

Female Science Advisors and the STEM Gender Gap*

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Abstract

To reduce the gender gap in science fields, policymakers often propose providing women with one-on-one mentoring by female scientists. However, there is no clear evidence on whether mentor or advisor gender can influence women’s participation in STEM. To address this question, we exploit a unique setting where students are randomly assigned to academic advisors—who are also faculty members—in their freshman year of college. 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

Over the past decade, employment in the fields of science, technology, engineering and mathematics (STEM) has been growing at a substantially higher rate than most other occupations. Recent evidence also indicates that there are large earnings gains from holding STEM versus non-STEM degrees (Hastings, Neilson and Zimmerman, 2013; Kirkbøen, Leuven and Mogstad, 2016; Canaan and Mouganie, 2018). Despite these significant labor market returns, women are still underrepresented in many STEM fields. In 2013, women accounted for 31 percent of U.S. postsecondary graduates in the sciences and merely a quarter of all STEM jobs. This gender disparity is apparent from the early stages of postsecondary education; in 2012, 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).

In light of this issue, discussions among policymakers and researchers on how to improve the status of women in the sciences have become more prominent. Mentorship has emerged as an “important key to increasing and keeping women engaged in scientific and technical careers” (White House OSTP, 2011). Accordingly, a variety of mentoring initiatives have been recently put in place with the goal of promoting women’s persistence in STEM 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. The program, which offers group mentoring by senior female economists, has shown to improve women’s publication records and access to grants (Blau et al., 2010). The premise for such programs is that *female scientists* can act as role models, inspiring other women to seek and persist in STEM careers. Exposure to female mentors or advisors can also mitigate the negative impacts of gender stereotypes. Indeed, lack of female role models and gender stereotyping are often put forth as some of the main reasons for the underrepresentation of women in science fields (Blickenstaff, 2005; Leslie et al., 2015).

In this paper, we present the first causal evidence on how advisor gender impacts the STEM gender gap. Despite considerable policy relevance, there is still no clear evidence on the role of one-on-one mentor or advisor gender in women’s decisions to pursue careers in STEM. The scarcity of work on this topic can be mainly attributed to difficulties with identifying causal effects. The few papers that focus on the role of advisor gender in the sciences cannot overcome this challenge. 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.¹ 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.

We examine whether women’s likelihood of enrolling and graduating with STEM degrees is influenced by their academic advisors’ gender in the first year of college. Most U.S. colleges offer academic advising in order to help undergraduate students set and achieve their educational goals. In general, an advisor’s duties are to monitor students’ academic progress, provide personalized assistance with selecting courses and developing a plan of study, give information on academic programs and majors, and offer academic and career mentoring. Additionally, first-year or pre-major advisors help students 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. Our focus on high-touch advising is consonant with recent studies showing that coaching and intensive advising programs substantially increase college enrollment and graduation (Avery, 2010; Bettinger and Baker, 2014; Lavecchia et al., 2016; Carrell and Sacerdote, 2017; Barr and Castleman, 2018; Castleman and Goodman, 2018; Kato and Song, 2018). However, our paper is the first to examine how advising impacts college *major choice*.

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 2.1, AUB is 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 several unique features of AUB’s advising system to answer the question at hand. First and foremost, 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. Second, 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. Third, students are *required* to meet one-on-one with their advisors at the beginning of each semester and prior to course

¹See for example, Neumark and Gardecki (1998); Hilmer and Hilmer (2007); Pezzoni et al. (2016); Gaule and Piacentini (2018).

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 female science advisor 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 percentage points. The impacts are long-lasting as we document a comparable 7 percentage point decrease in the gender gap in STEM graduation. These effects are substantial and the gender gaps in both STEM enrollment and graduation are significantly narrowed. We further find that female science advisors improve women's academic performance. Relative to male students, females experience an 18 percent of a standard deviation improvement in their freshman year GPA when matched with a female rather than a male science advisor. While academic performance is increased for women of all ability levels, the STEM enrollment and graduation effects are driven by students with high mathematical ability. This suggests that the documented increase in female STEM enrollment is not mainly driven by improved academic performance, but rather by affirmation effects through various interactions with female scientists. This is in line with our findings from in-person interviews conducted with female and male science advisors as further discussed in section 6.4. Finally, we find that the gender of a non-science advisor has no significant impact on students' major choice or academic performance. This highlights that female mentors are particularly important in the sciences. This is also consistent with evidence showing that the lack of female role models and negative gender stereotypes are major barriers to women entering STEM fields (Blickenstaff, 2005).

Our paper is related to a growing literature that looks at how 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 (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.² In line

²Several studies find that female teachers increase female students' performance in math and science courses (Bettinger and Long, 2005; Dee, 2007; Lim and Meer, 2017; Gong et al., 2018). Mansour et al.

with these findings, several randomized controlled trials have been recently conducted to raise women’s interest in STEM majors. Porter and Serra (forthcoming) recruit two female economics alumni of Southern Methodist University to discuss their careers, achievements and experiences in their major with students 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. 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.

Our study adds to this literature in several ways. First, to the best of our knowledge, this paper is the first to show that advisor gender significantly impacts the likelihood that women enroll and graduate with STEM degrees. Compared to the interventions that have been previously studied in the literature, academic advising is more intensive and high-touch. Indeed, an academic advisor’s main role is to provide students with continuous one-on-one mentoring and personalized support outside the classroom at a critical time in their postsecondary education. A second 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. Finally, the policy implications of our study are distinct from the rest of the literature. Our findings are more suitable to inform the design of mentoring programs aimed at engaging women in the sciences. Specifically, our results suggest that providing women with close mentoring by female scientists can significantly reduce the STEM gender gap.

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

(2018) show that professor gender can influence STEM occupation choice in the U.S. Air Force Academy. Additionally, Kofoed and mcGovney (2019) show that same-race or same-gender tactical officers at the United States Military Academy impact cadets’ occupational choices.

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 (UNDP, 2017). The university enrolls around 7,000 undergraduate students per year. 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% of full-time faculty have doctoral degrees. Importantly, 50% of students and around 40% 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% of all undergraduate students and 44% 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. 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. Many departments also impose additional grade requirements. Those requirements are not typically restrictive or necessarily difficult to meet.³ For example, the mathematics department requires that prospective students obtain a minimum grade of 70 on two relatively advanced mathematics courses (MATH 101 and MATH 102). However, students are free to select all other courses conditional on those courses meeting the credit requirements within each discipline. Third, 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.⁴ 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

³The only exception are engineering majors which require that students take a specific set of science and mathematic courses and obtain a minimum GPA of 80 during the freshman year. Furthermore, admission into engineering is not necessarily granted upon the fulfillment of these requirements, as these majors are very selective. Freshman students' applications are pooled with those who are applying directly to the sophomore year, and the admission rate is around 17%.

⁴The 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.

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 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 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.

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 3,415 incoming Freshman students enrolled at AUB from the academic years 2003-2004 to 2013-2014.⁵ For each student,

⁵Freshman 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.

we have detailed information on gender, university course grades and credits acquired. 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 columns (3) and (4) of Table 1 and show that female science advisors are equally distributed between male and female students. Additionally, men outscore women by an average 27 points on the mathematics portion of the SAT exam. Conversely, men and women score roughly the same on the verbal portion of the SAT exam. In terms of overall high school GPA, reported in standard deviations, freshman female students outperform men by a significant margin.⁶ 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.

The main outcome of interest in this paper is the likelihood of enrolling in a STEM major.⁷ Recall, in our context, field of study is determined directly after Freshman year.

⁶Almost 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.

⁷We define the following majors as STEM: Mathematics, Physics, Geology, Statistics, Computer Science,

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. 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 the first year; the average GPA for women is around 3 points higher—out of a scale of 100—than that of men during freshman year. Finally, around 82 percent of freshman students transition to the sophomore year, with women being 3.1 percentage points 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 whether they declared a major. This definition encompasses students who drop out and those who declare majorless status in their second year. Using this definition, the likelihood that all freshman male students declare a STEM major is 15 percent, compared to 6.6 percent for women—an 8.4 percentage point gap.⁸

3.3 Advisor Summary Statistics

In Table 2, we summarize information for all freshman faculty advisors.⁹ 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.¹⁰ 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

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.

⁸In our main analysis, we use this definition of STEM enrollment as our outcome of interest. We do so since persistence and major declaration are also outcomes that can be affected by freshman advisor gender.

⁹Though rare, we exclude any freshman advisors who advise less than 5 students for a specific year.

¹⁰Recall, 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.

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 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. To affirm that this effect is due to the lack of female role models in the sciences, we also look at whether being exposed to a female rather than male *non-science* advisor has an impact on students' outcomes. Importantly, the gender and department (science versus non-science) of a student's freshman advisor is random and does not depend on their preferred future major or academic ability, a result we confirm in section 5.1. Formally, we run the following triple differences regression model for all incoming freshman students:

$$Y_{iat} = \beta_0 + \beta_1 Femadv_a + \beta_2 Femst_i + \beta_3 Femst_i * Femadv_a + \beta_4 Deptsci_a + \beta_5 Femst_i * Deptsci_a + \beta_6 Femadv_a * Deptsci_a + \beta_7 Femst_i * Femadv_a * Deptsci_a + X'_i \gamma + A'_a \delta + \sigma_t + \epsilon_{iat} \quad (1)$$

where Y_{iat} refers to the outcome of interest for student i matched to advisor a in academic year t . $Femadv_a$ is a dummy variable that takes on values of 1 if advisor a is female and 0 otherwise. $Deptsci_a$ is another dummy variable that takes on values of 1 if advisor a is in a science department and 0 otherwise. $Femst_i$ is an indicator variable for whether freshman student i is female. Additionally, we include interaction terms for all 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. $\beta_3 + \beta_7$ is our main treatment parameter of interest and captures the relative change in the STEM gap between girls and boys when matched to a female rather than a male *science*

advisor. $\beta_2 + \beta_5$ is the average difference between female and male students matched to male science advisors which allows us to measure a baseline gender gap. Additionally, β_3 is another parameter of interest that measures the relative change in the gap between girls and boys when matched to a female rather than a male *non-science* advisor. 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 contains 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 most specifications, advisor controls are subsumed by advisor fixed effects, enabling us to control for any differences across advisors. Finally, σ_t is an academic year fixed effect that controls for unobserved changes across different years and 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.¹¹

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:

$$Y_{iatc} = \beta_0 + \beta_1 Femadv_a + \beta_2 Femst_i + \beta_3 Femst_i * Femadv_a + \beta_4 Deptsci_a + \beta_5 Femst_i * Deptsci_a + \beta_6 Femadv_a * Deptsci_a + \beta_7 Femst_i * Femadv_a * Deptsci_a + X'_i \gamma + A'_a \delta + \alpha_{ct} + \sigma_t + \epsilon_{iatc} \quad (2)$$

where Y_{iatc} refers to course level achievement outcomes for student i matched to 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), $\beta_3 + \beta_7$ is our main parameter of interest and measures the change in the course level achievement gap between female and male students when moving from a male to a female science advisor.

¹¹Results remain unchanged if we cluster our standard errors at the advisor level as we show in Table A2 of the Appendix.

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. In order to alleviate concerns over sample selection, we first check whether being assigned to a faculty advisor from a specific department is consistent with random matching. To do so, we regress a dummy variable for whether an advisor is in a science versus non-science department on predetermined student characteristics. Column 1 of Table 3 summarizes the results of this test. We find no significant relationship between the likelihood of having a science advisor and student gender or student ability, proxied by SAT scores and high school GPA. Other student characteristics such as high school location are also statistically unrelated to advisor department; the only exception is legacy status which is significant at the 10% level. We also find that these characteristics are jointly insignificant, as indicated by a p-value of 0.41 from a test of joint significance. These results confirm that students who are assigned to a science versus non-science advisor are similar in terms of observable characteristics, consistent with random student-advisor matching.

We next test whether students are randomly assigned to advisors of different genders. To do so, we regress the likelihood of being matched to a female rather than a male advisor on students' baseline characteristics. Column 2 of Table 3 shows the results of this test for all freshman students, i.e. those assigned to science and non-science advisors. We present results from a similar regression in column 3, but only for students matched to a science advisor. We find that students' gender, ability as well as legacy and foreigner status are individually and jointly unrelated to advisor gender. Taken together, these results are in line with our institutional setting which indicates that students are randomly assigned to faculty advisors, independently of advisors' department and gender.

5.2 STEM enrollment, STEM graduation and Academic Performance

5.2.1 Visual Evidence

We start by examining whether being matched to a female science advisor 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).

5.2.2 Regression Analysis

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 4 summarizes results from this exercise for various outcomes and specifications. We begin by reporting estimates on STEM enrollment in columns (1) to (3) of Table 4. Results from our most basic specification, that include no controls, are reported in column (1). The estimate on treatment ($\beta_3 + \beta_7$), our main parameter of interest, 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.¹² This implies a 77 percent reduction in the gender gap in STEM enrollment compared to a baseline 10.8 percentage point ($\beta_2 + \beta_5$) gap when students are matched to a male science advisor. The magnitude of this decrease is comparable to estimates reported by Carrell, Page and West (2010), who focus on the gender match between students and their professors in introductory math and science courses. Specifically, the authors document that for high-ability students, the gender gap in STEM graduation is completely eradicated when the fraction of female professors is raised from 0% to 100%. Additionally, we find no significant effect on the STEM gender gap when looking at non-science advisor gender match. Indeed, the coefficient β_3 on the interaction term *Female Advisor* \times *Female Student* is negative, relatively small in magnitude and statistically insignificant. This indicates that switching from a male to a female non-science advisor does

¹²Overall, this effect is driven by a statistically significant 4.7 percentage point ($\beta_1 + \beta_3 + \beta_6 + \beta_7$; p-value=0.065) benefit for female students and a statistically insignificant 3.7 percentage point ($\beta_1 + \beta_6$) reduction for male students when assigned a female advisor.

not narrow the STEM enrollment gender gap, rather it potentially slightly widens this gap. 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 advisor fixed effects allowing for identification from within-advisor variation in the gender match. In column (3), we additionally control for student baseline characteristics such as SAT scores, high school GPA, legacy and birth year fixed effects. Consistent with the random assignment of students to advisors, estimates on treatment ($\beta_3 + \beta_7$) remain statistically significant and similar in magnitude to those reported in column (1).

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 science and non-science advisor gender. In columns (4) through (6) of table 4, we present estimates on the likelihood of graduating with a STEM degree within 6 years of initial university enrollment.¹³ Estimates on treatment 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.¹⁴ Conversely, the statistically insignificant estimate of -0.035 on the interaction term *Female Advisor* \times *Female Student* indicates that women are not more likely than men to graduate with a STEM degree when matched with a female as opposed to male non-science advisor. In line with the random assignment of students to advisors, the addition of year and advisor fixed effects as well as student controls does not significantly alter estimates as shown in columns (5) and (6).

Finally, we examine whether science and non-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 4, we report estimates on the impact of student advisor gender match on standardized GPA at the end of freshman year. Interestingly, estimates from column (7) indicate that female students already outperform males by 21.4 percent of a standard deviation even when both are matched to a male science advisor. This gap increases by a significant 18.8 percent of a standard deviation when the science advisor is female rather male. However, for

¹³This 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.

¹⁴Overall, the absolute gain for female students from having a female advisor ($\beta_1 + \beta_3 + \beta_6 + \beta_7$) is on the order of 4.2 percentage points (p-value=0.081).

women matched to a non-science advisor we find that transitioning from a male to female advisor leads to a statistically insignificant (-0.074) decrease in performance as compared to men. The addition of student controls and year and advisor fixed effects does not alter the estimates in a meaningful way as shown in columns (8) and (9). Put together, findings from this section indicate that female students benefit significantly from exposure to female as opposed to male science advisors but are largely unaffected by the gender of non-science advisors.

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.¹⁵ Accordingly, in table 5, we examine whether having a female science advisor encourages women to take more science courses, and whether it also improves their course performance. We also analyze the effects of a female non-science advisor on the same outcomes. The coefficient on treatment in column (1) shows 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. 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. Additionally, the coefficient on the interaction term *Female Advisor* \times *Female Student* indicates no significant impact on this gap for women matched to a female as opposed to male non-science advisor.

Estimates on treatment from columns (2) to (4) further indicate that women substantially outperform men in science coursework when matched with female rather than male science advisors. Specifically, female students are 8 and 4.6 percentage points less likely to fail and withdraw from science courses as compared to men. They also experience a 0.2 standard deviation increase in science course grades, relative to men. We find no compelling evidence of improved academic performance on any of these outcomes for women matched to a female non-science advisor. We also examine how performance on non-science coursework is impacted by science and non-science advisor gender match. These results are summarized in columns (5) to (7) of Table 5. The estimates on treatment indicate that science advisor gender also has a significant impact on women’s performance in non-science course performance, though these effects are smaller than those found for science coursework. Indeed,

¹⁵Specifically, 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.

moving from a male to female science advisor decreases women’s chances of failing a non-science course by 3.4 percentage points and improves their performance in these courses by 14.8 percent of a standard deviation, relative to men. However, we find no significant impact on course withdrawal from non-science coursework. Our findings on course withdrawal are particularly interesting. Students have to decide on whether or not to withdraw from a specific course before sitting for the final exam. Having to make a decision before knowing their final performance on the course means that students may be more likely to seek advice and follow their advisor’s recommendation on the matter. More importantly, advisors directly influence whether students withdraw from courses since they have to provide written consent and a valid reason for course withdrawals. The fact that we observe a decrease in withdrawal from science but not from non-science courses, despite improved performance in both, further highlights the importance of female mentors in influencing women’s persistence in the sciences. Finally, we find that switching from a male to female non-science advisor does not affect the likelihood of failing or withdrawing from a non-science course for women, relative to men. However, it does seem to improve female students’ relative performance in these courses by around 9 percent of a standard deviation.

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 6 presents the corresponding heterogeneous treatment estimates for our main outcomes of interest where we include student controls as well as advisor and year fixed effects throughout. Noticeably, 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. The estimates on treatment ($\beta_3 + \beta_7$) 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 13.4 and 11.2 percentage points respectively. In contrast, the estimates on treatment for low ability students are statistically insignificant and quite small in magnitude, indicating that exposure to a female advisor does not improve lower ability

women’s likelihood of STEM investment.

In column (3) of Table 6, we present heterogeneous science advisor gender effects on GPA at the end of the freshman year. Strikingly, both high and low ability female students substantially outperform males when assigned a male science advisor. Additionally, estimates on treatment indicate that being matched to a female rather than male science advisor widens the gender gap in academic performance for both groups. Switching from a male to a female science advisor improves high ability female students’ academic performance, relative to men, by 19 percent of a standard deviation—significant at the 10% level. Low ability women also experience an improvement in their performance, albeit the estimate of 16.4 is statistically insignificant at conventional levels, most likely due to reduced precision. These results suggest that high and lower ability women experience some grade benefits from being matched to a same sex science advisor. However, in terms of increasing STEM degree attainment, science advisor gender impacts only female students who are already skilled in mathematics. Indeed, results from this section indicate that 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 also suggests that female students may be re-optimizing their degree choice towards their comparative advantage when exposed to female scientists.

Finally, we look at how science advisor gender affects high and low ability students’ course choice and performance. Appendix Table A3 summarizes the results of this exercise. We find that high ability women are 5.9 percentage points more likely than high ability men to take science courses when matched to a female rather than male science advisor. They are also 9.6 and 5.2 percentage points less likely to fail and withdraw from science courses respectively. In terms of grades in science course work, high ability female students experience an 14.2 percent of a deviation improvement in scores, relative to men—though this effect is statistically insignificant at conventional levels. In terms of course performance in non-science courses, high ability women are 4 percentage points less likely to fail a non-science course and their test scores in these courses are improved by 15.9 percent of a standard deviation, relative to men. For low ability women, we find that being matched to a female science advisor has no significant effect on science course-taking behavior. However, switching to a female advisor does lower the relative likelihood that female students fail a science course by 7.5 percentage points. It also substantially improves low ability students’ grades in science and non science coursework, though the estimate on science course grades is statistically insignificant, most likely due to reduced precision. Importantly, low ability female students experience an improvement in academic performance despite their course choices being unaffected by the gender of their advisor. 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.

6 Discussion

6.1 Could Rank of Faculty Advisor Be Driving Results?

In this paper, we show that women assigned to a female rather than male science advisor are more likely to enroll and graduate from a STEM major. We further show that these 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.¹⁶ The results of this exercise are reported in Appendix Table A4 and indicate that our main results are robust to the inclusion of these controls. Estimates on the treatment term for STEM enrollment and graduation as well as Freshman GPA are quantitatively similar to our most saturated specification presented in Table 4. Additionally, coefficients on the interaction term *Female Advisor* \times *Female Student* are similar to our previous findings of a null effect on non-science advisor gender match. This indicates that differences in student-gender responsiveness to advisor gender-rank are not driving our results.

6.2 Are Female Students More Likely to Pursue Female Advisors' Major?

We now turn to the question of why student-advisor gender match matters for women in the sciences. The simplest explanation of our results may be that female students are more likely to enroll in the same major as their female science advisor. To investigate this, we look at the effect of advisor gender on men and women's likelihood of enrolling in the

¹⁶Specifically, 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.

same major as their advisors. The results of this exercise are summarized in column (1) of Table 7. The coefficient on treatment is small in magnitude (0.004) and statistically insignificant. This suggests that switching from a male to a female science advisor does not result in women being more likely than men to pursue the same major as their advisors. We also find no evidence of this for women assigned to female non-science advisors. However, while the estimate on the interaction term *Female Advisor* \times *Female Student* is statistically insignificant, the magnitude of this coefficient is larger than that for science advisors. This suggests potentially small and positive effects on the relative likelihood female students enroll in the same major as their non-science female advisors. This could also help explain part of the documented negative, but insignificant, effects we found on the STEM gender gap for women matched to a female non-science advisor relative to a male advisor. Altogether, these results suggest that for students matched to science advisors, our main results are not driven by women being more likely to choose the same major as their female advisor.

6.3 Are Female Students Matched to Female Advisors More Likely Enroll in Classes with Female Instructors?

Another potential explanation for the documented effects on the STEM gender gap could be that our effects are driven by class instructor gender. Specifically, if moving from a male to female science advisor increases the likelihood that women take classes with female instructors, then this could potentially be driving our effects. We investigate this issue by looking at whether student-advisor gender match affects women’s likelihood of enrolling in classes with female instructors, relative to men. These results are summarized in column (2) of Table 7 for students matched to a science and non-science freshman advisor respectively. Both estimates reported in column (2) are statistically insignificant and small in magnitude indicating that moving from a male to a female advisor does not alter women’s relative likelihood of taking classes with a female instructor—regardless of advisor field.

6.4 Female Scientists as Role Models

In this paper, we find that exposure to female scientists not only impacts female students’ major choice but also their academic performance during freshman year. The documented improvement in students’ test scores could indicate that females work harder in order to meet the requirements for entry into science majors, which are typically more selective than non-science fields. It could also suggest that female students are simply more motivated when exposed to a female science mentor. A key question thus arises: is the increase in female STEM enrollment driven by improvement in academic performance, or is a woman’s

decision to pursue a STEM field also directly influenced by interactions with a female science advisor in ways that extend beyond grades?

While it is difficult to provide a definitive answer to this question, we nonetheless present suggestive evidence on what might be driving our main effects. First, the heterogeneity analysis presented in Table 6 is revealing. Both high and low ability female students experience increases in their freshman year GPA as a result of being assigned to a female rather than a male science advisor. However, only female students with high mathematical ability are driven to enroll in and graduate with a STEM degree. Low ability students are not more likely to pursue STEM fields despite the fact that they also experience gains in their Freshman GPA. Heterogeneous course level estimates presented in Appendix Table A3 are even more striking. Despite substantial improvement in course performance indicators for both high and low ability women, only high ability female students are more likely to take science courses during freshman year. These results indicate that the ideal type of student is being pushed towards the sciences—i.e., female students with high mathematical ability who would have otherwise not entered the STEM pipeline. They also suggest that female students’ decisions to take STEM courses and enroll in a STEM major are not solely the result of improved academic performance. Additionally, we show in column 3 of Table 7 that compared to males, female students are 3 percentage points more likely to take a science course in their *first* semester of the freshman year when assigned a female rather than a male science advisor.¹⁷ 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. This indicates that the documented improvement in course performance during freshman year is not driving the increase in science course taking for women, rather this change seems to be more consistent with a socio-psychological interpretation in which female advisors acts as a positive reinforcement for girls wanting to enter the STEM pipeline.

Finally, our finding of increased STEM enrollment and academic performance for female students is consistent with two broad interpretations; either girls 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 girls and boys. While it is beyond the scope of this paper to conclusively speak to the mechanisms driving our effects, we nonetheless provide some suggestive evidence on this issue. To do so, 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

¹⁷In results available upon request, we also find a statistically similar 3.2 percentage point difference when looking at the second semester of the freshman year.

in Appendix Table A5. 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 boys are more engaged in the advising process than girls. 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 girls spend more time in meetings than boys. This suggests that girls are more willing to engage with female rather than male science advisors.

In Panel B of Table A5, 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 A5. 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 boys and girls. 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 boys 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. 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 girls spend more time than boys 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.

6.5 Pre-Major versus 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 A6 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 34 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 (636) 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.¹⁸ The results of this exercise are summarized in Table 8. 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 advisor 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 8.3 percentage points more likely to graduate with a STEM degree, relative to men—an effect that is

¹⁸Indeed, it would be hard to disentangle the gender match effects of sophomore advising from earlier freshman advising for those students.

significant at the 5 percent level. Conversely, the statistically insignificant estimate of 0.032 on the interaction term *Female Advisor* \times *Female Student* indicates positive but relatively smaller and statistically insignificant effects on graduation for non-STEM students matched to female rather than male advisors. These estimates are robust to the inclusion of advisor fixed effects as illustrated in column (2). Additionally, estimates from columns (3) and (4) indicate that women matched to female rather than male mentors in STEM departments experience a 0.08 standard deviation increase in their overall GPA, relative to men—though this effect 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 mentoring 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.

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. Finally, given that most colleges already provide some type of academic advising, matching female students to female science advisors may be a scalable strategy to reduce the STEM gender gap.

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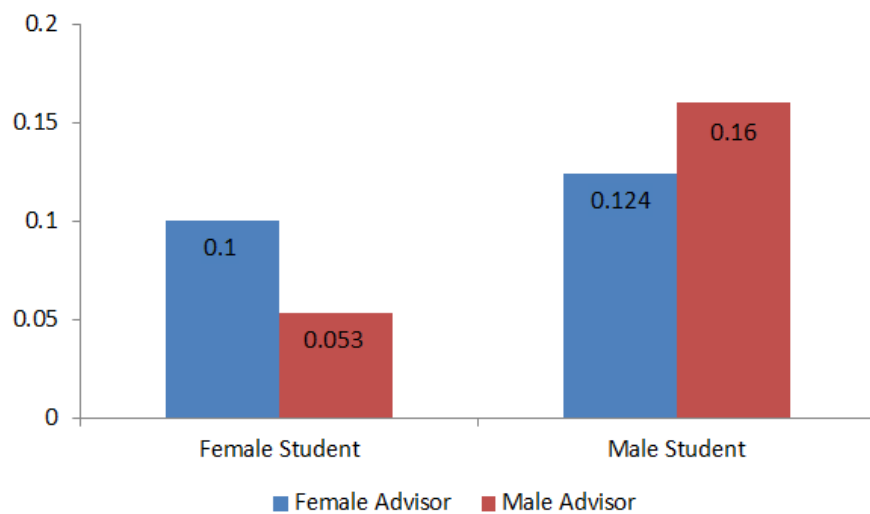
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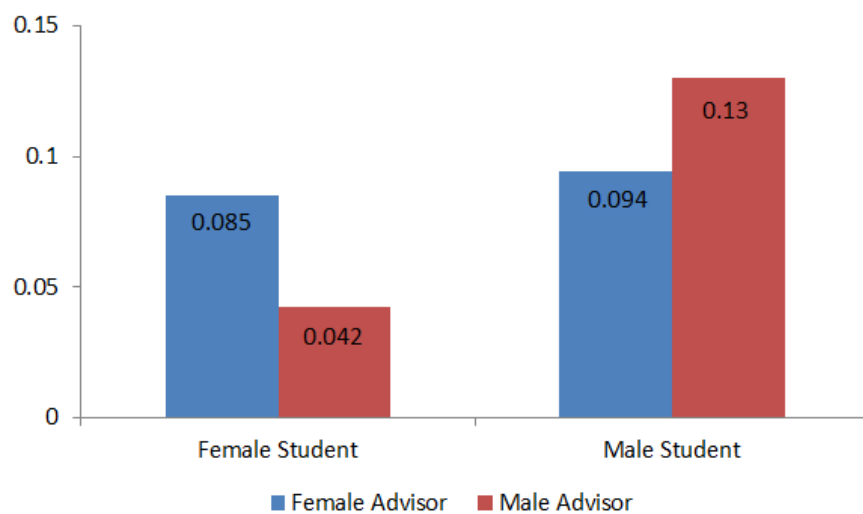
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A Figures

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.

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

*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 is 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 (0.302)	0.479 (0.500)	0.492 (0.500)	0.100 (0.300)
Share of advisors in the rank of Associate Professor	0.447 (0.498)	0.310 (0.463)	0.029 (0.167)	0.363 (0.481)
Share of advisors in the rank of Assistant Professor	0.452 (0.498)	0.168 (0.374)	0.397 (0.490)	0.458 (0.499)
Number of students per year	31.32 (5.194)	31.90 (7.281)	30.61 (6.424)	30.50 (8.349)
Number of female students per year	15.37 (2.706)	16.03 (5.064)	14.72 (3.891)	14.45 (4.282)
Mean students' Math SAT score	576.7 (72.12)	574.3 (75.50)	574.4 (74.17)	575.8 (75.91)
Mean students' Verbal SAT score	484.7 (82.99)	480 (78.11)	483.2 (85.37)	479.3 (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

	Likelihood of science advisor	Likelihood of female advisor	Likelihood of female advisor
	All freshman students	All freshman students	Freshman students with science advisor
	(1)	(2)	(3)
Female Student	0.019 (0.017)	-0.003 (0.017)	-0.008 (0.024)
SAT Math Score	-0.002 (0.013)	-0.009 (0.012)	0.003 (0.015)
SAT Verbal Score	0.001 (0.015)	0.019 (0.015)	0.013 (0.018)
Standardized High School GPA	-0.002 (0.010)	-0.007 (0.009)	-0.016 (0.012)
Legacy Student	0.044* (0.024)	-0.023 (0.021)	-0.040 (0.024)
Foreign High School	0.041 (0.034)	-0.044 (0.027)	-0.041 (0.039)
p-value: Joint significance of all individual covariates	0.41	0.39	0.48
Observations	3,409	3,409	1,804

Note: Coefficients in columns (1) represent estimates from a regression of the likelihood of having a science advisor on student level characteristics for all freshman students. Coefficients in columns (2) and (3) represent estimates from a regression of the likelihood of having a female advisor on student level characteristics for all freshman students and for students assigned to a faculty advisor in the sciences respectively. Standard errors clustered at the advisor-year level and reported in parentheses. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 4: The effects of having a female 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)
Treatment ($\beta_3 + \beta_7$)	0.084** (0.040)	0.074* (0.042)	0.071* (0.039)	0.078** (0.033)	0.065* (0.035)	0.065** (0.032)	0.188** (0.075)	0.185** (0.078)	0.179** (0.079)
Female Advisor \times Female Student (β_3)	-0.027 (0.034)	-0.025 (0.035)	-0.027 (0.034)	-0.035 (0.028)	-0.031 (0.028)	-0.032 (0.027)	-0.074 (0.100)	-0.063 (0.097)	-0.065 (0.099)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.108*** (0.017)	-0.105*** (0.018)	-0.083*** (0.017)	-0.088*** (0.016)	-0.083*** (0.016)	-0.064*** (0.016)	0.214*** (0.037)	0.206*** (0.037)	0.249*** (0.040)
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Fixed Effects		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls			Yes			Yes			Yes
Observations	3,409	3,409	3,409	3,409	3,409	3,409	3,409	3,409	3,409
R^2	0.030	0.058	0.090	0.025	0.055	0.083	0.043	0.065	0.100

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. Standard errors clustered at the advisor-year level and reported in parentheses. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 5: Freshman course level treatment effects when matched to a science female 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)
Treatment ($\beta_3 + \beta_7$)	0.031** (0.013)	-0.080*** (0.029)	-0.036*** (0.013)	0.202** (0.098)	-0.034** (0.017)	-0.004 (0.008)	0.148** (0.058)
Female Advisor \times Female Student (β_3)	0.002 (0.016)	0.024 (0.023)	0.021 (0.013)	-0.082 (0.094)	-0.018 (0.016)	0.005 (0.009)	0.089* (0.052)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.067*** (0.009)	-0.019 (0.013)	0.006 (0.007)	0.216*** (0.038)	-0.029*** (0.010)	-0.013** (0.005)	0.242*** (0.028)
Course-by-Semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,911	11,852	11,852	10,938	25,042	25,042	23,453

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. 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. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 6: 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 students (Math SAT \geq Median=575)			
Treatment ($\beta_3 + \beta_7$)	0.138** (0.067)	0.118** (0.058)	0.190* (0.085)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.109*** (0.027)	-0.089*** (0.031)	0.296*** (0.069)
Observations (High ability)	1,694	1,694	1,694
Lower ability students (Math SAT < Median=575)			
Treatment ($\beta_3 + \beta_7$)	-0.010 (0.034)	-0.002 (0.036)	0.164 (0.103)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.045*** (0.016)	-0.031** (0.012)	0.218*** (0.057)
Observations (Lower ability)	1,715	1,715	1,715
Year Fixed Effect	Yes	Yes	Yes
Advisor Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes

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. Standard errors clustered at the advisor-year level and reported in parentheses. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 7: Potential Channels

	Same Major as Advisor	Course with Female Teacher	Science Course in first Semester
	(1)	(2)	(3)
Treatment ($\beta_3 + \beta_7$)	0.004 (0.012)	-0.005 (0.015)	0.029* (0.016)
Female Advisor \times Female Student (β_3)	0.020 (0.020)	0.007 (0.016)	0.008 (0.015)
Year Fixed Effect	Yes	Yes	Yes
Advisor Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Observations	3,409	36,738	18,792

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. Standard errors clustered at the advisor-year level and reported in parentheses. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 8: Initial 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)
Treatment ($\beta_3 + \beta_7$)	0.083** (0.037)	0.077* (0.040)	0.080 (0.070)	0.089 (0.076)
Female Advisor \times Female Student (β_3)	0.032 (0.022)	0.031 (0.020)	-0.004 (0.040)	-0.002 (0.041)
Advisor Fixed Effects	No	Yes	No	Yes
Department Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes
Number of Observations	11,856	11,856	11,856	11,856
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 (Declared majors) and excludes students initially entering as Freshman students 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. Standard errors clustered at the advisor-year level and reported in parentheses. *** 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 effects of having a female 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)
Treatment ($\beta_3 + \beta_7$)	0.084** (0.042)	0.074* (0.043)	0.071* (0.042)	0.078** (0.037)	0.065* (0.038)	0.065* (0.037)	0.188** (0.039)	0.185** (0.043)	0.179** (0.044)
Female Advisor \times Female Student (β_3)	-0.027 (0.032)	-0.025 (0.032)	-0.027 (0.032)	-0.035 (0.035)	-0.031 (0.035)	-0.032 (0.035)	-0.074 (0.095)	-0.063 (0.090)	-0.065 (0.092)
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Fixed Effects		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls			Yes			Yes			Yes
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.108	-0.105	-0.083	-0.088	-0.083	-0.064	0.214	0.206	0.249
Observations	3,409	3,409	3,409	3,409	3,409	3,409	3,409	3,409	3,409
R^2	0.030	0.058	0.090	0.025	0.055	0.083	0.043	0.065	0.100

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. Standard errors clustered at the advisor level and reported in parentheses. *** p < 0.01 ** p < 0.05 * p < 0.1

Table A3: Heterogeneous freshmen course level effects of science advisor gender match based on student ability

	Take Sci. Course (1)	Fail Sci. Course (2)	Withdraw Sci. Course (3)	Grade Sci. Course (4)	Fail Non-Sci. Course (5)	Withdraw Non-Sci. Course (6)	Grade Non-Sci. Course (7)
High ability students (Math SAT \geq Median=575)							
Treatment ($\beta_3 + \beta_7$)	0.059*** (0.020)	-0.096*** (0.035)	-0.052*** (0.012)	0.142 (0.125)	-0.040** (0.019)	-0.017 (0.011)	0.159* (0.087)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.070*** (0.015)	-0.021 (0.018)	-0.001 (0.011)	0.319*** (0.067)	-0.033*** (0.011)	-0.015** (0.006)	0.296*** (0.045)
Observations (High ability)	18,242	6,558	6,558	6,148	11,678	11,678	11,021
Lower ability students (Math SAT \leq Median=575)							
Treatment ($\beta_3 + \beta_7$)	0.001 (0.022)	-0.075* (0.043)	-0.029 (0.022)	0.241 (0.148)	-0.027 (0.027)	0.011 (0.011)	0.155** (0.078)
Gender Gap With Male Science Advisor ($\beta_2 + \beta_5$)	-0.067*** (0.010)	-0.010 (0.022)	0.016 (0.011)	0.132 (0.079)	-0.027 (0.018)	-0.013 (0.008)	0.185*** (0.048)
Observations (Lower ability)	18,669	5,294	5,294	4,790	13,364	13,364	12,432
Course-by-semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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. 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. *** p < 0.01 ** p < 0.05 * p < 0.1

Table A4: 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)
Treatment ($\beta_3 + \beta_7$)	0.074* (0.040)	0.062* (0.034)	0.204** (0.080)
Female Advisor \times Female Student (β_3)	-0.029 (0.035)	-0.035 (0.028)	-0.077 (0.091)
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	3,409	3,409	3,409

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 individual controls. Standard errors clustered at the advisor-year level and reported in parentheses. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table A5: Results from advisor survey

	Female science advisors				Male science advisors			
	Female students	Male students	Similar	Don't know	Female students	Male students	Similar	Don't know
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>A. Advisor's perception of student behavior</i>								
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
<i>B. Advisor behavior</i>								
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	No	Don't know		Yes	No	Don't know	
	(1)	(2)	(3)		(4)	(5)	(6)	
<i>C. Advisor attitudes</i>								
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 3 female and 4 male science advisors. Each cell shows the fraction of female advisors 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 A6: Summary statistics for students entering AUB as Sophomores

	All	STEM Majors	Non-STEM Majors
	(1)	(2)	(3)
Female Student	0.472 (0.500)	0.276 (0.448)	0.638 (0.482)
Female Advisor	0.334 (0.473)	0.110 (0.309)	0.525 (0.500)
Math SAT Score	637.1 (73.18)	670.7 (64.15)	609.4 (67.73)
Verbal SAT Score	497.7 (93.19)	508.4 (99.77)	489 (86.48)
Standardized High School GPA	-0.0763 (1.004)	0.170 (0.930)	-0.281 (1.014)
Legacy Status	0.209 (0.407)	0.180 (0.384)	0.232 (0.422)
Likelihood of Graduating (Within 6 years)	0.831 (0.375)	0.855 (0.353)	0.814 (0.389)
Standardized Graduating GPA	-0.0109 (0.701)	-0.0211 (0.692)	0.00207 (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 the American University of Beirut for the academic years 2003-2004 to 2013-2014.