A STEM Professor Like Me: Female Faculty Improve STEM Outcomes Among Female Students

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Despite rising college enrollment among women, gender disparities persist in STEM fields. We leverage a large-scale setting in which STEM undergraduates are randomly assigned to instructors—a feature rarely feasible in higher education—to provide causal evidence on the effects of exposure to female faculty. Female students assigned to female faculty perform better academically and report lower STEM-related anxiety, with the largest gains among those with lower prior achievement, confidence, or belonging. Exposure to female faculty also shifts beliefs away from stereotypes about women's ability in STEM, especially among men. These effects are not explained by differences in teaching practices or grading but are consistent with the influence of female role models in reducing psychological barriers. Our findings show that exposure to female faculty improves outcomes for women and promotes more inclusive norms in STEM fields.

Women earn more college degrees than ever before, yet they remain markedly underrepresented in STEM fields such as computer science and engineering (*1*). This gap limits economic opportunities and innovation while reinforcing social and economic inequality (*2–4*). Stereotyping, performance expectations, and anxiety undermine women's participation and success in male-dominated STEM fields (*5–8*). These factors are shaped by institutional environments, where faculty, mentors, and peers influence students' trajectories (*9*). Understanding how these institutional factors interact with psychological barriers is key to addressing gender disparities in STEM (*10*).

Most causal studies examining the factors that affect the academic experiences of women in STEM focus on peer mentorship ("horizontal exposure"), while faculty influence ("vertical exposure") remains understudied. This is largely due to the rarity of large-scale, randomized faculty-student assignments (*11*). Research in social psychology shows that female role models can reduce stereotype threat, enhance confidence, and improve academic self-efficacy in STEM (*12–16*). Yet these findings, often from small samples or controlled settings, may not fully capture real-world classroom dynamics. Larger quasi-experimental studies in economics (*17–22*) provide evidence at scale. To date, Carrell et al. (*23*) is the only large-scale experimental study showing that female faculty improve female students' STEM achievement. However, it was conducted in the specialized context of the U.S. Air Force Academy and did not examine the underlying mechanisms driving these effects.

Our study addresses this gap by examining both the academic and psychological effects of female faculty exposure using a large-scale, randomized design across multiple institutions. We leverage data from engineering colleges in India, where students follow fixed curricula and are randomly assigned to instructors through a computerized procedure—an extremely rare setup in higher education research. This feature enables us to cleanly identify the causal impact of having female faculty by circumventing the self-sorting of students to classes typically seen in higher education.

We draw on our large-scale data collection effort (*24*), which collected academic outcomes, including course grades and standardized test scores, along with various psychological measures: STEM-related confidence and anxiety, sense of belonging, and gender beliefs. Our study takes place in real classrooms rather than in controlled experimental conditions, capturing authentic student-faculty interactions and mitigating the possibility that students adjust their behavior due to awareness of being observed, minimizing experimenter demand effects (*25*).

We find that female students earn 0.083 standard deviations (2.64 percentile points) higher grades when taught by female faculty, with the largest gains among those with lower prior achievement, lower STEM confidence, or weaker sense of belonging. Over two years, a 10 percentage point increase in female faculty exposure raises female students' standardized test scores by 0.033 standard deviations—closing 18 percent of the gender gap in academic skills observed at program entry. Female faculty also reduce STEM-related anxiety by 0.056 standard deviations and shift gender beliefs away from stereotypes, particularly among male students. These effects are not driven by grading standards or teaching practices but rather by reduced stereotype threat and changing perceptions of gender and ability in STEM.

Data and Research Design

This study uses randomized student assignment to sections within courses across computer science and electrical engineering programs in 11 undergraduate engineering colleges in India, providing a causal estimate of the effects of female faculty on student outcomes. The sample includes 1,793 students (1,216 male, 577 female), randomly assigned to 1,084 sections taught by 431 instructors in the first two years of their program. Students followed a fixed curriculum in the first two years, ensuring that faculty or peer characteristics did not influence course selection. Within each course, students were randomly assigned to sections, preventing selection based on faculty gender or peer composition. This design prevents selection bias—specifically, the concern that female students who might benefit most from female faculty may also be more likely to choose their courses.

Our empirical strategy leverages random assignment in two ways. First, we estimate the immediate effect of being assigned to a female instructor on course grades, using student and course fixed effects to adjust for differences in student ability and course characteristics. This improves precision and ensures that the effect of female faculty is estimated within courses, controlling for variation across courses. Second, we examine longer-term impacts by assessing how variation in the proportion of courses taught by female faculty over two years influences academic and psychological outcomes. Because instructor assignment is random, differences in amount of exposure to female faculty arise by chance rather than student choices, ensuring these estimates reflect the causal effect of exposure. Further details on estimation procedures and model specifications are provided in Materials and Methods.

To estimate these effects, we constructed a dataset combining administrative records, standardized tests, and faculty and student surveys, linking faculty data to the students they taught. Administrative data track course enrollments, instructor assignments, and course grades, enabling comprehensive monitoring of students' academic progress. Randomly selected 50 percent of the students took standardized academic skills test in mathematics and science (administered by the research team) at entry and two years later to measure learning gains. Out of these 896 students, 867 completed the mathematics assessment and 885 completed the science assessment at the end of two years. Psychological outcomes—including STEM-related confidence and STEM-related anxiety—were constructed from multiple survey items, weighted using the inverse covariance matrix approach to improve reliability by accounting for correlations between related responses (*26*). Lastly, gender beliefs were measured on a five-point scale and categorized as either stereotypical or non-stereotypical. High participation rates of approximately 95 percent in both survey rounds enhance data reliability (*24*).

Student and faculty characteristics and validity of random assignment

Female and male students in our sample differ in key academic and demographic indicators (Table S1). Women make up 32 percent of the sample, and on average, score about 0.20 SD ($P = 0.00$) lower than men on the academic skills test administered by the research team. Female students are 8.5 PP ($P = 0.00$) more likely to have a father with college education and 5.7 PP more likely to have a college-educated mother ($P = 0.02$), potentially reflecting the higher socioeconomic capital women need to overcome barriers to STEM education. Psychological measures, however, reveal fewer gender differences at baseline. Female students report marginally lower STEM-related confidence and higher STEM-related anxiety, but these differences are not statistically significant.

Tests of statistical balance support the validity of the random assignment of students (Table S2). We found no significant imbalances across a range of baseline characteristics. The one minor exception—a 1.9 PP ($P = 0.09$) difference in whether their father attended college—was statistically significant at the 10 percent level and can likely be attributed to chance variation (*27*).

Female and male faculty in our sample have similar professional and educational backgrounds, with few statistically significant differences (Table S3). Female faculty comprise 34 percent of the sample. They are slightly less likely than men to hold an associate professor position (*7.1 PP, P = 0.06*) or have a PhD (*8.7 PP, P = 0.06*). Differences in full professorship, years of experience, having a PhD in progress, holding a degree from an elite college, and eligibility for caste-based affirmative action are small and not statistically significant.

Results

Our results suggest that female students achieve higher course grades when taught by female faculty. On average, they earn 0.083 standard deviations (2.64 percentile points) higher grades compared to when they are taught by male faculty (*P = 0.01*; Table 1). Notably, these gains occur without any corresponding decline in male students' performance (*0.004 SD, P = 0.89*; Table S4), indicating that the presence of female faculty benefits female students without negatively affecting their male students.

The effect of female faculty on female students' grades is robust across a range of alternative specifications. It remains stable when restricting the sample to non-elite colleges, addressing concerns that the effect might be driven by highly selective institutions. It also holds when limiting the analysis to science, mathematics, and engineering courses, ruling out the influence of a small number of non-STEM classes present in the curriculum. The effect persists when weighting classrooms equally, addressing concerns about differential class sizes or potential distortions from errors in matching students to faculty. Finally, the result is consistent when using course rank instead of standardized grades, confirming that our findings are not sensitive to how student achievement is scaled (Table S5).

Course grades may, however, capture both effort and skill gains (*28*). To assess whether these benefits extend beyond grading outcomes, we analyze performance in a standardized assessment of academic skills. Over two years, a 10 percentage point increase in female faculty exposure improves female students' standardized mathematics and science scores by 0.033 SD (*P = 0.03*), closing 18 percent of the gender gap (*0.188 SD*) in academic skills (Table 1).

Greater exposure to female faculty lowers female students' STEM-related anxiety but does not boost STEM-related confidence. (Table 2). A 10 percentage point increase in female faculty exposure over two years lowers female students' STEM-related anxiety by 0.056 SD (*P = 0.00*). There is no statistically significant effect on female students' STEM-related confidence (*0.001 SD,*

$P = 0.93$). The asymmetry between reduced anxiety and unchanged confidence suggests that self-perceptions in STEM may be harder to shift than immediate emotional responses. Greater exposure to female faculty, however, fosters a stronger connection to STEM environments. Supplemental analyses show that increased exposure to female faculty is associated with greater classroom engagement (*2.5 PP*, $P = 0.05$) and a small, statistically non-significant increase in students' sense of departmental belonging (*0.8 PP*, $P = 0.43$; Table S6).

Faculty-student gender matching effects may operate through active or passive mechanisms (*29*). Active mechanisms involve direct faculty interventions, such as mentorship, encouragement, or tailored instruction. Passive mechanisms, by contrast, require no deliberate action but work through role modeling and implicit cues that shape students' beliefs about their abilities. Role models, by default, provide identity-specific information, signaling that success is attainable for individuals who share their observable characteristics.

Our data rules out active mechanisms as the primary drivers of our findings. First, female faculty do not provide more overt attention to female students—for example, by calling on them more frequently, engaging in informal discussions, or holding additional office hours—and they do not direct these extra efforts toward lower-performing female students (Table S7). Second, female and male faculty report similar teaching practices, with female faculty even spending slightly less time on advising and lesson planning (Table S8). Finally, grading bias is unlikely given that grading is centrally administered through standardized end-of-semester exams, which limits opportunities for differential treatment by student gender.

Active mechanisms may also arise from subtle differences in faculty mindset and beliefs (*30,31*), potentially leading faculty to allocate more time and effort to male students based on inaccurate forecasts about student ability (*32*). However, our evidence indicates that the impact of female faculty on female students does not differ significantly by whether the faculty have stereotypical or non-stereotypical beliefs (Table S9) or fixed or growth mindset (Table S10). This is unsurprising as, unlike in primary and secondary education settings (*33*), institutional factors in post-secondary settings do not provide many opportunities for differentiated instruction (*34, 35*).

The absence of active mechanisms suggests that passive mechanisms are likely the primary drivers of the impact of female faculty on female students. Eble and Hu (*36*) provide a formal model of how role models influence students' beliefs under uncertainty. Students update their beliefs about their ability based on the credibility and novelty of the signals they receive. Female students in STEM fields—who are often exposed to negative gender stereotypes—may underestimate their ability, have lower self-efficacy, or feel unwelcome. The presence of a female faculty member provides a credible counter-signal, particularly for students with higher uncertainty about their place in STEM. The model predicts that belief updates are largest when new information is both credible (due to shared identity) and novel (meaningfully different from prior beliefs).

Our results align with these predictions: female faculty have the greatest impact on students most susceptible to stereotype threat (*5*), belonging uncertainty (*37*), or low self-efficacy (*38*) (Table 3). The effects are substantially larger for female students with lower prior achievement (*0.120 SD,* $P = 0.03$) and for those reporting lower initial belonging in their department (*0.305 SD,* $P = 0.00$). Similarly, female faculty have greater effects on students with lower STEM-related confidence (*0.113 SD,* $P = 0.05$). Those already confident or integrated in STEM see smaller gains, consistent with belief formation models. While we cannot empirically disentangle these interrelated mechanisms, the consistent pattern of heterogeneity supports the role of role-model-driven belief updates rather than instructional or evaluative differences.

Passive mechanisms may also operate indirectly by altering classroom norms and social expectations, thereby fostering a more inclusive environment. Table 4 shows that students become more likely to endorse non-stereotypical views about gender ability in STEM. The effect is stronger among male students, who shift 2.6 percentage points ($P = 0.00$), compared to 1.3 percentage points among female students ($P = 0.05$). These belief shifts, particularly among male students, may help foster a more inclusive classroom environment, helping reinforce female students' sense of belonging and engagement in STEM.

Discussion

Women earn higher grades than men in STEM (*39*) but remain underrepresented in the most competitive, high-paying fields. Strong academic performance alone does not guarantee equal career opportunities, as women often face greater scrutiny in hiring, promotions, and evaluations (*6,40,41*). Their qualifications are judged more critically, requiring stronger academic records to be seen as equally competent (*42*). Even a small grade advantage—like the one female faculty provide—can help counter biases favoring male candidates with similar or weaker credentials (*3*). The boost female faculty give to female students may extend beyond the classroom, shaping access to graduate programs, leadership roles, and long-term career success.

However, higher grades do not always translate into stronger STEM skills. Women tend to score lower on standardized assessments, partly due to stereotype threat, which can undermine performance in high-pressure settings (*5*). Our findings suggest that female faculty help close this gap. Students taught by female faculty show measurable gains in standardized test performance, narrowing gender disparities in STEM achievement by 18 percent—a meaningful improvement, especially given that it occurs without any targeted intervention.

Psychological rather than pedagogical mechanisms drive these gains. Female faculty serve as role models, reducing stereotype threat and strengthening female students' sense of belonging, particularly in male-dominated fields like engineering (*1*). Merely seeing women in positions of expertise challenges the belief that men are inherently better suited for STEM, alleviating anxiety and self-doubt. These effects extend beyond female students—male students exposed to female faculty are more likely to reject gender stereotypes in STEM. While female students' beliefs about female ability shift modestly, changing male attitudes may help foster a more inclusive learning environment.

Alternative explanations do not account for these results. Differences in teaching practices, faculty beliefs, or grading policies are unlikely factors, as male and female faculty spend similar time on lectures, advising, and lesson planning, with no evidence of preferential treatment for female students. Instead, the role-model effect appears to work by reducing stereotype threat and psychological barriers, such as anxiety, that often discourage women from persisting in STEM. This aligns with the concept of stereotype inoculation, where exposure to "in-group" individuals who defy stereotypes strengthens confidence in one's ability to succeed (*12*).

Although our randomized design provides robust evidence that female faculty influence both academic and non-academic outcomes, we do not conduct a formal mediation analysis to statistically decompose the contribution of specific pathways (e.g., anxiety reduction, belonging, or shifts in beliefs). Mediation models are often prone to bias or misinterpretation, as their assumptions are difficult to fully satisfy, especially in large-scale, real-world settings (*43*). Instead, our random assignment design offers strong, albeit indirect, evidence (*44*) that these psychological mechanisms collectively contribute to the observed effects.

Some limitations warrant mention. First, we focus on short- to medium-term outcomes, such as test scores and shifts in beliefs, and do not observe whether female faculty representation translates into long-term STEM engagement or labor market outcomes. Second, while our setting includes a diverse set of engineering colleges with a standardized curriculum, our findings may not fully generalize to other higher education systems. That said, the underlying mechanisms—stereotype threat reduction and role model effects—are well-documented across varied educational contexts, supporting broader applicability, even if effect sizes vary by institutional setting. Moreover, India's engineering colleges enroll 4.5 million students (*45*), account for nearly 25 percent of global engineering degrees (*46*), and supply talent to international labor markets, including the United States—underscoring the global relevance of the context.

Female faculty shape more than academic performance. By serving as role models, they reduce anxiety, foster belonging, and shift gender norms, creating environments where women are more likely to persist in STEM. These psychological benefits, often missing from traditional teaching evaluations, help sustain women's engagement in STEM. Our findings suggest that faculty diversity can be a powerful lever for fostering an inclusive learning environment, reinforcing the importance of policies that support the hiring and retention of women in academia.

Table 1: **Effect of female faculty on female students' academic achievement.** This table presents the estimated effects of female faculty on female students' academic outcomes. Column I reports results for course grades using Equation S1, where the unit of observation is a student-course pair. Standard errors (in parentheses) are clustered at the faculty level. Column II reports estimates for academic skills using Equation S3, based on a standardized test administered to a randomly selected half of the sample. Students are observed twice, once for mathematics and once for science. Standard errors (in parentheses) are clustered at the student level. Both outcomes are reported as z-scores (mean = 0, SD = 1) for comparability. Female faculty share is scaled by a factor of 10. *** P < 0.01, ** P < 0.05, * P < 0.10.

	I	II
	Course grades	Standardized test score
Female faculty × Female student	0.083***	
	(0.032)	
Female faculty share × Female student		0.033**
		(0.015)
Female faculty share		-0.010
		(0.012)
Female student		0.009
		(0.067)
Student fixed effects	Yes	No
Classroom fixed effects	Yes	No
Faculty level controls	No	Yes
Student level controls	No	Yes
Observations	28,558	1,752

Table 2: **Effect of female faculty on female students' STEM-related confidence and anxiety.** This table presents the effects of female faculty on students' STEM-related confidence and anxiety. Column I reports results for confidence, and Column II reports results for anxiety, both measured as z-scores (mean = 0, SD = 1) using Equation S4. The sample consists of the randomly selected half of students who completed standardized assessments in mathematics and science. The unit of observation is a student, and robust standard errors are reported in parentheses. Female faculty share is scaled by a factor of 10. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I STEM-related confidence	II STEM-related anxiety
Female faculty share × Female student	0.001	-0.056***
	(0.015)	(0.015)
Female faculty share	0.001	0.009
	(0.012)	(0.012)
Female student	0.009	0.051
	(0.068)	(0.077)
Observations	1,749	1,749

Table 3: **Effect of female faculty on female students' academic achievement by prior achievement, belonging, and STEM-related confidence and anxiety.** This table presents estimates of the effect of female faculty on female students' course grade z-scores (mean = 0, SD = 1) by subgroups. The smaller sample sizes for prior academic achievement, STEM-related confidence, and STEM-related anxiety are due to these measures being collected alongside the standardized mathematics and science assessments, which were administered to a randomly selected half of the sample. Approximately 10 percent of students did not respond to the question about belonging in their department at program entry. Column I reports interaction effect of female faculty and female student using Equation S1, with standard errors (in parentheses) clustered at the faculty level. Column II provides the number of observations per subgroup. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II
	Female faculty × Female student	Observations
Prior academic achievement		
Low	0.120**	5,766
	(0.055)	
High	0.037	7,552
	(0.051)	
Belonging in department		
Low	0.305***	4,142
	(0.088)	
High	0.049	21,756
	(0.033)	
STEM-related confidence		
Low	0.113**	6,646
	(0.056)	
High	0.041	6,653
	(0.053)	
STEM-related anxiety		
Low	0.067	6,655
	(0.056)	
High	0.068	6,631
	(0.052)	

Table 4: **Effect of female faculty on student beliefs about female ability in STEM.** This table presents estimates of the effect of female faculty on students' beliefs about female ability in STEM. Column I reports results using Equation S4, where non-stereotypical beliefs are coded as 1 and stereotypical beliefs as 0. Beliefs about mathematics were collected from all respondents, while a randomly selected half of the sample were administered the corresponding question about science. Standard errors (in parentheses) are clustered at the student level. Female faculty share is scaled by a factor of 10. The table also reports the mean proportion of non-stereotypical beliefs among female and male students. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	Non-stereotypical beliefs
Female faculty share × Female student (β_1)	-0.013**
	(0.006)
Female faculty share (β_2)	0.026***
	(0.005)
Female student (β_3)	0.260***
	(0.029)
Female students mean	0.852
Male students mean	0.611
Observations	2,581

References and Notes

1. S. Cheryan, S. A. Ziegler, A. K. Montoya, L. Jiang, Why are some STEM fields more gender balanced than others? *Psychological Bulletin* **143** (1), 1 (2017).

2. K. Parker, What's behind the growing gap between men and women in college completion? (2021), `https://www.pewresearch.org/short-reads/2021/11/08/whats-behind-the-growing-gap-between-men-and-women-in-college-completion/`.

3. M. Bertrand, C. Goldin, L. F. Katz, Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics* **2** (3), 228–255 (2010).

4. National Center for Science and Engineering Statistics, Diversity and STEM: Women, Minorities, and Persons with Disabilities 2023 (2023), `https://ncses.nsf.gov/pubs/nsf23315/report`, accessed: 2024-08-08.

5. C. M. Steele, J. Aronson, Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology* **69** (5), 797 (1995).

6. E. Reuben, P. Sapienza, L. Zingales, How Stereotypes Impair Women's Careers in Science. *Proceedings of the National Academy of Sciences* **111** (12), 4403–4408 (2014), doi:10.1073/pnas.1314788111, `https://www.pnas.org/content/111/12/4403`.

7. M. Niederle, L. Vesterlund, Gender and competition. *Annu. Rev. Econ.* **3** (1), 601–630 (2011).

8. P. Bordalo, K. Coffman, N. Gennaioli, A. Shleifer, Beliefs about Gender. *American Economic Review* **109** (3), 739–73 (2019), doi:10.1257/aer.20170007, `https://www.aeaweb.org/articles?id=10.1257/aer.20170007`.

9. M. C. Murphy, C. M. Steele, J. J. Gross, Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science* **18** (10), 879–885 (2007).

10. B. Mitchneck, J. L. Smith, M. Latimer, A recipe for change: Creating a more inclusive academy. *Science* **352** (6282), 148–149 (2016).

11. M. Bertrand, E. Duflo, Field experiments on discrimination. *Handbook of Economic Field Experiments* **1**, 309–393 (2017).

12. N. Dasgupta, Ingroup experts and peers as social vaccines who inoculate the self-concept: The stereotype inoculation model. *Psychological Inquiry* **22** (4), 231–246 (2011).

13. J. G. Stout, N. Dasgupta, M. Hunsinger, M. A. McManus, STEMing the tide: Using ingroup experts to inoculate women's self-concept in science, technology, engineering, and mathematics (STEM). *Journal of Personality and Social Psychology* **100** (2), 255–270 (2011), doi:10.1037/a0021385, `https://doi.apa.org/doi/10.1037/a0021385`.

14. N. Dasgupta, M. M. Scircle, M. Hunsinger, Female peers in small work groups enhance women's motivation, verbal participation, and career aspirations in engineering. *Proceedings of the National Academy of Sciences* **112** (16), 4988–4993 (2015), doi:10.1073/pnas.1422822112, `https://pnas.org/doi/full/10.1073/pnas.1422822112`.

15. D. J. Wu, K. C. Thiem, N. Dasgupta, Female peer mentors early in college have lasting positive impacts on female engineering students that persist beyond graduation. *Nature Communications* **13** (1), 6837 (2022), doi:10.1038/s41467-022-34508-x, `https://www.nature.com/articles/s41467-022-34508-x`.

16. S. D. Herrmann, *et al.*, The Effects of a Female Role Model on Academic Performance and Persistence of Women in STEM Courses. *Basic and Applied Social Psychology* **38** (5), 258–268 (2016), doi:10.1080/01973533.2016.1209757, `https://www.tandfonline.com/doi/full/10.1080/01973533.2016.1209757`.

17. R. W. Fairlie, F. Hoffmann, P. Oreopoulos, A community college instructor like me: Race and ethnicity interactions in the classroom. *American Economic Review* **104** (8), 2567–2591 (2014).

18. S. Canaan, P. Mouganie, The impact of advisor gender on female students' STEM enrollment and persistence. *Journal of Human Resources* **58** (2), 593–632 (2023).

19. H. Mansour, D. I. Rees, B. M. Rintala, N. N. Wozny, The effects of professor gender on the postgraduation outcomes of female students. *ILR Review* **75** (3), 693–715 (2022).

20. E. P. Bettinger, B. T. Long, Do faculty serve as role models? The impact of instructor gender on female students. *American Economic Review* **95** (2), 152–157 (2005).

21. F. Hoffmann, P. Oreopoulos, A Professor Like Me: The Influence of Instructor Gender on College Achievement. *Journal of Human Resources* **44** (2), 479–494 (2009), doi:https://doi.org/10.3368/jhr.44.2.479.

22. B. Borges, F. Estevan, Does exposure to more women in male-dominated fields render female students more career-oriented? *Management Science* (2024).

23. S. E. Carrell, M. E. Page, J. E. West, Sex and Science: How Professor Gender Perpetuates the Gender Gap. *The Quarterly Journal of Economics* **125** (3), 1101–1144 (2010), `https://doi.org/10.1162/qjec.2010.125.3.1101`.

24. P. Loyalka, *et al.*, Skill levels and gains in university STEM education in China, India, Russia and the United States. *Nature Human Behaviour* **5** (7), 892–904 (2021), `https://doi.org/10.1038/s41562-021-01062-3`.

25. J. Mummolo, E. Peterson, Demand effects in survey experiments: An empirical assessment. *American Political Science Review* **113** (2), 517–529 (2019).

26. M. L. Anderson, Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association* **103** (484), 1481–1495 (2008), doi:10.1198/016214508000000841, `https://doi.org/10.1198/016214508000000841`.

27. R. Glennerster, K. Takavarasha, *Running randomized evaluations: A practical guide* (Princeton University Press) (2014).

28. R. Stinebrickner, T. R. Stinebrickner, The causal effect of studying on academic performance. *The BE Journal of Economic Analysis & Policy* **8** (1) (2008).

29. T. S. Dee, A Teacher Like Me: Does Race, Ethnicity, or Gender Matter? *American Economic Review* **95** (2), 158–165 (2005), `https://doi.org/10.1257/000282805774670446`.

30. S.-J. Leslie, A. Cimpian, M. Meyer, E. Freeland, Expectations of brilliance underlie gender distributions across academic disciplines. *Science* **347** (6219), 262–265 (2015), doi:10.1126/science.1261375, `https://www.science.org/doi/abs/10.1126/science.1261375`.

31. D. S. Yeager, *et al.*, A national experiment reveals where a growth mindset improves achievement. *Nature* **573** (7774), 364–369 (2019).

32. R. Rosenthal, L. Jacobson, Pygmalion in the classroom. *The Urban Review* **3** (1), 16–20 (1968).

33. S. Gershenson, S. B. Holt, N. W. Papageorge, Who believes in me? The effect of student–teacher demographic match on teacher expectations. *Economics of Education Review* **52**, 209–224 (2016), `https://doi.org/10.1016/j.econedurev.2016.03.002`.

34. R. Arum, J. Roksa, *Academically adrift: Limited learning on college campuses* (University of Chicago Press) (2011).

35. J. Biggs, C. Tang, G. Kennedy, *Teaching for quality learning at university 5e* (McGraw-hill Education (UK)) (2022).

36. A. Eble, F. Hu, Child beliefs, societal beliefs, and teacher-student identity match. *Economics of Education Review* **77**, 101994 (2020).

37. G. M. Walton, G. L. Cohen, A question of belonging: race, social fit, and achievement. *Journal of Personality and Social Psychology* **92** (1), 82 (2007).

38. A. Bandura, Self-efficacy mechanism in human agency. *American Psychologist* **37** (2), 122 (1982).

39. D. Voyer, S. D. Voyer, Gender differences in scholastic achievement: a meta-analysis. *Psychological bulletin* **140** (4), 1174 (2014).

40. C. A. Moss-Racusin, J. F. Dovidio, V. L. Brescoll, M. J. Graham, J. Handelsman, Science faculty's subtle gender biases favor male students. *Proceedings of the National Academy of Sciences* **109** (41), 16474–16479 (2012).

41. E. J. Castilla, S. Benard, The paradox of meritocracy in organizations. *Administrative Science Quarterly* **55** (4), 543–676 (2010).

42. J. A. Bohren, A. Imas, M. Rosenberg, The dynamics of discrimination: Theory and evidence. *American Economic Review* **109** (10), 3395–3436 (2019).

43. R. Agler, P. De Boeck, On the interpretation and use of mediation: Multiple perspectives on mediation analysis. *Frontiers in Psychology* **8**, 1984 (2017).

44. S. J. Spencer, M. P. Zanna, G. T. Fong, Establishing a causal chain: Why experiments are often more effective than mediational analyses in examining psychological processes. *Journal of Personality and Social Psychology* **89** (6), 845–851 (2005), doi:10.1037/0022-3514.89.6.845.

45. AICTE, Engineering Education in India – Short & Medium Term Perspectives (2023), `https://www.aicte-india.org/sites/default/files/AICTE_Engineering_Education_Perspectives.pdf`.

46. National Science Foundation, *National Science Board: Science and Engineering Indicators* (2016).

47. P. Loyalka, *et al.*, The Effect of Faculty Research on Student Learning in College. *Educational Researcher* **51** (4), 265–273 (2022), `https://doi.org/10.3102/0013189X221090229`.

48. K. Muralidharan, K. Sheth, Bridging Education Gender Gaps in Developing Countries: The Role of Female Teachers. *Journal of Human Resources* **51** (2), 269–297 (2016), `https://doi.org/10.3368/jhr.51.2.0813-5901R1`.

49. M. L. Anderson, Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association* **103** (484), 1481–1495 (2008).

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Data and materials availability: Data and code used to perform the analyses will be deposited in Open Science Framework.

Supplementary materials

Materials and Methods

Tables S1 to S10

Supplementary Materials for
A STEM Professor Like Me: Female Faculty Improve STEM Outcomes Among Female Students

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This PDF file includes:

Materials and Methods

Tables S1 to S10

Materials and Methods

We collected student, faculty and administrative data from a nationally representative, random sample of 50 engineering and technology colleges in India. Our sample included faculty and students from broadly defined computer science (CS) and electrical engineering (EE) majors, the two largest disciplines in engineering and technology colleges. In 12 of these 50 colleges, students were randomly assigned to course sections ("classrooms") for all first- and second-year courses through a formal, computerized procedure. One of these was an all-women institution and was excluded from the analysis. The final study sample thus consisted of 11 colleges. Further details on the population of colleges and sampling procedure are available in Loyalka et al. (*47*).

Students enroll in courses each semester. Courses are divided into multiple classrooms to maintain small class sizes. Each classroom represents a separate course section taught by a different faculty member in the same semester. For example, Electrical Engineering 101, Spring 2019, at a given college may have three classrooms: Section A taught by Faculty X, Section B by Faculty Y, and Section C by Faculty Z. The number of classrooms per course ranges from 1 to 15, with a median of 3.

Since students are assigned courses based on a fixed curriculum, and within each course they are randomly allocated to sections, there is no self-selection into classrooms based on faculty or peer characteristics. This allows us to estimate the causal effect of being taught by female faculty on students. Additionally, since students are randomly assigned to classrooms, the proportion of their courses taught by female faculty members is also randomly determined. This enables estimation of the impact of exposure to female faculty during the study period.

We collected administrative records, surveys, and standardized assessments to construct a dataset on students and faculty. Administrative records provided information on student course enrollments, classroom and instructor assignments, and course grades. Student surveys captured demographic details—including gender, parental education, caste or socioeconomic status, and rural or urban background—along with responses on STEM-related confidence, anxiety, and gender attitudes. To measure academic performance, we linked student records to standardized test scores from a mathematics and science (physics) assessment administered to a randomly selected half of the students at the start of the program and again after two years. Faculty surveys provided information on rank, qualifications, and demographic characteristics, as well as self-reported teaching activities and instructional practices. These data were linked to the students they taught in their first two years.

The study received substantial institutional support from key government agencies, including the Ministry of Human Resource Development and the All India Council for Technical Education, as well as from college and department administrators. A large team of enumerators was thoroughly trained to proctor the surveys and assessments in person at each participating college during the start of the first year and end of the second year. We achieved high participation rates of approximately 95 percent of enrolled students in both survey rounds.

Estimation Strategy

We investigate the impacts of female faculty on female students' academic outcomes using three specifications. First, we estimate the impact of being randomly assigned to a female instructor's classroom on female students' course grades using Equation S1:

$$Y_{ikcf} = \alpha + \beta_1 Fem_f \times Fem_i + \lambda_i + \lambda_c + \epsilon_{ikcf} \tag{S1}$$

Here, Y_{ikcf} is the percentile grade for student i for course k, assigned to classroom c taught by faculty f, Fem_f indicates whether faculty f is female, Fem_i indicates whether student i is female, λ_i are student fixed effects, and λ_c are classroom fixed effects. β_1 is the coefficient of interest and measures the additional gain in course grades for female students taught by a female faculty rather than a male faculty. The unit of observation is a student-course, and standard errors are clustered at the faculty level.

We also estimate another version of Equation S1 where we replace classroom fixed effects with linear controls for faculty characteristics to examine the effect of female faculty on male students (*48*):

$$Y_{ikcf} = \alpha + \beta_1 Fem_f \times Fem_i + \beta_2 Fem_f + \lambda_i + \epsilon_{ikcf} \tag{S2}$$

Now β_1 is the coefficient of interest and measures the additional improvement in course grades for female students taught by a female faculty rather than a male faculty, compared to the effect on male students. Course grades in our sample are primarily based on end-of-semester exams administered and graded by a centralized university authority, rather than individual faculty. This ensures that faculty within the same course do not directly control student assessments. In a few departments, faculty influence a small portion of the grading structure, but this never exceeds 30 percent. Grading systems, however, vary across colleges, with some using letter grades and others numerical scores from 1 to 100. To standardize across institutions, we rank students within each course, creating variation in rankings across classrooms taught by different faculty. By definition, course rankings have a mean of 50 and a standard deviation of 28.9, following a uniform distribution. We standardize these course ranks to have a mean of zero and standard deviation of one for ease of interpretation.

We also estimate the impacts of female faculty on students' performance on standardized tests on academic skills (mathematics and science), that were administered by the research team at program entry (baseline) and after two years (endline). Equation S3 estimates the effects of female students being assigned to a greater share of female faculty in their first two years, on their test score in said standardized tests, conditional on observable student and faculty characteristics, including students' score in the baseline test.

$$
\begin{aligned}
Y_{is} = \alpha &+ \beta_1 FemShare_{is} + \beta_2 Fem_i \\
&+ \beta_3 FemShare_{is} \times Fem_i \\
&+ \gamma^\intercal \bar{\Omega}_{is} + \delta^\intercal \eta_i + \lambda_l + \lambda_s + \epsilon_{is}
\end{aligned} \tag{S3}
$$

Here, Y_{is} is the standardized test score for student i in school/department s, $FemShare_{is}$ represents the proportion of courses in which student i had a female faculty during the first two years, $\bar{\Omega}_{is}$ is a vector of average faculty characteristics for student i in school s, η_i is a vector of student characteristics, λ_l are subject fixed effects with $l \in \{\text{mathematics, science}\}$, and λ_s are school/department fixed effects.

Beyond academic outcomes, we examine how exposure to female faculty influences students' STEM-related anxiety, confidence, sense of belonging, and gender beliefs about STEM ability, using Equation S4:

$$
\begin{aligned}
Y_{is} = \alpha &+ \beta_1 FemShare_{is} + \beta_2 Fem_i \\
&+ \beta_3 FemShare_{is} \times Fem_i \\
&+ \gamma^\intercal \bar{\Omega}_{is} + \delta^\intercal \eta_i + \lambda_s + \epsilon_{is}
\end{aligned} \tag{S4}
$$

We measured STEM-related anxiety and confidence using survey items assessing students' emotional responses and self-perceived abilities in mathematics and science. The anxiety index included seven items evaluating concerns about learning challenges, performance, and feelings of being lost or nervous when completing coursework. The confidence index consisted of three items measuring students' perceptions of their own ability, such as considering themselves fast learners, viewing STEM as a strong subject, and feeling capable of understanding difficult content. Participants responded on a 4-point Likert scale, and both indices were constructed using the inverse covariance matrix of item z-scores, following Anderson et al. (*49*).

We assessed students' connection to their academic environment using measures of sense of belonging and classroom engagement. Sense of belonging was assessed with a direct question: *If you could choose again, would you remain in this department?*, which captures whether students feel connected enough to want to remain. Given the randomized design, any unmeasured motives for switching departments (e.g., career interests, financial considerations) should be similarly distributed across male and female respondents, making this a practical indicator of identification with one's program. Classroom engagement was measured based on how often students reported asking questions in class. Students were classified as engaged if they participated at least once every few classes in both maths and science classes.

We estimated subgroup effects by baseline ability, sense of belonging in their department, STEM-related confidence, and STEM-related anxiety using Equation S1 to examine whether the intervention's impact varies by students' academic standing and psychological orientation toward STEM. Baseline ability was measured using standardized mathematics and science tests administered at the start of the study. Sense of belonging, STEM-related confidence, and STEM-related anxiety were measured using survey items on students' emotional responses and self-perceived abilities in mathematics and science, as detailed earlier.

Finally, student and faculty beliefs about gender differences in STEM ability were recorded using a five-point Likert scale. For student beliefs, responses ranged from 1 (strong belief that male students are much better) to 5 (strong belief that female students are much better). These responses were recoded into a binary variable, classifying beliefs as stereotypical if the students expressed beliefs that male students are better or much better and non-stereotypical otherwise. Faculty beliefs were measured similarly, eliciting their perceptions regarding student qualifications in mathematics and science when they start their undergraduate program and after two years, as well as student performance in major-specific core courses (apart from maths and science) after two years.

Faculty mindset was measured using two constructs. Fixed mindset was assessed with the statement *Intelligence is something that cannot be changed very much*. Faculty who strongly agreed or agreed were coded as having a fixed mindset, while the rest were classified as not having a fixed mindset (having a growth mindset). A second measure captured a related but distinct belief, which differentiates between learning skills and changing intelligence, using the statement *You can learn new things, but you can't change a person's intelligence*. Faculty who strongly agreed or agreed were again coded as having a fixed mindset, while the rest were coded as not having a fixed mindset (having a growth mindset).

We addressed missing data in control variables by imputing all missing values with zero and including missingness indicators in all regressions to account for potential differences between respondents and non-respondents. This approach preserves sample size while allowing for flexible adjustment for non-random missingness. Our results are robust to excluding these controls or restricting the sample to observations with complete data.

Table S1: **Baseline and demographic characteristics of students by gender.** This table presents summary statistics for key baseline characteristics of students, disaggregated by gender. Column I reports mean values for female students, and Column II reports mean values for male students. Column III presents the gender difference in means, with robust standard errors in parentheses. Column IV reports the sample size for each variable. Academic skills, STEM-related anxiety, and STEM-related confidence are reported as z-scores (mean = 0, SD = 1). *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II	III	IV
Student characteristic	Female student	Male student	Difference	Observations
Mathematics and science proficiency	-0.146	0.042	-0.188***	826
			(0.063)	
STEM-related anxiety	0.053	-0.006	0.059	822
			(0.072)	
STEM-related confidence	-0.057	-0.007	-0.049	822
			(0.071)	
Father attended college	0.554	0.469	0.085***	1,782
			(0.025)	
Mother attended college	0.395	0.338	0.057**	1,783
			(0.025)	
Eligible for caste-based affirmative action	0.524	0.541	-0.016	1,789
			(0.025)	

Table S2: **Balance checks for random assignment of students to classrooms.** This table assesses whether key student characteristics are balanced across classrooms taught by male and female faculty. Column I reports the difference in means of student characteristics between classrooms taught by female and male faculty. Column II presents the total number of observations for each characteristic. Robust standard errors are in parentheses. Academic skills, STEM-related anxiety, and STEM-related confidence are reported as z-scores (mean = 0, SD = 1). The table also reports the p-value from an F-test for the joint significance of all characteristics. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II
Student characteristic	Female faculty classroom	Observations
Mathematics and science proficiency	0.009	13,714
	(0.030)	
STEM-related anxiety	-0.035	13,637
	(0.033)	
STEM-related confidence	0.010	13,637
	(0.033)	
Father attended college	-0.019*	28,787
	(0.011)	
Mother attended college	-0.011	28,807
	(0.009)	
Eligible for caste-based affirmative action	0.012	28,900
	(0.010)	
Female	0.011	28,949
	(0.010)	
P-value from F-test for joint significance	0.394	

Table S3: **Baseline and demographic characteristics of faculty by gender.** This table presents summary statistics for key baseline characteristics of faculty, disaggregated by gender. Column I reports mean values for female faculty, and Column II reports mean values for male faculty. Column III presents the gender difference in means, with robust standard errors in parentheses. Column IV reports the sample size for each variable. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II	III	IV
Faculty characteristic	Female faculty	Male faculty	Difference	Observations
Associate Professor	0.137	0.208	-0.071*	430
			(0.037)	
Professor	0.068	0.077	-0.009	430
			(0.026)	
Experience in Years	9.669	10.099	-0.430	429
			(0.669)	
Highest Degree is PhD	0.279	0.366	-0.087*	429
			(0.047)	
Highest Degree is PhD in Progress	0.170	0.116	0.054	431
			(0.036)	
Degree from Elite College	0.336	0.324	0.012	430
			(0.048)	
Eligible for Caste-Based Affirmative Action	0.397	0.384	0.013	430
			(0.050)	

Table S4: **Effect of female faculty on female and male students' academic achievement.** This table presents estimates of the effect of female faculty on female students' academic outcomes, measured by z-scored course grades (mean = 0, SD = 1) using Equation S2. The unit of observation is a student-course pair, and standard errors (in parentheses) are clustered at the faculty level. β_1 estimates the reduction in the gender gap in academic achievement when female students are taught by female faculty compared to male faculty. β_2 captures the effect of female faculty on male students. The joint test ($H_0 : \beta_1 + \beta_2 = 0$) assesses whether the total effect of female faculty on female students differs significantly from zero. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I Course grade
Female faculty × Female student (β_1)	0.070**
	(0.030)
Female faculty (β_2)	0.004
	(0.027)
$\beta_1 + \beta_2$	0.074
	(0.032)
P-value ($H_0 : \beta_1 + \beta_2 = 0$)	0.02
Student fixed effects	Yes
Faculty level controls	Yes
Observations	28,878

Table S5: **Robustness of the effect of female faculty on female students' academic achievement.** This table presents robustness checks for the effect of female faculty on female students' academic outcomes. Column I reports estimates for student course grades using Equation S1. The unit of observation is a student-course pair, and standard errors (in parentheses) are clustered at the faculty level. The first panel restricts the sample to non-elite colleges to test whether the effect persists outside highly selective institutions. The second panel presents results with classrooms weighted equally to account for differences in class sizes. The third panel uses course rank as outcomes instead of z-scored grades. All specifications include student and classroom fixed effects and standard errors are clustered at the faculty level. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I Course grades
Sample restricted to non-elite colleges (N=26,786)	
Female faculty × Female student	0.083**
	(0.032)
Sample restricted to STEM courses (N=26,258)	
Female faculty × Female student	0.087***
	(0.033)
Equally weighted classrooms (N=28,376)	
Female faculty × Female student	0.090**
	(0.040)
Using course ranks as outcome (N=28,558)	
Female faculty × Female student	2.638***
	(0.934)
Student fixed effects	Yes
Classroom fixed effects	Yes

Table S6: **Effect of female faculty on belonging and classroom engagement.** This table presents estimates of the effect of female faculty exposure on female students' sense of belonging in their department (Column I) and engagement in class (Column II). Female faculty share represents the proportion of a student's courses taught by female faculty over two years. Sense of belonging is measured by students' responses to whether they would choose to remain in their department if given the option to decide again. Classroom engagement is defined as asking questions at least once every few classes. Estimates are based on Equation S4, with robust standard errors in parentheses. Female faculty share is scaled by a factor of 10. Sample means for each outcome are reported at the bottom. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II
	Belonging in department	Engagement in class
Female faculty share × Female student	0.008	0.025*
	(0.010)	(0.013)
Female faculty share	0.007	-0.036**
	(0.013)	(0.017)
Female student	-0.015	-0.101**
	(0.041)	(0.051)
Mean	0.859	0.698
Observations	1,748	1,747

Table S7: **Effect of female faculty on interactions with students in class and office hours.** This table presents estimates of the effect of female faculty on interactions with students in different academic settings. The outcomes take a value of 1 if the student engaged in the respective interaction and 0 otherwise. Each student is observed twice, once for mathematics and once for science. Standard errors (in parentheses) are clustered at the student level. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I	II	III
	Call on student in class	Discussion during breaks	Office hours
All students			
Female faculty share × Female student	-0.002	-0.017**	-0.011
	(0.009)	(0.008)	(0.009)
Female faculty share	-0.003	0.014**	0.005
	(0.006)	(0.006)	(0.006)
Female student	-0.006	0.082**	0.005
	(0.038)	(0.034)	(0.039)
Mean	0.705	0.766	0.637
Observations	1,749	1,742	1,746
Students with low prior performance			
Female faculty share × Female student	0.002	-0.008	0.020
	(0.014)	(0.010)	(0.014)
Female faculty share	0.003	0.013	-0.008
	(0.009)	(0.008)	(0.010)
Female student	-0.010	0.092*	-0.010
	(0.059)	(0.049)	(0.058)
Mean	0.733	0.799	0.664
Observations	692	688	689

Table S8: **Effect of faculty gender on teaching-related activities and teaching practices.** This table presents differences between male and female faculty in time spent on teaching-related activities and use of teaching practices, controlling for department fixed effects and faculty characteristics. Column I reports the estimated difference for female faculty relative to male faculty, Column II provides the mean of the dependent variable, and Column III reports the number of observations. The first panel reports differences in weekly hours spent on teaching-related activities. The second panel reports differences in Teaching Practices Inventory (TPI) scores, which measure different aspects of instructional practices. TPI scores are reported as z-scores (mean = 0, SD = 1). Standard errors are in parentheses.*** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I Female faculty	II Mean	III Observations
Hours spent weekly on:			
Tutoring	0.077	2.761	491
	(0.205)		
Homework and tests	0.005	3.724	491
	(0.231)		
Course-related work	0.029	2.771	491
	(0.263)		
Advising students	-0.671**	3.314	490
	(0.283)		
Lesson planning	-1.087**	7.176	491
	(0.498)		
Teaching classes	-1.482**	11.329	491
	(0.678)		
Teaching Practices Inventory scores			
In-class activities	-0.164	0	495
	(0.103)		
Assignments	0.229**	0	495
	(0.105)		
Feedback and testing	-0.004	0	495
	(0.094)		
Collaboration	-0.047	0	495
	(0.091)		

Table S9: **Effects of female faculty with stereotypical and non-stereotypical beliefs on female students' academic achievement.** This table examines the impact of female faculty with stereotypical or non-stereotypical beliefs on female students' course grade z-scores (mean = 0, SD = 1). Faculty gender beliefs indicate whether faculty perceive male and female students as at least equally capable (non-stereotypical) or believe male students are more qualified (stereotypical). These beliefs were elicited for mathematics and science (Column I) and for other major-specific courses (Column II) separately. Standard errors (in parentheses) are clustered at the faculty level. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I Course grade (maths and science)	II Course grade (other courses)
Beliefs about female student ability (at college entry)		
Female faculty with non-stereotypical beliefs × Female student	0.083**	
	(0.034)	
Female faculty with stereotypical beliefs × Female student	0.081	
	(0.057)	
Share of female faculty with stereotypical beliefs	0.245	
Share of male faculty with stereotypical beliefs	0.398	
Beliefs about female student ability (after two years of college)		
Female faculty with non-stereotypical beliefs × Female student	0.087***	0.070**
	(0.033)	(0.034)
Female faculty with stereotypical beliefs × Female student	0.037	0.082*
	(0.052)	(0.044)
Share of female faculty with stereotypical beliefs	0.177	0.245
Share of male faculty with stereotypical beliefs	0.275	0.306
Observations	28,053	27,914

Table S10: **Effects of female faculty with fixed and growth mindset on female students' academic achievement.** This table examines the impact of female faculty with fixed or growth mindset on female students' course grade z-scores (mean = 0, SD = 1). In the first panel, fixed mindset is based on the endorsement of the belief that intelligence is largely innate and unchangeable, while all other responses are categorized a growth mindset. In the second panel. fixed mindset reflects the belief that intelligence is largely innate and unchangeable but new skills can be learned. A growth mindset includes all other responses. Standard errors (in parentheses) are clustered at the faculty level. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

	I Course grade
Mindset about malleability of intelligence	
Female faculty with growth mindset × Female student	0.108**
	(0.044)
Female faculty with fixed mindset × Female student	0.067*
	(0.037)
Share of female faculty with fixed mindset	0.562
Share of male faculty with fixed mindset	0.644
Mindset that skills can be learned, but intelligence is fixed	
Female faculty with growth mindset × Female student	0.071*
	(0.043)
Female faculty with fixed mindset × Female student	0.085**
	(0.037)
Share of female faculty with fixed mindset	0.575
Share of male faculty with fixed mindset	0.559
Observations	28,211