Sex and Science: How Professor Gender Perpetuates the Gender Gap *

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Abstract

Why aren't there more women in science? Female college students are currently 37 percent less likely than males to obtain science and engineering BA's, and comprise only 25 percent of the science and engineering workforce. This paper begins to shed light on this question by exploiting a unique dataset of college students who have been randomly assigned to professors over a wide variety of mandatory standardized courses. We focus on the role of professor gender. Our results suggest that while professor gender has virtually no impact on male students, it has a powerful effect on female students' performance in math and science classes, their likelihood of taking future math and science courses, and their likelihood of graduating with a math, science or engineering degree. The estimates are substantively largest for students whose math SAT scores are in the top five percent of the national distribution. Indeed, the gender gap in course grades is completely eradicated and the gender gap in majoring in the sciences and engineering is cut in half when female students are assigned to a female professor. In contrast, the gender of professors teaching humanities and social sciences courses seems to have no impact on either male or female students' outcomes. We believe that these results are indicative of important environmental influences at work.

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"The inferior sex has got a new exterior. We got doctors, lawyers, politicians too..."
(Annie Lennox, Sisters are doing it for Themselves)

1 Introduction

Why aren't there more women in science? During the past forty years, women have infiltrated many prestigious careers that were formerly dominated by men, and today the number of graduate degrees in medicine, business and law are almost equally divided across the sexes. In contrast, female college students are currently 37 percent less likely than males to obtain science and engineering BA's, and comprise only 25 percent of the science and engineering workforce. What is the source of this discrepancy and why does it continue to exist when women have successfully infiltrated so many other corners of the labor market? This question has spurred hundreds of academic studies, widely publicized conferences, and government reports, but the answer (pretending for a moment that there is one answer) is still not well understood. As summarized in Xie and Shauman (2003), Women in Science

"Scholars have examined a variety of questions about women's participation in, exclusion from, and contributions to the fields of science and engineering. Despite the significant breadth and depth of this research, much of it suffers from conceptual and methodological limitations that restrict the significance and usefulness of its findings. As a consequence, we have only limited knowledge of the processes that produce the gender differences in science participation and attainment."

The exact manner in which cognitive and behavioral differences intertwine with social forces to produce differences in career outcomes is a subject of spirited debate. What we do know is that through 12th grade, the gender gap on math and science achievement tests is very small, and that it has been declining over the past 20 years.³ The small differences that do exist are not predictive of men's higher likelihood of majoring in science and engineering in college (Xie and Shauman 2003). Conditional on ability, the gender gap in the probability of completing a college degree in science or engineering is between 50 and 70 percent (Weinberger 1998). Nor are the nearly non-existent differences in college preparatory math and sciences courses predictive of gender differences in

¹National Bureau of Economic Research (2006)

²National Science Foundation (2006)

³ See Feingold (1988), Friedman (1989), Hyde (1981), Hyde, Fennema, and Lamon (1990), Leahey and Guo (2001), Linn and Hyde (1989), National Science Foundation (1004), Nowell and Hedges (1998), Xie and Shauman (2003).

college major (Xie and Shauman 2003). Since aptitude and preparedness of the two sexes seem roughly equal upon entering college, an important key to understanding the broader question of why men and women's representation in science careers is so different is understanding what happens to them in college.

This paper begins to shed light on this question by exploiting a unique dataset of college students who have been randomly assigned to professors over a wide variety of mandatory standardized courses. We focus on the role of professor gender. How does professor gender affect female students' propensity to persist in math, sciences, and engineering? Role model effects are frequently cited as potentially important factors affecting educational outcomes (Stake and Granger 1978, Kahle and Matyas 1987, Jacobs 1996, DiPrete and Buchmann 2006); other factors might include gender differences in the academic expectations of teachers, differences in teaching styles, or differences in the extent to which teachers provide advice and encouragement.

The randomized treatment nature of our data, together with the mandatory nature of the math and science courses that are required at the particular school we study allow us to investigate how professor gender influences student outcomes free of self-selection problems that plague existing research. At most universities students have a large degree of freedom in choosing both their courses and their professors, even in their first year, making it difficult to identify professors' causal impact. Students at our institution are also required to take specific follow-on courses in math and science, making it possible for us to examine the long-term effects of professor gender on female students' success in science without worrying about attrition bias. To our knowledge, we are the only study that is able to do address either the self-selection or attrition problems inherent in existing research.

It is important to point out that if professor gender impacts female students, then these influences occur at a critical juncture in the life-cycle. Decisions about majoring in math and science related fields are likely to have a substantial affect on future labor market opportunities in science. Furthermore, Xie and Shauman (2003) show that most women with bachelor's degrees in science and engineering had initially planned on majoring in a non-science related field. This suggests that the path towards a career in science is not primarily determined by the influence of social forces prior to college entry.

Our results suggest that while professor gender has virtually no impact on male students, it has a powerful effect on female students' performance in math and science classes, their likelihood of taking future math and science courses, and their likelihood of graduating with a math, science or engineering degree. The estimates are robust to the inclusion of controls for students' initial ability,

and they are substantively largest for students whose math SAT scores are in the top quartile of the distribution at the institution we study and top five percent nationally. Indeed, the gender gap in course grades for the highest ability students is completely eradicated when female students are assigned to a female teacher. In contrast, the gender of professors teaching humanities and social sciences courses seems to have virtually no impact on either male or female students' outcomes. We believe that these results are indicative of important environmental influences at work. The remainder of the paper unfolds as follows: Section 2 discusses background information. Section 3 reviews the data. Section 4 discusses the statistical methods used. Section 5 presents our results and Section 6 presents alternate specifications. Section 7 discusses possible mechanisms. Section 8 concludes.

2 Background

Understanding the factors that lead women to choose (or not to choose) science related careers is important for several reasons. First, gender differences in entry into science careers explain a substantial portion of the gender pay differential among college graduates (Eide 1994, Brown and Corcoran 1997, Weinberger 1998, Weinberger 1999, Weinberger 2001). Sociologists also argue that science is one of the most prestigious segments of the labor force (Hodge, Siegel, and Rossi 1964) and that compared to men, women's relatively low rates of participation in science careers contribute to their relatively lower social status (Jacobs 1996, Reskin 1984, Reskin, Hartmann, National Research Council Committee on Womens Employment and Related Social Issues, on Behavioral, Sciences, and Education 1986). Another concern is that the low representation of women in science and engineering careers leads to lower aggregate productivity than could be achieved if many of the women who choose non-science careers would have been qualified scientists and engineers (Xie and Shauman 2003, Weinberger 1998).

Most social scientist agree that gender differences in the labor market are likely attributable to a myriad of individual, familial and social factors. Economists typically focus on the potential effects of discrimination and on differences in preferences (Black and Strahan 2001, Blau and Kahn 2000, Goldin and Rouse 2000, Altonji and Blank 1999) but a rich psychological literature suggests that equally skilled men and women may exhibit important differences that affect their labor market decisions. Beyer (1997) and Beyer and Bowden (1997), for example, find that there are gender differences in individuals' self perceptions of ability. Further research by Boggiano, Main, and Katz (1988), Cutrona, Cole, Colangelo, Assouline, and Russell (1994), Elliott and Dweck (1988), Harackiewicz and Elliot (1993) suggests that these perceptions are linked to individuals'

expectations, aspirations, and preference for taking on difficult tasks. Women tend to have lower expectations about their future performance than men (Beyer 1997, Elliot and Harackiewicz 1994), and they are more risk averse (e.g. Eckel and Grossman (2008)). If science classes or science careers are considered to be particularly challenging then these gender differences may lead men and women to perform differently or make different choices about which college majors and/or careers to pursue even when they have comparable skills.

At the same time, evidence suggests that the gender gap in outcomes that arises from these psychological differences is mutable. For example, a growing body of experimental work shows that the phenomenon of "stereotype threat", can have substantive effects on individuals' test performance (Steele 1997, Spencer, Steele, and Quinn 1999), and that simply telling women that a math test does not show gender differences leads to improved test scores. Similarly, while Niederle and Yestrumskas (2008) find that men take on challenging tasks 50 percent more often than comparably performing women, they also find that changes in institutional design that provide more flexible choices eliminates the gender gap among high performers.

There are numerous ways in which students' experience in the classroom might lead to gender differences in orientation towards science and math. Teachers may have different academic expectations of boys and girls, they may employ different teaching styles, or provide different levels of attention, advice and encouragement. The presence of female role models teaching math and science could also be influential. Thus, there is ample reason to believe that female college students' interest and ability in pursuing the initial steps towards a career in science (e.g. doing well in math and science courses, choosing a science-related major) might be influenced by their learning environment.

While numerous studies have investigated the effects of teacher gender at the elementary and secondary school level (e.g. Nixon and Robinson (1999), Ehrenberg, Goldhaber, and Brewer (1995), Dee (2005), Dee (2007), Holmlund and Sund (2007), Carrington, Tymms, and Merrell (2005), Carrington, Tymms, and Merrell (2008), Lahelma (2000), Lavy and Schlosser (2007)) only a handful have considered the post-secondary level (Canes and Rosen 1995, Neumark and Gardecki 1998, Rothstein 1995, Bettinger and Long 2005, Hoffmann and Oreopoulos Forthcoming). None of the existing studies focus on math and science per se, and all of the existing post-secondary studies face self-selection problems (to varying degrees) because the traditional university path enables students to choose their schools, courses, and/or professors. This makes it impossible to cleanly identify the estimated relationship between professor gender and student outcomes. The data used in this paper are unique because the institution under study has a mandatory course of study in the first year, and employs class random assignment. Thus, neither the set of courses, nor the professor's gender

are under the student's control. A further advantage of our dataset is that core course grades are not determined by an individual student's professor. Instead, all faculty members teaching the same course use an identical syllabus and give the same exams during a common testing period.⁴

3 Data

The data for our study come from the United States Air Force Academy (USAFA). The Air Force Academy is a fully accredited undergraduate institution of higher education with an approximate annual enrollment of 4,200 students. All students attending the USAFA receive 100 percent scholarship to cover their tuition, room, and board. Additionally, each student receives a monthly stipend of \$845 to cover books, uniforms, computer, and other living expenses. All students are required to graduate within four years⁵ and typically serve a minimum five-year commitment as a commissioned officer in the United States Air Force following graduation.

Despite the military setting, much about the USAFA is comparable to selective universities in the United States. USAFA faculty have earned their graduate degrees from a broad sample of high quality programs in their respective fields, as would be found in comparable undergraduate liberal arts colleges. Approximately 40 percent of classroom instructors have terminal degrees, as one might find at a university where introductory coursework is taught by graduate student teaching assistants. The number of students per section of any given course rarely exceeds 25, and student interaction with faculty members in and outside of the classroom is encouraged. There are 32 academic majors offered at USAFA across the humanities, social sciences, basic sciences, and engineering.

The students at USAFA are relatively high achieving, with the average SAT scores in approximately the 80 to 85th percentiles compared to nationwide SAT test takers.⁶ Additionally, the 25^{th} and 75^{th} percentile distributions of SAT scores at USAFA are very similar to some of the top public universities in the United States such as UCLA, University of Michigan, University of Virginia, and

⁴While the students in Hoffman and Oreopoulos's dataset are not randomly assigned and do not take mandatory math and science courses, their dataset has one similarity to ours, which is that course grades are determined by a general exam that is given to all students enrolled in the course, regardless of which professor they have taken the course from.

⁵Special exceptions are given for religious missions, medical "set-backs", and other instances beyond the control of the individual.

 $^{^6}$ See http://professionals.collegeboard.com/profdownload/sat_percentile_ranks_2008.pdf for a SAT score distributions.

University of North Carolina-Chapel Hill. ⁷ Students are drawn from each Congressional district in the US by a highly competitive process, insuring geographic diversity. Approximately 17 percent of the students are female, five percent are black, seven percent are Hispanic and six percent are Asian. Seven percent of students at USAFA have a parent who graduated from a service academy and 17 percent have a parent who previously served in the military. In a survey administered to all entering freshman, 11.2 percent report applying only to USAFA and over 50 percent report applying to 3 or more universities.

3.1 The Dataset

The dataset consists of 9,481 students from the USAFA graduating classes of 2000 through 2008. Data for each student's high school (pre-treatment) characteristics and their achievement while at the USAFA were provided by USAFA Institutional Research and Assessment and were stripped of individual identifiers by the USAFA Institutional Review Board.

Approximately, seventeen-percent of the sample is female, five-percent is black, seven-percent is Hispanic and six-percent is Asian. Twenty-six percent are recruited athletes and 20-percent attended a military preparatory school. Seven-percent of students at USAFA have a parent who graduated from a service academy and seventeen-percent have a parent who previously served in the military.

Student-level pre-treatment data includes whether students were recruited as athletes, whether they attended a military preparatory school, and measures of their academic, athletic and leadership aptitude. Academic aptitude is measured through SAT verbal and SAT math scores and an academic composite computed by the USAFA admissions office, which is a weighted average of an individual's high school GPA, class rank, and the quality of the high school attended. The sample mean SAT score (combined verbal and math) is 1,285 for female students and 1,294 for male students. The sample mean academic composite is 1,307 for female students and 1,259 for male students. The sample mean algebra/trigonometry placement exam, given upon matriculation, is 59 for female students and 62 for male students. The measure of pre-treatment athletic aptitude is a score on a fitness test required by all applicants prior to entrance. The measure of pre-treatment leadership

⁷ For our sample the 25^{th} and 75^{th} percentile SAT scores were 620 and 700 for math and 590 and 670 for verbal. For information on SAT distributions for top public universities see: http://collegeapps.about.com/od/sat/a/SAT_Public_Univ.htm.

⁸Barron, Ewing, and Waddell (2000) found a positive correlation between athletic participation and educational attainment and Carrell, Fullerton, and West (2008) found a positive correlation between fitness scores and academic achievement.

aptitude is a *leadership composite* computed by the USAFA admissions office, which is a weighted average of high school and community activities (e.g., student council offices, Eagle Scout, captain of sports team, etc.).

Our academic performance outcome measures consist of final grades in core courses for each individual student by course by section-semester-year. Students at USAFA are required to take a core set of approximately 30 courses in mathematics, basic sciences, social sciences, humanities, and engineering. The primary courses we examine in this study are mandatory introductory and follow-on courses in mathematics, physics, chemistry, history, and English. A distinct advantage of our dataset is that even if a student has a particularly bad introductory course professor, they still are required to take the follow-on related curriculum. Grades are determined on an A, A-, B+, B ··· C-, D, F scale where an A is worth 4 grade points, an A- is 3.7 grade points, a B+ is 3.3 grade points, etc. For core science courses, the sample average grade point average is 2.72 for females and 2.85 for males. For core humanities courses, the sample average grade point average is 2.81 for females and 2.73 for males. Figure 1 plots the distribution of academic pre-treatment and outcome measures by gender.

We also examine students' decisions to enroll in follow-on related math and science coursework as well as which field to concentrate their academic major, and whether they graduate with a bachelors degree. Across our sample female students are less likely than males to take higher level elective math courses (34 vs. 50 percent) and less likely to major in math, science, or engineering (24 vs. 40 percent/footnoteFigures exclude the biological sciences, which require less mathematics and have historically higher rates of female participation. When including biological sciences the gender difference is smaller (40 vs. 45 percent).), but are more likely to graduate (84 vs. 81 percent).

Over the period of our study there were 251 different faculty members who taught introductory mathematics, chemistry, or physics courses. Nineteen-percent (47 of 251) were female faculty, who taught 23-percent (289 of 1,244) of the introductory math and science course-sections. For humanities introductory courses, there were 112 different faculty members over the period of our study, of which 21-percent (24) were female.

Individual professor-level data were obtained from USAFA historical archives and the USAFA Center for Education Excellence and were matched to the student achievement data for each course

⁹ Course descriptions for Math 130, 141, 142; Physics 110, 221; Chemistry 141, 142; History 101, 202; and English 111, 211 can be found at: http://www.usafa.edu/df/dfr/curriculum/CHB.pdf

taught by section-semester-year.¹⁰ Individual-level professor data includes: academic rank, gender, education level (M.A. or Ph.D.), years of teaching experience at USAFA.

Table 1 provides summary statistics of the data.

3.2 Student Assignment to Courses and Professors

Prior to the start of the freshman academic year, students take course placement exams in mathematics, chemistry, and select foreign languages. Scores on these exams are used to place students into the appropriate starting core courses (i.e., remedial math, Calculus I, Calculus II, etc.). Conditional on course placement, the USAFA Registrar randomly assigns students to core course sections and with professors.¹¹ Thus, students throughout their four years of study have no ability to choose their professors in the required core courses. Faculty members teaching the same course use an identical syllabus and give the same exams during a common testing period. Thus, grades in core courses are a consistent measure of relative achievement across all students.¹² These institutional characteristics assure there is no self-selection of students into (or out of) courses or towards certain professors.

Our summary statistics in Table 1 indicates that the types of students assigned to female faculty are nearly indistinguishable from those assigned to male faculty on observable characteristics. For math and science courses, the average class size for female faculty is 19.17 compared to 18.94 for male faculty. Additionally, female versus male faculty have a similar number of female students per section (3.32 vs. 3.35), SAT verbal (625.03 vs. 625.38), SAT math (653.07 vs. 650.62), Academic Composite (12.47 vs. 12.38), and algebra/trigonometry placement score (57.90 vs. 56.42).

To formally test whether course assignment is random with respect to student and faculty gender, we regressed student gender on faculty gender. Results for this analysis are shown in Table 2, Specifications 1 and 2. For both math and science courses and humanities courses, there is a small positive and statistically insignificant correlation between student and faculty gender. For math and science courses, the coefficient of 0.005 indicates that the probability of being assigned

¹⁰Due to the sensitivity of the data we were only able to obtain the professor observable data for the mathematics,, chemistry, physics, English, and history departments. Due to the large number of faculty in these departments, a set of demographic characteristics (e.g., female assistant professor, PhD with 3 years of experience) does not uniquely identify an individual faculty member.

¹¹ The one exception is introductory chemistry, where the 92 lowest ability freshman students each year are ability grouped into four separate sections and are taught by the most experienced professors.

¹²The one exception is that in some core courses at USAFA, 5 to 10-percent of the overall course grade is earned by professor/section specific quizzes and/or class participation.

a female faculty member is a statistically insignificant 0.5 percentage points higher for female students than male students. In Specification 3 through 5 we tested whether there were any differences in the types of female students who were assigned to female professors by regressing student attributes on an indicator variable for female professor. Results show there is no sizeable or systematic correlation between SAT math, SAT verbal, and Academic Composite and whether a female student is assigned to a female professor. For example, for math and science courses, female students who are assigned to female professors, on average, have slightly lower SAT math (1.5 points) and SAT verbal (4.7 points) scores, but slightly higher Academic Composite (9.7) scores. Results in Specification 7, which combine the SAT and Academic Composite indicate a small positive and statistically insignificant relations ship between female student academic attributes and female professor assignment. Additionally, in Carrell and West (2008) we also showed that student assignment to core courses at USAFA are random with respect to peer characteristics and faculty academic rank, experience, and terminal degree status. ¹³

4 Statistical Methods

To measure gender differences in academic performance in the initial course, we implement the following linear regression model:

$$Y_{icjst} = \phi_1 + \beta_1 Female_i + \beta_2 Female_j + \beta_3 Female_i Female_j + \phi_2 X_{icst} + \phi_3 P_j + \gamma_{ct} + \epsilon_{icjst}$$
 (1)

where Y_{icjst} is the outcome measure for student i in course c with professor j in section s in semesteryear t. For academic performance outcomes, we normalized grades in each course by semester to have a mean zero and variance of one. $Female_i$ is an indicator for whether student i is female and $Female_j$ is an indicator for whether professor j is female. The β coefficients are the primary coefficients of interest in our study. β_1 represents the difference in mean performance between female and male students. β_2 is the value added to student grades of female versus male professors. Finally, β_3 on the interaction between $Female_i$ and $Female_j$, indicates whether female students perform differently, relative to males, when assigned to a female professor. Estimates of the β coefficients are unbiased due to students inability to select their professors or their introductory coursework.

¹³In Carrell and West (2008) we regressed individual academic composite on the average peer academic composite for students in the same course and found (7.3 percent) were statistically significant at the 0.05-level. We also regressed the mean academic composite for each section on observable characteristics (e.g., experience, academic rank, etc.) of the professor. We found no statistically significant correlations between professor and student characteristics.

 X_{icst} is a vector of student-specific (pre-treatment) characteristics, including SAT math, SAT verbal, academic composite, math placement test score, fitness score, leadership composite, race/ethnicity, recruited athlete, and whether they attended a military preparatory school. P_j is the academic rank of professor j. γ_{ct} are course by semester-year fixed effects, which control for unobserved mean differences in academic achievement or grading standards across courses and time. Hence, the model identifies professor quality using only the within course by semester-year variation in student achievement. ϵ_{icjst} is the error term. Robust standard errors are clustered by professor.

We implement a slightly modified version of (1) to measure the effect of student gender and initial course professor gender on performance in follow-on coursework.

$$Y_{ic'js't'} = \phi_1 + \beta_1 Female_i + \beta_2 Female_j + \beta_3 Female_i Female_j + \phi_2 X_{icst} + \phi_3 P_j + \gamma_{c's't'} + \epsilon_{ic'js't'}$$
 (2)

 $Y_{ic'jks't'}$ is performance in the follow-on course, c' in section s' and semester-year t', having taken professor j in the initial coursework. To adjust for any possible professor, section, or time effects in the follow-on course, we include a section by course by semester-year fixed effect, $\gamma_{c's't'}$. As in (1), we are primarily interested in the β 's, which measure the effect of student gender, gender of the initial course professor j, and the effect of a female student being assigned to a female initial course professor, respectively. To measure possible gender effects on the choice of taking higher level math coursework or graduating with a technical degree, we estimate a variation on (2),

$$D_{ijt'} = \phi_1 + \beta_1 Female_i + \beta_2 Female_j + \beta_3 Female_i Female_j + \phi_2 X_{it} + \phi_3 P_j + \epsilon_{ijt'}$$
 (3)

Where $D_{ijt'}$ is a dummy variable to indicate whether student i who had professor j in the initial coursework at time t' chose to take a higher level math course or chose a technical major. As before, the β coefficients are of interest, as they measure the effect of own gender, initial course professor gender, and female student-female professor on the respective follow-on choice.

5 Estimated Effects of Introductory Course Professor Gender in Science and Math Classes

5.1 Estimated Effects on Course Performance in the Professor's Own Course

Table 3 provides the estimated effects of having a female math or science professor on course performance. The first two columns show the estimated effects for all students. Column 1 includes the detailed student level control variables described in the previous section and column 2 replaces

the control variables with student fixed effects. Both columns suggest that when male students are taught by female professors they end up with somewhat lower course grades than when they are taught by males: the coefficient on female professor is between -0.04 (column 2) and -0.05 (column 1), which suggests that course grades are lower by about 4 to 5 percent of a standard deviation. The magnitude of the teacher gender effects is swamped, however, by the estimated coefficient on the female student dummy (column 1, row 2), which indicates that women, on average, score 16 percent of a standard deviation lower than men whose math skills were comparable upon entry into the USAFA. Given that we are controlling for initial skills, this is a dramatic discrepancy. The third row of Table 3 displays the estimated coefficient on the female student × female professor interaction. Focusing first on column 1: the estimate is of substantive magnitude (10 percent of a standard deviation) and positive, indicating that female students' performance in math and science courses improves substantially when the course is taught by a female professor. In fact, taken together with the estimates in rows 1 and 2, the estimated coefficient on the interaction term suggests that having a female professor reduces the gender gap in course grades by approximately two thirds. This phenomenon reflects both the fact that male students do worse when they have a female professor, and that female students do better. The absolute gain to women from having a female professor is 5 percent of a standard deviation (-0.049 + 0.100).

The estimates shown in column 1 are based on regressions that control for ability by including observables, and they provide information about the relative gains to men and women from having a male vs. female professor in first year math and science classes. The next column replaces the student control variables with an individual fixed effect. In this regression, the coefficient on the interaction term indicates how much better female students do when they have female professors, compared to their own performance in other mandatory first year math and science courses. When the estimated coefficients on the female professor dummy and interaction term are added together (-.041 + 0.139) the resulting estimate indicates that, conditional on own ability, when female students are taught by female professors, their performance improves by 10 percent of a standard deviation.

Columns 3 - 6 focus on women who entered college with high math skills. Columns 3 and 4 show the regression estimates for students whose math SAT score was above 660 and Columns 5 and 6 show the same results for students who scored above 700 on the math SAT. These scores correspond to the median and 75^{th} percentile of the distribution at USAFA, and to the 90^{th} and 95^{th} percentiles of the national SAT Math distribution. Although not statistically different from one another, the pattern of the estimated coefficients provides suggestive evidence that the gender gap in course grades grows with entering math ability. Since we control for initial math scores

in our regressions, this is unlikely to reflect men's higher likelihood of scoring at the very top of the distribution prior to college. Rather, it suggests that either 1) there are gender differences in math/science ability that are not captured by the initial controls, or 2) something about the college experience has a particularly detrimental effect on highly skilled women.

The most striking pattern in Table 3, however, is that as female students' initial math skills increase, the relative importance of professor gender also increases, until, at the very top (column 5), female professors completely close the gender gap (-0.169 + 0.177). Notably, at higher skill levels, the evidence that professor gender matters to male students also weakens. Our interpretation, therefore, is that something about the classroom environment created by female math and science professors has a powerful affect on the performance of women with very strong math skills—with virtually no expense incurred by their male peers.

5.2 Long-term Effects of Professor Gender

The results above suggest that female students perform substantively better in their math and science courses when they are taught by a woman. Since we are interested in understanding why the prevalence of women in science careers is lower than that of men, our next task is to examine whether these effects extend into longer-term outcomes. Course performance itself is only interesting to the extent that it affects pathways into science. Table 4 shows the estimated effect of having a female professor in an initial math and science course on performance in mandatory follow-on math and science courses, which include second semester courses in calculus, physics and chemistry. The estimates in this table are strikingly similar to the estimates in Table 3: the coefficient estimates on the interaction terms all suggest that having a female professor in an initial math or science course reduces the gender gap in future course grades. As would be expected, the estimates are smaller than those presented in Table 3, and most are not statistically different from zero. Nevertheless, the pattern of the estimates is striking.

Table 5 provides the results from estimating the effect of professor gender on other long-term outcomes. We look at three outcomes: whether the student withdraws from the USAFA¹⁴, whether she chooses to take higher level math courses beyond those that are required for graduation with a nontechnical degree, and whether she graduates with a math, science, or engineering degree. All three of these outcomes are likely to be correlated with future career choices. The estimated coefficient on the female student dummy indicates that, even controlling for entering math skills,

¹⁴The results we present in Table 5 show attrition after the second year; however, results are qualitatively similar for 1-year and 4-year attrition

women are equally likely to withdraw, significantly less likely to take higher level math courses, and significantly less likely to graduate with a math, science, or engineering degree compared to observationally similar male students. We can also see that gender differences in college major are much larger when we exclude biological sciences (columns 4 vs. 3), which typically require less math, and have higher rates of female participation.¹⁵

The estimated effect of professor gender on these long-term outcomes varies across the samples, with the biggest effects, by far, accruing to women with high entering math ability. Across the full sample, there is no statistically significant evidence that having a female professor affects a woman's likelihood of withdrawing, her probability of taking higher level math courses, or her probability of graduating with a math or science major. However, as the sample narrows to include increasingly high skilled women, the estimated effects of professor gender become much larger and statistically significant. Focusing on the top quartile of female students (in terms of their math SAT performance), we see that having a female professor in an initial math or science course narrows the gender gap in both the likelihood of taking elective math courses, and graduating with a non-biological science degree by roughly 50 percent. At the same time, across-the-board, professor gender has negligible effects on a woman's likelihood of dropping out— suggesting that whatever it is about female professors that affects women in their first year math and science courses, it is not changing military retention rates, but is truly changing their preferences for math and science.

6 Robustness Checks

The next set of tables show the results from regression analyses whose purpose is to investigate the robustness of our main findings. We begin by looking at how our results change when we change our specification and then we supplement our analyses by estimating the effects of professor gender in humanities courses.

6.1 Alternative Specifications

Table 6 shows how our results change when we modify our specification by either 1) excluding individual controls, or 2) increasing the flexibility of our model by including interactions between the individual control variables and student gender. The first column of each panel (columns 1, 4 and 7) replicates our initial estimates for each outcome variable. The second column (columns 2, 5

¹⁵We find qualitatively similar results when we also exclude environmental engineering, a field with a relatively higher rate of female participation.

and 8) shows how our estimates change when we exclude the individual controls. The results from this exercise provide information about whether our estimates are somehow driven by an unobserved correlation between student ability and professor assignment. The estimates produced in this specification are very similar to those shown in columns 1, 4 and 7. The estimates shown in the third columns in each panel (columns 3, 6 and 9) are based on regressions that include interactions between student-level control variables and student gender. These are more flexible models than those estimated in Tables 3-5, and allow for the possibility that the relationship between entry-level student characteristics and student outcomes varies with gender. The estimated effects of professor gender that are produced by this more flexible model barely differ from those in columns 1, 4 and 7, however.

We have also run regressions that replace the female professor dummies with professor-level fixed effects. The purpose of this exercise is to explore whether our estimates are driven by a few female professors whose approach to teaching differs substantively from the rest of the faculty. We find that over 2/3 of the female professor fixed effects are positive and statistically significant, which suggests that our estimated professor gender effects are pervasive, rather than driven by a handful of teachers.

Finally, Figure 4 shows the unconditional mean outcomes by student and professor gender. The patterns of estimates are quantitatively and qualitatively similar to those found in the fully specified regression models.

6.2 Estimated Effects of Professor Gender in English and History Classes

In Tables 7 and 8, we look at the effect of professor gender in humanities courses. Panel A of Table 7 shows the estimated relationship between the gender of the professor in mandatory introductory courses in English and history and student performance in those courses. Columns 1, 3 and 5 show estimates from regressions that control for initial ability by including observable student control variables. These are strikingly different from the estimates for math and science. There is no observable gender gap in course performance, and there is no evidence that female students' course grades are improved when they have a female professor. As in Tables 3 and 4, there is weak evidence that course grades for both men and women are lower when the course is taught by a professor, but most of the coefficient estimates on the female professor dummy are barely significant at the 10 percent level.

Columns 2, 4 and 6 provide the results from student fixed effects analyses, which yield a somewhat different picture. The estimates in these columns tell us how differently men and women

perform when they have a female professor, compared to their own performance in other mandatory humanities classes. The estimates in the first row suggest that male students course grades are about 20 percent of a standard deviation lower than their performance in similar classes, when they are taught by women. Course performance among female students, however, seems to be unrelated to professor gender. The estimated coefficient on the interaction term is generally positive and of similar magnitude to the estimated coefficient in row 1.

Panel B shows the effect of having a female professor in an initial history or English course on performance in mandatory follow-on history and English courses. Again in columns 1, 3, and 5 we find virtually no evidence that professor gender plays a significant role in student performance. Columns 2, 4 and 6, which include a student fixed effect, again provide a somewhat different picture. Results indicate that high ability women perform significantly better, relative to their own performance, when taught by a female versus male professor.

Table 8 carries forward our analyses for long-term outcomes in both humanities and science. We look at the effect of professor gender in initial humanities courses on the probability of taking future courses in both the humanities and math/science, and of majoring in the humanities and math/science. All of the estimated effects of having a female professor (row 1) are small and none are statistically significant, indicating that professor gender in initial humanities courses has no effect on male students' long-term choices. Most of the estimated coefficients on the interaction term are also small, and only one is statistically different from zero, suggesting that female students' long run choices are also unrelated to the sex of the professor who teaches their humanities courses.

In summary, while we find some evidence that professor gender in the humanities differentially affects the initial course performance of male and female students, we find no evidence that these effects carry forward to longer-term choices that might affect future careers. These results stand in direct contrast to the estimated effects of professor gender in math and science courses, where we see evidence that female students with strong math skills are much more likely to keep the door to a math/science career open when their initial math and science courses are taught by a woman. In the next section, we explore mechanisms that might be behind this effect.

7 Possible Mechanisms

7.1 Does the Effect of Professor Gender Operate Through Initial Course Grades?

Table 3 shows, quite clearly, that female students have substantively higher grades in their initial math and science courses, when those courses are taught by a woman. The effects are particularly

strong among female students in the upper quartile of the math SAT distribution. In this section, we investigate whether the effect of female professors on female students' long term choices operates, in part, through their effect on initial course grades. Table 9, Column 1 replicates results shown in Table 4 while including initial course grade as an additional control variable and an interaction between initial course grade and female student. We see that initial course grade is a very strong predictor of performance in mandatory follow on math/science courses, even with controls for entering math ability, with results significantly larger for males. The estimates suggest that a 1-standard deviation increase in the initial course grade results in a 0.65 standard deviation increase in follow-on course grades for men and a 0.61 increase for women. Results in Panels B and C indicate that the relationship between initial and follow-on course performance grows stronger as ability increases and the differential between men and women becomes statistically insignificant. Equally noteworthy is that the magnitude of the estimated coefficients on the female student×female professor interaction terms drops dramatically. It appears that the influence of female professors on their female students' future performance in math and science operates largely through environmental factors that affect the students' performance in their initial classes.

Results in Columns 2 and 3 examine how controlling for initial course grades affects students' future decisions, and the role of professor gender in those decisions. Again, we see that even controlling for observable measures upon school entry, the effect of initial course grades on the likelihood of taking higher level math courses and graduating with a degree in math or science is non-negligible, and precisely estimated. Additionally, the negative and significant result for the grade×female student interaction variables indicate that initial course performance plays an even more important role in female decisions to pursue a technical degree. Estimates in Column 3 of Panel A suggest that, conditional on incoming ability, a female student with performance that is one-standard deviation above the mean in the introductory math and science curriculum is 0.05 percentage points (roughly 12-percent) less likely to graduate with a math, science, engineering degree compared to her male counterpart with equal performance. The estimated effect of grade performance on taking future math coursees and graduating with a math, science or engineering degree is even larger among higher ability students (Panels B and C, Columns 2 and 3), although the differential effect for female students diminishes and becomes statistically insignificant. Furthermore, controlling for initial course grades reduces, but does not eliminate, the estimated importance of professor gender for high ability students. These results suggest that female taught classrooms affect female students' career paths in math, science, and engineer through increase performance in the introductory course as well as through other unmeasured factors.

7.2 The Influence of Professor Gender in Follow-on Courses

We have seen evidence that female students' math and science trajectories are influenced by the sex of the professors who teach their initial math and science courses. Table 9 shows that at least part of the mechanism through which the influence of professor gender operates is through its effect on female students' initial course grades. Students with higher introductory course grades in math and science are more likely to choose future courses and majors that will easily translate into science and engineering careers. Table 10, however shows that the influence of professor gender is only manifest in introductory courses. In this table, we estimate the effect of professor gender in the mandatory follow on math and science courses on own course grades, whether the student takes higher level math, and whether the student graduates with a degree in math, science or engineering. None of the estimated interaction terms are statistically different from zero, most are small in magnitude, and a few are in the opposite direction from our earlier estimates. This suggests that the classroom environment early in the college career has an important influence on female students' career trajectories.

8 Conclusion

This paper presents empirical evidence on the role of professor gender in student performance in initial math and science courses, performance in mandatory follow-on math, science and engineering coursework, the choice of whether to take a higher level math elective, and graduation with a math, science or engineering degree. We find that, correcting for all other exogenous attributes, there is an observed gender gap in most dimensions of performance that we measure in the math, science, and engineering disciplines. The gender gap is substantially mitigated when female students take their initial math and science coursework with a female professor, and completely eliminated for female students in the upper quartile of the SAT Math distribution. This boost in performance persists into follow-on math, science and engineering coursework. Female students of female professors in initial coursework were also more likely to choose higher level math elective coursework, and more likely to graduate with a math, science or engineering degree. We find no such effects of professor gender for male students in math and science courses. Nor do we find any statistically significant gender effects for female students in humanities coursework.

Our results are robust with respect to the inclusion of controls for students' initial ability and student level fixed effects. We can also eliminate self-selection into coursework as a potential cause of our observed correlations, as we restrict our sample to performance in coursework required of

all majors at the institution we study. In each semester, all faculty members teaching a given course are required to use a common textbook, common syllabus, common major assignments, and identical exams across sections. In introductory mathematics courses, the common exams are even separated by question with one faculty member grading the same question for all students in the entire course in an attempt to minimize the influence of individual instructors on earned grades. Additionally, both students and faculty members are randomly assigned to sections of large mandatory coursework. These factors together provide us a powerful natural experiment with which to study gender effects upon student performance.

We find that the gender of the professor in mandatory follow-on coursework in math, science and engineering does not significantly affect the grade in the contemporaneous course or affect the probability of taking higher level math coursework or the probability of graduating with a degree in math, science or engineering. From this, we conclude that the early classroom environment exerts a much larger effect on the choices of female students than subsequent classroom environments. We hope in future research to be able to investigate the potential mechanisms driving the effects we observe. More specifically, we intend to examine whether female faculty encourage female students with a predisposition toward a technical career or whether female faculty encourage female students to choose technical careers.

References

- ALTONJI, J. B., AND R. BLANK (1999): "Race and Gender in the Labor Market," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 3c, pp. 3144–3259. Elsevier.
- BARRON, J. M., B. T. EWING, AND G. R. WADDELL (2000): "The Effects of High School Participation on Education and Labor Market Outcomes," *The Review of Economics and Statistics*, 82(3), 409–421.
- Bettinger, E., and B. T. Long (2005): "Do Faculty Serve as Role Models? The Impact of Instructor Gender on Female Students," *American Economic Review*, 95(2), 152–157.
- BEYER, S. (1997): "Gender Differences in the Accuracy of Self-Evaluations of Performance," *Personality and Social Psychology Bulletin*, 23(1), 960–970.
- BEYER, S., AND E. M. BOWDEN (1997): "Gender Differences in Self-Perceptions: Convergent Evidence from Three Measures of Accuracy and Bias," *Personality and Social Psychology Bulletin*, 23(1), 157–172.

- BLACK, S. L., AND P. E. STRAHAN (2001): "The Division of Spoils: Rent-sharing and discrimination in a regulated industry," *American Economic Review*, 91(4), 814–831.
- Blau, F. D., and L. M. Kahn (2000): "Gender Differences in Pay," *The Journal of Economic Perspectives*, 14(4), 75–99.
- Boggiano, A. K., D. S. Main, and P. A. Katz (1988): "Children's Preference for Challenge: The Role of Perceived Competence and Control," *Journal of Personality and Social Psychology*, 54(1), 134–141.
- Brown, C., and M. Corcoran (1997): "Sex-Based Differences in School Content and the Male-Female Wage Gap," *Journal of Labor Economics*, 15(3), 431–465.
- CANES, B., AND H. ROSEN (1995): "Following in Her Footsteps? Faculty Gender Composition and Womens Choices of College Majors," *Industrial and Labor Relations Review*, 48(3), 486–504.
- CARRELL, S. E., R. L. FULLERTON, AND J. E. WEST (2008): "Does Your Cohort Matter? Estimating Peer Effects in College Achievement," Working Paper 14032, National Bureau of Economic Research.
- CARRELL, S. E., AND J. E. WEST (2008): "Does Professor Quality Matter? Evidence from Random Assignment of Students to Professors," Working Paper 14081, National Bureau of Economic Research.
- CARRINGTON, B., P. TYMMS, AND C. MERRELL (2005): "Forget Gender: Whether a Teacher is Male or Female Doesn't Matter," in *Teacher*, vol. 11. Australian Council for Educational Research.
- ———— (2008): "Role Models, School Improvement and the 'Gender Gap': Do Men Bring Out the Best in Boys and Women the Best in Girls?," *British Educational Research Journal*, 34(3), 315–327.
- Cutrona, C. E., V. Cole, N. Colangelo, S. G. Assouline, and D. W. Russell (1994): "Perceived Parental Social Support and Academic Achievement: An Attachment Theory Perspective," *Journal of Personality and Social Psychology*, 66(2), 369–378.
- DEE, T. S. (2005): "A Teacher Like Me: Does Race, Ethnicity, or Gender Matter?," American Economic Review, 95(2), 158–165.
- ———— (2007): "Teachers and the Gender Gaps in Student Achievement," J. Human Resources, 42(3), 528–554.

- DIPRETE, T. A., AND C. BUCHMANN (2006): "Gender-Specific Trends in the Value of Education and the Emerging Gender Gap in College Completion," *Demography*, 43(1), 1–24.
- ECKEL, C. C., AND P. J. GROSSMAN (2008): "The Difference in the Economic Decisions of Men and Women: Experimental Evidence," in *Handbook of Experimental Economics Results*, ed. by C. Plott, and V. Smith, vol. 1. Elsevier.
- EHRENBERG, R. G., D. D. GOLDHABER, AND D. J. BREWER (1995): "Do Teachers' Race, Gender, and Ethnicity Matter? Evidence from the National Educational Longitudinal Study of 1988," *Industrial and Labor Relations Review*, 48(3), 547–561.
- EIDE, E. (1994): "College Major Choice and Changes in the Gender Wage Gap," Contemporary Economic Policy, 12(2), 55–64.
- Elliot, A. J., and J. M. Harackiewicz (1994): "Goal Setting, Achievement Orientation, and Intrinsic Motivation: A Mediational Analysis," *Journal of Personality and Social Psychology*, 66(5), 968–980.
- ELLIOTT, E. S., AND C. S. DWECK (1988): "Goals: An approach to motivation and achievement," Journal of Personality and Social Psychology, 54(1), 5–12.
- FEINGOLD, A. (1988): "Does Cognitive Gender Differences are Disappearing," American Psychologist, 43(2), 95–103.
- FRIEDMAN, L. (1989): "Mathematics and the Gender Gap: A Meta-Analysis of Recent Studies on Sex Differences in Mathematical Tasks," *Review of Educational Research*, 59(2), 185–213.
- Goldin, C., and C. Rouse (2000): "Orchestrating Impartiality: The Impact of "Blind Auditions on Female Musicians," *American Economic Review*, 90(4), 715–742.
- HARACKIEWICZ, J. M., AND A. J. ELLIOT (1993): "Achievement Goals and Intrinsic Motivation," Journal of Personality and Social Psychology, 65(5), 904–915.
- HODGE, R. W., P. M. SIEGEL, AND P. H. ROSSI (1964): "Occupational Prestige in the United States, 1925-63," *American Journal of Sociology*, 70(3), 286.
- HOFFMANN, F., AND P. OREOPOULOS (Forthcoming): "Professor Qualities and Student Achievement," Review of Economics and Statistics.
- HOLMLUND, H., AND K. SUND (2007): "Is the Gender Gap in School Performance Affected by the Sex of the Teacher," *Labour Economics*, 15(1), 37–53.

- HYDE, J. S. (1981): "How Large are Cognitive Gender Differences? A Meta-Analysis using $!w^2$ and d," American Psychologist, 36(8), 892–901.
- Hyde, J. S., E. Fennema, and S. J. Lamon (1990): "Gender Differences in Mathematics Performance: A Meta-Analysis," *Psychological Bulletin*, 107(2), 139–155.
- JACOBS, J. A. (1996): "Gender Inequality and Higher Education," *Annual Review of Sociology*, 22(1), 153–185.
- Kahle, J. B., and M. L. Matyas (1987): "Equitable Science and Mathematics Education: A Discrepancy Model," in *Women: Their Underrepresentation and Career Differentials in Science and Engineering*, ed. by L. S. Dix, vol. 3c. National Academy Press.
- LAHELMA, E. (2000): "Lack of Male Teachers: A Problem for Students or Teachers?," *Pedagogy*, Culture and Society, 8(2), 173–186.
- LAVY, V., AND A. SCHLOSSER (2007): "Does Being with More Girls in School Improve Students Human Capital Outcomes and Behavior? Evidence on Effects and Mechanisms," unpublished manuscript.
- Leahey, E., and G. Guo (2001): "Gender Differences in Mathematical Trajectories," *Social Forces*, 80(2), 713–732.
- LINN, M. C., AND J. S. HYDE (1989): "Gender, Mathematics, and Science," *Educational Researcher*, 18(8), 17–27.
- NATIONAL BUREAU OF ECONOMIC RESEARCH (2006): "Diversifying the Science and Engineering Workforce: Women, Underrepresented Minorities, and Their Science and Engineering Careers," .
- NATIONAL SCIENCE FOUNDATION (1004): "Women, Minorities, and Persons with Disabilities in Science and Engineering: 1994," Discussion Paper NSF 94-333, National Science Foundation, Division of Science Resources Studies.
- ———— (2006): "Science and Engineering Degrees: 1966-2004," Discussion Paper NSF 07-307, National Science Foundation, Division of Science Resources Statistics.
- NEUMARK, D., AND R. GARDECKI (1998): "Women Helping Women? Role Model and Mentoring Effects on Female Ph.D. Students in Economics," *Journal of Human Resources*, 33(1), 220–46.

- NIEDERLE, M., AND A. H. YESTRUMSKAS (2008): "Gender Differences in Seeking Challenges: The Role of Institutions," Working Paper 13922, National Bureau of Economic Research.
- NIXON, L. A., AND M. D. ROBINSON (1999): "The Educational Attainment of Young Women: Role Model Effects of Female High School Faculty," *Demography*, 36(2), 185–194.
- NOWELL, A., AND L. V. HEDGES (1998): "Trends in Gender Differences in Academic Achievement from 1960 to 1994: An Analysis of Differences in Mean, Variance, and Extreme Scores," Sex Roles: A Journal of Research, 39(1-2), 21–43.
- Reskin, B. F. (1984): Sex Segregation in the Workplace: Trends, Explanations, Remedies. National Academy Press.
- RESKIN, B. F., H. I. HARTMANN, NATIONAL RESEARCH COUNCIL COMMITTEE ON WOMENS EMPLOYMENT AND RELATED SOCIAL ISSUES, N. R. C. C. ON BEHAVIORAL, S. SCIENCES, AND EDUCATION (1986): Womens Work, Mens Work: Sex Segregation on the Job. National Academy Press.
- ROTHSTEIN, D. S. (1995): "Do Female Faculty Influence Female Students Educational and Labor Market Attainments?," *Industrial and Labor Relations Review*, 48(3), 515–30.
- Spencer, S. J., C. M. Steele, and D. M. Quinn (1999): "Stereotype Threat and Womens Math Performance," *Journal of Experimental Social Psychology*, 35(1), 4–28.
- STAKE, J. E., AND C. R. GRANGER (1978): "Same-Sex and Opposite-Sex Teacher Model Influences on Science Career Commitment Among High School Students," *Journal of Educational Psychology*, 70(2), 180–186.
- STEELE, C. M. (1997): "A Threat in the Air: How Stereotypes Shape Intellectual Identity and Performance," *American Psychologist*, 52(6), 613–629.
- Weinberger, C. J. (1998): "Race and Gender Wage Gaps in the Market for Recent College Graduates," *Industrial Relations*, 37(1), 67–84.
- ———— (1999): "Mathematical College Majors and the Gender Gap in Wages," *Industrial Relations*, 38(3), 407–413.
- ———— (2001): "Is Teaching More Girls More Math the Key to Higher Wages?," in *Squaring Up:* Policy Strategies to Raise Womens Incomes in the U.S., ed. by M. C. King. The University of Michigan Press.

XIE, Y., AND K. A. SHAUMAN (2003): Women in Science: Career Processes and Outcomes. Harvard University Press, Cambridge, MA.

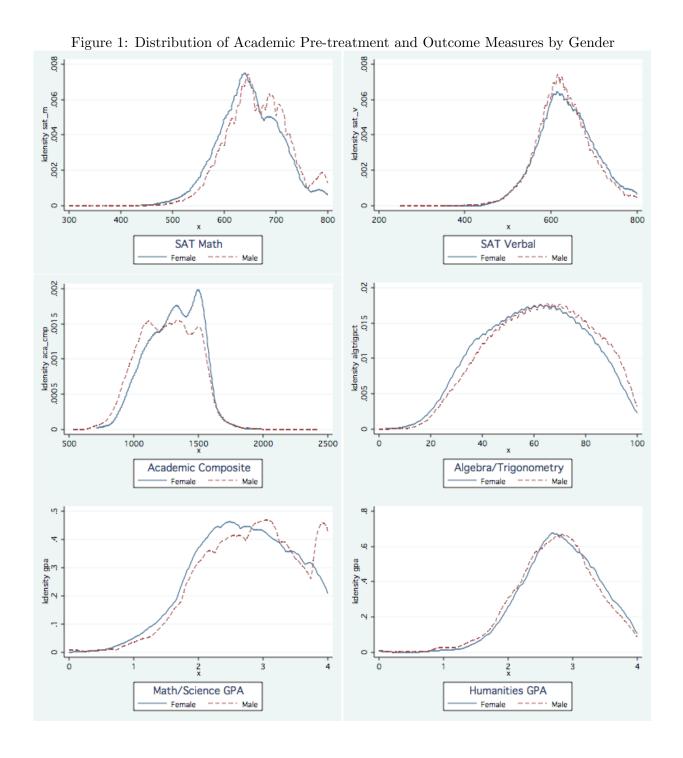


Figure 2: Math and Science Courses: Distribution of Female Student Pre-treatment Characteristics by Professor Gender

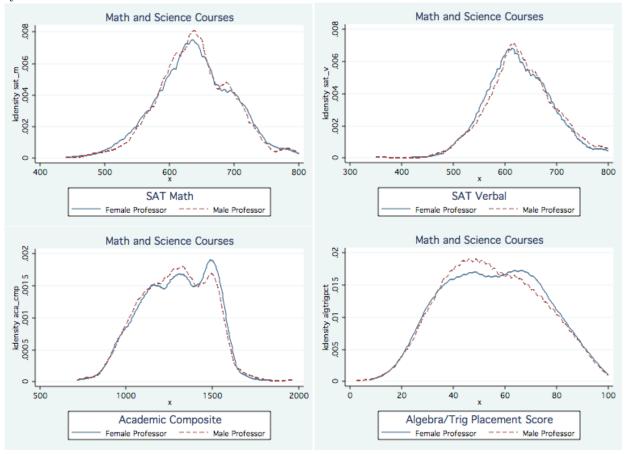
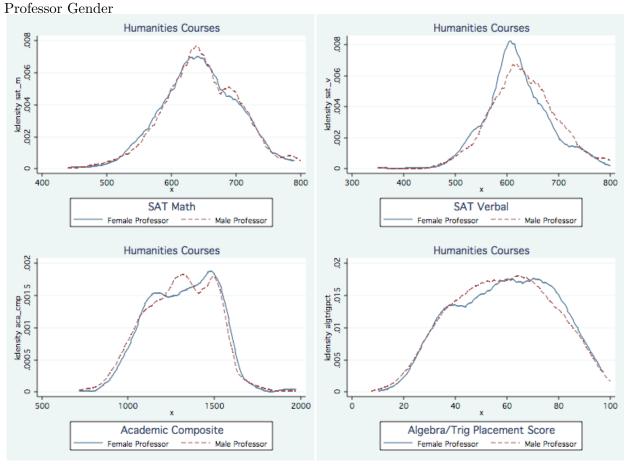


Figure 3: Humanities Courses: Distribution of Female Student Pre-treatment Characteristics by



Section A: Math & Science Introductory Course Grades Full Sample SAT Math > 660 SAT Math > 700 0.05 0 0.3 -0.05 0.30 -0.10 0.15 -0.15 -0.20 Female Students Male Students Female Students Male Students Female Students Male Students Female Professors Male Professors Section B: Math & Science Follow-on Course Grades SAT Math > 660 SAT Math > 700 Full Sample 0 -0.02 0.3 0.353 -0.04 0.2 0.235 -0.06 0.1 0.118 -0.08 0 Female Students Male Students Female Students Male Students Female Students Male Students Female Professors Male Professors Section C: Take Higher Level Math SAT Math > 660 Full Sample SAT Math > 700 0.700 0.500 0.525 0.350 0.250 0.175 0.125 0.2 0 0 Male Students Female Students Male Students Female Students Male Students Female Professors Male Professors Section D: Graduate with a Math, Science, or Engineering Major SAT Math > 660 SAT Math > 700 Full Sample 0.500 0.4 0.60 0.3 0.375 0.45 0.2 0.250 0.30 0.1 0.125 0.15 Female Students Male Students Female Students Male Students Female Students Male Students Female Professors Male Professors

Figure 4: Unconditional Mean Performance by Student and Professor Gender

Table 1: Summary Statistics

Common C			Female Students				!
Institutions 1,595 2,500 6,45 7,886 24,96 6,59 1,000	Student-Level Variables						
Math and Science Core Course Grades (coremalized course by semester) 7,825 0.10 30.99 37,949 0.10 1.00 English and History Core Course Grades (cormalized by course by semester) 5,680 0.08 0.09 28,882 -0.02 1.00 Withdram (1-year) 1,595 0.01 0.34 1,788 0.05 0.23 Take Higher Level Math Elective 1,595 0.04 0.47 7,886 0.05 0.23 Take Higher Level Humanities Elective 1,595 0.34 0.47 7,886 0.03 0.02 Take Higher Level Humanities Elective 1,595 0.40 0.49 7,886 0.04 0.50 Graduate with a Math, Science or Engineering Degree 1,595 0.10 0.09 7,886 0.07 0.02 Graduate with a Humanities Degree 1,595 0.10 0.09 7,886 0.07 0.02 Graduate with a Humanities Degree 1,595 0.10 0.09 7,886 0.07 0.02 Graduate with a Humanities Degree 1,595 0.10 0.							
Figilish and History Core Course Grades 5,880		, and the second second					
December 1,508 0.08 0.99 28,88 0.09 0.00	(normalized course by semester)	7,825	-0.10	0.99	37,949	0.02	1.00
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Withdraw (2-year) 1,595 0.13 0.34 0.74 7,886 0.15 0.05 Take Higher Level Math Elective 1,595 0.24 0.44 7,886 0.23 0.02 Take Higher Level Humanities Elective 1,595 0.24 0.40 7,886 0.23 0.03 Graduate with a Math, Science or Engineering Degree 1,595 0.40 0.40 7,886 0.40 0.09 Graduate with a Math, Science or Engineering Degree 1,595 0.61 0.03 7,886 0.40 0.09 Graduate with a Humanities Degree 1,595 0.61 0.00 7,886 0.40 0.09 SAT Math 1,595 0.61 66,67 7,886 0.22 1.64 3.0 1.0 3.0 7,886 0.02 1.64 3.0 1.0 3.0 7,886 0.0 0.2 1.64 3.0 1.0 3.0 7,886 0.0 0.2 1.6 3.0 1.0 3.0 0.2 2.0 1.0 1.0 7.8	(normalized by course by semester)	3,080	0.08	0.99	28,882	-0.02	1.00
Take Higher Level Humanities Elective 1,595 0.34 0.44 7,886 0.23 0.42 Graduate 1,595 0.84 0.36 7,886 0.23 0.42 Graduate with a Math, Science or Engineering Degree (excludes biological sciences) 1,595 0.40 0.49 7,886 0.40 0.05 Graduate with a Math, Science or Engineering Degree (excludes biological sciences) 1,595 0.10 0.03 7,886 0.02 0.02 SAT Verbal 1,595 0.16 0.66 7,886 0.02 0.02 SAT Wath Humanities Degree 1,595 0.16 0.66 7,886 60.29 0.12 SAT Wath Humanities Degree 1,595 0.18 0.66 7,886 60.29 0.26 SAT Wath 1,595 0.18 0.66 7,886 60.29 0.12 SAT Wath 1,595 0.07 1,595 0.16 1,595 0.27 7,886 60.29 1.18 1,595 0.07 0.25 7,886 0.05 1.18 1,505 <td></td> <td>1,595</td> <td>0.05</td> <td>0.23</td> <td>7,886</td> <td>0.06</td> <td>0.24</td>		1,595	0.05	0.23	7,886	0.06	0.24
Take Higher Level Humanities Elective 1,595 0,24 0,44 7,886 0,23 0,42 Graduate with a Math, Science or Engineering Degree (excludes biological sciences) 1,595 0,44 0,49 7,886 0,45 0,50 Graduate with a Math, Science or Engineering Degree (excludes biological sciences) 1,595 0,24 0,43 7,886 0,04 0,04 Graduate with a Humanities Degree 1,596 1,508 1,509 1,508 1,508 1,509 1,508 1,509 1,788 1,503 1,508 1,509 1,788 1,503 1,508 1,509 1,508 1,509 1,788 1,509 1,508 1,509 1,508 1,509 1,508 1,509 1,508 1,509 1,508 1,509 1,508 1,509 1,509 1,508 1,509		1,595	0.13	0.34	7,886	0.15	0.36
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Instructor is an Associate Professor 24 0.00 0.00 88 0.07 0.25 Instructor is a Full Professor 24 0.04 0.20 88 0.08 0.27 Instructor has a Terminal Degree 24 0.17 0.38 88 0.32 0.47 Instructor's Teaching Experience 24 3.35 3.31 88 4.42 5.04 Class Level Variables Observations Mean Std. Dev. Observations Mean 8td. Dev. Observations Mean Std. Dev. Observations 18 2.5 18 0.2 8 1.2 788 1.0 1.2 1.2 1.2 1.2 1.2 1.2 1.2 </td <td>Instructor is a Lecturer</td> <td>24</td> <td>0.54</td> <td>0.51</td> <td>88</td> <td>0.52</td> <td>0.50</td>	Instructor is a Lecturer	24	0.54	0.51	88	0.52	0.50
Instructor is a Full Professor 24 0.04 0.20 88 0.08 0.27 Instructor has a Terminal Degree 24 0.17 0.38 88 0.32 0.47 Instructor's Teaching Experience 24 3.35 3.31 88 4.42 5.04 Class-Level Variables 0bservations Mean Std. Dev. Observations Mean Std. Dev. Class Size 167 15.17 4.83 788 16.15 3.87 Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96							
Instructor has a Terminal Degree 24 0.17 0.38 88 0.32 0.47 Instructor's Teaching Experience 24 3.35 3.31 88 4.42 5.04 Class-Level Variables Observations Mean Std. Dev. Observations Mean Std. Dev. Class Size 167 15.17 4.83 788 16.15 3.87 Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96							
Instructor's Teaching Experience 24 3.35 3.31 88 4.42 5.04 Class-Level Variables Observations Mean Std. Dev. Observations Mean Std. Dev. Class Size 167 15.17 4.83 788 16.15 3.87 Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96							
Class-Level Variables Observations Mean Std. Dev. Observations Mean Std. Dev. Class Size 167 15.17 4.83 788 16.15 3.87 Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96							
Class Size 167 15.17 4.83 788 16.15 3.87 Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96	Instructor's Teaching Experience	24	3.35	3.31	88	4.42	5.04
Average Number of Female Students 167 2.58 1.82 788 2.59 1.73 Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96	Class-Level Variables	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.
Average Class SAT Verbal 167 622.88 28.28 788 627.68 27.91 Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96		167			788		3.87
Average Class SAT Math 167 658.89 28.39 788 662.11 27.20 Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96		167	2.58		788	2.59	1.73
Average Class Academic Composite 167 12.75 0.94 788 12.64 0.96	Average Class SAT Verbal	167	622.88	28.28	788	627.68	27.91
e .	· ·		658.89		788	662.11	
Average Class Algebra/Trig Score 167 61.67 8.54 788 61.90 8.03							
	Average Class Algebra/Trig Score	167	61.67	8.54	788	61.90	8.03

Table 2: Randomness Check Regressions of Faculty Gender on Student Characteristics

Sample	All St	udents	Female Students				
Dependent Variable	Female	Female	SAT	SAT	Academic	Total =	Algebr/Trig
Dependent variable	Student	Student	Math	Verbal	Composite	SAT +AC	Placement
Specification	1	2	3	4	5	6	7
Math and Science Courses	0.006	0.005	-1.462	-4.688*	9.682	3.532	0.405
Math and Science Courses	(0.006)	(0.006)	(2.393)	(2.784)	(8.281)	(10.61)	(0.679)
Observations	23,630	23,455	4,076	4,076	4,076	4,076	4,056
Humanities Courses	0.015	0.012	-0.679	-8.626**	24.250**	14.944	1.273
Humanities Courses	(0.009)	(0.009)	(3.484)	(3.601)	(11.432)	(14.355)	(1.136)
Observations	15,261	15,132	2,471	2,471	2,471	2,471	2,458
Mean and Std Dev of	0.1	68	642.3	630.5	1,292.9	2,565.6	56.6
Dependent Variable	(0.3	574)	(58.4)	(65.4)	(197.2)	(243.6)	(18.9)
Individual Control Variables	No	Yes	No	No	No	No	No

Notes: Each cell represents results for separate regression where the independent variable is an indicator variable for female faculty and the dependent variable is listed above. All specifications include a course by semester by year fixed effect. Individual control variables in Specification 2 include SAT verbal, SAT math, academic composite, algebra/trig placement score, leadership composite, fitness score, and indicator variables for black, hispanic, asian, recruited athlete, and attended a preparatory school. Standard errors are clustered at the course by semester by section level. * Significant at the 0.10 level, ** Significant at the 0.05 level, *** Significant at the 0.01 level.

Table 3: Math and Science Introductory Course Professor Gender Effects on Initial Course Per-

formance

Sample	All St	All Students $\begin{array}{c} SAT \text{ Math} > 660 & SAT \text{ Mat} \\ \text{(median)} & (75\text{th p}) \end{array}$				
Specification	1	2	3	4	5	6
Female Professor	-0.049*	-0.041**	-0.049	-0.015	-0.021	0.032
remaie Professor	(0.028)	(0.021)	(0.035)	(0.026)	(0.037)	(0.034)
Female Student	-0.156***	NIA	-0.160***	NIA	-0.169***	NIA
Female Student	(0.021)	NA	(0.032)	NA	(0.043)	NA
E 10/1/#E 1 B C	0.100**	0.139**	0.125*	0.079	0.177**	0.169**
Female Student * Female Professor	(0.045)	(0.034)	(0.071)	(0.058)	(0.079)	(0.069)
Observations	23,383	23,557	9,255	9,317	4,070	4,105
\mathbb{R}^2	0.2756	0.7586	0.2497	0.7685	0.2484	0.7746
Individual Fixed Effect	No	Yes	No	Yes	No	Yes
Indiviual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Math and Science Introductory Course Professor Gender Effects on Follow-on Course

Performance

Sample	All Students			SAT Math > 660		SAT Math > 700	
			(med	lian)	(75th ₁	octile)	
Specification	1	2	3	4	5	6	
Female Professor	-0.032*	-0.028**	-0.006	0.011	-0.022	0.001	
remaie Professor	(0.017)	(0.012)	(0.025)	(0.018)	(0.037)	(0.027)	
Female Student	-0.067***	NA	-0.085***	NA	-0.095**	NA	
remaie Student	(0.018)	INA	(0.030)	INA	(0.040)	11/1	
Famala Stadent * Famala Dasfaran	0.066	0.063**	0.102	0.008	0.151	0.054	
Female Student * Female Professor	(0.044)	(0.030)	(0.068)	(0.040)	(0.095)	(0.069)	
Observations	20,073	20,220	8,353	8,409	3,723	3,753	
\mathbb{R}^2	0.3107	0.7767	0.3532	0.7930	0.4467	0.8033	
Individual Fixed Effect	No	Yes	No	Yes	No	Yes	
Indiviual Controls	Yes	No	Yes	No	Yes	No	
Section Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Graduation Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	

Table 5: Math and Science Introductory Course Professor Gender Effects on Subsequent Course

Taking and Choice of Major

Panel A. All Students				
Specification	1	2	3	4+
Outcome	Withdraw in First 2-Years	Take Higher Level Math	Science, or	with Math, Engineering
Female Professor	-0.002	-0.002	0.009	0.004
	(0.005) -0.004	(0.007) -0.124***	(0.007) -0.026***	(0.007) -0.120***
Female Student	(0.007)	(0.009)	(0.009)	(0.008)
Female Student * Female Professor	-0.016 (0.016)	0.027 (0.017)	0.011 (0.019)	0.009 (0.015)
Observations	23,383	23,383	23,383	23,383
R^2	0.0485	0.2409	0.1698	0.1838
Panel B. SAT Math > 660 (median)				
Specification	1	2	3	4+
Female Professor	-0.005	-0.017	0.001	-0.015
	(0.008)	(0.011)	(0.012)	(0.012)
Female Student	-0.006	-0.156***	-0.051***	-0.159***
remaie Student	(0.010)	(0.017)	(0.018)	(0.017)
Female Student * Female Professor	-0.025	0.064*	0.075**	0.080***
	(0.020)	(0.036)	(0.037)	(0.031)
Observations	9,255	9,255	9,255	9,255
R^2	0.0397	0.1646	0.1208	0.1311
Panel C. SAT Math > 700 (75th pctil	e)			
Specification	1	2	3	4+
Female Professor	-0.010	-0.016	0.016	0.013
Tentale Trolessor	(0.013)	(0.020)	(0.020)	(0.022)
Female Student	0.007	-0.242***	-0.078***	-0.247***
Temale Student	(0.017)	(0.029)	(0.029)	(0.030)
Female Student * Female Professor	-0.045	0.115**	0.080*	0.151***
n	(0.035)	(0.050)	(0.049)	(0.048)
Observations	4,070	4,070	4,070	4,070
R ²	0.0331	0.1575	0.1181	0.1312
Individual Fixed Effect	No	No	No	No
Indiviual Controls	Yes	Yes	Yes	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes	Yes
Time of Day Dummies	Yes	Yes	Yes	Yes

⁺ Specificatino 4 excludes biological sciences.

Table 6: Robustness Checks: Math and Science Introductory Course Professor Gender Effects

	aun ana sei		addidiy
Panel A. All Students			
Specification/Dependent Variable	1	2	3
Initial Course Performance	0.101**	0.089**	0.092**
mitial Course i cironnance	(0.045)	(0.045)	(0.042)
Follow-on Course Perfomance	0.066	0.069	0.063
1 onow-on Course 1 erromance	(0.044)	(0.046)	(0.040)
Take Higher Level Math	0.027	0.019	0.029*
Take Higher Level Math	(0.017)	(0.019)	(0.017)
Graduate with Math, Science, or	0.009	0.003	0.013
Engineering Degree+	(0.015)	(0.016)	(0.015)
Panel B. SAT Math > 660 (median)			
Specification/Dependent Variable	1	2	3
Initial Course Performance	0.125*	0.135*	0.135**
ilitial Course refrontiance	(0.071)	(0.081)	(0.067)
Follow-on Course Perfomance	0.102	0.139	0.102*
ronow-on Course Ferromance	(0.068)	(0.086)	(0.062)
Take Higher Level Math	0.064*	0.069*	0.064*
Take Higher Level Math	(0.036)	(0.037)	(0.036)
Graduate with Math, Science, or	0.080***	0.084**	0.087**
Engineering Degree+	(0.031)	(0.033)	(0.031)
Panel C. SAT Math > 700 (75th pctile)			
Specification/Dependent Variable	1	2	3
Initial Course Performance	0.177**	0.115	0.191**
ilitial Course refrontiance	(0.079)	(0.092)	(0.081)
	0.151	0.102	0.118
Follow-on Course Perfomance	(0.095)	(0.111)	(0.089)
	0.115**	0.101**	0.116**
Take Higher Level Math	(0.050)	(0.049)	(0.049)
Graduate with Math, Science, or	0.151***	0.129***	0.151***
Engineering Degree+	(0.048)	(0.050)	(0.050)
Individual Fixed Effect	No.	No	No
Individual Controls	Yes	No	Yes
Individual Controls * Female Student	No	No	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes
Time of Day Dummies	Vec	Vec	Vec

Time of Day Dummies

Yes
Yes
Yes
Yes
Notes: Each cell represent the coefficient for the Female Student * Female
Professor variable. * Significant at the 0.10 level, ** Significant at the 0.05 level,
*** Significant at the 0.01 level. Robust standard errors in parentheses are
clustered by instructor. All specifications control for the academic rank of the
professor. Individual-level controls include: SAT verbal, SAT math, academic
composite, leadership composite, fitness score, algebra/trig placement score and
indicator variables for students who are black, Hispanic, Asian, female, recruited
athlete, and attended a preparatory school.

⁺ Excludes biological sciences.

Table 7: English and History Introductory Course Professor Gender Effects on Initial and Follow-on

Course Performance

Course Pertormance			O ATT 3.5	4	CATE > C	4 . 700
Sample	All S	tudents	SAT Math > 660 (median)			ath > 700 pctile)
A. Initial Course Performance	1	2	3	4	5	6
	-0.128*	-0191***	-0.127*	-0.238***	-0.106	-0.171***
Female Professor	(0.071)	(0.063)	(0.071)	(0.042)	(0.102)	(0.047)
T 1 0 1 .	-0.018	,	0.053	,	0.028	` ′
Female Student	(0.037)	NA	(0.046)	NA	(0.053)	NA
F 1 C 1 .*F 1 D C	0.029	0.167**	0.079	0.245**	0.075	0.299**
Female Student * Female Professor	(0.073)	(0.063)	(0.083)	0.245** (0.095) 7,054 0.7934	(0.103)	(0.118)
Observations	15,132	15,261	6,998	7,054	3,407	3,407
\mathbb{R}^2	0.1741	0.7709	0.1948	0.7934	0.2226	0.8111
B. Follow-on Course Performance	1	2	3	4	5	6
Female Professor	-0.038	-0.070***	-0.031	-0.088***	0.007	-0.039
remaie Professor	(0.029)	(0.026)	(0.036)	(0.026)	(0.053)	(0.034)
Female Student	0.020	NA	0.043	NA	0.049	NA
remaie student	(0.047)	NA	(0.054)	NA	(0.075)	NA
Female Student * Female Professor	0.013	0.131	0.085	0.346***	0.185	0.399**
remaie Student - Female Floressoi	(0.112)	(0.096)	(0.121)	(0.112)	(0.152)	(0.132)
Observations	13,745	13,862	6,441	6,495	3,165	3,198
\mathbb{R}^2	0.2874	0.7750	0.3458	0.7974	0.4661	0.8143
Individual Fixed Effect	No	Yes	No	Yes	No	Yes
Indiviual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: English and History Introductory Course Professor Gender Effects on Subsequent Course

Taking and Choice of Major

Sample	All Str	udanta	SAT Mat	th > 660	SAT Ma	th > 700	
Sample	All Su	idents	(median) (75		(75th	h pctile)	
		Graduate with		Graduate with		Graduate with	
	Take Higher	English,	Take Higher	English,	Take Higher	English,	
Outcome	Level English	History, or	Level English	History, or	Level English	History, or	
	or History	Humanities	or History	Humanities	or History	Humanities	
		Degree		Degree		Degree	
A. Humanities Outomes	1	2	3	4	5	6	
Female Professor	-0.008	-0.008	0.002	-0.005	-0.007	-0.009	
remaie Floressoi	(0.008)	(0.012)	(0.012)	(0.009)	(0.013)	(0.009)	
Female Student	0.023**	-0.015***	0.007	0.012	-0.007	-0.006	
remaie Student	(0.011)	(0.007)	(0.014)	(0.010)	(0.020)	(0.013)	
Famala Student * Famala Drafaggar	0.010	0.002	0.008	-0.013	0.076*	0.042	
Female Student * Female Professor	(0.026)	(0.017)	(0.030)	(0.020)	(0.044)	(0.031)	
Observations	15,132	15,132	6,998	6,998	3,407	3,407	
\mathbb{R}^2	0.0808	0.0283	0.0505	0.0265	0.0536	0.0217	

Outcome	Take Higher Level Math	Graduate with Math, Science, or Engineering Degree+	Take Higher Level Math	Graduate with Math, Science, or Engineering Degree+	Take Higher Level Math	Graduate with Math, Science, or Engineering Degree+
B. Math and Science Outcomes	1	2	3	4	5	6
Female Professor	0.008	-0.003	0.007	0.036	-0.0001	-0.011
remaie riolessoi	(0.009)	(0.011)	(0.048)	(0.055)	(0.018)	(0.020)
Female Student	-0.119***	-0.127***	-0.143***	-0.152***	-0.187***	-0205***
remaie student	(0.010)	(0.009)	(0.017)	(0.018)	(0.028)	(0.030)
Female Student * Female Professor	-0.044	-0.013	0.007	0.036	0.006	0.049
remaie Student · Female Floresson	(0.029)	(0.026)	(0.048)	(0.055)	(0.065)	(0.073)
Observations	15,132	15,132	6,998	6,998	3,407	3,407
\mathbb{R}^2	0.2505	0.1897	0.1539	0.1237	0.1268	0.1088
Individual Fixed Effect	No	No	No	No	No	No
Indiviual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day Dummies	Yes	Yes	Yes	Yes	Yes	Yes

⁺ Excludes biological sciences.

Table 9: Math, Physics, and Chemistry Introductory Course Professor Gender Effects, controlling

c			C
tor	initial	course	performance

B 14 All Ct 1 t			
Panel A. All Students			
Specification	1	2	3
	Follow-on		Graduate with
Outcome		Take Higher	Math, Science,
Outcome	Course	Level Math	or Engineering
	Performance		Degree+
E 1 C 1 . * E 1 B C	0.014	0.019	0.002
Female Student * Female Professor	(0.032)	(0.017)	(0.015)
12210 0 1	0.646***	0.112***	0.101***
Initial Course Grade	(0.008)	(0.004)	(0.004)
1 2 1 G	-0.038**	-0.043***	-0.047***
Initial Course Grade * Female Student	(0.016)	(0.007)	(0.006)
Observations	20,073	23,383	23,383
\mathbb{R}^2	0.5433	0.2741	0.2138
Panel B. SAT Math > 660 (median)			
Specification	1	2	3
	- ·		Graduate with
	Follow-on	Take Higher	Math, Science,
Outcome	Course		or Engineering
	Performance	Level Math	Degree+
	0.025	0.051	0.065**
Female Student * Female Professor	(0.050)	(0.031)	
	0.676***	0.030)	(0.030) 0.128***
Initial Course Grade	(0.013)	(0.006)	(0.006)
	-0.045	-0.031**	-0.013
Initial Course Grade * Female Student	(0.032)	(0.014)	(0.013)
Observations	8,353	9,255	9,255
R ²	0.5862	0.2098	0.1723
.K	0.3002	0.2000	0.1723
Panel C. SAT Math > 700 (75th pctile)			
Specification yes (year pense)	1	2	3
oper in the control of the control o	<u> </u>		Graduate with
	Follow-on	Taka Higher	Math, Science,
Outcome	Course	-	
	Performance	Level Math	or Engineering
	0.000	0.005#	Degree+
Female Student * Female Professor	0.022	0.095*	0.125**
	(0.078)	(0.051)	(0.046)
Initial Course Grade	0.706***	0.111***	0.129***
	(0.021)	(0.009)	(0.010)
Initial Course Grade * Female Student	-0.044	-0.001	0.026
	(0.060)	(0.021)	(0.023)
Observations	3,723	4,070	4,070
R^2	0.6518	0.1877	0.1706
Individual Fixed Effect	No	No	No
Indiviual Controls	Yes	Yes	Yes
Course by Semester Fixed Effects	Yes	Yes	Yes
Graduation Class Fixed Effects	Yes	Yes	Yes
Time of Day Dummies	Yes	Yes	Yes
Notes: * Significant at the 0.10 level. ** Significant at the 0.10 level. **	nificant at the 0.05	level. *** Sig	nificant at the

Table 10: Math, Physics, and Chemistry Follow-on Course Professor Gender Effects on Subsequent

Course Taking and Choice of Major

Panel A. All Students			
Specification Specification	1	2	3
Outcome	Grade in Course	Take Higher Level Math	Graduate with Math, Science, or Engineering
			Degree+
Female Professor	0.020	0.015	0.006
1 chiaic 1 foressor	(0.030)	(0.007)	(0.009)
Female Student	-0.057***	-0.128***	-0.130***
	(0.022) 0.011	(0.011) -0.004	(0.009) -0.010
Female Student * Female Professor	(0.041)	(0.019)	(0.018)
Observations	20,952	20,952	20,952
R ²	0.2528	0.2316	0.1860
K			
Panel B. SAT Math > 660 (median)			
Specification	1	2	3
			Graduate with
0.4	Grade in Course	Take Higher	Math, Science,
Outcome	Grade in Course	Level Math	or Engineering
			Degree+
Female Professor	0.024	0.009	-0.0001
remaie Floressor	(0.032)	(0.011)	(0.014)
Female Student	-0.088**	-0.134***	-0146***
remaie Student	(0.034)	(0.019)	(0.016)
Female Student * Female Professor	0.077	-0.011	-0.022
-	(0.064)	(0.044)	(0.041)
Observations	8,759	8,759	8,759
R ²	0.2334	0.1589	0.1372
Panel C. SAT Math > 700 (75th petile)			
Specification	1	2	3
Outcome	Grade in Course	Take Higher Level Math	Graduate with Math, Science, or Engineering Degree+
Female Professor	0.016	-0.002	-0.013
remaie Floressor	(0.037)	(0.015)	(0.018)
Female Student	-0.095**	-0.198***	-0.208***
Temale Student	(0.048)	(0.029)	(0.028)
Female Student * Female Professor	-0.001	-0.017	-0.062
-	(0.077)	(0.044)	(0.046)
Observations	3,951	3,951	3,951
\mathbb{R}^2	0.2349	0.1539	0.1436
Individual Fixed Effect	No	No	No
Individual Controls	Yes	Yes	Yes
Course by Semester Fixed Effects Graduation Class Fixed Effects	Yes Yes	Yes Yes	Yes Yes
Time of Day Dummies	Yes	Yes	Yes
Time of Buy Building	100	100	103

⁺ Excludes biological sciences.