Can Curricular Reform Close the STEM Gender Gap? Evidence from an Introductory Computer Science Course

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Abstract

Introductory STEM courses may disproportionately deter women by understating these fields' societal relevance or presuming prior technical knowledge. Leveraging a curricular reform in an introductory computer science course at a liberal arts college that shifted emphasis from technical foundations to social relevance, we show that the reform increased women's likelihood of majoring in computer science compared with men without diminishing their academic performance. This effect operates primarily through greater retention of women who entered intending to major in computer science. The reform also increased women's earnings after graduation by shifting them into higher-paying occupations.

Keywords: STEM, gender gap, curricular reform, major choice

JEL Classification Numbers: J16; J24; I23; I24

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1 Introduction

The underrepresentation of women in science, technology, engineering, and math (STEM) has been widely studied. While the gender gap is less pronounced in fields like biology, chemistry, and mathematics in the U.S. (Cheryan et al., 2017), women remain significantly underrepresented in computer science (CS), physics, and engineering, with the female-to-male ratio plateauing at approximately 1-to-4 (Cheryan et al., 2017; Hill, Corbett and St. Rose, 2010). These disparities are driven in part by faster growth in male participation and higher attrition rates among women (Penner and Willer, 2019). Given that differential selection into math- and science-intensive fields explains a substantial share of the gender wage gap, increasing gender parity in college major choice could meaningfully reduce this gap (Brown and Corcoran, 1997; Blau and Kahn, 2000). It could also narrow gender differences in the accumulation of STEM-related human capital, reduce misallocation of talent, shape the future workforce, promote both efficiency and equality, and ease constraints on long-term economic growth (Altonji, Blom and Meghir, 2012; Hsieh et al., 2019).

Past literature has emphasized two major channels behind women's underrepresentation in STEM majors: differences in preferences for major attributes, such as expected returns, job amenities, and social values (Arcidiacono, 2004; Reuben, Wiswall and Zafar, 2017; Ngo and Dustan, 2024; Shi, 2018), and differences in prior knowledge of STEM (Stinebrickner and Stinebrickner, 2014; Akyol, Krishna and Lychagin, 2024; Arcidiacono et al., 2020). Numerous interventions have been designed and implemented to target these channels. To address the first channel, offering opportunities to interact with female instructors, role models, or advisors has been shown to increase women's likelihood of choosing and persisting in STEM majors (Bettinger and Long, 2005; Breda et al., 2023; Carrell, Page and West, 2010; Porter and Serra, 2020; Riley, 2024; Canaan and Mouganie, 2022; Mulhern, 2023). To address the second channel, in-person, individualized counseling and coaching have been shown to substantially increase academic performance in STEM, particularly among female students (Bettinger and Baker, 2014; Carrell and Sacerdote, 2017; Canaan, Deeb and Mouganie, 2022). Although these interventions are effective, they risk disproportionately burdening female faculty and students, potentially reinforcing existing gender disparities, as women already spend more time on service-related activities than men (Guarino and Borden, 2017; Buckles, 2019).

This paper focuses on an overlooked input: the in-class curriculum accompanied by small-scale complementary initiatives. We exploit a quasi-experimental setting at a STEM-focused liberal arts college in the United States, where in 2006 the CS department revised its introductory course to attract more women. Because this introductory course is required for *all* freshmen admitted to the college throughout the sample period, regardless of whether they choose to major in CS, the reform affected the entire student body. The redesigned course placed greater emphasis on the social relevance of CS, aiming to correct women's misconceptions about the discipline and to reduce feelings of inadequacy. Additionally, two complementary initiatives aimed at encouraging participation in CS were launched around the same time: (1) offering research opportunities to approximately 10 students immediately after their first year of college, regardless of gender, and (2) sending approximately 5 female students per year to a CS conference. Given that the redesigned course and complementary initiatives were introduced together, our estimates capture their combined effect; we refer to this package as the curricular reform. Using a difference-in-differences framework, we estimate the differential effect of the reform on women relative to men by comparing changes in outcomes for women before and after the reform to contemporaneous changes for men. The outcomes of interest include major choices and subsequent post-graduation outcomes, drawing on detailed individual-level institutional data that link academic records to post-graduation outcomes.

We find that the reform increased the probability that female students majored in computer science by 12.1 percentage points relative to male students. The reform also significantly increased women's post-graduation earnings, with women earning about 16.9% more than men after graduation, driven by sorting into higher-paying occupations. In addition, the reform reduced female students' probability of pursuing graduate study immediately after college by 9 percentage points relative to their male peers. Since graduate study is typically associated with lower stipends than full-time employment, this decline in graduate school enrollment accounts for roughly half of the observed earnings gains.

To assess potential unintended consequences and alternative explanations for our findings, we conduct several additional analyses. First, despite concerns that delaying exposure to specific foundational programming tools (e.g., object-oriented programming) could negatively affect students' subsequent academic performance, we find no evidence of deterioration in any academic outcomes. Second, based on descriptive evidence, it is unlikely that our results are driven by the nationwide increase in CS popularity among female students. Lastly, institutional features remain stable over the study period. Based on interviews with faculty and administrators, the reform was initiated solely by the CS department and was not part of a broader college-wide reform. Instructor assignments for this course remained the same before and after the reform.

We find that the primary channel through which the reform increased female students' probability of majoring in CS is improved retention among students who intended to major in CS at admission. Prior to the reform, female CS intenders were 22.9 percentage points less likely than their male counterparts to ultimately choose a CS major. After the reform, however, the probability that female CS intenders majored in CS increased by 27.6 percentage points relative to men, effectively eliminating the gender gap in retention. In contrast, we find limited evidence for alternative channels, such as increased switching into CS among female students who did not initially intend to major in CS or compositional changes in entering cohorts toward a higher share of female CS intenders.

The contribution of this paper is threefold. First, we provide causal evidence that curricular design, combined with initiatives that reshape departmental culture, can reduce gender gaps in STEM. Relative to interventions that rely on role models or mentoring, which may impose additional burdens on women or are difficult to scale, curricular reforms operate through changes to required coursework and may therefore offer a more sustainable policy instrument. Existing STEM curricula and departmental practices often place limited emphasis on the broader relevance of the discipline and its applications to other fields and society. These features may differentially affect women, who on average enter college with less prior STEM-related preparation (Carlana and Fort, 2022; Shi, 2018) and place greater weight on prosocial considerations in career choice (Burbano, Padilla and Meier, 2024; Burbano et al., 2024; Shi, 2018). We contribute to this literature by identifying the causal effect of reforming an introductory STEM course together with an accompanying cultural shift, and by documenting the mechanisms through which these changes increase female participation. We also show that the reform does not adversely affect the academic performance of male students.

Second, we provide evidence that the way STEM fields are presented can influence students' major choices, particularly for women. Prior research emphasizes the role of preferences for job amenities (Wiswall and Zafar, 2018; Zafar, 2013), family expectations (Wiswall and Zafar, 2021), and prosocial preferences (Burbano, Padilla and Meier, 2024; Burbano et al., 2024; Shi, 2018), as well as misperceptions about expected earnings across majors (Reuben, Wiswall and Zafar, 2017). Related work shows that emphasizing communal or social goals increases women's interest and engagement in STEM (Boucher et al., 2017; Barrera et al., 2024). We add to this literature by showing that curricular reforms that more accurately reflect the breadth and societal relevance of STEM fields can substantially increase women's persistence in STEM majors.

Third, we contribute to the literature on pedagogical practices and student outcomes. Prior work demonstrates that instructional context and assessment design can shape performance, including evidence that students from low socioeconomic backgrounds perform worse on mathematics questions involving fictitious monetary contexts (Duquennois, 2022) and that female students perform worse on free-response mathematics questions than on multiple-choice questions (Griselda, 2024). Other studies identify pedagogical approaches that improve outcomes, such as interactive and collaborative learning and the use of real-world examples, which increase female students' performance in introductory economics (Avery et al., 2024; Owen and Hagstrom, 2021) and mathematics (Di Tommaso et al., 2024). We extend this literature by showing that curricular design affects not only academic performance but also major choice and post-graduation labor market outcomes.

2 Background

In this section, we describe the institutional setting and the curricular reform. Our setting is a STEM-focused liberal arts college in the United States that offers six core majors: CS, engineering, mathematics, physics, biology, and chemistry. Students may also pursue joint majors (e.g., mathematics and CS or mathematics and biology) by completing coursework across departments. All first-year students, regardless of intended major, are required to take a common set of introductory courses in their first semester, including the introductory CS course that is the focus of this study.

Prior to 2006, the introductory CS course was Java-based and emphasized object-oriented programming and problem solving. Faculty identified several limitations of this course. First, the course pace did not accommodate the wide dispersion in students' prior programming experience: the material was too elementary for some students and overly challenging for others. Second, the emphasis on object-oriented programming limited students' exposure to CS as a broader discipline and provided little context for its applications to other fields or to real-world problems.

In response to these concerns, the CS department implemented a redesigned introductory course beginning with the 2006 entering cohort. The new curriculum adopted Python, rather than Java, as the primary programming language and reduced the emphasis on object-oriented programming. While the redesigned course continued to cover core programming skills, it placed greater emphasis on applications drawn from science and engineering, highlighting the role of CS across disciplines and its relevance to real-world problem solving (Dodds et al., 2008; Alvarado, Dodds and Libeskind-Hadas, 2012).[1]

A central goal of the redesign was to reduce the salience of differences in prior programming experience. Introductory courses in CS often create the perception that some students possess substantially more background knowledge than others, which can disproportionately discourage female students and reduce persistence in the field (Fischer, 2017; Mouganie and Wang, 2020). To address this concern, the redesigned course begins with hands-on assignments using a programming language developed by faculty specifically for the course. Since this language is new to all students, the approach helps level the playing field and reduces the salience of pre-college experience.

The redesigned course also introduced a split-track structure to accommodate heterogeneous skill levels. Before matriculation, all admitted students take an assessment exam measuring prior CS and programming knowledge. Students with little or no prior experience are assigned to a standard section, while those with demonstrated experience are assigned to an enrichment section. Both tracks cover the same core concepts, but the enrichment section engages with more advanced applications of these concepts. This structure allows experienced students to remain challenged while reducing barriers to entry for students new to CS.

Concurrent with the curricular redesign, the CS department implemented two complementary initiatives aimed at increasing student engagement in the field. First, the department expanded undergraduate research opportunities after the first year, open to both women and men, with approximately ten students selected annually. Second, the department provided financial support

[1] Bayer et al. (2020) presents a similar pedagogical approach in economics.

for a small number of female students, approximately five per year, to attend the Grace Hopper Celebration of Women in Computing conference. To assess whether other institutional changes might confound our estimates, we conducted interviews with CS faculty and staff from the Office of Institutional Research. All interviewees confirmed that the 2006 curricular reform and accompanying initiatives were developed independently by the CS department and were not part of a broader college-wide effort to increase female participation in STEM. Instructor assignments for the introductory course also remained unchanged before and after the reform.

The reform applied to students entering the college in Fall 2006 and later; students who matriculated prior to Fall 2006 were unaffected. Because the curricular redesign, split-track system, and complementary initiatives were introduced simultaneously, our estimates capture their combined effect. However, the initiatives that explicitly targeted female students, namely, support for attendance at the Grace Hopper conference, were limited in scale. With an average post-reform female cohort size of 81.2 students, these initiatives reached approximately 6.2 percent of female students, suggesting that their contribution to the estimated gender differential is likely to be modest.

3 Data

3.1 Student Academic and Demographic Data

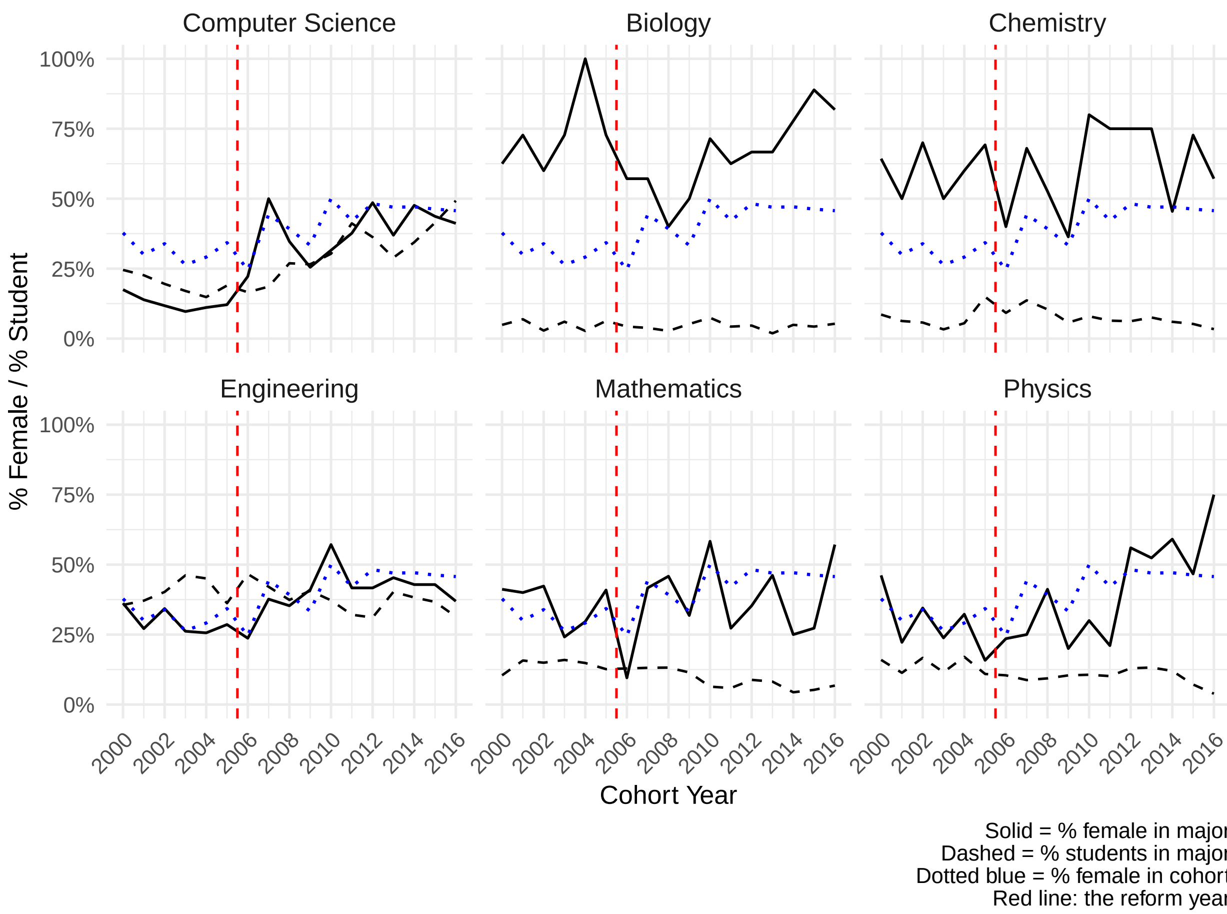
We obtain detailed administrative data covering all students who entered the college between 2000 and 2016. Each entering cohort consists of approximately 160 to 220 students. Information recorded at admission includes gender, race, SAT and/or ACT scores, additional academic qualifications (such as SAT subject tests and advanced high school coursework), and intended major at the time of admission. Graduation records include students' declared major, cumulative GPA, major GPA, graduation year, and whether the student left the college without completing a degree. We also observe detailed academic records for the introductory CS course and subsequent advanced CS courses, including the semester in which each course was taken and the grades received.

In addition to single majors, the college offers joint majors across departments. During the sample period, 460 students (14.7 percent) completed a joint major. We classify joint majors as follows: Chemistry and Biology as Chemistry; Computer Science and Mathematics as Computer Science; Mathematics and Biology as Mathematics; Mathematical and Computational Biology as Biology; and Mathematics and Physics as Mathematics. A small fraction of students (135 students, or 4.3 percent of the sample) completed a second major. For these students, we classify outcomes based on the primary major.

Figure 1 plots the share of female students and the share of all students by major across cohorts, along with the overall female share at the college. Biology and chemistry consistently exhibit high female representation throughout the period, although these majors enroll relatively few students (see Appendix Figure A1). Mathematics and physics also enroll a relatively high share of female students compared to men, though less so than biology and chemistry. Engineering remains one of the most popular majors throughout the period, and its female share closely tracks the overall college trend, with no visible change around the reform.

In contrast, prior to 2006, CS had the lowest female representation among all majors, with women accounting for approximately 15 to 20 percent of CS majors. Following the reform, the share of female students majoring in CS increased sharply, reaching over 40 percent by 2016. While the overall share of students majoring in CS also rose after the reform, the increase among women was substantially larger. These changes coincide with the timing of the curricular reform and contrast with the relatively stable trends observed in other STEM fields, suggesting a CS-specific response rather than a broad institutional shift.

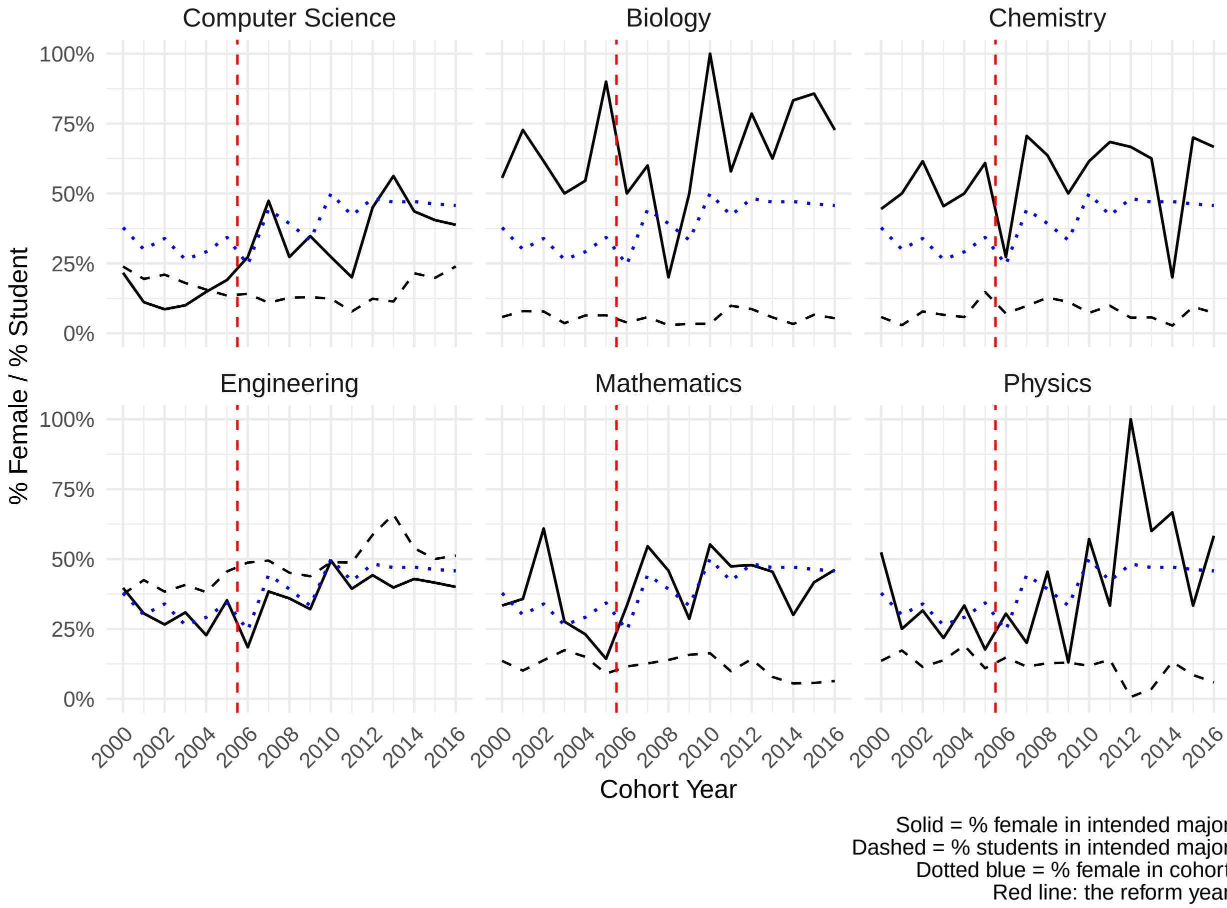
Figure 1: Share of Female and All Students by Majors, 2000 to 2016 Cohorts



Notes: This figure presents the evolution of the percentage of female (solid black) and all students (dashed black) within each core major by admission cohort from 2000 to 2016, along with the percentage of female students at the college (dotted blue). The red vertical dashed line indicates the CS curriculum reform in 2006.

Figure 2 presents analogous trends based on students' intended majors at admission. Prior to the reform, the female share among CS-intending students was again the lowest across majors, at approximately 15 to 20 percent. Following the reform, the share of women intending to major in CS increased steadily, exceeding 30 percent by 2016. Appendix Figure A2 reports the corresponding total number of students by intended major.

Figure 2: Share of Female and All Students by Intended Majors at Admission, 2000 to 2016 Cohorts



Notes: This figure presents the evolution of the percentage of female students (solid black) and all students (dashed black) within each intended core major by admission cohort from 2000 to 2016, as well as the overall percentage of female students at the college (dotted blue). The vertical red dashed line indicates the 2006 curriculum reform.

3.2 Labor Market Earnings Data

To measure post-graduation labor market outcomes, we obtain placement data collected by the Office of Advancement. These records include employer names, job titles, and, when available, employment start and end dates for graduates' post-college positions. Employment information is primarily obtained through alumni self-reports on online profiles. For alumni who do not update their profiles, the Office of Advancement manually verifies employment histories using publicly available online sources, including LinkedIn. LinkedIn has been shown to provide broadly representative information on the employment outcomes of college-educated workers in white-collar occupations

(Amanzadeh, Kermani and McQuade, 2024), and has been increasingly used in economic research on workforce composition and earnings (Berry, Maloney and Neumark, 2024; Amanzadeh, Kermani and McQuade, 2024; Wheeler et al., 2022). Because our data incorporate manual verification rather than conventional web scraping, they are of higher quality than typical LinkedIn-based datasets.

We focus on earnings at the start of graduates' careers by examining the first job observed after graduation, which has the lowest rate of missing information. For each position, we verify employer names using official company websites and map job titles and industries to the closest Standard Occupational Classification (SOC) code. We then assign to each student the median annual wage associated with that SOC code using data from the Occupational Employment and Wage Statistics (OEWS).[2] Our earnings measure therefore captures differences in occupational sorting rather than within-occupation wage variation.

Among students with available earnings data, 93 percent begin their first observed job within five years of graduation. Employment information is missing for 47.0 percent of students in the full sample, a rate slightly lower than that reported in prior studies using similar data sources (Firoozi, 2025). Although the share of missing earnings observations is higher for post-reform cohorts (55.1 percent) than for pre-reform cohorts (29.4 percent), there are no statistically or economically meaningful differences in missingness by gender (Appendix Table A1).

Approximately 28.1 percent of students in the sample pursue graduate education. For students entering graduate school, we assign stipend earnings using data from the PhD Stipends website, which reports self-reported stipend information by year.[3] Specifically, we assign the median stipend reported for U.S. graduate programs in the year the student enters graduate school. Because graduate stipends are typically lower than entry-level labor market earnings, and graduate school attendance varies substantially across majors,[4] we examine labor market earnings separately for

[2] https://www.bls.gov/oes/tables.htm (retrieved July 12, 2025).

[3] https://www.phdstipends.com/ (retrieved July 13, 2024).

[4] In our sample, the share of students pursuing a PhD is 12.2 percent in computer science, 19.9 percent in engineering,

graduate school attendees and non-attendees in Section 5.

3.3 Summary Statistics

Table 1: Summary Statistics

	Female (N=1,223)		Male (N=1,902)		Difference (Male – Female)	
	Mean	SD	Mean	SD	Mean	SE
Panel A: CS Major Outcomes						
Majoring in CS	0.23	0.42	0.30	0.46	0.07***	0.02
Intending to Major in CS	0.11	0.31	0.17	0.38	0.06***	0.01
Took 1st Optional CS Course	0.50	0.50	0.51	0.50	0.01	0.02
Took 2nd Optional CS Course	0.36	0.48	0.43	0.50	0.08***	0.02
Panel B: Post-Graduation Outcomes						
Salary at First Job ($1,000)	65.79	33.25	71.56	34.31	5.77***	1.70
Pursued Graduate Studies	0.31	0.46	0.26	0.44	-0.04*	0.02
Panel C: Academic Outcomes						
Cumulative GPA	3.30	0.42	3.34	0.46	0.04**	0.02
Major GPA	3.30	0.44	3.38	0.44	0.08***	0.02
Years to Graduation	4.06	0.54	4.07	0.48	0.00	0.02
Dropped Out	0.04	0.21	0.04	0.20	-0.00	0.01
Panel D: Pre-College Information						
SAT Math Score	748.31	41.12	760.34	49.47	12.03***	1.63
SAT Verbal Score	713.36	61.40	712.86	66.31	-0.50	2.32
SAT Total Score	1461.19	81.91	1473.88	99.50	12.70***	3.27
Took SAT STEM Subject Test	0.82	0.38	0.79	0.41	-0.04***	0.01
Took SAT Non-STEM Subject Test	0.03	0.17	0.03	0.18	0.01	0.01
Panel E: Race/Ethnicity						
Asian	0.23	0.42	0.17	0.38	-0.06***	0.01
Black	0.01	0.10	0.02	0.14	0.01**	0.00
Hispanic	0.02	0.15	0.04	0.20	0.02***	0.01
White	0.52	0.50	0.53	0.50	0.01	0.02
Multi-race	0.05	0.22	0.03	0.18	-0.02**	0.01
Other	0.16	0.37	0.20	0.40	0.04***	0.01

Notes: This table reports summary statistics on students' academic and demographic characteristics. Panel A reports measures related to CS major choice. Students who major in CS are required to complete two optional advanced CS courses; the first course is a prerequisite for the second, although students may place out of the first and enroll directly in the second. Panel B reports first-job earnings and graduate school enrollment. Panel C presents academic outcomes. Panel D reports pre-college academic characteristics measured at admission; ACT scores are converted to SAT scores using ACT–SAT concordance tables. Panel E summarizes racial and ethnic composition. The "Other" category includes American Indian/Alaska Native, Native Hawaiian/Other Pacific Islander, Unknown race, and Nonresident. P-values for differences in means are calculated using Welch's t-test. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

36.2 percent in biology, 65.9 percent in chemistry, and 55.0 percent in physics.

Table 1 reports summary statistics for students in the 2000–2016 cohorts, separately by gender. Panel A summarizes outcomes related to CS major choice, including intended major at admission, completion of the CS major, and enrollment in advanced CS coursework. Panel B reports post-graduation outcomes, including first-job earnings and graduate school enrollment. Panel C presents academic outcomes, Panel D reports pre-college academic characteristics measured at admission, and Panel E summarizes racial and ethnic composition.

Consistent with prior evidence on gender gaps in STEM, female students exhibit substantially lower engagement with CS than male students. Relative to men, women are 7 percentage points less likely to major in CS and 6 percentage points less likely to report an intention to major in CS at admission. Female students are also 8 percentage points less likely to enroll in optional advanced CS courses, which are not capacity-constrained and therefore reflect students' choices rather than enrollment limits.

Panel B shows differences in post-graduation outcomes by gender. Female students are 4 percentage points more likely than male students to enroll in graduate school immediately after graduation. Among students with available earnings data, women earn on average $5,770 less annually than men in their first observed job. As discussed in Section 5, these differences partly reflect variation in occupational sorting and graduate school attendance across majors.

Panel C indicates that female students have slightly lower academic performance on average, with cumulative GPAs lower by 0.04 points and major GPAs lower by 0.08 points relative to male students. However, these differences are small in magnitude. Panel D shows modest gender differences in academic preparation at admission: female students score approximately 12 points lower on the SAT math section and 13 points lower on total SAT scores.[5]

Finally, Panel E documents racial and ethnic composition by gender. Female students are more

[5]ACT scores are converted to SAT scores using the 2018 ACT–SAT concordance tables: https://www.act.org/content/dam/act/unsecured/documents/ACT-SAT-Concordance-Tables.pdf (retrieved April 2, 2024).

likely to identify as Asian or multiracial and less likely to identify as Black, Hispanic, or in the "Other" category. These demographic characteristics, along with pre-college academic measures, are included as controls in all regression specifications.

4 Empirical Specification

We adopt a difference-in-differences framework to estimate the differential effect of the curricular reform on female students relative to male students. Since the introductory CS course is mandatory for all students, both women and men were exposed to the reform. Identification therefore comes from differential changes in outcomes for women relative to men across cohorts before and after the reform.

We begin by estimating an event-study specification that allows the effect of the reform to vary flexibly by entering cohort:

$$Outcome_i = \sum_{t=2000, t \neq 2005}^{2016} \beta_1^t \, \mathbb{1}[c(i) = t] \times Female_i + \beta_2 Female_i + X_i' \gamma_1 + Post_{c(i)} \times X_i' \gamma_2 + \tau_{c(i)} + \epsilon_i, \quad (1)$$

where $Outcome_i$ denotes the outcome of interest for student i. Our primary outcomes include (i) major choice, where $Outcome_i$ equals one if student i majors in CS; (ii) labor market earnings, measured as the natural logarithm of estimated annual earnings in the first post-graduation job; and (iii) graduate school enrollment, where $Outcome_i$ equals one if student i enrolls in graduate school immediately after graduation. We also examine a range of academic outcomes, including cumulative GPA, major GPA, time to graduation, and dropout.

$Female_i$ is an indicator equal to one if student i is female. $\tau_{c(i)}$ denotes cohort fixed effects, which absorb cohort-specific factors, including changes in cohort composition and aggregate conditions at graduation.[6] The vector X_i includes student-level academic and demographic characteristics measured at admission, including race indicators, SAT math and verbal scores, and indicators for advanced high school coursework and SAT subject tests. We interact X_i with a post-reform indicator, $Post_{c(i)}$, to allow for changes in the relationship between student characteristics and outcomes after the reform. Standard errors are clustered at the cohort level to account for within-cohort correlation (Abadie et al., 2023).

The coefficients of interest in equation 1 are β_1^t for $t \geq 2006$, which capture the differential effect of the reform on female students relative to male students in each post-reform cohort. The identifying assumption is parallel trends: absent the reform, outcomes for female and male students would have evolved similarly across cohorts. While this assumption is not directly testable, the coefficients β_1^t for $t < 2006$ provide evidence on the plausibility of parallel trends prior to the reform.

To summarize the average effect of the reform, we also estimate a more parsimonious difference-in-differences specification that replaces the cohort-specific interactions with a single post-reform interaction:

$$Outcome_i = \beta_1 Post_{c(i)} \times Female_i + \beta_2 Female_i + X_i' \gamma_1 + Post_{c(i)} \times X_i' \gamma_2 + \tau_{c(i)} + \epsilon_i. \qquad (2)$$

In this specification, β_1 captures the average differential effect of the reform on female students relative to male students across all post-reform cohorts. We report estimates from equation 2 alongside event-study plots derived from equation 1.

We estimate both specifications using ordinary least squares. Since treatment timing is common across cohorts, and identification relies on differential responses by gender rather than staggered adoption, OLS provides consistent estimates in this setting (see, e.g., Baker et al., Forthcoming; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021;

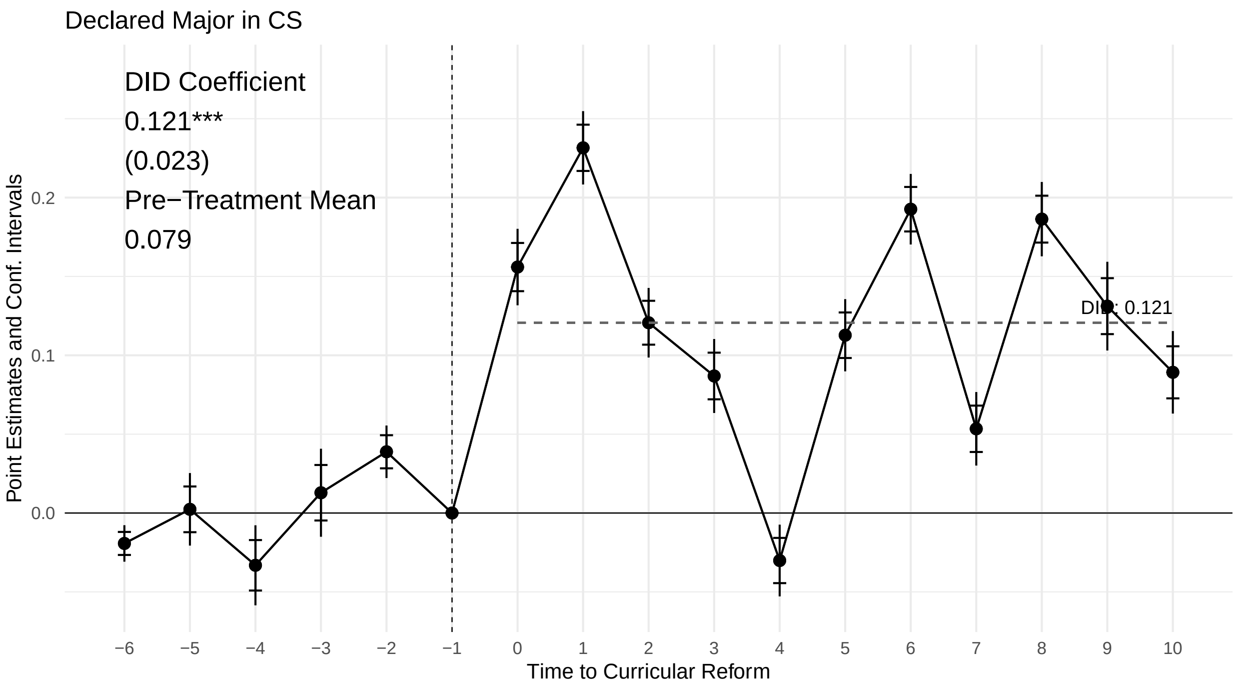
[6] Nearly all students graduate in four years, so entering cohort and graduation year align closely. As a result, cohort fixed effects also absorb graduation-year labor market conditions and institution-wide shocks that vary by cohort.

Sun and Abraham, 2021).

5 Results

5.1 Effect on Major Choice

Figure 3: Effect of Curricular Reform on Major Choice



Notes: This figure presents point estimates and 80% and 95% confidence intervals for β_1^t from equation 1. The outcome is a binary indicator representing whether a student majored in CS. The curricular reform was implemented in 2006, and the coefficient for the baseline cohort (2005) is normalized to zero. Standard errors are clustered at the cohort-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 3 presents event-study estimates of the effect of the curricular reform on the probability that female students major in CS, relative to male students. The coefficients are normalized to the cohort immediately preceding the reform. Standard errors are clustered at the cohort level.

The pre-reform coefficients indicate that the gender gap in CS major choice was stable in the years leading up to the reform. This pattern is consistent with the parallel trends assumption underlying our difference-in-differences design. Beginning with the 2006 entering cohort, the estimates increase sharply and remain persistently positive across post-reform cohorts.

Averaging across post-reform cohorts, the reform increased the probability that female students major in CS by approximately 12.1 percentage points relative to men. Given a pre-reform female CS major rate of roughly 15–20 percent, this represents a substantial increase in women's participation in the major. While the overall share of students majoring in CS also rose after the reform, the increase among women was markedly larger, resulting in a significant narrowing of the gender gap.

Taken together, these results indicate that the curricular reform had a large and sustained effect on women's entry into the CS major. In contrast, trends in other STEM majors remained relatively stable over the same period (Figure 1), suggesting that the observed changes reflect a CS-specific response rather than a broader shift in students' major preferences.

Table 2: Effects of Reform on Academic Outcomes

Sample:	All Graduates				CS Graduates			
Outcome:	Cum. GPA (1)	Major GPA (2)	Yrs to grad. (3)	Dropped Out (0/1) (4)	Cum. GPA (5)	Major GPA (6)	Yrs to grad. (7)	Dropped Out (0/1) (8)
Female × Post	0.019	0.027	-0.083	-0.010	0.009	0.010	-0.028	-0.005
	(0.039)	(0.042)	(0.050)	(0.014)	(0.114)	(0.088)	(0.051)	(0.061)
Female	-0.059*	-0.095**	0.063	0.013	-0.051	-0.092	-0.014	-0.008
	(0.032)	(0.037)	(0.047)	(0.013)	(0.109)	(0.082)	(0.040)	(0.059)
Cohort Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Pre-Treatment Mean	3.206	3.239	4.077	0.055	3.176	3.231	4.104	0.077
Adj. R-squared	0.111	0.095	0.012	0.009	0.117	0.094	0.060	0.034
Observations	3122	3104	2990	3122	864	862	817	864

Notes: This table presents OLS estimates of equation 2. The model is estimated for various academic outcomes (i.e., cumulative GPA, major GPA, years to graduate, likelihood of dropping out) among all and CS graduates. Standard errors are clustered at the cohort-year level and are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Academic Outcomes A potential concern is that the redesigned introductory course, by delaying coverage of certain foundational topics such as object-oriented programming, could adversely affect students' academic performance in subsequent coursework. Another concern is that increased entry into the major by students with less prior experience could lower average academic performance among CS majors.

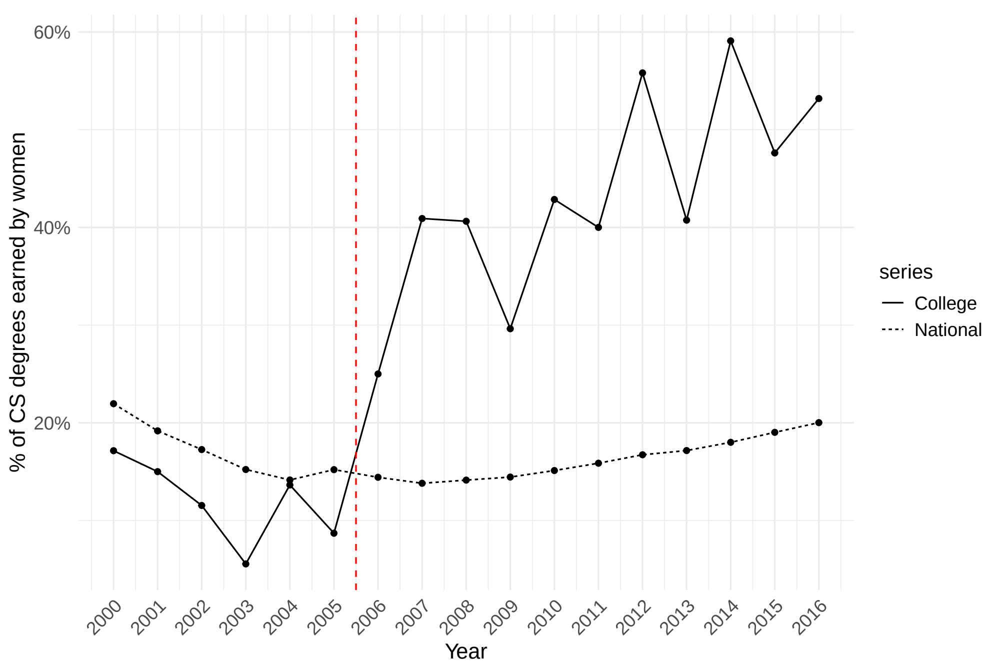
Table 2 reports difference-in-differences estimates for a range of academic outcomes. Columns

(1)–(4) present results for all students, while columns (5)–(8) restrict the sample to students who ultimately graduated with a CS major. Across all specifications, we find no evidence that the reform negatively affected female students' academic outcomes relative to male students.

For the full sample, the estimated effects on cumulative GPA, time to graduation, and dropout are small and statistically insignificant. Among CS graduates, the reform has no detectable effect on any of the academic outcomes either. Point estimates are generally close to zero, indicating that the increased participation of women in CS did not come at the expense of academic performance.

Overall, these results suggest that the reform increased women's entry into the CS major without reducing academic performance either overall or within the major. The absence of negative effects among CS graduates also indicates that the reform did not dilute academic standards or hinder preparation for advanced coursework.

Figure 4: Share of CS Degrees Earned by Women: National vs the College, 2000 to 2016 Cohorts



Notes: This figure plots the percentage of CS degrees earned by women at the college level (the solid line) and the national level (the dashed line) for cohorts entering in years 2000 to 2016. The data are from the Integrated Postsecondary Education Data System (IPEDS). We define CS degrees as those classified under "Computer and Information Sciences, General" (CIP Code 11.0101) or "Computer Science" (CIP Code 11.0701).

College vs. National Trend of CS Majors Another concern is that the observed increase in female participation in CS reflects broader national trends rather than the curricular reform. To assess this possibility, Figure 4 compares the share of CS degrees earned by women at the college to national trends using data from the Integrated Postsecondary Education Data System (IPEDS).[7]

For cohorts entering between 2000 and 2005, the share of CS degrees earned by women at the college consistently lagged behind the national average. Beginning with the 2006 entering cohort, the year the curricular reform was implemented, the pattern diverges: female representation in CS at the college increased sharply and surpassed the national level, while the national share declined in the early 2000s and recovered only gradually thereafter. By 2016, the national share of CS degrees earned by women remained below its 2000 level, whereas the college's share had increased substantially.

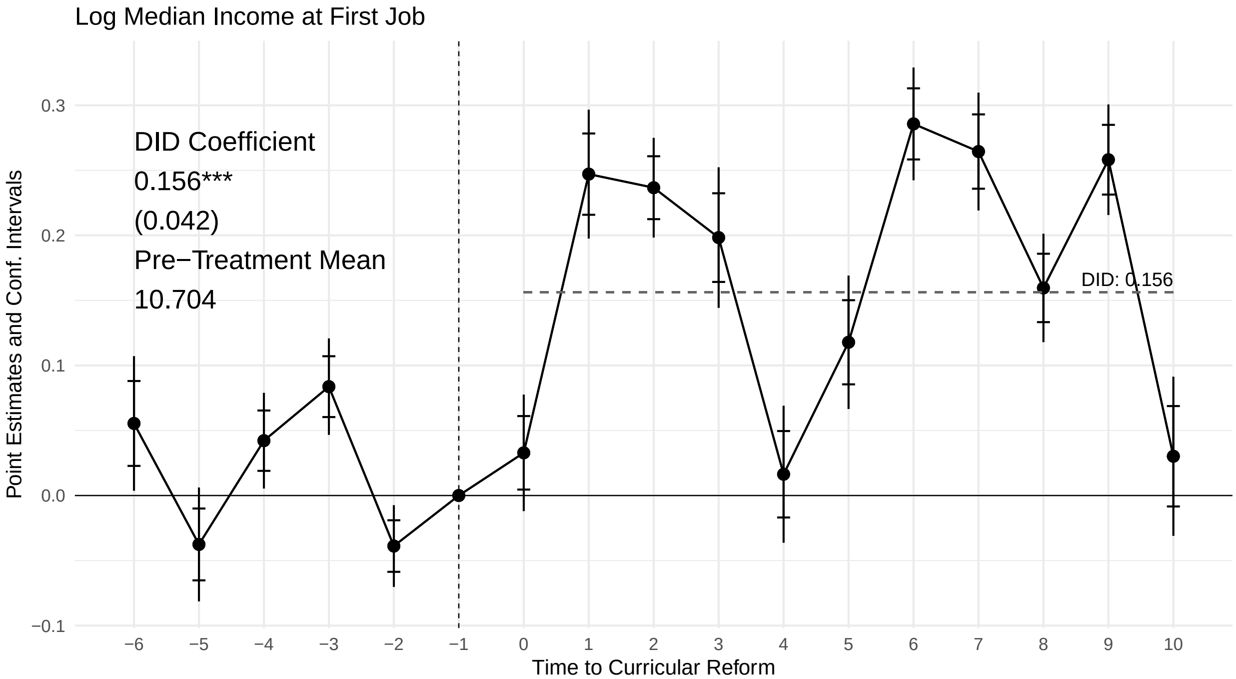
This comparison suggests that national trends alone are unlikely to explain the magnitude and timing of the post-reform increase. While the national data are descriptive and do not provide a formal counterfactual, the divergence in trends coinciding with the timing of the reform is consistent with the interpretation that the observed changes reflect a college-specific response rather than a broad, nationwide shift in women's interest in computer science.

5.2 Effects on Post-Graduation Outcomes

Labor Market Earnings Figure 5 presents event-study estimates of the effect of the curricular reform on female students' earnings in their first post-graduation job, relative to male students. Earnings are measured using the median wage associated with the student's occupation, as defined by Standard Occupational Classification codes. As a result, the estimates capture changes in occupational sorting rather than within-occupation wage differences.

[7] https://nces.ed.gov/ipeds/ (retrieved July 21, 2025). We define CS degrees as those classified under "Computer and Information Sciences, General" (CIP Code 11.0101) or "Computer Science" (CIP Code 11.0701).

Figure 5: Labor Market Earnings Effects of Reform



Notes: This figure plots point estimates and 80% and 95% confidence intervals of β_1^t from equation 1. The outcome is the natural logarithm of labor market earnings at a student's first post-graduation job, measured using the median salary associated with the student's SOC code based on employer and job title. The curricular reform was implemented in 2006, and the coefficient for the baseline cohort (2005) is normalized to zero. Standard errors are clustered at the cohort-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

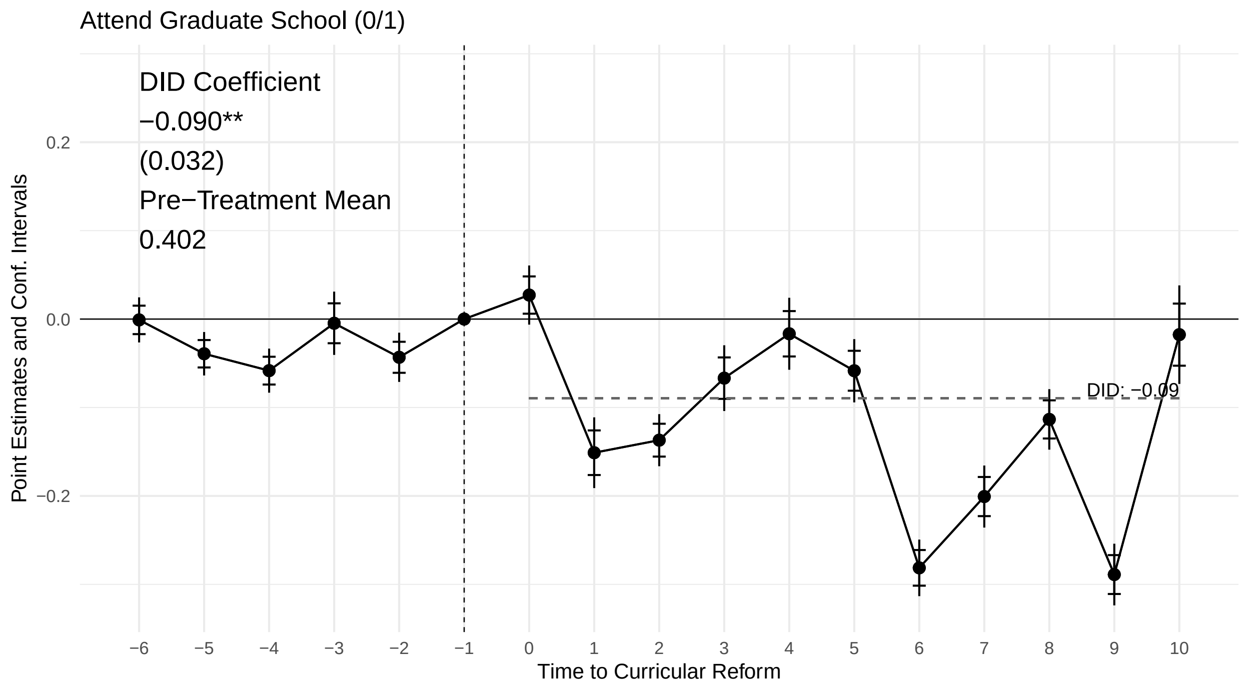
The pre-reform coefficients do not display systematic upward or downward trends, providing little evidence of differential pre-trends in earnings between women and men. Beginning with post-reform cohorts, the estimates increase and remain positive. Averaged across post-reform cohorts, the reform increased women's post-graduation earnings by approximately 16.9 percent relative to men ($e^{0.156} - 1 \approx 0.169$). Evaluated at the pre-reform mean for female students, this corresponds to an increase of roughly $7,500 in annual earnings at the first job.[8] These gains are economically meaningful, particularly given that they occur at the start of graduates' careers.

Since earnings are assigned at the occupation level, we assess whether the observed gains reflect improved occupational sorting. When we include fixed effects for occupation in the earnings

[8] With a pre-reform mean of logged median income of 10.704 for women, the implied median annual income is about $44,500 ($e^{10.704} = \$44,534$). Applying the estimated 16.9 percent effect implies an earning increase of roughly $7,500 for women after the reform.

regression, the estimated reform effect disappears (Appendix Figure A6). This result indicates that the earnings gains are driven by women sorting into higher-paying occupations rather than higher wages within occupations.

Figure 6: Effects on Graduate School Enrollment



Notes: This figure presents point estimates and 80% and 95% confidence intervals of β_1^t from equation 1. The outcome variable is a dummy indicator representing whether a student chose to attend graduate school after graduating from the college. The curricular reform was implemented in 2006, with the coefficient for the baseline cohort (2005) normalized to zero. Standard errors are clustered at the cohort-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Graduate School Attendance Figure 6 reports event-study estimates of the effect of the reform on the probability that female students enroll in graduate school immediately after graduation, relative to men. The estimates show a decline in graduate school enrollment among women beginning with post-reform cohorts.

On average, the reform reduced female students' probability of enrolling in graduate school by approximately 9 percentage points relative to male students. An important limitation of the data is that graduate enrollment is observed only immediately after graduation; students who enter graduate school after a period in the labor market are not captured.

One concern is that the earnings gains documented above are driven mechanically by reduced graduate school enrollment, since graduate stipends are typically lower than entry-level labor market earnings. To investigate this, Appendix Table A2 reports earnings effects separately for students who enter the labor market immediately after graduation and those who enroll in graduate school. Among students who do not attend graduate school, the reform increases women's earnings by approximately 8 percent relative to men ($e^{0.077} - 1 \approx 0.080$), which accounts for roughly half of the overall earnings gain.[9] The remaining earnings increase is attributable to the reduction in graduate school enrollment.

These results indicate that the reform improved women's early-career labor market outcomes through two channels: reduced graduate school enrollment immediately after graduation and improved occupational sorting among labor market entrants.

5.3 Male Students' Outcomes

Given that the introductory computer science course is required for all students, male students were also exposed to the curricular reform. Identification in our difference-in-differences framework therefore relies on comparing changes in outcomes for women to contemporaneous changes for men. A potential concern is that the estimated effects for women reflect changes in male students' outcomes in the opposite direction rather than genuine gains among women.

To examine this, we examine changes in male students' outcomes before and after the reform using specifications analogous to equation 2, restricting the sample to male students and controlling for academic and demographic characteristics measured at admission. Table 3 reports estimated post-reform changes in major choice and post-graduation outcomes for male students. Appendix Figure A3 shows that male students' outcomes do not exhibit sharp declines around the reform

[9] The results remain quantitatively similar after controlling for intended major fixed effects in column 2.

year, consistent with the regression evidence.

Following the reform, male students' probability of majoring in CS increased by 8.9 percentage points, and their post-graduation earnings increased by approximately 18 percent (log-point estimate: 0.165). Additionally, while not statistically significant, the estimated effect suggests a decrease in the probability of enrolling in graduate school immediately after graduation. These changes are in the same direction as those observed for female students. As a result, the estimated effects for women do not reflect relative gains driven by deterioration in male outcomes; if anything, accounting for these positive trends among men would suggest even larger absolute increases in women's outcomes.

We also report corresponding results for academic outcomes among male students in 4. As shown in the table, their cumulative GPA and major GPA increased modestly after the reform, while time to graduation and dropout rates remained statistically unchanged.

These results suggest that the curricular reform did not adversely affect male students' academic or labor market outcomes. Instead, male students experienced modest improvements along several dimensions, reinforcing the interpretation that the estimated effects for women reflect genuine gains rather than relative changes driven by declines among men.

Table 3: Male Students' Main Outcomes

Sample:	All Graduates		
Outcome:	CS Major (1)	Log Earnings (2)	Grad School (3)
Post	0.089** (0.039)	0.165 (0.098)	-0.059 (0.073)
Controls	Y	Y	Y
Pre-Treatment Mean	0.248	10.929	0.292
Adj. R-squared	0.025	0.040	0.016
Observations	1900	1037	1038

Notes: This table reports OLS estimates from regressions of male students' main outcomes on a post-reform indicator (post = 1 for cohorts entering in 2006 or later). All specifications include controls for race, math and verbal SAT scores, and indicators for SAT STEM subject tests, with standard errors clustered at the cohort-year level.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Male Students' Academic Outcomes

	All Graduates				CS Graduates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cum. GPA	Major GPA	Yrs to Grad.	Dropped Out	Cum. GPA	Major GPA	Yrs to Grad.	Dropped Out
Post	0.093***	0.050*	-0.003	-0.016	0.091	0.084	0.016	-0.005
	(0.029)	(0.027)	(0.021)	(0.009)	(0.055)	(0.057)	(0.040)	(0.033)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Pre-Treatment Mean	3.280	3.351	4.052	0.047	3.246	3.357	4.105	0.074
Adj. R-squared	0.100	0.084	0.014	0.015	0.088	0.076	0.020	0.013
Observations	1,900	1,890	1,823	1,900	577	576	543	577

Notes: This table reports OLS estimates from regressions of male students' academic outcomes on a post-reform indicator (post = 1 for cohorts entering in 2006 or later). All specifications include controls for race, math and verbal SAT scores, and indicators for SAT STEM subject tests. Standard errors are clustered at the cohort-year level and reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.4 Mechanisms for Major Choice

The increase in female students' probability of majoring in computer science may operate through several channels. We consider three potential mechanisms: (i) improved *retention* among students who intended to major in CS at admission; (ii) increased *switching* into CS among students who did not initially intend to major in CS; and (iii) *compositional changes* in entering cohorts toward a higher share of female CS intenders.

To examine these channels, we extend equation 2 to allow the effect of the reform to vary by whether a student intended to major in CS at admission:

$$\begin{aligned} Outcome_i = {} & \beta_1 Post_{c(i)} \times Female_i \times IntendCS_i + \beta_2 Post_{c(i)} \times Female_i + \beta_3 Female_i \times IntendCS_i \\ & + \beta_4 Post_{c(i)} \times IntendCS_i + \beta_5 Female_i + \beta_6 IntendCS_i \\ & + X_i' \gamma_1 + Post_{c(i)} \times X_i' \gamma_2 + \tau_{c(i)} + \epsilon_i, \end{aligned} \tag{3}$$

where $IntendCS_i$ is an indicator equal to one if student i reported an intention to major in CS at admission. The coefficient $\beta_1 + \beta_2$ captures the reform's effect on female CS intenders relative to male CS intenders and therefore reflects changes in retention. The coefficient β_2 captures the reform's effect on female students who did not initially intend to major in CS, relative to their male counterparts, and therefore reflects switching into CS. We estimate this specification both with and without intended-major fixed effects. Including these fixed effects absorbs changes in the composition of intended majors at admission, thereby isolating the retention and switching channels from compositional changes.

Table 5 reports the results. Panel A documents substantial gender gaps prior to the reform. Before 2006, female students who intended to major in CS were 22.9 percentage points less likely than comparable male students to ultimately major in CS. Female students who did not intend to major in CS were also less likely than men to end up in the CS major, although the gap was smaller in magnitude.

Panel B shows that the reform primarily operates through improved retention among CS intenders. Among students who intended to major in CS at admission, the reform increased women's probability of majoring in CS by 27.6 percentage points relative to men ($p < 0.01$), effectively eliminating the pre-reform gender gap. In contrast, among students who did not initially intend to major in CS, the estimated effect of the reform is small and statistically insignificant. The difference between the retention and switching effects (β_1) is statistically significant, indicating that the reform's impact on major choice was concentrated among women who entered college intending to pursue CS.

Panel C reports the corresponding effects for male students and shows no statistically significant change in CS major completion among male CS intenders after the reform. Column 2 adds intended-major fixed effects, which absorb changes in the composition of intended majors at admission. The results are nearly identical, ruling out compositional changes in entering cohorts as a primary driver of the observed effects.[10]

[10] Appendix Figure A5 shows that once intended-major fixed effects are included, the overall reform effect is attenuated, reflecting the fact that the reform primarily affects the subset of students who entered intending to major in CS.

These results suggest that the increase in women's participation in the CS major is driven primarily by improved persistence among female students who initially intended to major in CS, rather than by increased switching or changes in the composition of entering cohorts.

Table 5: Mechanisms: Reform Effects by Intended Major

	CS Major		Graduate School		Log Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Pre-Reform Gender Gap (Women − Men)						
CS-intenders ($\beta_3 + \beta_5$)	-0.229***	-0.231***	0.125	0.118	-0.226**	-0.218*
	(0.078)	(0.077)	(0.087)	(0.091)	(0.104)	(0.109)
Non-CS-intenders (β_5)	-0.074***	-0.067***	0.102***	0.092***	-0.200***	-0.182***
	(0.010)	(0.012)	(0.016)	(0.021)	(0.021)	(0.018)
B. Reform Effect on Women Relative to Men						
CS-intenders ($\beta_1 + \beta_2$)	0.276***	0.275***	-0.053	-0.057	0.149	0.152
	(0.092)	(0.091)	(0.110)	(0.112)	(0.149)	(0.152)
Non-CS-intenders (β_2)	0.025	0.020	-0.082**	-0.093**	0.128**	0.141***
	(0.023)	(0.024)	(0.035)	(0.038)	(0.045)	(0.045)
Difference (β_1)	0.250**	0.255**	0.029	0.036	0.021	0.011
	(0.101)	(0.102)	(0.122)	(0.128)	(0.162)	(0.170)
C. Reform Effect on Men						
Male CS-intenders (β_4)	-0.095	-0.103	-0.036	-0.060	-0.054	-0.023
	(0.063)	(0.065)	(0.046)	(0.046)	(0.049)	(0.050)
Intended Major FE	N	Y	N	Y	N	Y
Cohort Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Pre-Treatment Mean	0.079	0.079	0.402	0.402	10.704	10.704
Adj. R-squared	0.233	0.241	0.098	0.129	0.144	0.173
Observations	3,122	3,122	1,672	1,672	1,669	1,669

Notes: This table presents OLS estimates of equation 3, decomposing the reform effect by whether a student intended to major in CS at admission. Panel A reports pre-reform gender gaps. Panel B reports reform effects on women relative to men: "Retention" captures effects among CS-intenders (improved retention), while "Switching" captures effects among non-CS-intenders. Panel C shows reform effects on men. Odd columns exclude intended major fixed effects; even columns include them to control for composition changes. All specifications include cohort-year fixed effects and demographic controls. Standard errors clustered at the cohort-year level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5.5 Mechanisms for Post-Graduation Outcomes

Graduate School Enrollment We next examine whether the mechanisms underlying post-graduation outcomes differ by students' intended major at admission. Columns 3 and 4 of Table 5 report results for graduate school enrollment.

Prior to the reform, women, particularly those who did not intend to major in CS, were more likely than men to enroll in graduate school immediately after graduation. Female non-CS intenders exceeded their male counterparts by 10.2 percentage points. Following the reform, the decline in graduate school enrollment among women is concentrated primarily among non-CS intenders. For this group, graduate school attendance falls by 8.2 percentage points ($p < 0.05$), while the estimated effect for CS intenders is smaller and statistically indistinguishable from zero. These results are unchanged when intended-major fixed effects are included.

Labor Market Earnings Columns 5 and 6 examine earnings at the first post-graduation job. Prior to the reform, women faced substantial earnings penalties relative to men, regardless of intended major. Post-reform earnings gains, by contrast, are broad-based. Female non-CS intenders experience a statistically significant increase in earnings of 13.7 percent relative to men ($e^{0.128} - 1 \approx 0.137$), while the estimated effect for female CS intenders is of similar magnitude but not statistically significant due to larger standard errors. The difference between the retention and switching effects is small and statistically insignificant, indicating that earnings gains are not concentrated among women who initially intended to major in CS. Earnings estimates remain stable when intended-major fixed effects are included, ruling out compositional changes as an explanation.

Overall, these findings indicate that the post-reform reduction in graduate school enrollment and the associated earnings gains are not mechanically tied to increased retention among CS intenders. Instead, labor market benefits accrue broadly to female students, regardless of their initial intention to major in CS.

6 Conclusion

This paper provides causal evidence that curricular reform in a required introductory STEM course can substantially increase women's participation in computer science. Exploiting the introduction of a redesigned introductory CS course at a STEM-focused liberal arts college, we show that the reform increased the probability that female students major in CS by approximately 12 percentage points relative to male students. This increase is driven primarily by improved persistence among women who entered college intending to major in CS.

The reform did not adversely affect academic performance. Female students' cumulative GPA, major GPA, time to graduation, and persistence are unchanged relative to men, and male students' academic outcomes also do not deteriorate following the reform. These results indicate that increased female participation in CS did not come at the expense of academic standards or student performance.

The reform also affected post-graduation outcomes. Female students' early-career earnings increased by approximately 17 percent relative to men, reflecting both improved occupational sorting and a reduction in graduate school enrollment immediately after graduation. Roughly half of the earnings gain is attributable to reduced graduate school attendance, with the remainder driven by sorting into higher-paying occupations among labor market entrants.

Several limitations are worth noting. The estimated effects capture the combined impact of the curricular redesign and two small complementary initiatives, which were implemented simultaneously and cannot be separately identified. In addition, our earnings measures capture only early-career outcomes and reflect occupational wages rather than within-occupation pay. Whether similar reforms would generate comparable effects at larger institutions or in different institutional settings remains an open question.

Despite these limitations, our findings suggest that relatively low-cost changes to the design of required introductory STEM courses can meaningfully influence who persists in STEM fields and shape early-career labor market outcomes. Curricular reforms that broaden students' understanding of the discipline and its applications, particularly in required introductory courses, may therefore represent an effective policy lever for narrowing gender gaps in STEM.

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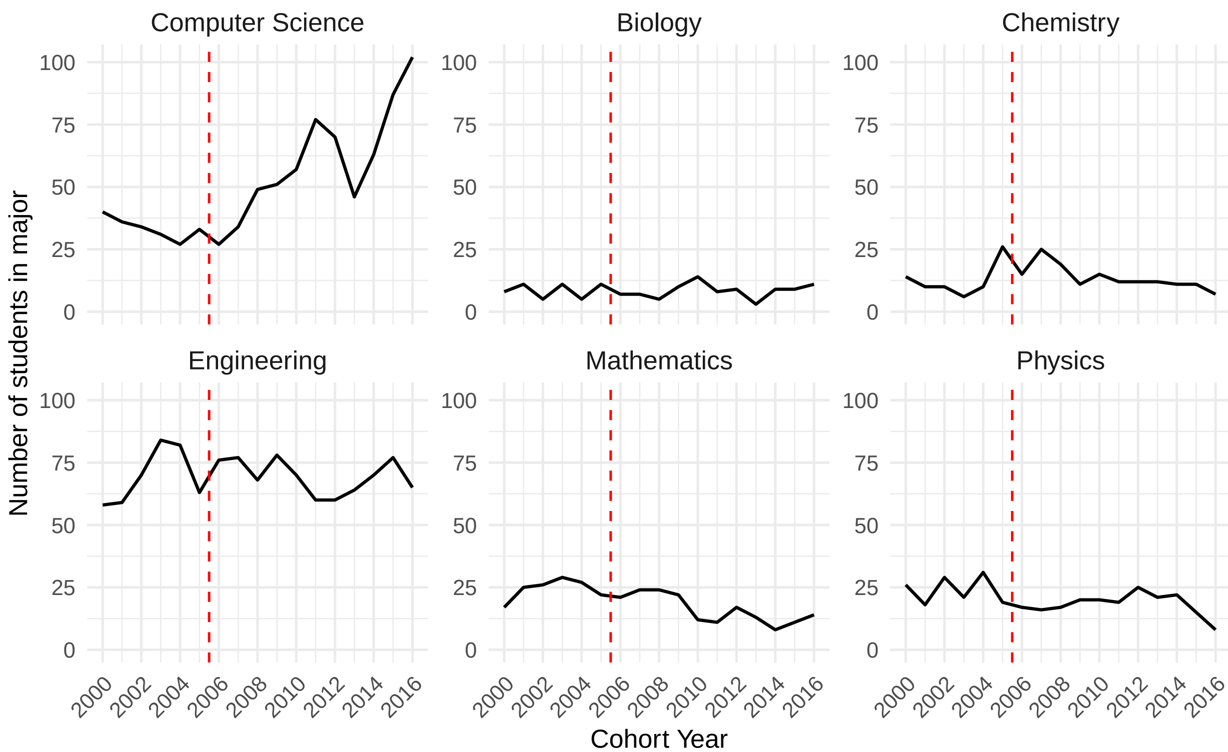
Appendix

A Additional Figures and Tables

Figure A1: Number of Students by Majors, 2000 to 2016 Cohorts



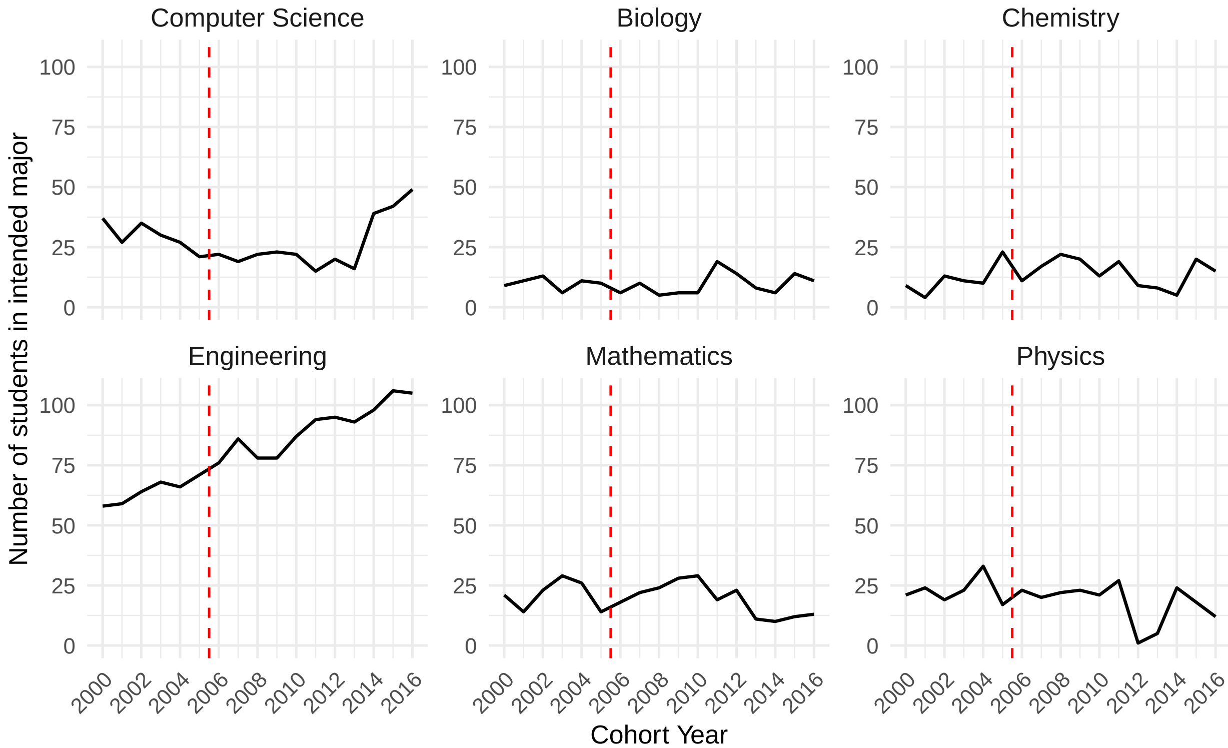
Notes: This figure presents the evolution of the number of students across cohorts from 2000 to 2016 within each core major. The red vertical dashed line indicates the CS curriculum reform in 2006.

Table A1: Percentage of Students with Missing Placement Data

Gender	Pre	Post	Post − Pre
Female	28.2%	55.8%	27.6pp***
Male	30.0%	54.6%	24.7pp***
Male − Female	1.8pp	-1.1pp	-2.9pp

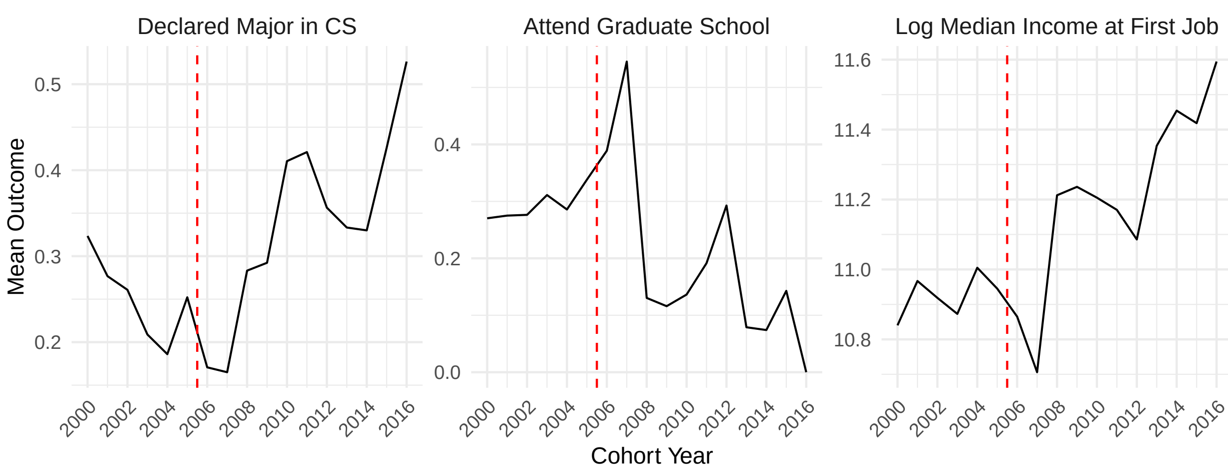
Notes: This table reports the percentage of students with missing placement data, by reform period, gender, and their interactions. All reported differences are tested using t-tests of mean differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Figure A2: Number of Students by Intended Majors, 2000 to 2016 Cohorts



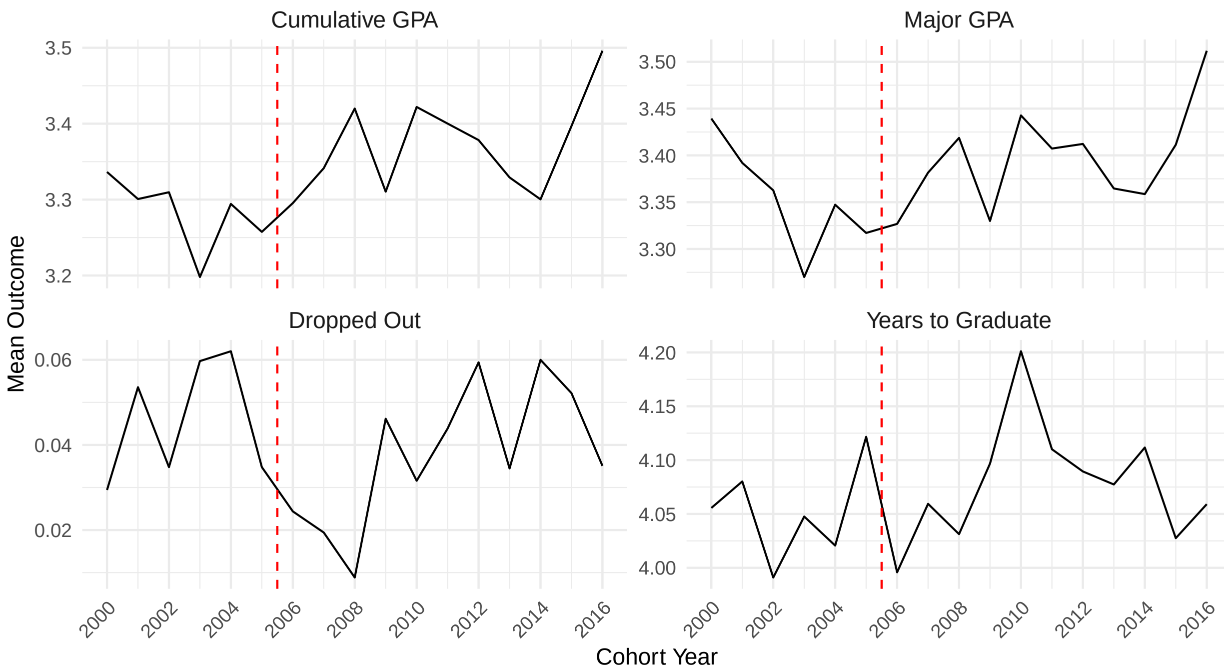
Notes: This figure presents the evolution of the number of students across cohorts from 2000 to 2016 within each core intended major. The red vertical dashed line indicates the CS curriculum reform in 2006.

Figure A3: Male Students' Main Outcomes over Time



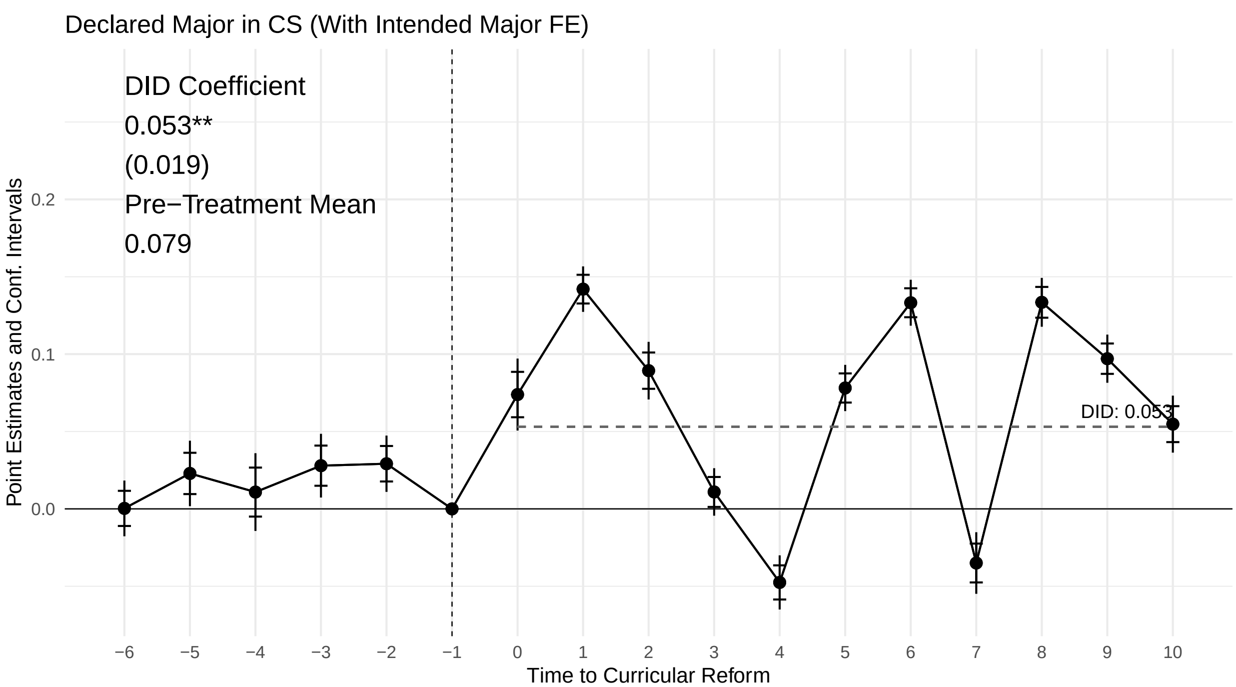
Notes: This figure plots the mean of our main outcomes, including CS major, log median income, and graduate school attendance among men over the study period (years 2000 to 2016), where the CS curriculum reform in 2006 is marked with a red dashed vertical line.

Figure A4: Male Students' Academic Outcomes over Time



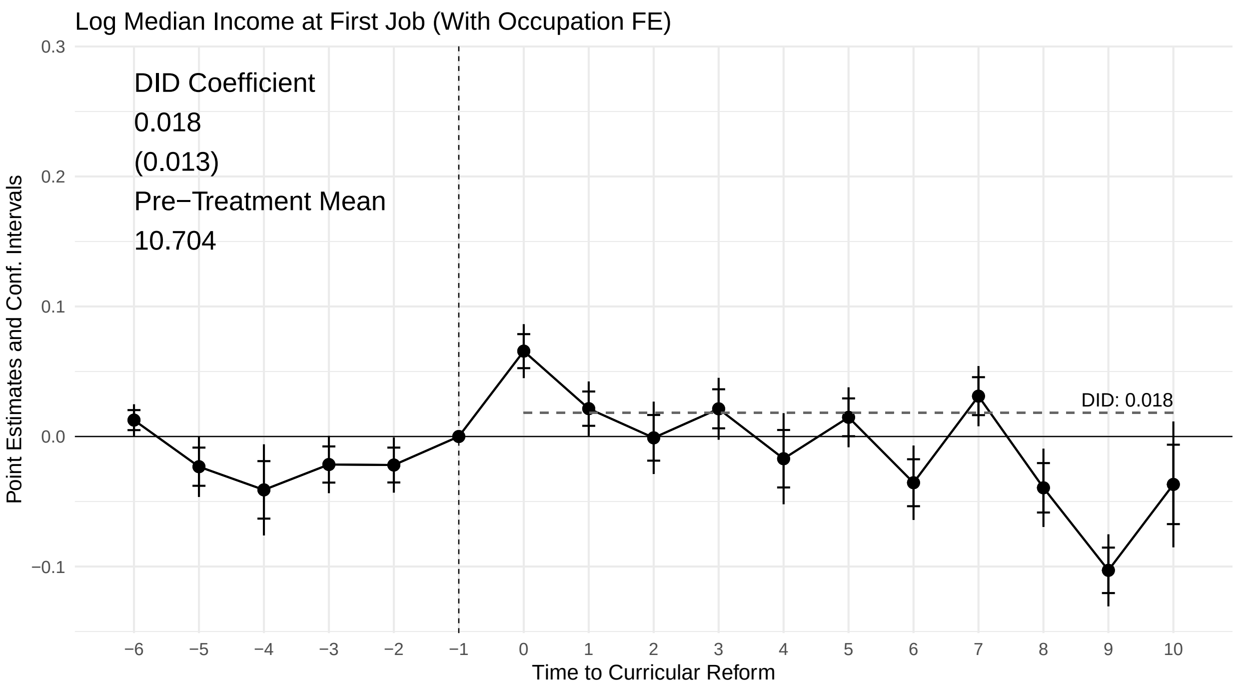
Notes: This figure plots the mean of four academic outcomes, including cumulative GPA, major GPA, years to graduation, and dropout rate among men over the study period (years 2000 to 2016), where the CS curriculum reform in 2006 is marked with a red dashed vertical line.

Figure A5: Effect of Curricular Reform on Major Choice (With Intended Major Fixed Effects)



Notes: This figure presents point estimates and 80% and 95% confidence intervals for β_1^t from equation 1 when fixed effects for students' intended major at admission are added as an additional control. The outcome is a binary indicator representing whether a student majored in CS. The curricular reform was implemented in 2006, and the coefficient for the baseline cohort (2005) is normalized to zero. Standard errors are clustered at the cohort-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure A6: Labor Market Earnings Effects of Reform (With Occupation Fixed Effects)



Notes: This figure plots point estimates and 80% and 95% confidence intervals of β_1^t from equation 1 when fixed effects for the SOC code of students' first job are added as an additional control. The outcome is the natural logarithm of labor market earnings at a student's first post-graduation job, measured using the median salary associated with the student's SOC code based on employer and job title. The curricular reform was implemented in 2006, and the coefficient for the baseline cohort (2005) is normalized to zero. Standard errors are clustered at the cohort-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Reform Effects by Graduate School Attendance

	Log Earnings	
	(1)	(2)
A. Pre-Reform Gender Gap (Women − Men)		
GS-attendees ($\beta_3 + \beta_5$)	-0.019***	-0.004
	(0.005)	(0.008)
Non-GS-attendees (β_5)	-0.132***	-0.121***
	(0.038)	(0.036)
B. Reform Effect on Women Relative to Men		
GS-attendees ($\beta_1 + \beta_2$)	0.019*	0.015
	(0.011)	(0.013)
Non-GS-attendees (β_2)	0.077*	0.071*
	(0.043)	(0.040)
Difference (β_1)	-0.058	-0.056
	(0.043)	(0.044)
C. Reform Effect on Men		
Male GS-attendees (β_4)	-0.023	-0.020
	(0.038)	(0.037)
Intended Major FE	N	Y
Cohort Year FE	Y	Y
Controls	Y	Y
Pre-Treatment Mean	10.704	10.704
Adj. R-squared	0.843	0.844
Observations	1,669	1,669

Notes: This table presents OLS estimates of equation 2, allowing the effect to vary by students' graduate school enrollment status post-graduation. The model is estimated for the log median income at the first job after graduation. Column 2 includes intended major fixed effects. Standard errors are clustered at the cohort-year level and are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.