but overlooked determinant of the STEM gender gap in college: the role of a pre-major academic advisor. Most U.S. 4-year colleges offer academic advising—that is often conducted by faculty members—in order to help undergraduate students set and achieve their educational goals. In general, a first-year or pre-major advisor's duties are to monitor students' academic progress, provide personalized assistance with selecting courses and developing a plan of study, and help them select an appropriate field of study (NACADA, 2011). Advising is high-touch as students typically interact closely with their advisors, meeting with them one-on-one and continuously throughout the academic year.

In this paper, we examine whether women's likelihood of enrolling and graduating with STEM degrees is influenced by their pre-major advisors' gender in the first year of college—particularly for students matched to faculty advisors from science departments. Our focus on female science advisors is motivated by the fact that women are underrepresented in STEM fields and female scientists can potentially act as role models for young women at a very early stage of post-secondary education. We use rich administrative data linking students to their advisors taken from the American University of Beirut (AUB), a private 4-year college located in Lebanon. As further discussed in section 2, AUB and its academic advising system are in many ways comparable to a typical private nonprofit 4-year college in the United States. Importantly, 50 percent of undergraduate students and 40 percent of faculty at AUB are female. Nonetheless, among students declaring a major after their freshman year, only 9.3 percent of females compared to 25.9 percent of males enroll in a STEM degree. We exploit a unique feature of AUB's advising system to answer the question at hand. Specifically, students are *randomly* assigned to advisors at the beginning of their freshman year of college. This enables us to overcome selection bias and identify the causal effects of being matched to an advisor of the same gender.

Advisors are faculty members from various departments. Hence, regardless of their intended majors, students may be matched to faculty advisors from either science or non-science departments. This enables us to not only examine whether being assigned to a female rather than a male science advisor impacts the gender gap in STEM degree attainment, but to also estimate the effects of gender match for non-science advisors. Furthermore, students are required to meet one-on-one with their advisors at the beginning of each semester and prior to course enrollment, and have the option of going to their advisors' weekly office hours. During these meetings, advisors mainly discuss with students their intended majors and help them select courses and create a plan of study. Students also apply for a major at the end of their freshman year. This ensures that they are interacting repeatedly with their advisors at a critical time in their postsecondary studies, that is in the year right before they decide on a major.

Our results indicate that being matched to a science advisor of the same gender in the first year of college substantially increases women's likelihood of enrolling in a STEM major after freshman year and, eventually graduating with a degree in a STEM field. Specifically, exposure to a female rather than a male science advisor reduces the gender gap in STEM enrollment by approximately 8.6 percentage points. This reduction in the gender gap is driven by a 5.4 percentage point increase in STEM enrollment likelihood for women and a statistically insignificant 3.2 percentage point decrease for men. The impacts are long-lasting as we document a comparable 7.2 percentage point decrease in the gender gap in STEM graduation, driven by a 4.3 percentage point increase in the likelihood that women graduate from STEM. We further find that same-gender science advisors improve women's academic performance. Relative to male students, females experience a 17.7 percent of a standard deviation improvement in their freshman year GPA when matched with a female rather than a male science advisor. The absolute gain in women's academic performance is 11.3 percent of a standard deviation, while men's GPA decreases by a smaller and statistically insignificant 6.3 percent of standard deviation. We further show that, although academic performance is increased for women of all ability levels, the STEM enrollment and graduation effects are driven by students with high mathematical ability.

Looking at mechanisms, we find suggestive evidence that the documented increase in female STEM enrollment is mainly driven by affirmation effects through interactions with female scientists. First, we show that women are 2.8 percentage points more likely to take science courses in their first semester due to having a female rather than a male science advisor. Students choose their first-semester courses right after meeting with their advisor and before taking any exams at AUB. This indicates that the documented increase in women's STEM enrollment is not necessarily driven by their improved freshman-year academic performance. Second, we document that having a female rather than a male science advisor increases the probability that women enroll in the same broad discipline as their advisor's field of study by 3 percentage points. Third, while science advisor gender has strong effects on women's STEM outcomes, we show that the gender of a non-science advisor does not significantly impact major choice. Taken together, these results suggest that role model or socio-psychological effects may explain our main findings. We further conduct in-person interviews with female and male science advisors, which also point to this channel; albeit they also reveal that we cannot rule out differential advising practices by female and male advisors as another mechanism driving our effects.

Finally, a unique feature of our setting is that some students are eligible to enroll in their first year at AUB with a declared major. These students are also randomly assigned to advisors within their major's department. This allows us to examine whether women who have already enrolled in STEM majors can also benefit from exposure to a science advisor of the same gender. Indeed, we find that having a female rather than male science advisor increases the probability that these women graduate with a STEM degree by 4 percentage points and improves their academic performance by around 0.09 standard deviations. On the other hand, women in non-STEM departments are not significantly impacted by their advisor's gender. These results highlight that exposure to a female mentor is important to improve women's persistence in the sciences even after they have chosen to enroll in these fields—and not just to increase their access to STEM majors.

This paper presents new evidence that the gender of an advisor significantly impacts women's STEM degree attainment. In doing so, our paper is related to several strands of literature. The first is a body of work which focuses on whether *in-classroom* female role models influence the STEM gender gap. In their seminal study, Carrell, Page and West (2010) exploit the random assignment of students to introductory math and science courses at the U.S. Air Force Academy, and show that female instructors substantially increase the share of high-ability women graduating with STEM majors. Lim and Meer (2017; 2019) further find that being matched to a female middle school teacher in South Korea raises the probability that female students enroll in STEM-tracks in high school and aspire to pursue STEM degrees.[1] In line with these findings, several randomized controlled trials have been recently conducted to raise women's interest in STEM and other male-dominated majors. Porter and Serra (2020) recruit two female economics alumni of Southern Methodist University to discuss their careers, achievements and experiences in their major with students

[1]Several studies find that female teachers increase female students' performance in math and science courses (Bettinger and Long, 2005; Dee, 2007; Gong et al., 2018). Hoffmann and Oreopoulos (2009) detect small effects from having a same-gender instructor on college students' academic performance. Mansour et al. (2018) show that professor gender can influence STEM occupation choice in the U.S. Air Force Academy.

taking Principles of Economics classes. The authors find that women who are exposed to these role models are more likely to enroll in intermediate microeconomics and to major in economics. Breda et al. (2018) document that a one-hour visit to French high school classes by female researchers or professionals in science fields decreases the gender gap in STEM major enrollment in college.[2]

We add to this literature by showing that *advisor* gender significantly impacts the likelihood that women enroll and graduate with STEM degrees. The main difference between advising and other previously studied interventions is that students' interactions with their advisors are one-on-one, high-touch and individualized. Indeed, the role of an advisor is to provide students with one-on-one mentoring and personalized support outside the classroom at a critical time in their postsecondary education. Furthermore, advisors have a direct impact on major choice since their main job is to help students select a major. Another advantage of our study is that we are able to show that exposure to a female science advisor has long-lasting effects, as it substantially increases the likelihood that women *graduate* with STEM degrees. This is important as women are less likely than men to not only enroll but also persist in STEM majors (Griffith, 2010). Aside from Carrell, Page and West (2010), previous studies do not have information on the major that students graduate from.

Our paper further relates to an emerging literature that focuses on whether out-of-classroom advising, coaching and mentoring influence student outcomes. Recent evidence shows that access to coaching and advising substantially increases college performance and graduation.[3] Other studies focus on whether mentor gender impacts student outcomes but do not examine whether it affects women's decisions to pursue STEM fields. Kofoed and

[2]While these two studies highlight that female scientists provide information or inspiration to female students and subsequently change their educational choices, their focus is different than ours. Specifically, they do not focus on one-on-one mentoring and do not examine whether the gender of the role model matters—i.e., they compare students who receive to those who do not receive in-classroom visits by female scientists, but do not compare students who interact with female rather than male scientists. Focusing on the gender of a mentor is potentially important as it contributes to our understanding of how to best design mentoring or advising programs.

[3]See for example Bettinger and Baker (2014); Kot (2014); Lavecchia et al. (2016); Carrell and Sacerdote (2017); Barr and Castleman (2018); Canaan, Deeb and Mouganie (2019); Oreopoulos and Petronijevic (2019).

mcGovney (2019) find that female cadets at the United States Military Academy are more likely to choose the branch of their tactical officers among their top occupations, when they are exposed to female officers. Kato and Song (2018) find that same-gender advisors increase college students' retention in their freshman and sophomore years, and their graduating GPA.[4] In contrast, recent studies show that being matched to a female rather than a male high school counselor or virtual advisor does not affect women's college enrollment rate (Barr and Castleman, 2019; Gurantz et al., 2020). Other studies further explore the role of peer mentors in college students' success. Ellis and Gershenson (2020) show that male students are more likely to persist in college when they are assigned to a same-gender peer advisor, but find no significant effects for women. Lusher, Campbell and Carrell (2018) find that the racial match between undergraduate students and their graduate teaching assistants significantly improves academic achievement.

Our paper adds to this literature by presenting the first causal evidence linking women's STEM choices to the gender of a one-on-one mentor—whether be it an academic advisor or any other type of one-on-one mentor. Indeed, the few other papers that study the role of advisor gender in the sciences cannot overcome the issue of selection bias. For example, a series of studies examine the impact of having a female PhD advisor on women's productivity, graduation rates and probability of holding academic positions, and yield mixed results (Neumark and Gardecki, 1998; Hilmer and Hilmer, 2007; Pezzoni et al., 2016; Gaule and Piacentini, 2018). In these settings, individuals self-select into advising relationships. As a result, the gender match between students and advisors is likely correlated with unobservable factors that may also influence educational choices.

Our findings indicate that exposing women to a one-on-one female science mentor can be an effective way to decrease the STEM gender gap. This is important given that from

[4] In addition to focusing on women's STEM outcomes, a unique feature of our paper is that we distinguish between advisors from science and non-science departments. This is an important distinction since we find that female science advisors increase women's STEM enrollment, while non-science advisors do not. Additionally, advisors in Kato and Song (2018) are also their students' teachers during the first semester in college, while advisors in our setting do not typically teach their students' courses.

a policy perspective, close mentorship has emerged as an "important key to increasing and keeping women engaged in scientific and technical careers" (White House OSTP, 2011). Furthermore, a variety of mentoring initiatives have been recently put in place with the goal of promoting women's persistence in STEM and other male-dominated fields. For example, the Department of Energy STEM Mentoring Program was launched in 2011, to provide female undergraduates with one-on-one mentoring by female scientists. The American Economic Association's Committee on the Status of Women in the Economics Profession (CSWEP) also organizes a yearly mentoring workshop (CeMENT) to help female assistant professors in economics prepare for tenure (Blau et al., 2010). Importantly, since academic advising is part of most colleges, our results suggest that increasing women's representation among pre-major science advisors can be a scalable way to promote female students' STEM degree attainment.

The rest of this paper is organized as follows. Section 2 provides a detailed description of our institutional setting. Sections 3 and 4 outline our data and identification strategy, respectively. Section 5 presents our randomization tests and main results. We discuss our findings in section 6 and conclude in section 7.

2 Institutional Background

2.1 The Freshman Year

In order to examine the impacts of student-advisor gender match, we focus on the advising system at the American University of Beirut (AUB). AUB is a nonprofit private university that offers a liberal arts education and degrees awarded by the university are officially registered with the New York Board of Regents. The focus is mostly on undergraduate education although the university does provide a variety of master's and a few PhD programs. The average tuition for the Freshman year during the period of our study is \$14,000, which is large relative to the average yearly income of \$14,846 in Lebanon. In many ways, AUB is comparable to an average private nonprofit 4-year college in the United States. The student to faculty ratio is 11 to 1 and the average class size is less than 25. 83 percent of full-time faculty have doctoral degrees. Importantly, 50 percent of students and around 40 percent of full-time faculty are female. For comparison, the average student to faculty ratio is 10 to 1 at private nonprofit 4-year colleges, and 14 to 1 at public 4-year institutions in the United States. Additionally, women account for around 55 percent of all undergraduate students and 44 percent of all full-time faculty at U.S. postsecondary institutions (National Center for Education Statistics, 2018). AUB offers around 50 majors across a variety of disciplines such as humanities, social sciences, sciences, engineering and medicine. Most bachelor's degrees take four years to complete. The only exceptions are engineering and architecture which require five and six years, respectively.

Admission into the freshman year is based on a composite score that is a weighted average of SAT1 scores (50%) and high school GPA in grades 10 and 11 (50%). Freshman students are not typical Lebanese college students. Most students in Lebanon have to take national exams at the end of their last year of high school. Upon passing those exams, they are awarded a baccalaureate degree (or *Baccalauréat*) which is required to enroll in postsecondary institutions. Students who pursue a baccalaureate track in high school are not eligible to enroll in university as freshman students, as the Baccalaureate year is considered equivalent to freshman year. Instead, they apply directly to the sophomore year and simultaneously declare a specific major. Freshman students at AUB are individuals who either attended foreign high schools or went to Lebanese schools that follow the U.S. high school education system. Every year, around 2,000 students are enrolled as first-year students at AUB, of which 15 percent are freshmen (and the rest are sophomores). Compared to those who are admitted directly into the sophomore year, freshman students are lower skilled on average.

Freshman students apply for a major at the end of their first year of college. Admission is granted based upon the fulfillment of credit and course requirements set by different departments. Table A1 gives an example of the requirements for two majors: history and mathematics. A few things are worth highlighting. First, all students have to take courses in a variety of disciplines regardless of their major choice. However, the number of courses taken within each discipline varies across intended major. For example, students planning on pursuing a history major have to take two humanities courses in their freshman year, while those wishing to apply for mathematics are required to take only one.

Second, some but not all departments require students to take specific courses. However, students are free to select all other courses conditional on those courses meeting the credit requirements within each discipline. Most departments also impose additional grade requirements. STEM departments typically have more admissions requirements than non-STEM majors. All STEM departments except engineering, require that prospective students take and at least pass two advanced mathematics courses (Calculus I and II), as well as obtain a GPA of 70 or more during the freshman year. Applicants are guaranteed admission if they meet the minimum requirements set by the corresponding department. Around 90 percent of freshman students who eventually enrolled in these majors meet this requirement. On the other hand, engineering majors require taking Calculus I and II, Physics 101 and Chemistry 101 as well as attaining an overall average of 80 or above during the freshman year. Furthermore, students are not necessarily granted admission into those majors if they meet the minimum requirements. Freshman students' applications are pooled with those who are applying directly to the sophomore year, and the admission rate is around 30 percent. Approximately, 98 percent of all freshman students who eventually enrolled as engineers meet the minimum requirements.

Finally, there is substantial overlap in the requirements for different majors. As a result, many students—intentionally or unintentionally—end up fulfilling the requirements for several different majors simultaneously. This also implies that it is not costly for students to change their minds about their intended major at any point during the freshman year.

2.2 Advising during the Freshman Year

The process of selecting and matching advisors to students is coordinated by university administrators working in the advising unit. Advisors are full-time faculty chosen from various departments within the faculty of arts and sciences.[5] All full-time faculty are eligible to be advisors. However, preference is given to faculty who are not up for promotion and who do not have a large number of administrative duties. Advising is optional but faculty members are offered incentives to serve as advisors such as additional research funds or a course release. Faculty commit to advising for the full academic year, and many eventually advise for multiple years.

After the advising unit decides on the final pool of advisors, university administrators randomly assign them to freshman students. Students are first sorted by their university ID numbers or by their last names. Freshman advisors are then randomly sorted in a separate list. The first student from this ordered list is then matched to the first advisor and the second student is matched to the second advisor and so on. Once all advisors have at least one student, this process is repeated over again until all students are matched to an advisor. Importantly, no student or advisor characteristic—such as intended major, past academic achievement or gender—are taken into consideration when deciding on the match. In section 5.1, we present formal evidence that the assignment of students to advisors is consistent with that of a random process. Students are assigned to academic advisors at the beginning of their freshman year, and have the same advisor throughout the year.

Prior to the start of the academic year, advisors have to attend a training session. During this session, university administrators and faculty members who previously served as advisors, discuss the role and duties of an advisor, how the advising process works and how the freshman year is organized. Advisors are instructed to conduct one group advising session

[5] The faculty of arts and sciences (FAS) includes most majors in AUB. This implies that students can be assigned to advisors from humanities, social sciences, physical sciences, life sciences, mathematics and computer science. However, freshman students cannot be assigned to an advisor from the engineering department since it is not part of FAS.

at the beginning of the academic year, where they introduce students to the general requirements for completing the freshman year and enrolling in majors, university resources and the code of conduct. Advisors are also required to meet individually with students for 15 to 25 minutes at the beginning of each semester and prior to course registration. The advising unit provides guidance on how to conduct these individualized advising sessions. Specifically, advisors are told to help students with choosing a major, selecting courses and developing a plan of study that will allow them to meet the requirements for their intended majors. Advisors have access to students' full academic records and are encouraged to tailor their advice to students' interests and abilities. Advisors are also responsible for monitoring students' academic progress, are notified when students are placed on academic probation and have to approve withdrawal from courses. They must hold weekly office hours throughout the semester, and students have the option of contacting them and setting up additional meetings. The university does not keep records of the number and duration of advisor-student meetings. However, as we detail in section 6.1.2, we conducted in-person interviews with advisors and asked them about their interactions with students. Advisors report that some students meet with them between 2 to 3 times per semester and these meetings are between 15 and 30 minutes long—while some students do not attend any office hours. Students discuss with their advisors academic and sometimes personal problems, talk about their career plans and ask for advice on how to manage their time, study efficiently and how to succeed in their coursework. Advisors also schedule a one-on-one meeting with students placed on academic probation in order to help them identify and resolve their academic problems.

An interesting question is how the main features of AUB's academic advising system compare to other universities. First, advising in our setting is conducted by faculty members. A significant share of colleges in the United States have faculty members who advise students. According to a 2011 College Board survey, 52.4 percent of responding U.S. 4-year colleges report that full-time faculty advise more than three-fourths of their first-year students. However, a higher share of baccalaureate-granting institutions compared to research universities (84.1 versus 22.5 percent) have faculty members who advise more than three-fourths first-year students. Second, AUB advisors' main responsibilities are to help students select a major and develop a plan of study, and students are required to meet with them one-on-one at least once at the beginning of each semester. A survey by the National Academic Advising Association (NACADA, 2011) finds that students at over 91 percent of responding U.S. 4-year colleges have advisors whose duties are to help them develop a plan of study and decide on a major. Additionally, in 69 percent of 4-year colleges, students are required to meet with their first-year advisor at least once per term (College Board, 2011). Our setting is most similar to pre-major advising typically found at private 4-year colleges in the United States. For example, liberal arts colleges such as Amherst College, Middlebury College, Wesleyan University, Swarthmore College and Williams College and many private research universities—such as Vanderbilt, Duke, Harvard, Princeton and Yale—have pre-major advisors who are required to meet with students one-on-one and whose main tasks are to assist students with choosing courses and their major. Further, the liberal arts pre-major advisors are full-time faculty members, while at research universities both faculty and staff typically advise. This indicates that the academic advising system at AUB is in many ways comparable to private 4-year colleges in the U.S.

3 Data

3.1 Data Description

This paper uses student-level administrative data accessed through the registrar's office at the American University of Beirut (AUB). Our data include 3,409 incoming Freshman students enrolled at AUB from the academic years 2003-2004 to 2013-2014.[6] For each student, we have detailed information on gender, university course grades and credits acquired.

[6]Freshman students entering university before 2003-2004 had a different advising system in place. We also limit our sample to students entering AUB on or before 2013-2014 in order to observe graduation status for all students.

Our data also include semester GPA, class-year (freshman, sophomore, etc...), as well as field of study for every semester enrolled. Importantly, we also have information on all students' academic advisors including their gender, professorial rank, and department. These data were then matched, by the registrar's office, to student baseline information taken from the admissions office at AUB. This gives us access to students' Verbal and Math SAT scores, GPA during last two years of high school, high school location, year of birth and legacy status.

3.2 Student Summary Statistics

Summary statistics for all students in our sample are presented in column (1) of Table 1. While our data include students matched to freshman faculty advisors from all departments, our main analysis focuses on students matched to advisors in the sciences. As a result, we also present summary statistics for the 1,804 freshman students randomly matched to science advisors in column (2). Female students are equally distributed across both samples. Additionally, mean students characteristics and outcomes reported in columns (1) and (2) are also similar; the only notable difference between both samples is that there are less female science advisors (28.5 percent) as compared to female advisors in general. This is in line with aggregate data from AUB which show that 27 percent of all science faculty at AUB are female. The treatment of interest in this paper is the gender of a student's science advisor. Accordingly, we focus this section on highlighting mean differences between male and female students matched to science advisors. These statistics are reported in Table 1 where we report mean outcomes for male and female students who are matched to science advisors in columns (3) and (4) respectively. Additionally, p-values for the difference between these men and women are reported in column (5).

Female science advisors are equally distributed between male and female students and their difference is statistically insignificant as indicated by a p-value of 0.556. Additionally, men outscore women by an average 27 points on the mathematics portion of the SAT exam, a statistically significant difference. Conversely, men and women score roughly the same on the verbal portion of the SAT exam and the difference between the two is statistically insignificant. In terms of overall high school GPA, reported in standard deviations, freshman female students outperform men by a significant margin.[7] Approximately 21 percent of all students in the science advisor sample have a close relative who attended AUB (legacy students), equally distributed across both genders. Further, around half of all freshman students attended a high school outside of Lebanon with no statistically significant differences found across male and female students who are matched to science advisors.

The main outcome of interest in this paper is the likelihood of enrolling in a STEM major.[8] Recall, in our context, field of study is determined directly after freshman year. Statistics from Table 1 reveal that, among those declaring a major after their freshman year, the likelihood a female student pursues a STEM degree is 9.3 percent, which is in stark contrast to men who have a 25.9 percent overall likelihood of declaring a STEM major. This indicates a 16.6 percentage point STEM enrollment gender gap for students initially enrolled as freshmen, a statistically significant difference as indicated by the p-value of 0 in column (5). Table 1 also shows that, for students declaring a major, women are 6.8 percent likely to graduate with a STEM degree within 6 years of initial enrollment compared to 18.8 percent of men. Interestingly, these disparities exist despite women outperforming men during freshman year; the average GPA for women is a statistically significant 2.91 points higher—out of a scale of 100—than that of men. Finally, around 82 percent of freshman students transition to the sophomore year, with women being 3.1 percentage points (p-value =0.089) more likely to do so compared to men. Given that male students are more likely to dropout, we also define the likelihood of STEM enrollment for all students regardless of

[7] Almost all high schools in Lebanon fall into one of two categories: the French or English high school system. High school grades are reported out of a scale of 100 under the English system and out of 20 for students attending high school under the French system. For comparison and interpretation, we standardize these grades (by year and grade scale) to have a mean of zero and variance of one.

[8] We define the following majors as STEM: Mathematics, Physics, Geology, Statistics, Computer Science, Chemistry and all branches of engineering (Computer, Electrical, Chemical, Mechanical, etc...). These STEM field groups (Physical Sciences, Engineering, Computer Sciences & Mathematics) are those that have persistent underrepresentation of women.

whether they declared a major. This definition encompasses students who drop out and those who declare majorless status in their second year.[9] Using this definition, the likelihood that all freshman male students declare a STEM major is 15 percent, compared to 6.6 percent for women—a significant 8.4 percentage point gap. In our main analysis, we use this definition of STEM enrollment as our outcome of interest.[10]

3.3 Advisor Summary Statistics

In Table 2, we summarize information for all freshman faculty advisors.[11] Overall, our data contain 38 unique academic advisors; 18 of these advisors are faculty members in a science department and 20 are in a non-science department.[12] Further, faculty advisors generally interact with numerous freshman cohorts, serving for a period of 3 years each, on average. Columns (1) and (2) present advisor characteristics for science freshman advisors—the advisors of interest in this study. Male science advisors are generally of higher rank compared to female. Approximately 48, 31 and 16.8 percent of male science advisors are full professors, associate professors and assistant professors, respectively. This contrasts with female science advisors who are mostly assistant and associate professors; only 10.1 percent of female advisors are full professors. Further, male scientists advise an average of 16.03 female students and around 32 total students. Female scientists advise around 15.37 female students and approximately 31.3 students, on average. Finally, the baseline academic performance of students, measured by average SAT scores, are equally distributed across science advisor gender. Freshman students matched to female scientists score 576.7 and 484.7 points on the Math and Verbal SAT exam respectively. Freshman students matched to male scientists score a similar 574.3 and 480 points on the Math and Verbal SAT exam

[9] Students typically declare a major at the end of their freshman year. However, those who do not meet the requirements for admission into their preferred major can remain majorless in the first semester of their sophomore year.

[10] We do so since persistence and major declaration are also outcomes that can be affected by freshman advisor gender.

[11] Though rare, we exclude any freshman advisors who advise less than 5 students for a specific year.

[12] Recall, all advisors are part of the faculty of arts and sciences. We define a science advisor as a faculty member in the department of Physics, Mathematics, Computer Science, Geology or Chemistry.

respectively. Finally, columns (3) and (4) present advisor characteristics for non-science freshman advisors. In contrast to the science advisor sample, non-science female advisors are on average of higher rank compared to men. However, similar to the science advisor sample, the number of female and total students as well as students' academic ability are balanced across both advisor gender groups.

4 Identification Strategy

Our empirical strategy exploits the random assignment of faculty advisors to students in their freshman year at college. Our main focus is on how female students' STEM outcomes are affected by being matched to a female rather than a male advisor in the *sciences*. This is motivated by the fact that women are underrepresented in STEM fields and female scientists can potentially act as role models for young women at a very early stage of post-secondary education. Importantly, whether a student is matched to a faculty advisor in a science or non-science department is random and does not depend on students' preferred future major or academic ability, a result we confirm in section 5.1. Formally, we run the following linear regression model for freshman students matched to faculty advisors in *science* departments:[13]

$$Y_{iat} = \beta_0 + \beta_1 Femadv_a + \beta_2 Femst_i + \beta_3 Femst_i * Femadv_a + X_i'\gamma + A_a'\delta + \sigma_t + \epsilon_{iat} \quad (1)$$

where Y_{iat} refers to the outcome of interest for student i matched to science advisor a in academic year t. $Femadv_a$ is a dummy variable that takes on values of 1 if an advisor a is female and 0 otherwise. $Femst_i$ is another indicator variable for whether freshman student i is female. Additionally, we include an interaction term of both of these indicators. Our simplest specification includes only these variables. Due to the random nature of student-advisor assignment, all β coefficients should be unbiased and can be interpreted as causal.

[13] To affirm that our effects are driven by the lack of female role models in the sciences, later analysis also looks at whether being exposed to a female rather than male non-science advisor has a similar impact on students.

Throughout our main analysis, we focus on three main parameters of interest: β_1, β_3 and the sum of both. In particular, β_1 enables us to measure the effect of having a female versus male science advisor for male students and $(\beta_1 + \beta_3)$ measures the same treatment for female students. Finally, β_3 captures the relative change in the STEM gap between women and men when matched to a female rather than a male *science* advisor.[14]

In alternate specifications, we add a rich set of controls that should improve precision by reducing residual variation in the outcome variable, but should not significantly alter the treatment estimates. These include a vector of student controls X_i' that contain information on students' math and verbal SAT scores, GPA in the final 2 years of high school and legacy admission status as well as birth year fixed effects. The vector A_a' controls for advisor level variables including academic rank and department. In some specifications, advisor controls are subsumed by advisor fixed effects, enabling us to control for any differences across advisors. σ_t is an academic year fixed effect that controls for unobserved changes across different years. Additionally, we control for the interaction of all our baseline covariates and fixed effects with the student gender indicator variable $Femst_i$ to account for differential impacts on female and male students. ϵ_{iat} represents our error term.

Standard errors are clustered at the advisor-year level throughout to account for correlations among students exposed to the same advisor in the same year.[15] We also report randomization inference based p-values with our main results. This method of inference has the benefit of not relying on asymptotic properties of estimators and only requires that researchers have knowledge of the randomization process for implementation (Heß, 2017). This involves first replicating the advisor assignment process at AUB and randomly reassigning all students to advisors within the same academic year. We then re-estimate our main regressions under this new assignment and repeat this process 1,000 times. Finally, we construct empirical p-values representing the proportion of simulated estimates that are

[14] β_2 is the average difference between female and male students matched to male science advisors.

[15] Results remain unchanged if we cluster our standard errors at the advisor level as we show in Table A3 of the Appendix.

larger than the observed estimate in the data.

To analyze potential mechanisms, we run a modified version of equation (1) that allows us to examine the effect of advisor-student gender match on course level outcomes:

$$Y_{iatc} = \beta_0 + \beta_1 Femadv_a + \beta_2 Femst_i + \beta_3 Femst_i * Femadv_a + X_i'\gamma + A_a'\delta + \alpha_{ct} + \sigma_t + \epsilon_{iatc} \tag{2}$$

where Y_{iatc} refers to course-level achievement outcomes for student i matched to science advisor a in academic year t enrolled in course c. In these specifications, interpretation remains largely unchanged except for the fact that we are looking at student-course level outcomes which results in an increased number of observations. Another significant difference is that we include course-by-semester (α_{ct}) fixed effects in equation (2) to control for unobserved mean differences in academic achievement or grading standards across courses and time. As in equation (1), β_1 and $(\beta_1 + \beta_3)$ measure changes in course performance when moving from a male to a female science advisor for male and female students, respectively. Additionally, β_3 measures the change in the course level achievement gender gap when transitioning from a male to a female science advisor. To account for the fact the students take multiple courses, we cluster our standard errors at the student level.[16]

5 Results

5.1 Tests of the Identifying Assumption

To identify causal effects, it is important that freshman students' characteristics are uncorrelated with those of their advisors'. While our institutional setting provides for random assignment of students to advisors, we perform a series of tests to confirm that our data are consistent with such a process. First, we check whether male and female students' baseline characteristics are balanced across science and non-science advisor gender. To do so, we

[16]Results remain unchanged if we cluster our standard errors at the advisor-year level instead.

run equation (1)—without the inclusion of student and advisor controls—using students' Math and Verbal SAT scores, standardized high school grades, foreign high school status and legacy student status as outcomes of interest. This enables us to check whether being matched to a female as opposed to male science advisor is correlated with men and women's predetermined student characteristics. Table 3 summarizes the results of this exercise where we separately report coefficients for male and female students in the first and second rows respectively, while the third row presents estimates on the difference between women and men. Panel A of Table 3 reports estimates for students matched to science advisors.

We find that male students matched to female as opposed to male science advisors have similar Math and Verbal SAT scores as indicated by the estimates in the first row of columns (1) and (2). We also find that women have balanced SAT scores across science advisor gender as shown in the second row. Additionally, we find no statistically significant differences in SAT scores between women and men transitioning from male to female science advisors as highlighted by the insignificant estimates in the third row. We find that high school GPA is also balanced across science advisor gender for both male and female students as shown in column (3). Other student characteristics such as legacy status and high school location are also statistically insignificant for men and women; however the difference in effects between female and male students with regards to foreign high school status is significant at the 10% level. Finally, Panel B shows estimates for students matched to non-science advisors. We find that all student characteristics are balanced for both men and women exposed to female as opposed to male non-science advisors. Additionally, the differences in these effects are all statistically insignificant. Taken together, these results are in line with our institutional setting which indicates that students are randomly assigned to faculty advisors, independent of students' gender and advisors' department or gender.

To further check if our data are are consistent with what would be expected under a random assignment process, we complement the above results using additional tests of randomization based on resampling techniques in the spirit of Lehmann and Romano (2005) and Good (2006). These tests are similar to those conducted in Carrell and West (2010) and Lim and Meer (2019). Specifically, we first randomly draw 10,000 student samples of equal size for each advisor-year combination without replacement. For each randomly sampled combination, we then calculate the sum of female students, the sum of SAT math scores and the sum of SAT verbal scores in that sample respectively. We next construct empirical p-values for each advisor-year based on the proportion of simulations where the number of female students, total SAT math scores and total SAT verbal scores are smaller than the observed or actual number. Finally, we test whether the distribution of empirical p-values is uniform for each of these three variables, as would be expected under random assignment.[17]

We test for the uniformity of these distributions using both a Kolomogrov-Smirnov one-sample of equality of distribution test and a χ^2 goodness of fit test. These results are summarized in Panel A of Table 4. For all 11 years of our data, we fail to reject the null hypothesis of random assignment based on either test of uniformity for p-values related to the number of female students and total SAT math scores. For uniformity tests related to the p-values attributed to total SAT verbal scores, we fail to reject 1 out of all 22 tests (4.5 percent). In summary, we find no evidence of nonrandom assignment of students to advisors based on student gender or academic ability. As an additional test, we also regress these empirical p-values on advisor characteristics such as whether an advisor was female, a scientist or a full/associate professor. These involve regressions from 111 observations corresponding to the 111 advisor-year combinations in our data. We report these results in Panel B of Table 4 where we find no statistically significant relationship between our computed p-values and advisor characteristics.

[17]The intuition here is that if students are randomly assigned to advisors, then we should expect any unique p-value to be equally likely to be observed—i.e., that the distribution of empirical p-values should be uniform.

5.2 STEM enrollment, STEM graduation and Academic Performance

We start by examining whether being matched to a female as opposed to a male science advisor differentially impacts students' STEM outcomes for men and women. As previously discussed, advisors help students decide on a field of study, and guide them on how to meet the requirements for admission into their chosen majors. Additionally, students declare a major at the end of their freshman year, thereby interacting repeatedly with their advisors before deciding on a field of study. Figure 1a shows graphically the unconditional STEM enrollment means of different student-advisor gender match combinations. The figure indicates that only 5.3 percent of female students matched to a male science advisor enroll in a STEM degree. Strikingly, moving from a male to a female science advisor doubles the likelihood to 10 percent. In contrast, male students matched to a male science advisor are 16 percent likely to enroll in a STEM major and this probability drops to 12.4 percent when assigned a female advisor. Figure 1b shows that these enrollment disparities persist into graduation. Female students matched to male science advisors are 4.2 percent likely to graduate with a STEM degree and this likelihood increases to 8.5 percent when matched to a female advisor. Conversely, men are more likely to graduate when matched to a male advisor (13 percent) as opposed to a female advisor (9.4 percent).

Having shown the raw patterns of STEM enrollment and graduation by student and advisor gender, we now turn to regression-based estimates from equation (1). Table 5 summarizes the effects of being matched to female as opposed to male science advisors for various outcomes and specifications. Table 5 takes the same form as those after in that we separately report estimates for male and female students in the first and second rows respectively, while the third row presents effects on the overall student gender gap. We report clustered standard errors in parentheses followed by randomization inference based p-values in brackets.

We begin by reporting estimates on STEM enrollment in columns (1) to (3) of Table 5. Results from our most basic specification, that includes no controls, are reported in column

(1). The estimate of -0.037 in the first row suggests that male students are less likely to enroll in a STEM major when matched with a female as opposed to male advisor, though this effect is not statistically significant. Conversely, the statistically significant estimate of 0.048 reported in the second row indicates that female students are 4.8 percentage points more likely to enroll in a STEM degree when matched with a female rather than a male science advisor. The combined effect of 0.084, presented in the third row, indicates that switching from a male to a female science advisor narrows the gap in STEM enrollment between female and male students by 8.4 percentage points. This 8.4 percentage point reduction implies a 77 percent decrease in the gender gap in STEM enrollment compared to a baseline 10.8 percentage point gap when students are matched to a male science advisor.[18]

In column (2), we report the same coefficients from alternate specifications of equation (1). Specifically, we include year fixed effects to control for any unobserved time-varying shocks that are common to all students, as well as student and advisor controls such as SAT scores, high school GPA, legacy and birth year fixed effects as well as advisor rank and department. Additionally, we include interactions of student gender with year fixed effects, as well as interactions of student gender with the covariates in order to control for differential gender effects. Results remain largely unchanged as we find that having a female science advisor has a negative (-0.032) but insignificant effect on STEM enrollment for men but increases female students' likelihood by 5.4 percentage points. Combined this results in a statistically significant 8.6 percentage point reduction in the STEM gender gap. In column (3), we further include advisor fixed effects allowing for identification only from within-advisor variation in the gender match. Consistent with the random assignment of students to advisors, the estimate on the gender gap (0.084) remains statistically significant and similar in magnitude to those reported in columns (1) and (2).

As mentioned in Section 4, we compute randomization inference based p-values which we report in brackets throughout. These empirical p-values are based on estimates from

[18]The 10.8 percentage point gap is obtained from $\beta 2$ in equation (1).

simulations that re-randomize students to advisors. In particular, they show the proportion of simulated estimates that are larger than the observed estimate in the data. If our documented findings are the result of a positive match for female students and female science advisors, then we would expect the empirical p-values to only exceed our actual estimate at most 5 percent of the time, corresponding to a p-value of 0.05. Results from this exercise are in line with this as we estimate p-values less than 0.05 on the coefficients representing effects on female students as well as the gender gap.

We document that female scientists lead to a reduction in the STEM enrollment gender gap. However, it is important to understand whether the women induced into STEM persist in these fields. Accordingly, we next look at how students' likelihood of graduating with a STEM degree is affected by freshman science advisor gender. In columns (4) through (6) of Table 5, we present estimates on the likelihood of graduating with a STEM degree within 6 years of initial university enrollment.[19] Estimates from our least saturated specification in column (4) indicate that the STEM graduation gender gap decreases by a statistically significant 7.8 percentage points when moving from a male to female science advisor. This is due to a statistically insignificant reduction in STEM graduation for men (-0.036) combined with a significant 4.2 percentage point increase for women. In line with the random assignment of students to advisors, the addition of year fixed effects as well as student and advisor controls does not significantly alter estimates on men, women or the gender gap as shown in column (5). The addition of advisor fixed effects also does not significantly change the estimate on the STEM graduation gap (0.070) as reported in column (6).

Next, we examine whether science advisor gender match impacts academic performance. Indeed, advisors are responsible for monitoring students' academic progress during the freshman year and exposure to a female advisor could potentially influence female students' motivation and academic performance. In columns (7) through (9) of Table 5, we report estimates

[19]This definition of graduation allows more time for students to complete their degrees. However, one drawback of this measure is that students entering AUB in the year 2013-2014 can only be observed for 5 years after initial enrollment.

on the impact of student advisor gender match on standardized GPA at the end of freshman year. The statistically insignificant estimate of -0.106 reported in the first row of column (7) suggests that male students have a lower freshman GPA when matched with a female as opposed to male advisor. However, for female students, we find a positive 8.2 percent of a standard deviation grade improvement when matched to a female rather than male advisor, though this estimate is not statistically significant (p-value=0.106) at conventional levels. Notably, women already outperform men by 21.4 percent of a standard deviation even when both are matched to a male science advisor. Transitioning to a female advisor increases this gap by a statistically significant 18.8 percent of a standard deviation, as shown in the third row of column (7).

The addition of year fixed effects as well as student and advisor controls reduces the estimate on male students (-0.063) but increases the effect on female students to a statistically significant 11.3 percent of a standard deviation. These results are robust to the addition of advisor fixed effects as shown by the statistically significant 0.168 estimate in column (9). Put together, results from this section indicate that female students benefit significantly from exposure to female as opposed to male science advisors. In contrast, we find suggestive but inconclusive evidence that male students are slightly harmed by having a female rather than a male science advisor.

Finally, it is possible that women who enrolled in STEM would have instead dropped out of AUB had they not been exposed to a female science advisor. In Appendix Table A2, we examine whether science advisor gender impacts students' likelihood of dropping out of AUB or not declaring a major at the end of their freshman year. Estimates in column (1) are all statistically insignificant and suggest that exposure to a female rather than a male advisor does not result in women (men) being less (more) likely to drop out or not declare a major. These results hold even after we control for student and advisor characteristics in column (2) and advisor fixed effects in column (3).

5.3 Course Selection and Performance During Freshman Year

One of the main tasks of an academic advisor is to assist students with course selection. Furthermore, students wanting to enroll in STEM fields are required to take a higher number of mathematics and science courses compared to students wanting to pursue non-science majors.[20] Accordingly, in Table 6, we examine whether having a female science advisor encourages women to take more science courses, and whether it also improves their course performance. Looking at the first row of column (1), the insignificant estimate of -0.07 indicates that men's likelihood of taking science courses during freshman year is unaffected by science advisor gender. Conversely, women matched with a female as opposed to male advisor are 2.3 percentage points more likely to take science courses during freshman year. Combined, this indicates that transitioning from a male to female science advisor increases the likelihood of taking a science course by 3.1 percentage points for women relative to men.[21]

Estimates from columns (2) to (4) further indicate that being assigned to female rather than male science advisors improves women's science course performance, relative to men. Specifically, estimates reported in the third row indicate that female students are 8.4 and 3.4 percentage points less likely to fail and withdraw from science courses as compared to men. They also experience a 0.223 standard deviation increase in science course grades, relative to men. The effects on course performance are driven by women; we find a statistically significant 5 percentage point reduction in the likelihood of failing a science course and a 0.14 standard deviation increase in science course grades for women. Conversely, the effects on science course withdrawal are driven by men as we find a 2.7 percentage point increase in the likelihood of men withdrawing from science coursework and no effect on women.

We also examine how performance on non-science coursework is impacted by science advisor gender match. These results are summarized in columns (5) to (7) of Table 6. We

[20]Specifically, all STEM majors require that students take at least half of their courses during the freshman year in math or sciences. Humanities and social sciences only require 30% of all courses to be in math and sciences. However, students can take additional math and science courses as electives.

[21]This represents a 46 percent reduction in the science course-taking gap as compared to a baseline 6.7 percentage point gap when students are matched to male science advisors.

find that science advisor gender also significantly reduces women's likelihood of failing non-science courses, though these effects are smaller than those found for science coursework. Indeed, we uncover that having a female advisor decreases women's likelihood of non-science course failure by 2.6 percentage points but has no effect on men. Additionally, having a female science advisor increases the non-science grade performance of women relative to men by a significant 13.4 percent of a standard deviation, driven by a 0.057 standard deviation increase in women's and a 0.077 standard deviation decrease in men's performance (albeit not statistically significant at conventional levels). Finally, as shown in column (6), we find no statistically significant effects on non-science course withdrawal for either men or women.

5.4 Heterogeneous Effects of Science Advisor Gender Match

Given that exposure to a female rather than a male science advisor increases women's STEM degree attainment, we next examine whether these effects are more pronounced for students with high initial mathematics ability. We consider students to be highly skilled in math if their SAT math score is greater than the median in our sample—575 points. This typically corresponds to the 70th percentile of the distribution of scores among all SAT-takers (College Board, 2012). Table 7 presents the corresponding heterogeneous treatment estimates for our main outcomes of interest where we include student and advisor controls as well as year fixed effects throughout. The estimates on the gender gap (β_3) reported in columns (1) and (2) indicate that for high ability students, moving from a male to female science advisor reduces the STEM gender gap in enrollment and graduation by 14.4 and 11.1 percentage points, respectively. These effects are driven by women as they are 10 and 8.3 percentage points more likely to respectively enroll and graduate from STEM and we find no statistically significant effects on men. In contrast, estimates for low-ability men and women are statistically insignificant and the overall effect on the gender gap is insignificant and quite small in magnitude, indicating that exposure to a female advisor does not improve lower ability women's likelihood of STEM investment.[22]

In column (3) of Table 7, we present heterogeneous effects on GPA at the end of the freshman year. High ability male students are unaffected by the gender of their advisor as indicated by the insignificant -0.036 estimate in the first row of column (3). However, high ability female students realize large and significant gains from being exposed to female rather than male science advisors on the order of 18.2 percent of a standard deviation. Combined, this leads to a 21.8 percent of a standard deviation increase in the performance of women relative to men. In contrast, lower ability men and women realize no significant absolute gains from exposure to female rather than male science advisors, though the estimates of -0.073 and 0.107 reported in rows 4 and 5 are not small in magnitude. Indeed, these combined estimates result in a significant 18 percent of a standard deviation increase in the performance of women relative to men. These results suggest that high and lower ability women experience some grade benefits, relative to men, when matched to a female science advisor. On the other hand, the documented overall increase in STEM attainment is driven by high ability female students in mathematics—the group of students most likely to benefit from investing in a STEM degree. This suggests that female students may be re-optimizing their degree choice towards their comparative advantage when exposed to female scientists.

Next, we look at how science advisor gender affects high and low ability students' course choice and performance. Appendix Table A4 summarizes results from this exercise. We find that high ability women are 5.7 percentage points more likely than high ability men to take science courses when matched to a female rather than male science advisor. This effect is almost entirely driven by female students who realize a 4.2 percentage point increase in science course taking behavior. In terms of academic performance, estimates from the third row reveal gains for high ability women relative to high ability men. These improvements are mainly driven by absolute benefits for high ability women. Specifically, women are 3.9

[22]The initial gender gaps in STEM enrollment and graduation are larger among high ability students compared to low ability students. Specifically, women are around 10.9 and 8.9 percentage points less likely than men to enroll in and graduate with STEM degrees when both are assigned a male science advisor. For low ability students, these differences are 4.5 and 3.1 percentage points respectively.

and 3.5 percentage points less likely to fail science and non-science courses, respectively. Additionally, while high ability women experience no significant improvement in science grades (0.032), they do realize grade gains in non-science courses (0.128). When looking at the overall decrease in the course withdrawal gender gap, we find that it is primarily driven by increases in course withdrawal rates for high ability men.

Finally, we show that being matched to a female science advisor has no significant effect on science course-taking behavior for lower ability men and women. However, switching to a female advisor does lower the relative likelihood that lower ability female students fail a science course by 7.3 percentage points, driven by a 5.3 percentage point increase for men. It also substantially improves lower ability female students' grades in science and non-science coursework relative to lower ability men, though the estimate on non-science course grades is primarily driven by a reduction for male students. Importantly, even though statistically insignificant—most likely due to reduced precision—estimates from column (4) suggest that low ability female students experience a large improvement in science course grades (0.157) despite their course choices being unaffected by the gender of their advisor (column 1). This suggests that the documented overall improvement in course performance we find for the average female student in section 5.3 is not driven by the endogenous change in course selection; rather most of the academic gains seem to be directly driven by exposure to an advisor of the same gender.

5.5 The Impact of Non-Science Advisor Gender

So far, we have documented the importance of advisor gender among female students assigned to science advisors. We next turn to whether being exposed to a female rather than male *non-science* advisor has similar impacts on students' performance and their decision to pursue a STEM field. Table 8 presents the corresponding estimates for our main outcomes of interest. As shown in the first row of column (1), being matched to a female non-science advisor has no meaningful impact on male students' (0.003) likelihood of enrolling in a

STEM major after freshman year. Estimates from the second row indicate that female students are also largely unaffected, though the direction and magnitude of this effect (-0.024) is opposite that of men. Combined, these effects lead to a statistically insignificant and relatively small 2.7 percentage point increase in the STEM enrollment gender gap, suggesting that switching to a female non-science advisor potentially slightly widens the initial STEM enrollment gap. In line with the random assignment of students to advisors, the addition of student and advisor controls as well as year and advisor fixed effects does not alter these estimates in any meaningful way as shown in columns (2) and (3). The estimates for STEM graduation in column (4) through (6) are in line with those for STEM enrollment. Indeed, we find relatively small and statistically insignificant coefficients for men and women and these estimates suggest a small, but insignificant, increase in the STEM graduation gender gap when matched with a female non-science advisor. Finally, results presented in columns (7) through (9) show that transitioning from a male to female advisor has no statistically significant impact on females' absolute or relative performance.

In Appendix Table A5, we look at whether non-science advisor gender impacts course-level outcomes. Estimates from column (1) indicate that both female and male students' science course taking behavior is unaffected by the gender of their academic non-science advisor. Additionally, switching from a male to a female non-science advisor has no statistically significant effect on the gender course performance gap in science courses as indicated by the coefficients on the interaction term β_3 in columns (2) through (4). However, estimates in column (7) indicate that the gender gap in non-science course performance increases by 9.1 percent of a standard deviation; this gap is due to a 3.8 percent of a standard deviation improvement and a 5.3 percent of standard deviation decrease in women and men's respective performance on these courses—both statistically insignificant at conventional levels. Overall, results from this section indicate that female students are largely unaffected by the gender of non-science advisors despite realizing large and significant benefits when exposed to female science advisors.

6 Discussion

6.1 Mechanisms

Our findings of increased STEM enrollment and academic performance for female students are consistent with two broad interpretations: either women experience an increased sense of fit when matched with a female scientist (i.e., role model or socio-psychological effect) or female science advisors engage in differential advising practices towards women and men. It is beyond the scope of this paper to conclusively speak to the mechanisms driving our effects. Nonetheless, in this section, we provide some suggestive evidence on this issue.

6.1.1 Advisor Rank and Peer Formation

Before examining which of the two above interpretations is more plausible in our setting, we first rule out some other mechanisms that could be driving our effects. In our main analysis, we show that our results are robust to the inclusion of various controls, including advisor fixed effects. This is important as female and male science advisors differ in their academic ranks for example; a larger share of advising women are assistant professors as compared to men. However, to the extent that specific characteristics of an advisor are correlated with advisor gender and vary with student sex, then an advisor fixed effect on its own would not be sufficient to capture these dynamics. For example, male and female students may respond differently to having advisors of different gender and professorial rank.

To investigate this further, we run a specification of equation (1) that includes an interaction term for faculty advisor rank with advisor gender and an interaction term for faculty advisor rank with student gender.[23] The results of this exercise are reported in Appendix Table A6 and indicate that our main results are robust to the inclusion of these controls. Estimates on men, women and the gender gap are quantitatively similar to our most saturated

[23]Specifically, we group faculty rank into 2 broad categories, experienced and less-experienced advisors. Experienced advisors include associate and full professors. Inexperienced advisors include assistant professors and lecturers. Our results are robust to different categorizations.

specification presented in Table 5 for all outcomes of interest. This indicates that differences in student-gender responsiveness to advisor gender-rank are not driving our results.

Another potential explanation for our effects is that female science advisors encourage women to interact with their female peers which could in turn affect their academic performance and major choice. This would be in line with recent studies showing that women's decision to pursue and persist in science fields can be affected by the gender of their peers (Bostwick and Weinberg, 2018; Mouganie and Wang, 2020). To explore this mechanism, we look at whether the gender of a science advisor affects the likelihood that women take classes together—which would indicate whether female science advisors facilitate the creation of female peer networks. In column (1) of Table 9, we use as an outcome the leave-one-out share of female students in advisees' freshman-year classes. Estimates are small and statistically insignificant, indicating that the gender composition of students' classes is unaffected by their advisors' gender. These results suggest that female science advisors do not influence women's outcomes through changing their peer networks and instead, other channels are more likely to be at play.

6.1.2 Female Scientists as Role Models

While it is difficult to disentangle the exact mechanisms, we present several pieces of evidence suggesting that at least part of our main effects are driven by female science advisors acting as role models to female students.

First, we show that women's likelihood of pursuing a STEM field is directly influenced by their interactions with female science advisors. Recall that in our main analysis, we document a change in female students' major choice but also an increase in their academic performance during freshman year. This improvement in female students' GPA is in line with two explanations. It could indicate that females are encouraged to enroll in a STEM field after meeting with their advisor and therefore end up working harder to meet the requirements for entry into science majors—which are typically more selective than non-science fields. On the other hand, it is possible that female science advisors do not directly influence women's major choice; but rather they help them increase their GPA (through for example, providing encouragement or advising them on how to study) which in turn raises their STEM enrollment. In column (2) of Table 9, we provide evidence that favors the former interpretation. Specifically, we find that female students are 2.8 percentage points more likely to take a science course in their *first* semester of freshman year when assigned a female rather than a male science advisor, while no significant effects are detected for men. This is important as freshman students choose their first semester courses before taking any classes or exams at AUB but after meeting with their academic advisor.[24] This indicates that the documented improvement in course performance during freshman year is not solely driving the increase in women's STEM enrollment, rather this change seems to be more consistent with a socio-psychological interpretation in which female advisors acts as a positive reinforcement for women wanting to enter the STEM pipeline.

Second, our role model interpretation is reinforced by the fact that *non-science* advisors' gender has no impact on women's academic performance or STEM enrollment (see Table 8). If women are affected through other channels such as being more comfortable talking to a female rather than a male advisor, then we would expect to see changes in their performance due to non-science advisors' gender. Instead, our results highlight that to improve women's STEM attainment, it is not sufficient to assign them to any female advisor but instead they need to be exposed to *female scientists*, since lack of female role models is an important contributor to women's underrepresentation in these fields.

To further bolster this argument, we examine how our main effects change when we include in our definition of STEM (i.e., in our definition of students' STEM major and the

[24]Additionally, in results not reported in the paper, we run additional regressions to further understand the extent to which effects on STEM enrollment are driven by initial course choice. To do so, we construct a predicted STEM enrollment variable based on OLS regressions of STEM enrollment on dummy indicators for science freshman courses and year fixed effects. We then re-estimate our main analysis using predicted STEM enrollment as outcome. We find smaller—compared to those found in Table 5—but still significant effects of science advisor gender on female students' predicted STEM enrollment. This suggests that the documented effects on course choice could be a primary driver of our STEM findings.

advisor's department): (i) biology, a science major in which women are not underrepresented and, (ii) economics, a non-science major in which women are underrepresented. Results presented in Column (1) of Table A7 show that having a female rather than a male science or biology advisor increases women's likelihood of declaring a STEM or a biology major by 3.4 percentage points. However, this effect is only statistically significant at the 10 percent level and its magnitude is lower than the previously documented 4.8 percentage point increase in STEM enrollment when we do not include biology. On the other hand, when we add economics to our STEM definition, effects are stronger as women are 5.6 percentage points more likely to enroll in STEM or economics when they are matched to a female rather than a male science or economics advisor. The fact that advisor gender matters most in fields where women are underrepresented—regardless of whether or not these fields are sciences—suggests that role model effects explain at least part of our main results.

Finally, if women perceive female science advisors to be role models, we would expect them to pursue a major that is similar or close to their advisor's field of study. We examine this channel in columns (3) and (4) of Table 9. Column (3) shows that exposure to a female rather than a male advisor has no impact on women's (or men's) likelihood of enrolling in the exact same major as their science (and non-science) advisor. However, some interesting patterns emerge when we broaden our definition of the similar major by looking at majors that are in the same discipline (i.e., social sciences, sciences, engineering, etc.) as the advisor's field of study. Column (4) reveals that when women are matched to female rather than male science advisors, they are 3 percentage points more likely to enroll in the same broad discipline as their advisor's field of study. Women exposed to female non-science advisors are also 4.7 percentage points more likely to pursue a major within their advisor's discipline. This result is consistent with the statistically insignificant decrease in women's STEM enrollment due to exposure to a female non-science advisor in column (1) of Table 8. Interestingly, column (4) of Table 9 shows that men are unaffected by their science and non-science advisors' gender. These findings provide further support for the idea that female advisors act as role models and inspire other women to pursue similar careers.

6.1.3 Results from In-Person Survey

In an effort to further uncover the mechanisms driving our effects, we conducted in-person surveys and interviews with current and former freshman science advisors at AUB. We contacted four female and four male science advisors. All male and three female advisors were available to be interviewed. The results of this survey are reported in Appendix Table A8. The questions in panel A focus on how advisors believe students of different genders behave during advising. Most advisors report no differences in the behavior of students of different genders. However, some (both female and male advisors) report that compared to males, female students are more likely to attend office hours, spend more time in advising sessions and are more likely to follow the advisor's suggestions—while none of the advisors feel that men are more engaged in the advising process than women. This is consistent with previous studies showing that women are more likely than men to participate and benefit from academic support services (Angrist et al., 2009; Carrell and Sacerdote, 2017). One interesting observation is that while all male advisors state that students of different genders spend an equal amount of time in advising meetings, most female advisors report that women spend more time in meetings than men. This suggests that female students are more willing to engage with female rather than male science advisors.

In Panel B of Table A8, we summarize findings based on questions related to how advisors behave towards female and male students. Unsurprisingly, the vast majority of advisors state that they do not invest more time or follow up more with students of a certain gender. Finally, we asked advisors about their style of advising and their attitudes concerning women's position in the sciences. These results are summarized in panel C of Table A8. While all male advisors report using a similar advising style for students of different genders, two out of the three female advisors stated that they use different advising styles for men and women. When asked to elaborate, both female advisors said that compared to females, male students are less likely to follow their recommendations and listen to their advice, and are more belligerent. As a result, over time, they had to change the way they approach and talk to male students. The fact that female advisors report difficulties with advising male students but male advisors do not, is consistent with our finding that men matched to female science advisors are less likely to pursue STEM degrees compared to those matched to male science advisors.

All male advisors stated that they would encourage women to pursue science fields and do not feel that it is more difficult for women to make it in the sciences. Strikingly, two out of the three female advisors said that they would not encourage women to pursue science careers as it is harder for women to be successful in these fields.[25] However, both emphasized that they do not deliberately discourage female students from pursuing STEM degrees. This suggests that female science advisors are not actively and knowingly pushing female students towards STEM majors. Combined with our finding that women spend more time than men with female science advisors, results from our survey suggest that socio-psychological effects or an increased sense of fit on the part of students is the most likely mechanism driving our main findings. However, we cannot rule out that part of our effects are driven by female science advisors using different advising styles with women and men.

6.1.4 Policy Implications

Next, we discuss the policy implications of our findings. We first conduct back-of-the-envelope calculations to gauge the share of female science advisors needed to completely close the STEM gender gap in our setting. Our main analysis indicates that being matched to a female rather than a male science advisor reduces the gender gap in STEM enrollment by 8.4 percentage points. The initial gap between men and women assigned to science advisors

[25]The fact that male advisors report encouraging women to pursue science fields while female advisors do not is consistent with findings from a study by Thompson (2017). Indeed, the author shows that male advisors are more likely than female advisors to recommend mathematics as a major for both male and female students.

is 16.6 percentage points.[26] Assuming that advisor gender effects are linear, this implies that we would need to replace two male science advisors (with two female science advisors) to eradicate the gap in STEM enrollment. In other words, the share of female science advisors that would close the STEM gender gap in our setting is around 44 percent. The magnitude of this estimate is close to the share of female college instructors found in majors where women are not underrepresented. For example, Bettinger and Long (2005) estimate that in Ohio, the share of female college freshmen enrolling in a sociology major is 61.8 percent, while the share of female instructors in the same major is 48.9 percent.

Finally, while our results show that gender matching in academic advising increases women's STEM enrollment, the policy implications of our study are more ambiguous. Given that most colleges already provide some type of academic advising, it is possible that matching female students to female science advisors may be a scalable strategy to reduce the STEM gender gap. However, it is difficult to predict how manipulating the gender match would affect student outcomes. For example, Carrell, Sacerdote and West (2013) sort college students into peer groups designed to optimally improve their academic performance. However, the impact of the intervention differed from initial predictions as students ended up forming endogenous peer groups. Another potential avenue for policymakers would be to increase the share of female scientists among academic advisors. Nevertheless, this may be difficult to achieve given the scarcity of women in science fields and since, on average, women in academia already shoulder a disproportionate amount of service work compared to men (Buckles, 2019). Our results do nonetheless suggest that mentoring programs intended to raise women's representation in the sciences can better fulfill their goals if they recruit female scientists to act as mentors.

[26] Columns (3) and (4) of Table 1 show that 25.9 percent of men versus 9.3 percent of women assigned to a science advisors enroll in a STEM major.

6.2 Post-Major Academic Advising

In this paper, we focus on student-advisor gender match during freshman year—prior to students declaring a major. Our results highlight that pre-major female science advisors can play a key role in encouraging women to enroll and persist in STEM degrees. This begs the question: is gender match in post-major advising also important? In other words, do women who have already pre-committed to a STEM field also benefit from female mentors? We take advantage of another aspect of our setting in order to shed light on this question. Indeed, as detailed in section 2.1, a significant portion of students at AUB are eligible to directly enter college as sophomores with declared majors, thus enabling us to compare our findings on pre-major mentoring to post-major mentoring within the same university setting. Specifically, students who sit for and pass the Lebanese Baccalaureate national exam directly enroll in a major as sophomores—without ever enrolling in the freshman year. These students are in fact ineligible to enroll as freshmen, since their last year of high school (Baccalaureate year) is considered to be equivalent to the freshman year. Importantly, and similar to the freshman advising system, sophomore students are randomly assigned to an advisor within their major's department.

Appendix Table A9 summarizes key statistics for the sample of students who initially enroll at AUB as sophomores for the academic years 2003-2004 to 2013-2014. Approximately half of all first time enrolling sophomore students are female and 33.4 percent of sophomore advisors are female. Noticeably, while freshman and sophomore entering students have comparable scores on the Verbal SAT exams, the average Mathematics SAT score (637) for sophomores is significantly higher than that of freshmen.

In order to examine how initial post-major advising (or sophomore year advisor) impacts students, we re-run equation (1)—with the addition of department fixed effects—on the sample of students who directly enroll in university as sophomores. We exclude sophomore students who initially enrolled as freshmen from this analysis as these students' major choice is endogenous to the gender of their freshman advisor.[27] The results of this exercise are summarized in Table 10. Estimates presented in columns (1) and (3) include student controls as well as year and department fixed effects. We include department fixed effects since randomization occurs at the departmental level in the sophomore year. Additionally, we include department-by-year fixed effects in estimates presented in columns (2) and (4).

We begin by reporting the effects of gender match on graduation from the initial major each student enrolled in, i.e. persistence in the major. The estimate on treatment in column (1) indicates that female STEM students matched to a female as opposed to male advisor are 8 percentage points more likely to graduate with a STEM degree, relative to men. This is driven by a significant 4 percentage point increase in the likelihood that women graduate from STEM when matched with a female rather than male advisor—and a statistically insignificant 3.3 percentage point decrease in men's STEM graduation rate. Conversely, the gender match between advisors and students in non-STEM departments has a smaller and statistically insignificant positive effect (2.7 percentage points) on women's graduation rates. These estimates are robust to the inclusion of department-by-year fixed effects as illustrated in column (2).

Additionally, estimates from columns (3) and (4) indicate that women matched to female rather than male advisors in STEM departments experience between a 0.088 and 0.110 standard deviation increase in their overall GPA—though the effect in column (3) is statistically insignificant at conventional levels. We find no compelling evidence of GPA effects for women in non-STEM departments. Put together, these results suggest that post-major advising is beneficial for the persistence of female students in the sciences but is not as impactful for women pursuing non-STEM fields. Importantly, these results replicate those found in the freshman population further emphasizing the importance of female role models in the sciences.

[27] Indeed, it would be hard to disentangle the gender match effects of sophomore advising from earlier freshman advising for those students.

7 Conclusion

Despite the reversal of the gender gap in college attainment, females are still underrepresented in the sciences. This has given rise to numerous programs that provide women with personalized mentoring by female scientists in an effort to decrease the STEM gender gap. In this paper, we present some of the first causal evidence on the role of advisor or mentor gender in encouraging women to pursue STEM degrees. We utilize the unique advising system at the American University of Beirut—a private 4-year university—where students are randomly assigned to faculty advisors in their first year of college. Students apply for majors at the end of their freshman year, allowing them to repeatedly interact with their advisors prior to deciding on a major. Similar to most academic settings, an advisor's main task is to help students choose a major and courses, as well as monitor their academic progress.

We find that the gender gaps in STEM enrollment and graduation are substantially narrowed following exposure to a female rather than a male science advisor. Women also experience improvements in their GPA when assigned to a female science advisor. We further find that while both high and low ability women experience gains in their academic performance, the documented increase in STEM degree attainment is entirely driven by students with high mathematical ability—the women most likely to benefit from entering the STEM pipeline. We also show that non-science advisor gender has no significant impact on any of our outcomes of interest. Finally, we show that for students who have already declared a STEM major, having a female major advisor also improves female students' persistence in these fields. This suggests that receiving one-on-one mentoring by female scientists is important at all stages of postsecondary education.

Our findings indicate that providing one-on-one high-touch advising or mentoring by female scientists can play a key role in decreasing the STEM gender gap. This is in line with recent studies showing that intensive one-on-one mentoring and advising programs are effective in increasing college-going and breaking down educational barriers (Carrell and Sacerdote, 2017; Barr and Castleman, 2018). Our results complement these studies by highlighting how these programs can be used to influence major choice and increase the participation of women in STEM fields.

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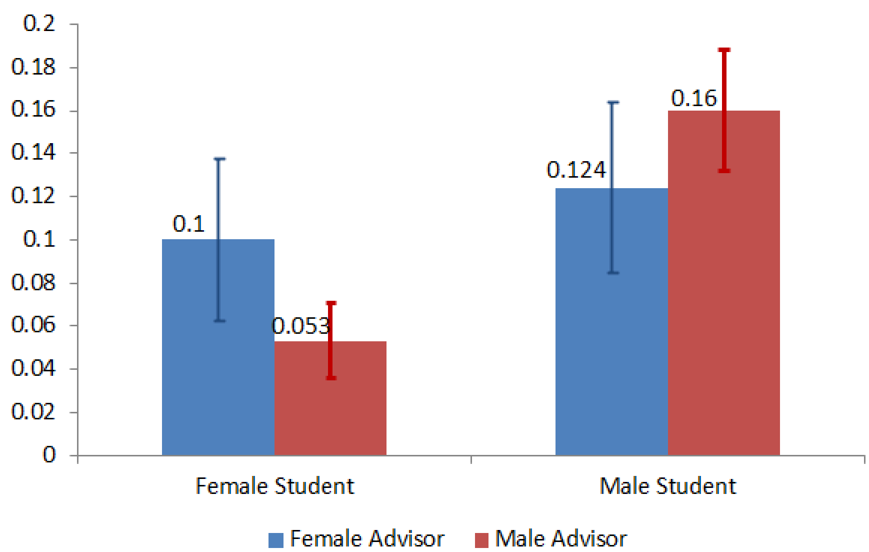
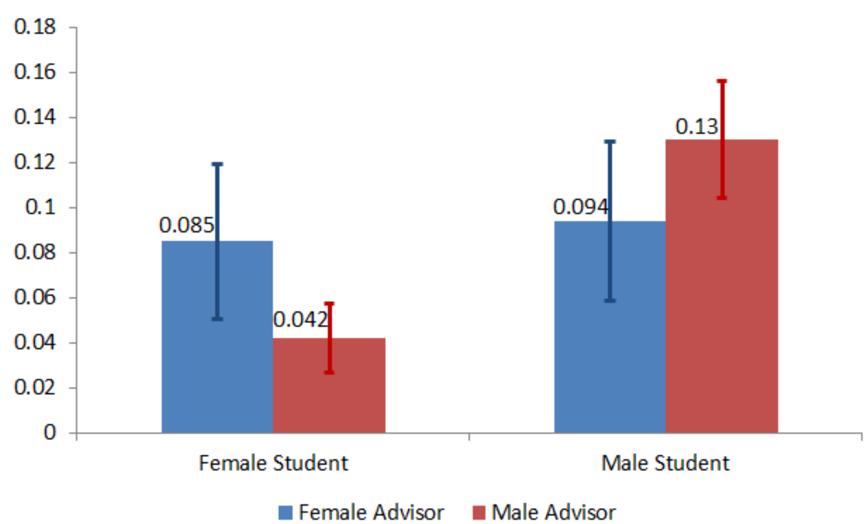
A Figures

Figure 1: Unconditional means of student and science advisor gender match



(a) Likelihood of enrolling in a STEM major



(b) Likelihood of graduating with a STEM degree

Notes: Sample includes all freshman students matched to a science advisor at AUB for the academic years 2003-2004 to 2013-2014. 95% Confidence Intervals presented in Bars.

B Tables

Table 1: Summary statistics for sample of freshman students

	All Advisors All Students	Science Advisors All Students	Science Advisors Male Students	Science Advisors Female Students	P-value of Diff. (3)-(4)
	(1)	(2)	(3)	(4)	(5)
Female Student	0.484	0.494			
	(0.500)	(0.500)			
Female Advisor	0.438	0.285	0.292	0.279	0.556
	(0.496)	(0.452)	(0.460)	(0.442)	
Math SAT Score	575.4	575.6	589	561.8	0.000
	(73.24)	(73.47)	(71.79)	(72.65)	
Verbal SAT Score	483.3	483.5	483.8	483.1	0.971
	(79.78)	(80.09)	(82.76)	(77.34)	
Standardized High School GPA	0.0343	0.0459	-0.0897	0.184	0.000
	(0.988)	(0.967)	(0.985)	(0.930)	
Legacy Status	0.197	0.211	0.215	0.206	0.134
	(0.398)	(0.408)	(0.411)	(0.404)	
Foreign High School	0.482	0.489	0.477	0.501	0.249
	(0.500)	(0.500)	(0.500)	(0.500)	
Likelihood of Enrolling in STEM degree* (Conditional on Declaring Major)	0.169	0.168	0.259	0.093	0.000
	(0.375)	(0.374)	(0.439)	(0.291)	
Likelihood of Graduating with STEM degree* (Within 6 years)	0.117	0.122	0.188	0.068	0.000
	(0.319)	(0.324)	(0.400)	(0.227)	
Freshman GPA	75.97	76.01	74.57	77.48	0.000
	(11.37)	(11.34)	(11.39)	(11.10)	
Likelihood of Becoming Sophomore	0.822	0.824	0.809	0.840	0.089
	(0.382)	(0.381)	(0.393)	(0.367)	
Likelihood of enrolling in STEM degree (Including Dropouts and Majorless Students)	0.105	0.108	0.150	0.066	0.000
	(0.307)	(0.311)	(0.357)	(0.248)	
Observations	3,409	1,804	912	892	

Note: Means and standard deviations (in parentheses) reported. Sample includes all freshman students matched to a science and non-science advisor at AUB for the academic years 2003-2004 to 2013-2014. p-values for the differences in means between male and female students matched to science advisors are reported in column 5.
*These two STEM variables are defined conditional on students declaring a major in their sophomore year. As a result, the number of observations for these variables are lower than the total number of observations.

Table 2: Freshman advisor characteristics

	Female Science Advisors	Male Science Advisors	Female Non-Science Advisors	Male Non-Science Advisors
	(1)	(2)	(3)	(4)
Share of advisors in the rank of Full Professor	0.101	0.479	0.492	0.100
	(0.302)	(0.500)	(0.500)	(0.300)
Share of advisors in the rank of Associate Professor	0.447	0.310	0.029	0.363
	(0.498)	(0.463)	(0.167)	(0.481)
Share of advisors in the rank of Assistant Professor	0.452	0.168	0.397	0.458
	(0.498)	(0.374)	(0.490)	(0.499)
Number of students per year	31.32	31.90	30.61	30.50
	(5.194)	(7.281)	(6.424)	(8.349)
Number of female students per year	15.37	16.03	14.72	14.45
	(2.706)	(5.064)	(3.891)	(4.282)
Mean students' Math SAT score	576.7	574.3	574.4	575.8
	(72.12)	(75.50)	(74.17)	(75.91)
Mean students' Verbal SAT score	484.7	480	483.2	479.3
	(82.99)	(78.11)	(85.37)	(79.93)
Number of unique advisors	6	12	9	11
Number of advisor-year observations	19	39	32	21

Note: Means and standard deviations (in parentheses) reported. Sample includes all freshman students matched to faculty advisors at AUB for the academic years 2003-2004 to 2013-2014. Faculty advisors who are promoted while advising are listed in the share of advisors in two separate ranks. One female non-science advisor is at the rank of "Lecturer" and is coded as assistant professor.

Table 3: Tests of balance of student baseline characteristics

	Math SAT Score	Verbal SAT Score	High School GPA	Foreign High School	Legacy Student
	(1)	(2)	(3)	(4)	(5)
Panel A: Female Versus Male Science Advisor					
Effect on male students (β_1)	-0.012	-0.003	-0.001	0.002	-0.005
	(0.069)	(0.050)	(0.028)	(0.028)	(0.026)
Effect on female students ($\beta_1 + \beta_3$)	0.040	0.025	0.040	0.067	-0.020
	(0.065)	(0.049)	(0.037)	(0.044)	(0.034)
Difference between female and male students (β_3)	0.052	0.028	0.041	0.065*	-0.015
	(0.082)	(0.061)	(0.042)	(0.039)	(0.042)
Observations (Science Advisor)	1,804	1,804	1,804	1,804	1,804
Panel B: Female Versus Male Non-Science Advisor					
Effect on male students (β_1)	-0.026	0.016	-0.010	0.016	-0.005
	(0.069)	(0.059)	(0.037)	(0.048)	(0.038)
Effect on female students ($\beta_1 + \beta_3$)	0.048	0.051	0.006	0.042	-0.011
	(0.090)	(0.054)	(0.040)	(0.043)	(0.034)
Effect on gender gap (β_3)	0.075	0.036	0.016	0.026	-0.006
	(0.081)	(0.067)	(0.037)	(0.038)	(0.049)
Observations (Non-Science Advisor)	1,605	1,605	1,605	1,605	1,605

Note: Each column represents estimates from separate regressions of student baseline characteristics when matched with a female versus male advisor. All regressions include academic year fixed effects. High School GPA and SAT scores are standardized by year. Standard errors clustered at the advisor-year level and reported in parentheses. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 4: Random assignment check

	Female Student Empirical P-Value (1)	Math SAT Empirical P-Value (2)	Verbal SAT Empirical P-Value (3)
A. Test for Student Characteristics			
Kolmogorov-Smirnow test (no. failed/total tests)	0/11	0/11	1/11
χ^2 goodness of fit test (no. failed/total tests)	0/11	0/11	0/11
B. Test for Advisor Characteristics			
Female Advisor	0.049	0.019	0.033
	(0.059)	(0.039)	(0.052)
Science Advisor	0.051	-0.025	- 0.032
	(0.59)	(0.49)	(0.054)
Associate/Full Professor	-0.040	0.033	0.063
	(0.067)	(0.057)	(0.056)
Number of Advisor-Years	111	111	111

Notes: Standard errors in parentheses are clustered at the advisor level. All regressions include year fixed effects. The empirical p-value of each advisor represents the proportion of the 10,000 simulated groups of students with a summed value less than that of the observed group. Sample includes students from academic years 2003-2004 till 2013-2014. The Kolmogorov-Smirnov and χ^2 goodness of fit test results indicate the number of tests of the uniformity of the distribution of p-values that failed at the 5 percent level. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table 5: The effect of having a female versus male science advisor on STEM outcomes and Freshman GPA

	Enroll in STEM			Graduate with STEM degree (within 6 years)			Freshman GPA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Effect on male students (β_1)	-0.037	-0.032		-0.036	-0.029		-0.106	-0.063	
	(0.029)	(0.022)		(0.027)	(0.023)		(0.065)	(0.059)	
	[0.097]	[0.064]		[0.115]	[0.090]		[0.020]	[0.111]	
Effect on female students ($\beta_1 + \beta_3$)	0.048**	0.054**		0.042**	0.043**		0.082	0.113**	
	(0.021)	(0.024)		(0.019)	(0.022)		(0.050)	(0.047)	
	[0.012]	[0.006]		[0.044]	[0.032]		[0.106]	[0.020]	
Effect on the gender gap (β_3)	0.084**	0.086**	0.084**	0.078**	0.072**	0.070**	0.188**	0.177***	0.168**
	(0.040)	(0.039)	(0.039)	(0.034)	(0.033)	(0.033)	(0.075)	(0.064)	(0.063)
	[0.002]	[0.000]	[0.002]	[0.005]	[0.005]	[0.006]	[0.001]	[0.001]	[0.002]
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Controls		Yes	No		Yes	No		Yes	No
Advisor Fixed Effects			Yes			Yes			Yes
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.022	0.108	0.116	0.018	0.093	0.110	0.034	0.138	0.153

Note: Dependent variable in columns 1 through 3 is the likelihood of students enrolling in a STEM major after freshman year. Dependent variable in columns 4 through 6 is the likelihood of graduating with a STEM degree within 6 years of enrollment. Dependent variable in columns 7 through 9 is freshman GPA. Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table 6: Freshman course level treatment effects when matched to a female versus male science advisor

	Take Sci. Course	Fail Sci. Course	Withdraw Sci. Course	Grade Sci. Course	Fail Non-Sci. Course	Withdraw Non-Sci. Course	Grade Non-Sci. Course
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effect on male students (β_1)	-0.007	0.034	0.027***	-0.087	0.017	0.006	-0.077
	(0.013)	(0.024)	(0.010)	(0.092)	(0.012)	(0.007)	(0.047)
	[0.270]	[0.042]	[0.010]	[0.043]	[0.052]	[0.290]	[0.051]
Effect on female students ($\beta_1 + \beta_3$)	0.023*	-0.050**	-0.007	0.140**	-0.026***	-0.004	0.057
	(0.013)	(0.024)	(0.009)	(0.056)	(0.009)	(0.006)	(0.031)
	[0.010]	[0.007]	[0.150]	[0.010]	[0.008]	[0.860]	[0.064]
Effect on gender gap (β_3)	0.031**	-0.084***	-0.034**	0.223**	-0.043**	-0.010	0.134**
	(0.014)	(0.027)	(0.013)	(0.099)	(0.017)	(0.009)	(0.054)
	[0.006]	[0.000]	[0.000]	[0.001]	[0.003]	[0.210]	[0.000]
Course-by-Semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,344	6,355	6,355	5,899	12,981	12,981	12,162

Note: Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include rank and department. Additionally, we interact all controls with student gender. Regressions in columns (2) through (7) also include course-by-semester fixed effects to control for unobserved mean differences in academic achievement or grading standards across courses and time. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table 7: Heterogeneous effects of science advisor gender match based on student ability

	Declare STEM major	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
High-ability student			
Math SAT$\geq$ Median=575			
Effect on male			
students (β_1)	-0.045	-0.028	-0.036
	(0.046)	(0.047)	(0.081)
	[0.137]	[0.326]	[0.528]
Effect on female			
students ($\beta_1 + \beta_3$)	0.100**	0.083*	0.182**
	(0.050)	(0.046)	(0.081)
	[0.018]	[0.032]	[0.024]
Effect on gender			
gap (β_3)	0.144*	0.111*	0.218*
	(0.073)	(0.066)	(0.114)
	[0.001]	[0.004]	[0.005]
Lower-ability student			
Math SAT< Median=575			
Effect on male			
students (β_1)	0.034	0.007	-0.073
	(0.023)	(0.017)	(0.094)
	[0.072]	[0.637]	[0.208]
Effect on female			
students ($\beta_1 + \beta_3$)	0.031	0.019	0.107
	(0.022)	(0.017)	(0.074)
	[0.197]	[0.359]	[0.110]
Effect on gender			
gap (β_3)	-0.003	0.013	0.180**
	(0.030)	(0.027)	(0.089)
	[0.883]	[0.485]	[0.022]
Year Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes
Observations (High ability)	898	898	898
Observations (Lower ability)	906	906	906

Note: Each column represents estimates from separate regressions. Graduating with STEM degree defined within 6 years of enrollment. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table 8: The effect of having a female versus male non-science advisor on STEM outcomes and Freshman GPA

	Enroll in STEM			Graduate with STEM degree (within 6 years)			Freshman GPA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Effect on male students (β_1)	0.003	0.018		0.029	0.018		0.110	0.036	
	(0.028)	(0.033)		(0.025)	(0.025)		(0.078)	(0.103)	
	[0.877]	[0.292]		[0.095]	[0.343]		[0.076]	[0.381]	
Effect on female students ($\beta_1 + \beta_3$)	-0.024	-0.015		-0.005	-0.021		0.036	0.029	
	(0.015)	(0.022)		(0.013)	(0.021)		(0.062)	(0.098)	
	[0.108]	[0.382]		[0.636]	[0.268]		[0.165]	[0.410]	
Effect on the gender gap (β_3)	-0.027	-0.034	-0.037	-0.035	-0.038	-0.038	-0.074	-0.065	-0.059
	(0.034)	(0.033)	(0.034)	(0.028)	(0.024)	(0.024)	(0.101)	(0.092)	(0.074)
	[0.130]	[0.133]	[0.123]	[0.091]	[0.088]	[0.076]	[0.122]	[0.146]	[0.112]
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Controls		Yes	No		Yes	No		Yes	No
Advisor Fixed Effects			Yes			Yes			Yes
Observations	1,605	1,605	1,605	1,605	1,605	1,605	1,605	1,605	1,605
R^2	0.040	0.136	0.140	0.035	0.124	0.130	0.051	0.189	0.200

Note: Dependent variable in columns 1 through 3 is the likelihood of students enrolling in a STEM major after freshman year. Dependent variable in columns 4 through 6 is the likelihood of graduating with a STEM degree within 6 years of enrollment. Dependent variable in columns 7 through 9 is freshman GPA. Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table 9: Potential mechanisms

	Ratio Female Peers in Same Class	Science Course (1st Semester)	Same Major as Advisor	Same Broad Field as Advisor
	(1)	(2)	(3)	(4)
Panel A: Science Advisor				
Effect on male students (β_1)	-0.004	-0.001	-0.006	0.007
	(0.003)	(0.017)	(0.008)	(0.022)
	[0.250]	[0.960]	[0.300]	[0.450]
Effect on female students ($\beta_1 + \beta_3$)	-0.004	0.028**	0.005	0.030*
	(0.004)	(0.014)	(0.006)	(0.017)
	[0.332]	[0.068]	[0.290]	[0.112]
Effect on the gender gap (β_3)	0.0003	0.029*	0.011	0.022
	(0.010)	(0.028)	(0.003)	(0.016)
	[0.191]	[0.190]	[0.820]	[0.059]
Panel B: Non-Science Advisor				
Effect on male students (β_1)	-0.012	0.026	0.004	-0.010
	(0.003)	(0.020)	(0.024)	(0.024)
	[0.210]	[0.261]	[0.340]	[0.130]
Effect on female students ($\beta_1 + \beta_3$)	0.004	0.008	0.015	0.047*
	(0.003)	(0.019)	(0.021)	(0.027)
	[0.336]	[0.681]	[0.230]	[0.010]
Effect on the gender gap (β_3)	0.000	0.018	0.027	0.021
	(0.002)	(0.016)	(0.018)	(0.032)
	[0.780]	[0.072]	[0.054]	[0.160]
Year Fixed Effect	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes
Number of Observations (Panel A)	19,344	9,811	1,804	1,804
Number of Observations (Panel B)	17,576	8,940	1,605	1,605

Note: Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table 10: Gender advising effects for students entering AUB as sophomore majors (Declared majors)

	Graduate from initial major	Graduate from initial major	Overall GPA	Overall GPA
	(1)	(2)	(3)	(4)
Panel A: STEM Majors				
Effect on male students (β_1)	-0.033	-0.021	0.012	0.022
	(0.037)	(0.040)	(0.070)	(0.076)
	[0.110]	[0.260]	[0.700]	[0.430]
Effect on female students ($\beta_1 + \beta_3$)	0.047*	0.042	0.088	0.110*
	(0.028)	(0.026)	(0.057)	(0.66)
	[0.101]	[0.133]	[0.190]	[0.090]
Effect on the gender gap (β_3)	0.080***	0.064	0.075	0.088
	(0.027)	(0.040)	(0.080)	(0.077)
	[0.002]	[0.010]	[0.152]	[0.134]
Panel B: Non-STEM majors				
Effect on male students (β_1)	0.001	-0.008	0.009	0.034
	(0.034)	(0.024)	(0.039)	(0.038)
	[0.960]	[0.390]	[0.590]	[0.092]
Effect on female students ($\beta_1 + \beta_3$)	0.027	0.010	0.014	0.031
	(0.028)	(0.022)	(0.023)	(0.025)
	[0.072]	[0.270]	[0.270]	[0.260]
Effect on the gender gap (β_3)	0.027	0.018	0.004	-0.003
	(0.028)	(0.019)	(0.043)	(0.042)
	[0.690]	[0.070]	[0.700]	[0.681]
Student Controls	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes
Department Fixed Effect	Yes	No	Yes	No
Year Fixed Effect	Yes	No	Yes	No
Department-year Fixed Effect	No	Yes	No	Yes
Number of Observations (STEM)	5,583	5,583	5,583	5,583
Number of Observations (Non-STEM)	6,207	6,207	6,207	6,207
Number of Unique Advisors	231	231	231	231

Note: Each column represents estimates from separate regressions. The above table uses the sample of students entering AUB as sophomore students (i.e. declared majors) and excludes those initially enrolled as freshmen and those in advisor groups with less than 5 students. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

C Appendix Tables

Table A1: Requirements for enrolling in history and mathematics

Number of credits required in each discipline by major

Major	English Level 200	Arabic	Humanities	Math[1]	Natural Sciences	Social Sciences	Electives
History	3	3	6	3	6	3	6
Mathematics	3	3	3	6	9	3	3

Notes: The above table shows the number of credits that a student must pass during the freshman year within each discipline in order to be eligible to enroll in history (first row) or mathematics (second row). Each course is typically equivalent to 3 credits.

Additional course and grade requirements by major

History	a minimum cumulative average of 70 in English courses taken in the freshman year
Mathematics	a minimum cumulative average of 70 in MATH 101 and 102, and a minimum grade of 70 in MATH 102

Notes: The above table shows specific courses and grades that students must obtain during the freshman year to be eligible to enroll in history or mathematics. For example, the mathematics department requires that students take Math 101 and Math 102. By passing these two courses, students receive 6 credits, thus obtaining the number of math credits required to enroll in the major (the first table shows that students need 6 credits in math).

Table A2: The effect of having a female science advisor on the likelihood of dropping out or not declaring a major

	Dropout or Undeclared Major	Dropout or Undeclared Major	Dropout or Undeclared Major
	(1)	(2)	(3)
Effect on male			
students (β_1)	0.025	0.004	
	(0.041)	(0.037)	
	[0.402]	[0.887]	
Effect on female			
students ($\beta_1 + \beta_3$)	-0.019	-0.025	
	(0.034)	(0.040)	
	[0.661]	[0.567]	
Effect on the			
gender gap (β_3)	-0.044	-0.029	-0.032
	(0.041)	(0.042)	(0.044)
	[0.210]	[0.427]	[0.445]
Year Fixed Effect		Yes	Yes
Student Controls		Yes	Yes
Advisor Controls		Yes	No
Advisor Fixed Effects			Yes
Observations	1,804	1,804	1,804

Note: Dependent variable in columns 1 through 3 is the likelihood that freshman students drop out or do not declare a major after their first year. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table A3: The effect of having a female versus male science advisor on STEM outcomes and Freshman GPA (Clustering at advisor level)

	Enroll in STEM			Graduate with STEM degree (within 6 years)			Freshman GPA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Effect on male students (β_1)	-0.037	-0.032		-0.036	-0.029		-0.106*	-0.063	
	(0.038)	(0.022)		(0.041)	(0.024)		(0.053)	(0.060)	
Effect on female students ($\beta_1 + \beta_3$)	0.048*	0.054**		0.042*	0.043**		0.082*	0.113**	
	(0.028)	(0.018)		(0.022)	(0.015)		(0.043)	(0.044)	
Effect on the gender gap (β_3)	0.084**	0.086**	0.084**	0.078*	0.072**	0.070**	0.188***	0.177***	0.168***
	(0.042)	(0.038)	(0.038)	(0.038)	(0.030)	(0.030)	(0.040)	(0.052)	(0.050)
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Controls		Yes	No		Yes	No		Yes	No
Advisor Fixed Effects			Yes			Yes			Yes
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.022	0.108	0.116	0.018	0.093	0.110	0.034	0.138	0.153

Note: Dependent variable in columns 1 through 3 is the likelihood of students enrolling in a STEM major after freshman year. Dependent variable in columns 4 through 6 is the likelihood of graduating with a STEM degree within 6 years of enrollment. Dependent variable in columns 7 through 9 is freshman GPA. Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor level and reported in parentheses. *** p <0.01 ** p <0.05 * p <0.1

Table A4: Heterogeneous freshman course level effects of science advisor gender match based on student ability

	Take Sci. Course	Fail Sci. Course	Withdraw Sci. Course	Grade Sci. Course	Fail Non-Sci. Course	Withdraw Non-Sci. Course	Grade Non-Sci. Course
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High ability students (Math SAT$\geq$ Median=575)							
Effect on male students (β_1)	-0.015	0.042	0.023*	-0.107	0.022	0.018*	-0.040
	(0.017)	(0.030)	(0.013)	(0.114)	(0.014)	(0.010)	(0.064)
	[0.112]	[0.030]	[0.010]	[0.070]	[0.110]	[0.042]	[0.063]
Effect on female students ($\beta_1 + \beta_3$)	0.042**	-0.039**	-0.016	0.032	-0.035**	-0.008	0.128***
	(0.017)	(0.017)	(0.011)	(0.087)	(0.013)	(0.006)	(0.046)
	[0.009]	[0.010]	[0.091]	[0.720]	[0.020]	[0.400]	[0.050]
Effect on gender gap (β_3)	0.057***	-0.081**	-0.039**	0.140	-0.057***	-0.027**	0.168**
	(0.021)	(0.037)	(0.017)	(0.139)	(0.021)	(0.012)	(0.083)
	[0.040]	[0.000]	[0.000]	[0.100]	[0.110]	[0.050]	[0.050]
Lower ability students (Math SAT< Median=575)							
Effect on male students (β_1)	-0.000	0.053*	0.040**	-0.055	0.018	-0.005	-0.116**
	(0.021)	(0.031)	(0.016)	(0.098)	(0.019)	(0.009)	(0.052)
	[0.970]	[0.008]	[0.010]	[0.111]	[0.074]	[0.500]	[0.000]
Effect on female students ($\beta_1 + \beta_3$)	0.004	-0.020	0.006	0.157	-0.022	-0.004	0.026
	(0.015)	(0.025)	(0.014)	(0.099)	(0.014)	(0.008)	(0.051)
	[0.720]	[0.133]	[0.530]	[0.070]	[0.120]	[0.810]	[0.650]
Effect on gender gap (β_3)	0.004	-0.073**	-0.033	0.212	-0.040	0.001	0.143**
	(0.024)	(0.036)	(0.021)	(0.131)	(0.025)	(0.012)	(0.070)
	[0.630]	[0.000]	[0.061]	[0.032]	[0.040]	[0.490]	[0.000]
Course-by-semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (High ability)	9,569	3,497	3,497	3,292	6,070	6,070	5,719
Observations (Lower ability)	9,775	2,858	2,858	2,607	6,911	6,911	6,443

Note: Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include rank and department. Additionally, we interact all controls with student gender. Regressions in columns (2) through (7) also include course-by-semester fixed effects to control for unobserved mean differences in academic achievement or grading standards across courses and time. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table A5: Freshman course level treatment effects when matched to a female versus male non-science advisor

	Take Sci. Course	Fail Sci. Course	Withdraw Sci. Course	Grade Sci. Course	Fail Non-Sci. Course	Withdraw Non-Sci. Course	Grade Non-Sci. Course
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effect on male students (β_1)	-0.006	-0.005	0.001	0.128	0.015	-0.006	-0.053
	(0.012)	(0.013)	(0.010)	(0.099)	(0.012)	(0.007)	(0.037)
	[0.660]	[0.381]	[0.512]	[0.080]	[0.053]	[0.072]	[0.089]
Effect on female students ($\beta_1 + \beta_3$)	-0.002	0.024	0.014	0.003	0.006	0.006	0.038
	(0.011)	(0.015)	(0.010)	(0.068)	(0.009)	(0.004)	(0.038)
	[0.830]	[0.052]	[0.510]	[0.780]	[0.750]	[0.630]	[0.065]
Effect on gender gap (β_3)	0.004	0.029	0.014	-0.125	-0.009	0.012	0.091*
	(0.015)	(0.022)	(0.014)	(0.096)	(0.016)	(0.009)	(0.052)
	[0.800]	[0.033]	[0.061]	[0.082]	[0.190]	[0.250]	[0.030]
Course-by-Semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,576	5,505	5,505	5,062	12,062	12,062	11,288

Note: Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include rank and department. Additionally, we interact all controls with student gender. Regressions in columns (2) through (7) also include course-by-semester fixed effects to control for unobserved mean differences in academic achievement or grading standards across courses and time. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table A6: The effect of having a female science advisor on student outcomes—with additional controls

	Enroll in STEM	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
Effect on male			
students (β_1)	-0.040	-0.036	-0.060
	(0.032)	(0.030)	(0.069)
	[0.067]	[0.062]	[0.085]
Effect on female			
students ($\beta_1 + \beta_3$)	0.053*	0.040*	0.100
	(0.028)	(0.021)	(0.070)
	[0.018]	[0.047]	[0.109]
Effect on gender gap			
(β_3)	0.094**	0.076**	0.159**
	(0.040)	(0.034)	(0.065)
	[0.000]	[0.001]	[0.001]
Year Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes
Advisor Rank X Advisor Gender	Yes	Yes	Yes
Advisor Rank X Student Gender	Yes	Yes	Yes
All Observations	1,804	1,804	1,804

Note: Each column represents estimates from separate regressions. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include academic rank and department. Additionally, we control for the interaction of student gender and all controls. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table A7: The effect of science advisor gender using alternative definitions of STEM

	Declare STEM major	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
Adding Biology to STEM			
Effect on male students (β_1)	-0.002	0.005	-0.046
	(0.021)	(0.020)	(0.042)
	[0.860]	[0.680]	[0.171]
Effect on female students ($\beta_1 + \beta_3$)	0.034*	0.030*	0.092*
	(0.019)	(0.017)	(0.049)
	[0.040]	[0.032]	[0.030]
Effect on gender gap (β_3)	0.037	0.024	0.138**
	(0.030)	(0.027)	(0.052)
	[0.120]	[0.112]	[0.001]
Adding Economics to STEM			
Effect on male students (β_1)	-0.041	-0.019	-0.070
	(0.025)	(0.023)	(0.058)
	[0.062]	[0.210]	[0.062]
Effect on female students ($\beta_1 + \beta_3$)	0.056**	0.047**	0.107**
	(0.027)	(0.022)	(0.047)
	[0.008]	[0.020]	[0.070]
Effect on gender gap (β_3)	0.097**	0.066**	0.177**
	(0.039)	(0.031)	(0.067)
	[0.001]	[0.001]	[0.000]
Year Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes
Observations (+Biology)	2,414	2,414	2,414
Observations (+Economics)	1,844	1,844	1,844

Note: Each column represents estimates from separate regressions. We add Biology (Economics) faculty advisors and students declaring majors in Biology (Economics) in new definitions of STEM respectively. Graduating with STEM degree defined within 6 years of initial enrollment. Student controls include verbal and math SAT scores, high school GPA, legacy status and birth year fixed effects. Advisor controls include faculty rank and department. We interact all controls and fixed effects with student gender. Standard errors clustered at the advisor-year level and reported in parentheses. Randomization inference based p-values reported in brackets. *** p <0.01 ** p <0.05 * p <0.1

Table A8: Results from advisor survey

	Female science advisors				Male science advisors			
	Female students (1)	Male students (2)	Similar (3)	Don't know (4)	Female students (5)	Male students (6)	Similar (7)	Don't know (8)
A. Advisor's perception of student behavior								
Who is more likely to attend or schedule meetings	1/3	0/3	1/3	1/3	1/4	0/4	3/4	0/4
Who spends more time in meetings	2/3	0/3	1/3	0/3	0/4	0/4	4/4	0/4
Who is more likely to follow your advice	1/3	0/3	2/3	0/3	1/4	0/4	2/4	1/4
Who is more comfortable talking to you	0/3	0/3	3/3	0/3	2/4	0/4	2/4	0/4
Who is more likely to follow up with you	1/3	0/3	2/3	0/3	1/4	0/4	3/4	0/4
Who is more confident about their math/science abilities	0/3	1/3	2/3	0/3	0/4	3/4	0/4	1/4
B. Advisor behavior								
Who are you more likely to schedule meetings with	0/3	0/3	3/3	0/3	0/4	0/4	4/4	0/4
Who do you give more time to during advising sessions	0/3	0/3	3/3	0/3	0/4	0/4	4/4	0/4
Who are you more likely to follow up with	0/3	1/3	2/3	0/3	0/4	0/4	4/4	0/4

	Female science advisors			Male science advisors		
	Yes (1)	No (2)	Don't know (3)	Yes (4)	No (5)	Don't know (6)
C. Advisor attitudes						
Do you use a different style of advising with female and male students	2/3	1/3	0/3	0/4	4/4	0/4
Do you feel it's harder for women to be successful in the sciences	2/3	1/3	0/3	0/4	4/4	0/4
Would you encourage women to pursue science fields	1/3	2/3	0/3	4/4	0/4	0/4

Note: This table reports answers to a survey conducted among three female and four male science advisors. Each cell shows the fraction of female and male advisors who gave a specific answer to each question. The answers of female science advisors are reported in columns (1) to (4) of panels A and B, and columns (1) to (3) of panel C. The answers of male science advisors are shown in columns (5) to (8) of panels A and B, and columns (4) to (6) of panel C.

Table A9: Summary statistics for students entering AUB as sophomores (Declared majors)

	All	STEM Majors	Non-STEM Majors
	(1)	(2)	(3)
Female Student	0.472	0.276	0.638
	(0.500)	(0.448)	(0.482)
Female Advisor	0.334	0.110	0.525
	(0.473)	(0.309)	(0.500)
Math SAT Score	637.1	670.7	609.4
	(73.18)	(64.15)	(67.73)
Verbal SAT Score	497.7	508.4	489
	(93.19)	(99.77)	(86.48)
Standardized High School GPA	-0.0763	0.170	-0.281
	(1.004)	(0.930)	(1.014)
Legacy Status	0.209	0.180	0.232
	(0.407)	(0.384)	(0.422)
Likelihood of Graduating (Within 6 years)	0.831	0.855	0.814
	(0.375)	(0.353)	(0.389)
Standardized Graduating GPA	-0.0109	-0.0211	0.00207
	(0.701)	(0.692)	(0.698)
Observations	11,856	5,391	6,426

Note: Means and standard deviations (in parentheses) reported. Sample includes all first time entering sophomore students matched to an academic advisor (with at least 5 students) at AUB for the academic years 2003-2004 to 2013-2014.