Female Science Advisors and the STEM Gender Gap*

Serena Canaan†

Pierre Mouganie‡

This Version: May 26, 2019

Abstract

In an effort to reduce the gender gap in the fields of science, technology, engineering and mathematics (STEM), policymakers often propose providing women with close mentoring by female scientists. This is based on the idea that female scientists might act as role models and counteract negative gender stereotypes that are pervasive in science fields. However, as of yet, there is still no clear evidence on the role of mentor or advisor gender in reducing the STEM gender gap. We use rich administrative data from a private 4-year college to provide some of the first causal evidence on the impact of advisor gender on women's STEM degree attainment. We exploit a unique setting where students are *randomly* assigned to academic advisors—who are also faculty members—in their freshman year of college. A college advisor's main role is to provide students with one-on-one personalized mentoring regarding course and major selection. Students declare a major at the end of their freshman year, after having had the opportunity to repeatedly interact with their advisors. We find that being matched to a female rather than a male science advisor substantially narrows the gender gaps in STEM enrollment and graduation, with the strongest effects occurring among students who are highly skilled in math. In contrast, the gender of an advisor from a non-science department has no impact on students' major choice. Our results suggest that providing close mentoring or advising by *female scientists* can play an important role in promoting women's participation and persistence in STEM fields.

JEL Classification: I23, I24, J16

Keywords: STEM, Gender Gap, Advising

*We thank David Card, Scott Carrell, Ciprian Domnisoru, Mark Hoekstra, Andrea Ichino, Patrick Kline, Shelly Lundberg, Heather Royer, Giovanni Peri, Jesse Rothstein, Monica Singhal, Jenna Stearns, Christopher Walters, and seminar participants at UC Davis, UC Berkeley labor lunch, UCSB labor lunch, USC CESR Brown Bag Series, the 4th IZA Junior/Senior Symposium, the 2019 SOLE meeting and the Texas A&M PLIO Alumni conference for helpful comments and suggestions. We also thank Jana Kontar for excellent research assistance. Finally, we thank Zaher Bu Daher and Solange Constantine for assistance in providing us with the data used in this paper. All errors are our own.

†Department of Economics, American University of Beirut, e-mail: sc24@aub.edu.lb.

‡Department of Economics, American University of Beirut, e-mail: pm10@aub.edu.lb.

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 some of 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 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*.

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

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 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. In our main analysis, we therefore examine whether being assigned to a female rather than a male science advisor impacts the gender gap in STEM degree attainment, as well as students' academic performance. We also investigate separately whether the gender match matters for students assigned to 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 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

8.4 percentage points. The impacts are long-lasting as we document a comparable 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. Female students 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 from repeated interactions with female scientists. 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 with these findings, several randomized controlled trials have been recently conducted to raise women's interest in STEM majors. Porter and Serra (2018) recruit two female economics alumni of Southern Methodist University to discuss their careers, achievements and

[2]Several other studies find that female teachers increase female students' performance in math and science courses (Bettinger and Long, 2005; Dee, 2007; Lim and Meer, 2017; Eble and Hu, 2018; Gong et al., 2018) and can influence STEM occupation choice (Mansour et al., 2018).

experiences in their major with students taking Principles of Economics classes. The authors find that women who are exposed to these "role models" are twice as likely to enroll in intermediate microeconomics and to report that they intend on majoring 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.

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 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. 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.[3] 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

[3] 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. 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).

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.[4] 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.

[4]The 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%.

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. 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. Advisors 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 also meet individually with students at the beginning of each semester and prior to course registration. Students have to attend the one-on-one meetings

[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.

in order to receive a PIN that is required for course registration and that can only be provided by the advisor. During those required meetings, academic advisors discuss and help students choose a major, select courses and develop a plan of study that will allow them to meet the requirements for their intended majors. Advisors have access to the student's full academic records allowing them to tailor their advice to the student's interests and ability. 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 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 Freshmen 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. 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, legacy status, and whether or not students applied for financial aid.

[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.

3.2 Student Summary Statistics

For our main analysis, we restrict our sample to freshmen students matched to a science faculty advisor. This leaves us with a final sample of 1,804 students enrolled in 19,344 freshman courses. In later analysis, we also present results for the remaining 1,611 students matched to non-science faculty advisors. Summary statistics for the main sample of students used in our analysis are shown in Table 1. In column 1, we present means and standard deviations for all freshmen students matched to science advisors. We report these statistics separately for male and female students in columns 2 and 3. Female students constitute 49.4 percent of individuals in our sample, compared to 50.6 percent male. Table 1 also indicates that 28.5 percent of science advisors are female, equally distributed across student gender. The average Mathematics SAT score for students in our sample is 575.6 points with men scoring around 27 points higher than women, on average. 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, freshmen females outperform men by a significant margin.[7] Approximately 21 percent of all students in our sample have a close relative who attended AUB (legacy students), equally distributed across both genders. Further, around half of all freshmen 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.[8] Recall, in our context, field of study is determined directly after Freshman year. Table 1 reveals that, among those declaring a major in their sophomore 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

[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 suffer from persistent underrepresentation of women.

percentage point STEM enrollment gender gap for students initially enrolled as freshman. Table 1 also indicates 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, 82.4 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 dropout and those who declare majorless status in their 2nd 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.[9] Summary statistics for all freshmen students, including those matched to non-science advisors, are similar in composition to our main sample and are summarized in Appendix Table A2.

3.3 Advisor Summary Statistics

In Table 2, we summarize information for all freshmen faculty advisors.[10] 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.[11] 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

[9]In 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.

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

[11]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.

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 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 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 advisor in the sciences. To capture these effects, we focus our analysis on incoming freshmen students matched to advisors working in science departments. 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 freshmen students matched to faculty advisors in science departments:

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

where Y_{iat} refers to the outcome of interest for student i matched to 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. We also include an interaction term of both of these indicators. β_1 measures the average impact of female science advisors relative to male science advisors for male students. β_2 is the average difference between female and male students matched to male science advisors. β_3 is our main parameter of interest and captures the relative change in the gap between girls and boys when matched to a female rather than a male advisor. 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. 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, financial aid 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. 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.

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:

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

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), β_3 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.

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 science department is consistent with random matching. To do so, we regress a dummy variable for whether the 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, and financial aid status 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 0.49 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, foreigner and financial aid 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' departments and gender.

5.2 STEM enrollment, STEM graduation and Academic Performance in Freshman Year

We start by examining whether the student-science advisor gender match impacts STEM outcomes. 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. However, moving from a male to a female science advisor increases 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 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). Column (1) of table 4 displays the results from our most basic specification that includes no controls. The estimate on the female advisor indicator (β_1) is statistically insignificant, though not small in magnitude, and suggests that male students are 3.7 percentage points less likely to enroll in a STEM major when they are assigned to a female rather than a male science advisor. The estimate on the female student dummy (β_2) is even larger and statistically significant, and indicates that female students are 10.8 percentage points less likely than males to enroll in a STEM degree when both are matched to a male science advisor. The coefficient on the interaction term (β_3), our main parameter of interest, reveals that switching from a male to a female advisor narrows the gap in STEM enrollment between female and male students by 8.4 percentage points. This implies a 77 percent (β_3/β_2) reduction in the gender gap in STEM enrollment. 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%. Overall, the absolute benefit of being assigned a woman science advisor for female students is a statistically significant (p-value=0.025) 4.7 percentage points (β_1+β_3). In column (2), we add 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 students' baseline characteristics such as SAT scores, high school GPA, legacy and financial aid status and birth year fixed effects. Consistent with random assignment of students to advisors, estimates for both the female student indicator and the interaction term remain statistically significant and similar in magnitude to those reported in column (1).

We document that female students are more likely than men to declare a STEM major when assigned a female science advisor. It is important to understand whether these women persist in the sciences. Accordingly, we next look at how students' likelihood of graduating with a STEM degree is affected by science advisor gender. Columns (4) through (6) of table 4 present estimates for the likelihood of graduating with a STEM degree within 6 years of initial university enrollment.[12] Estimates from our least saturated specification in column (4) indicate that the STEM gender graduation gap decreases by a statistically significant 7.8 percentage points when moving from a male to female science advisor. Overall, the absolute gain for female students from having a female advisor ($\beta_1+\beta_3$) is on the order of 4.2 percentage points (p-value=0.031). As shown in columns (5) and (6), and 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 these estimates.

Finally, we examine whether assigning students to advisors of the same gender impacts their academic performance. Indeed, advisors are responsible for monitoring students' academic progress during the freshman year. Exposure to a female advisor can thus influence female students' motivation and academic performance. Column (7) of table 4 shows the impact of student advisor gender match on GPA at the end of freshman year. Female students outperform males by 21.4 percent of a standard deviation 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 a woman rather than a man. Part of this increase is driven by male students scoring a statistically insignificant 10.6 percent of a standard deviation worse when matched to a female rather than male advisor. Nonetheless, the absolute benefit for female students exposed to a female science advisor is positive and on the order of 8.2 percent of a standard deviation, though not statistically significant (p-value of $\beta_1+\beta_3= 0.12$). The addition of student controls and year and advisor fixed effects in columns (8) and (9) does not alter the estimates in a meaningful way.

[12]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.

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 wishing 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.[13] 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. Column (1) shows that compared to male students, women are 7 percentage points less likely than men to take science courses when matched to a male science advisor. However, being assigned a female science advisor reduces this gap by 3.2 percentage points. Estimates from columns (2) and (3) further indicate that compared to men, women are substantially less likely to fail and withdraw from science courses, when assigned a female science advisor. Column (4) indicates that moving from a male to female advisor does not significantly affect men's grades in science courses but substantially improves women's performance, relative to men, by approximately 19.3 percent of a standard deviation. In columns (5) to (7), we also examine how performance on non-science courses is impacted by the gender match. We find that science advisor gender does not affect men's performance in non-science coursework, but having a female advisor does decrease women's chances of failing a non-science course and improves their performance in these courses by 14.5 percent of a standard deviation. However, it has no impact on the likelihood that students withdraw from non-science coursework.

Two results are worth highlighting here. First, female science advisors increase women's likelihood of taking science courses. In results available upon request, we find that this effect is present in the first semester of the freshman year—i.e., prior to the beginning of classes.[14]

[13] 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.

[14] When assigned a female rather than male science advisor, female students are 3 percentage points more likely to take a science course in their first semester, relative to men. We also find a statistically similar 3.2 percentage point difference when looking at the second semester of the freshman year.

In other words, course taking behavior is affected by advisor gender, even prior to the start of the school year. This is important as it indicates that the documented improvement in course performance during freshman year is not driving the increase in science course taking, rather women's course choice seems to be directly affected by exposure to an advisor of the same gender. Second, the results for course withdrawal are also 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.

5.4 Heterogeneous Effects

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 higher initial mathematics ability. We consider students to be high skilled in math if their SAT math score is greater than the median in our sample—575 points. This typically corresponds to around the 70th percentile of the distribution of scores among all SAT-takers (College Board, 2012). Table 6 displays heterogeneous effects for our main outcomes of interest. Estimates from columns (1) and (2) indicate that the gender gap in STEM enrollment and graduation is larger among high ability students compared to low ability students. Specifically, women are around 10 and 8 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 5 and 3.1 percentage points respectively. The estimates on the interaction term (β_3) indicate that, for high ability students, moving from a male to female advisor reduces the STEM gender gap in enrollment and graduation by 13.4 and 11.2 percentage points respectively. In contrast, the estimates on the interaction term for low ability students are statistically insignificant and 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. For both ability subgroups, female students outperform males when assigned a male science advisor. 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 19.8 percent of a standard deviation—significant at the 10% level. Low ability women also experience an improvement in their performance, albeit the estimate of 15.2 is statistically insignificant at conventional levels, most likely due to reduced precision. These results suggest that higher 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 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 5.8 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 9.3 and 5 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 11.5 percent of a deviation improvement in scores, relative to men—though this effect is statistically insignificant. In terms of non-science course performance, 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 15.5 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 likelihood that female students fail a science or non-science course, relative to men, by 8 and 4 percentage points respectively. It also improves their performance 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.

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. 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. 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 7 presents the corresponding estimates for our main outcomes of interest, controlling for student and advisor characteristics as well as year fixed effects. As shown in column (1), and similar to results from the science advisor sample, female students are 8.6 percentage points less likely to enroll in a STEM field, relative to men, when matched to a male non-science advisor. However, the estimate on the interaction term is negative, relatively small in magnitude and statistically insignificant, suggesting that switching to a female non-science advisor potentially slightly widens the initial STEM enrollment gap. The estimates for STEM graduation in column (2) are in line with those for STEM enrollment. Furthermore, advisor gender does not seem to be an important determinant of female students' academic performance. Estimates from column (3) indicate that female students matched to male advisors perform better than their male counterparts at the end of the freshman year, consistent with previous results. However, in contrast to estimates from the science sample, switching to a female advisor does not widen the performance gender gap.

In table 8, we look at whether non-science advisor gender impacts course-level outcomes. Estimates from Columns (1) and (2) indicate that compared to male students, females are 6.5 and 7.1 percentage points less likely to take and fail science courses when assigned a male advisor. Strikingly, switching to a female non-science advisor does not affect this gap; female advisors do not significantly impact female students' likelihood of taking or failing a science course. Indeed, the estimates on the interaction term are not statistically different from zero and reasonably precise. Further, estimates from columns (3) and (4) reveal that being matched to a female rather than male non-science advisor does not influence a female student's decision to withdraw from a science course, but it does seem to lower female students' performance in science courses, relative to men—though this effect is statistically insignificant. Finally, switching from a male to female non-science advisor does not affect the likelihood of failing or withdrawing from a non-science course for either gender. However, it does improve female students' grades in these courses by around 9 percent of a standard deviation, relative to men.

5.6 Pre-Major versus Post-Major Academic Advising

In this paper, we focus on the student-advisor gender match during the freshman year—prior to students declaring a major. Our results highlight that the gender match in pre-major advising can play a key role in encouraging women to enroll and persist in STEM degrees. This begs the question: is the gender match in post-major advising also important? In other words, once women are already enrolled in a STEM major, are they more likely to persist in that major if they are matched to an advisor of the same gender? We take advantage of our unique setting in order to shed light on this question. Specifically, as detailed in section 2.1, students who sit for and pass the Lebanese Baccalaureate national exam, directly enroll in a specific 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 is considered to be equivalent to the freshman year. Importantly, and similar to the freshmen advising system, sophomore students are randomly assigned to an advisor within their major's department. Appendix table A4 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 freshmen 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 the 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.[15] The results of this exercise are summarized in Table 9. Columns (1) and (2) report estimates for sophomore students enrolled in STEM majors. We find that female STEM students matched to a female as opposed to male advisor are 7.3 percentage points more likely to graduate with a STEM degree, relative to men—an effect that is significant at the 10 percent level. Estimates from column (2) suggest that this match does not differentially affect students' academic

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

performance, as proxied by their overall GPA. We also present estimates for students enrolled in non-STEM majors in columns (3) and (4) of Table 9. These estimates suggest that women matched to a female rather than male advisor are not more likely to graduate with a non-STEM degree as compared to men nor do they perform better overall. Altogether, these results suggest that, even after declaring a STEM major, post-major advising is beneficial for the persistence of female students in the sciences.

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 relative to men. 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 A5 and indicate that our main results are robust to the inclusion of these controls. Estimates on the interaction term for STEM enrollment and graduation as well as Freshman GPA are quantitatively similar to our most saturated specification presented in Table 4. This

[16]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.

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 science advisor gender on men and women's likelihood of enrolling in the same major as their advisor. The results of this exercises are summarized in column (1) of table 10. For the sample of students who were initially assigned a science freshman advisor, the coefficient on the interaction term *($FemaleAdvisor \times FemaleStudent$)* is small in magnitude and statistically insignificant. This suggests that switching from a male to a female advisor does not result in women being more likely than men to pursue the same major as their advisors. Estimates from column (2) summarize results for the sample of students assigned to non-science advisors. While the estimate on the interaction term is statistically insignificant, the magnitude of these effects are larger than in column 1. This suggests potentially small and positive effects on the likelihood female students enroll in the same major as their non-science female advisor, compared to male students. This could 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 a science advisor, 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 Teachers?

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 columns (3) and (4) of Table 10 for students matched to a science and non-science freshman advisor respectively. The estimates on the interaction term are statistically insignificant for both samples 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

Our results indicate that the gender of a science advisor is an important determinant of female students' academic performance and STEM degree attainment. In contrast, non-science advisor gender has no impact on students' outcomes. A natural question is whether students benefit from being matched to a science versus non-science advisor, regardless of advisor gender. In Appendix table A6, we present estimates of the impact of having a science versus a non-science advisor for all students, as well as for female and male students separately. Estimates from columns (1) through (3) indicate that exposure to a science advisor does not increase the likelihood of enrolling in or graduating with a STEM degree nor does it improve academic performance. These estimates are also statistically insignificant when looking at effects by student gender separately.

In section 5.2, we find that exposure to female scientists not only impacts female students' major choice but also their academic performance during the freshman year. The documented improvement in students' performance could indicate that female students 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 women's decision to pursue a STEM field also directly influenced by repeated 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. The heterogeneity analysis presented in table 7 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 some gains in their academic performance. 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. Importantly, these effects also occur in the first semester, prior to the beginning of the academic year.

Put together, these results suggest that female students' decisions to invest in a STEM major are not solely the result of improved academic performance, but instead these choices are more likely directly driven by affirmation effects from repeated interactions with female science advisors. While it is beyond the scope of this paper to fully understand the transmission of this role model effect, we can conclude 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.

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 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. Finally, we show that non-science advisor gender has no significant impact on any of our outcomes of interest.

Our findings suggest 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.

References

Avery, Christopher. 2010. The effects of college counseling on high-achieving, low-income students. *NBER Working Paper* No. 16359.

Barr, Andrew, and Benjamin Castleman. 2018. An engine of economic opportunity: Intensive advising, college success, and social mobility. *Texas A&M Working Paper*.

Bettinger, Eric P., and Bridget Terry Long. 2005. Do faculty serve as role models? The impact of instructor gender on female students. *American Economic Review Papers & Proceedings* 95 (2): 152-157.

Bettinger, Eric P., and Rachel B. Baker. 2014. The effects of student coaching: An evaluation of a randomized experiment in student advising. *Educational Evaluation and Policy Analysis* 36 (1): 3-19.

Blau, Francine D., Janet M. Currie, Rachel T.A. Croson, and Donna K. Ginther. 2010. Can mentoring help female assistant professors? Interim results from a randomized trial. *American Economic Review Papers & Proceedings* 100 (2): 348-352.

Blickenstaff, Clark J., 2005. Women and Science Careers: Leaky Pipeline or Gender Filter? *Gender and education* 17 (4), 369-386.

Breda, Thomas, Julien Grenet, Marion Monnet, and Clémentine Van Effenterre. 2018. Can female role models reduce the gender gap in science? Evidence from classroom interventions in French high schools. *Paris School of Economics Working Paper*.

Canaan, Serena, and Pierre Mouganie. 2018. Returns to education quality for low-skilled students: Evidence from a discontinuity. *Journal of Labor Economics* 36 (2): 395-436.

Carrell, Scott E., Marianne E. Page, and James E. West. 2010. Sex and science: How professor gender perpetuates the gender gap. *The Quarterly Journal of Economics* 125 (3): 1101-1144.

Carrell, Scott E., and Bruce I. Sacerdote. 2017. Why do college-going interventions work? *American Economic Journal: Applied Economics* 9 (3): 124-151.

Castleman, Benjamin, and Joshua Goodman. 2018. Intensive college counseling and the enrollment and persistence of low-income students. *Education Finance and Policy* 13 (1): 19-41.

College Board. 2012. SAT Percentile Ranks. Retrieved from: http://media.collegeboard.com/digitalServices/pdf/research/SAT-Percentile-Ranks-2012.pdf

Dee, Thomas S. 2007. Teachers and the gender gaps in student achievement. *Journal of Human Resources* 42 (3): 528-554.

Eble, Alex, and Feng Hu. 2017. Stereotypes, role models, and the formation of beliefs. *Unpublished Manuscript*.

Gaule, Patrick, and Mario Piacentini. 2018. An advisor like me? Advisor gender and post-graduate careers in science. *Research Policy* 47 (4): 805-813.

Gong, Jie, Yi Lu, and Hong Song. 2018. The effect of teacher gender on students' academic and noncognitive outcomes. *Journal of Labor Economics* 36 (3): 743-778.

Griffith, Amanda L. 2010. Persistence of women and minorities in STEM field majors: Is it the school that matters?. *Economics of Education Review* 29 (6): 911-922.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman. 2013. Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. *NBER Working Paper* No. 19241.

Hilmer, Christiana, and Michael Hilmer. 2007. Women helping women, men helping women? Same-gender mentoring, initial job placements, and early career publishing success for economics PhDs. *American Economic Review Papers & Proceedings* 97 (2): 422-426.

Kato, Takao, and Yang Song. 2018. An advisor like me: Does gender matter? *IZA Discussion Paper* No. 11575.

Kirkebøen, Lars J., Edwin Leuven, and Magne Mogstad. 2016. Field of study, earnings, and self-selection. *The Quarterly Journal of Economics* 131 (3): 1057-1111.

Lavecchia, Adam M., Heidi Liu, and Philip Oreopoulos. 2016. Behavioral economics of education: Progress and possibilities. *In Handbook of the Economics of Education*, vol. 5: 1-74. Elsevier.

Leslie, Sarah-Jane, Andrei Cimpian, Meredith Meyer, and Edward Freeland. 2015. Expectations of brilliance underlie gender distributions across academic disciplines. *Science* 347 (6219): 262-265.

Lim, Jaegeum, and Jonathan Meer. 2017. The impact of teacher-student gender matches: Random assignment evidence from South Korea. *Journal of Human Resources* 52 (4): 979-997.

Lim, Jaegeum, and Jonathan Meer. 2019. Persistent effects of teacher-student gender matches. *Journal of Human Resources*.

Mansour, Hani, Daniel I. Rees, Bryson M. Rintala, and Nathan N. Wozny. 2018. The effects of professor gender on the post-graduation outcomes of female students. *IZA DP no. 11820.*

NACADA National Survey of Academic Advising. 2011. Retrieved from https://www.nacada.ksu.edu/Resources/Clearinghouse/View-Articles/2011-NACADA-National-Survey.aspx

Neumark, David, and Rosella Gardecki. 1998. Women helping women? Role model and mentoring effects on female Ph.D. students in economics. *Journal of Human Resources* 33 (1): 220-247.

Oreopoulos, Philip, Robert S. Brown, and Adam M. Lavecchia. 2017. Pathways to education: An integrated approach to helping at-risk high school students. *Journal of Political Economy* 125 (4): 947-984.

Pezzoni, Michele, Jacques Mairesse, Paula Stephan, and Julia Lane. 2016. Gender and the publication output of graduate students: A case study. *PloS One* 11 (1): e0145-146.

Porter, Catherine, and Danila Serra. 2018. Gender differences in the choice of major: The importance of female role models. *Southern Methodist University Working Paper*.

U.S. Chamber of Commerce Foundation. 2015. Reaching the Full Potential of STEM for Women and the U.S. Economy. *Washington, DC*.

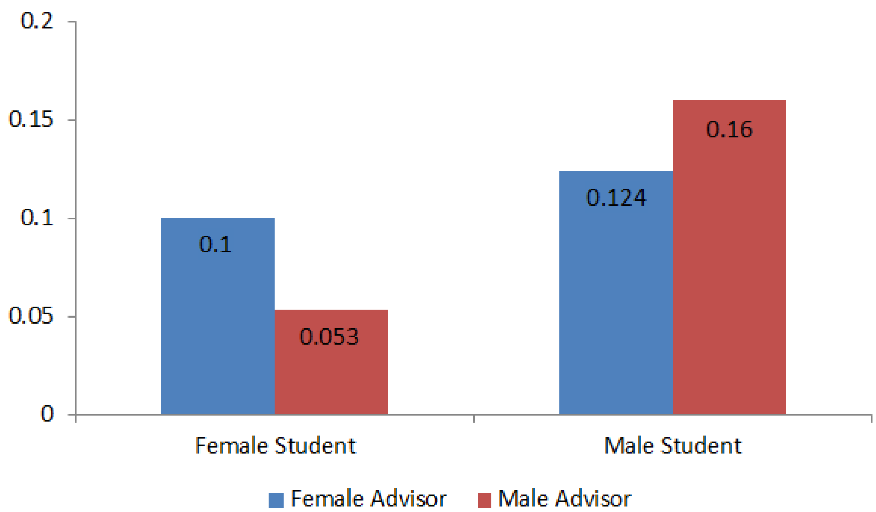
U.S. Department of Education, National Center for Education Statistics. 2018. The Condition of Education 2018 (NCES 2018-144).

Saliba, Edwin, Walid Sayegh, and Talal F. Salman. 2017. Assessing Labor Income Inequality in Lebanon's Private Sector: Findings, Comparative Analysis of Determinants, and Recommendations. *UNDP Fiscal Policy Advisory and Reform Project at the Lebanese Ministry of Finance Report*.

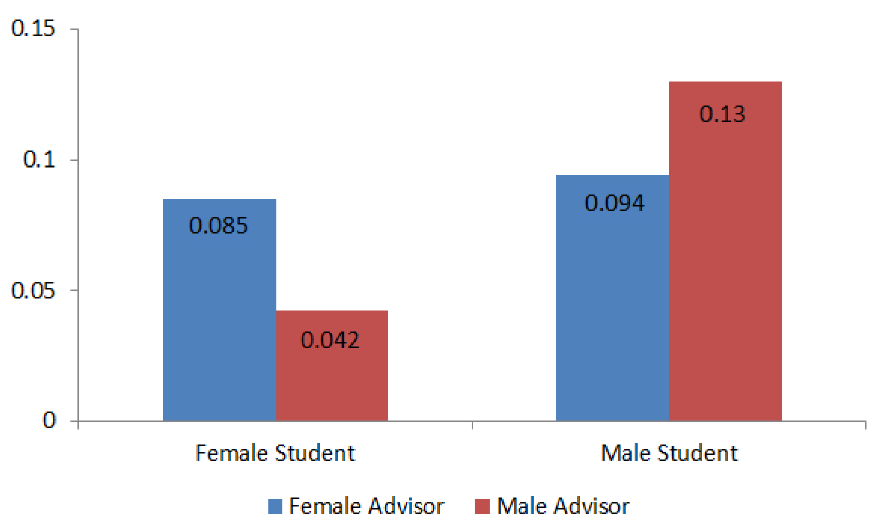
White House Office of Science and Technology Policy. 2011. Women and Girls in Science, Technology, Engineering, and Math (STEM).

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 Freshmen 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 Freshmen Students Matched to Science Advisors

	All	Male	Female
	(1)	(2)	(3)
Female Student	0.494		
	(0.500)		
Female Advisor	0.285	0.292	0.279
	(0.452)	(0.460)	(0.442)
Math SAT Score	575.6	589	561.8
	(73.47)	(71.79)	(72.65)
Verbal SAT Score	483.5	483.8	483.1
	(80.09)	(82.76)	(77.34)
Standardized High School GPA	0.0459	-0.0897	0.184
	(0.967)	(0.985)	(0.930)
Legacy Status	0.211	0.215	0.206
	(0.408)	(0.411)	(0.404)
Foreign High School	0.489	0.477	0.501
	(0.500)	(0.500)	(0.500)
Likelihood of Enrolling in STEM degree*			
(Conditional on Declaring Major)	0.168	0.259	0.093
	(0.374)	(0.439)	(0.291)
Likelihood of Graduating with STEM degree*			
(Within 6 years)	0.122	0.188	0.068
	(0.324)	(0.400)	(0.227)
Freshman GPA	76.01	74.57	77.48
	(11.34)	(11.39)	(11.10)
Likelihood of Becoming Sophomore	0.824	0.809	0.840
	(0.381)	(0.393)	(0.367)
Likelihood of enrolling in STEM degree			
(Including Dropouts and Majorless Students)	0.108	0.150	0.066
	(0.311)	(0.357)	(0.248)
Observations	1,804	912	892

Note: Means and standard deviations (in parentheses) reported. Sample includes all Freshmen students matched to a 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	0.479	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

	Likelihood of science advisor	Likelihood of female advisor	Likelihood of female advisor
	All freshman students	All freshmen students	Freshman students with science advisor
	(1)	(2)	(3)
Female Student	0.019	-0.004	-0.008
	(0.017)	(0.017)	(0.024)
SAT Math Score	-0.001	-0.009	0.003
	(0.013)	(0.012)	(0.015)
SAT Verbal Score	0.001	0.019	0.013
	(0.015)	(0.015)	(0.018)
Standardized High School GPA	-0.001	-0.007	-0.017
	(0.010)	(0.009)	(0.012)
Legacy Student	0.044*	-0.023	-0.040
	(0.024)	(0.021)	(0.024)
Foreign High School	0.041	-0.044	-0.041
	(0.034)	(0.027)	(0.039)
Applied Financial Aid	0.034	0.023	0.036
	(0.048)	(0.052)	(0.073)
p-value: Joint significance of all individual covariates	0.49	0.56	0.50
Observations	3,415	3,415	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 freshmen 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 freshmen 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 Freshmen GPA

	Enroll in STEM			Graduate with STEM degree (within 6 years)			Freshman GPA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female Advisor	-0.037			-0.036			-0.106		
	(0.029)			(0.027)			(0.065)		
Female Student	-0.108***	-0.105***	-0.083***	-0.088***	-0.083***	-0.064***	0.214***	0.206***	0.249***
	(0.017)	(0.018)	(0.017)	(0.016)	(0.016)	(0.016)	(0.037)	(0.037)	(0.040)
Female Advisor × Female Student	0.084**	0.074*	0.070*	0.078**	0.063*	0.063**	0.188**	0.189**	0.178**
	(0.040)	(0.041)	(0.039)	(0.033)	(0.035)	(0.032)	(0.075)	(0.079)	(0.079)
Year Fixed Effect		Yes	Yes		Yes	Yes		Yes	Yes
Advisor Fixed Effects		Yes	Yes		Yes	Yes		Yes	Yes
Student Controls			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	0.059	0.084	0.018	0.057	0.081	0.035	0.060	0.124

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, financial aid application 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 effects from being 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)
Female Advisor	-0.003	0.031	0.027***	-0.035	0.010	0.002	-0.052
	(0.013)	(0.023)	(0.010)	(0.078)	(0.012)	(0.007)	(0.041)
Female Student	-0.070***	-0.026**	0.003	0.228***	-0.024**	-0.012**	0.235***
	(0.009)	(0.012)	(0.008)	(0.039)	(0.010)	(0.005)	(0.028)
Female Advisor × Female Student	0.032**	-0.086***	-0.039***	0.193**	-0.041**	-0.007	0.145***
	(0.013)	(0.028)	(0.013)	(0.097)	(0.016)	(0.008)	(0.053)
Course-by-semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,334	6,349	6,349	5,881	12,975	12,975	12,146

Note: Each column represents estimates from separate regressions. Student Controls include verbal and math SAT scores, high school GPA, legacy status, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. 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 treatment effects based on student ability

	Declare STEM major	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
High ability students (Math SAT≥ Median=575)			
Female Advisor	-0.067	-0.056	-0.053
	(0.042)	(0.038)	(0.085)
Female Student	-0.100***	-0.079**	0.286***
	(0.030)	(0.033)	(0.073)
Female Advisor × Female Student	0.134**	0.112*	0.198*
	(0.068)	(0.060)	(0.109)
Lower ability students (Math SAT< Median=575)			
Female Advisor	0.023	0.001	-0.057
	(0.024)	(0.018)	(0.104)
Female Student	-0.051***	-0.033**	0.226***
	(0.017)	(0.013)	(0.060)
Female Advisor × Female Student	0.010	0.017	0.152
	(0.028)	(0.030)	(0.108)
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, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. Standard errors clustered at the advisor-year level and reported in parentheses. *** p <0.01 ** p <0.05 * p <0.1

Table 7: The effect of having a non-science female advisor

	Declare STEM major	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
Female Advisor	0.016	0.011	0.034
	(0.030)	(0.022)	(0.101)
Female Student	-0.086***	-0.064***	0.414***
	(0.028)	(0.017)	(0.075)
Female Advisor × Female Student	-0.027	-0.033	-0.066
	(0.035)	(0.027)	(0.092)
Year Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes
Observations	1,611	1,611	1,611

Note: Each column represents estimates from separate regressions. Graduating with STEM degree and graduating university defined within 6 years of enrollment. Student Controls include verbal and math SAT scores, high school GPA, legacy status, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. Standard errors clustered at the advisor-year level and reported in parentheses. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 8: Freshman course-level effects of having a non-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)
Female Advisor	-0.004	-0.001	0.001	0.096	0.021	-0.004	-0.046
	(0.013)	(0.013)	(0.009)	(0.063)	(0.013)	(0.007)	(0.038)
Female Student	-0.065***	-0.071***	-0.018	0.322***	-0.058***	-0.027***	0.254***
	(0.012)	(0.018)	(0.011)	(0.063)	(0.013)	(0.009)	(0.040)
Female Advisor × Female Student	0.002	0.026	0.014	-0.104	-0.014	0.010	0.090*
	(0.015)	(0.023)	(0.014)	(0.095)	(0.016)	(0.009)	(0.051)
Course by Semester Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,595	5,518	5,518	5,085	12,070	12,070	11,296

Note: Each column represents estimates from separate regressions. Student Controls include verbal and math SAT scores, high school GPA, legacy status, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. 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 9: Initial Gender Advising Effects for Students Entering AUB as Sophomore Majors (Declared Majors)

	STEM Major	STEM Major	Non-STEM Major	Non-STEM Major
	Graduate STEM degree	Overall GPA	Graduate Non-STEM degree	Overall GPA
	(1)	(2)	(3)	(4)
Female Advisor	-0.025	0.011	-0.020	0.012
	(0.025)	(0.034)	(0.022)	(0.034)
Female Student	0.050***	0.233***	0.081***	0.311***
	(0.013)	(0.027)	(0.016)	(0.027)
Female Advisor × Female Student	0.073*	0.061	0.030	0.008
	(0.044)	(0.058)	(0.020)	(0.037)
Department Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes
Number of observations	5,559	5,559	6,679	6,679

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. Columns (1) and (2) represent the sample of Sophomore students entering AUB as Science majors. Columns (3) and (4) represent the sample of Sophomore students entering AUB as Non-Science majors. All regressions include student controls and advisor controls as well as department and 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 10: Potential Mechanisms

	Science Advisor Same Major	Non-Science Advisor Same Major	Science Advisor Female Teacher	Non-Science Advisor Female Teacher
	(1)	(2)	(3)	(4)
Female Advisor	-0.003	-0.028	-0.006	0.021
	(0.008)	(0.024)	(0.010)	(0.014)
Female Student	-0.006	-0.003	0.021**	0.024*
	(0.005)	(0.016)	(0.008)	(0.014)
Female Advisor × Female Student	0.005	0.021	-0.002	0.005
	(0.012)	(0.022)	(0.014)	(0.017)
Year Fixed Effect	Yes	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes	Yes
Number of observations	1,804	1,611	19,233	17,511

Note: Each column represents estimates from separate regressions. All regressions include student controls and advisor controls as well as 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: Summary statistics for all freshmen students

	All	Male	Female
	(1)	(2)	(3)
Female Student	0.484		
	(0.500)		
Female Advisor	0.438	0.437	0.439
	(0.496)	(0.496)	(0.496)
Math SAT Score	575.4	588	562.1
	(73.24)	(70.78)	(73.47)
Verbal SAT Score	483.3	482.3	484.3
	(79.78)	(82.01)	(77.31)
Standardized High School GPA	0.0243	-0.106	0.163
	(0.988)	(1.013)	(0.941)
Legacy Status	0.197	0.200	0.194
	(0.398)	(0.400)	(0.396)
Foreign High School	0.482	0.465	0.500
	(0.500)	(0.499)	(0.500)
Likelihood of Enrolling in STEM degree (Conditional on Declaring Major)	0.169	0.281	0.073
	(0.375)	(0.450)	(0.260)
Likelihood of Graduating with STEM degree (Within 6 years)	0.115	0.188	0.051
	(0.318)	(0.391)	(0.220)
Likelihood of Becoming Sophomore	0.822	0.801	0.845
	(0.382)	(0.400)	(0.362)
Likelihood of enrolling in STEM degree (Including Dropouts and Majorless)	0.105	0.154	0.053
	(0.307)	(0.361)	(0.225)
Freshman GPA	75.97	74.44	77.60
	(11.37)	(11.59)	(10.89)
Observations	3,415	1,761	1,654

Note: Means and standard deviations (in parentheses) reported. Sample includes all Freshmen students matched to an advisor (science and non-science) for the academic years 2003-2004 to 2013-2014.

Table A3: Heterogeneous Freshman course level effects of having 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)
High ability students (Math SAT≥ Median=575)							
Female Advisor	-0.012	0.039	0.025**	-0.044	0.014	0.014	-0.014
	(0.017)	(0.025)	(0.012)	(0.104)	(0.015)	(0.010)	(0.061)
Female Student	-0.072***	-0.021	-0.005	0.296***	-0.023*	-0.012*	0.270***
	(0.015)	(0.014)	(0.011)	(0.066)	(0.012)	(0.007)	(0.048)
Female Advisor × Female Student	0.058***	-0.093***	-0.050***	0.115	-0.040*	-0.018	0.155*
	(0.020)	(0.034)	(0.017)	(0.126)	(0.022)	(0.013)	(0.083)
Lower ability students (Math SAT≤ Median=575)							
Female Advisor	0.006	0.025	0.031*	0.009	0.013	-0.006	-0.104**
	(0.020)	(0.034)	(0.018)	(0.100)	(0.018)	(0.008)	(0.047)
Female Student	-0.079***	-0.012	0.019	0.083	-0.017	-0.012	0.144***
	(0.010)	(0.022)	(0.014)	(0.080)	(0.017)	(0.008)	(0.045)
Female Advisor × Female Student	0.008	-0.081*	-0.034	0.210	-0.040*	0.004	0.181**
	(0.023)	(0.042)	(0.026)	(0.146)	(0.024)	(0.010)	(0.070)
Course-by-semester Fixed Effect	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student & Advisor Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (High ability)	9,565	3,494	3,494	3,285	6,067	6,067	5,707
Observations (Lower ability)	9,769	2,855	2,855	2,596	6,908	6,908	6,439

Note: Each column represents estimates from separate regressions. Student Controls include verbal and math SAT scores, high school GPA, legacy status, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. 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: Summary statistics for students entering AUB as Sophomores

	All	STEM Majors	Non-STEM Majors
	(1)	(2)	(3)
Female Student	0.480	0.278	0.634
	(0.500)	(0.448)	(0.482)
Female Advisor	0.338	0.107	0.515
	(0.473)	(0.309)	(0.500)
Math SAT Score	636.0	670.5	608.2
	(73.18)	(64.15)	(67.73)
Verbal SAT Score	497	508	488.5
	(93.19)	(99.77)	(86.48)
Standardized High School GPA	-0.0811	0.175	-0.288
	(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)	0.814	0.837	0.803
	(0.389)	(0.369)	(0.398)
Standardized Graduating GPA	-0.0395	-0.0484	-0.0249
	(0.757)	(0.753)	(0.745)
Observations	14,967	6,404	8,473

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

Table A5: 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)
Female Advisor	-0.032	-0.024	-0.050
	(0.032)	(0.028)	(0.067)
Female Student	-0.104***	-0.075**	0.289***
	(0.036)	(0.029)	(0.060)
Female Advisor × Female Student	0.073*	0.060*	0.153**
	(0.041)	(0.035)	(0.075)
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, financial aid application 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 A6: The effect of having a science advisor in Freshman year

	Declare STEM major	Graduate with STEM degree	Freshman GPA
	(1)	(2)	(3)
All Students	0.001	0.014	-0.030
	(0.019)	(0.026)	(0.086)
Female Students	0.017	0.015	0.017
	(0.027)	(0.034)	(0.157)
Male Students	-0.004	0.016	-0.069
	(0.043)	(0.029)	(0.056)
Year Fixed Effect	Yes	Yes	Yes
Student Controls	Yes	Yes	Yes
Advisor Controls	Yes	Yes	Yes
All Observations	3,415	3,415	3,415
Female Observations	1,654	1,654	1,654
Male Observations	1,761	1,761	1,761

Note: Each column represents estimates from separate regressions. The treatment in all above regressions is the likelihood of having a science faculty advisor. Student controls include verbal and math SAT scores, high school GPA, legacy status, financial aid application status and birth year fixed effects. Advisor controls include academic rank and department. Standard errors clustered at the advisor-year level and reported in parentheses. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$