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

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February 1, 2026

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, where the gender gap has plateaued at approximately 4-to-1 (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). Because 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 would 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 with the goal of attracting more women. Because this introductory course is required for *all* incoming 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. Because the redesigned course and the 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 (DID) framework, we compare outcomes of women and men before and after the reform, treating male students as the control group. We estimate the reform's impact on women's major choices and subsequent post-graduation outcomes relative to men, 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 CS by 12.1 percentage points relative to male students. Furthermore, the reform significantly increased the earnings of female students in the labor market, with women's post-graduation earnings being about 16.9% higher than those of their male peers, driven by sorting into higher-paying jobs. The reform also decreased female students' probability of pursuing graduate study right after college by 9 percentage points relative to their male peers. The drop in graduate school attendance rate – where stipends are typically lower than the salaries of typical college graduate jobs – explains half of the earnings gain.

Despite concerns that delaying exposure to specific foundational programming tools (e.g., object-oriented programming) could negatively affect students' subsequent academic performance, we do not find deterioration in any academic outcomes. We also do not find evidence that the effect is driven by the increase in CS popularity among female students at the national level. We confirmed through interviews with faculty and administrators that the reform was initiated solely by the CS department and not part of a broader college-wide reform. Instructor assignments for this course remained the same before and after the reform.

The primary channel through which the reform increased female students' probability of majoring in CS is improved retention of students who intended to major in CS at admission. Prior to the reform, female students who intended to major in CS were 22.9 percentage points less likely to actually choose a CS major than their male counterparts. The reform, however, increased their probability of choosing a CS major by 27.6 percentage points relative to men, making the gender gap in retention negligible. Our results provide limited evidence for other channels: switching by female students who did not initially intend to major in CS, or compositional changes in entering cohorts toward more female CS intenders.

The contribution of this paper is threefold. First, it identifies curricular design, paired with initiatives that reshape departmental culture, as an effective policy lever for reducing gender gaps in STEM. Compared to role model interventions that may impose additional burdens on women in

STEM fields, curricular reforms can offer a more sustainable solution. Traditional structures and curricula of STEM courses and STEM department culture often fail to cultivate students' deeper appreciation and understanding of a discipline's broader relevance and contributions to other fields and society, which may disproportionately affect women, who on average enter the college with less prior STEM-related knowledge (Carlana and Fort, 2022; Shi, 2018) and place greater weight on prosocial values in their careers (Burbano, Padilla and Meier, 2024; Burbano et al., 2024; Shi, 2018). Our study contributes to this literature by identifying the causal effect of reforming an introductory STEM course and the accompanying cultural shift and uncovering the mechanisms that drive increased female participation. Importantly, we find that the academic performance of male students was not negatively affected by the curricular reform, indicating that the reform benefits women without disadvantaging men.

Second, we add to a growing literature demonstrating the influence of pedagogical practices on student achievement. Duquennois (2022) shows that students from low socioeconomic backgrounds perform worse on math exam questions involving calculations with fictitious money and subsequent questions due to the attention-capture effects of poverty. Similarly, Griselda (2024) reveals that female students perform worse in free-entry mathematics questions than in multiple-choice questions. Other work identifies practices that improve outcomes. For example, interactive and collaborative learning, together with real-world examples and data, improves female students' grades in introductory economics courses (Avery et al., 2024; Owen and Hagstrom, 2021) and mathematics scores (Di Tommaso et al., 2024). We complement this literature by linking curricular design to academic outcomes, major choice, and post-graduation outcomes.

Lastly, we demonstrate how a more accurate presentation of STEM fields can reshape students' major decisions, especially among women. Previous studies argue that differences in preferences for job amenities (Wiswall and Zafar, 2018; Zafar, 2013) and family expectations (Wiswall and Zafar, 2021), as well as women's greater emphasis on prosocial values (Shi, 2018) are the main drivers of women's decisions not to enter STEM fields, while others show that women underestimate expected future earnings associated with certain majors, which in turn affects their major choices (Reuben, Wiswall and Zafar, 2017). Furthermore, a related literature finds that emphasizing communal or social goals increases women's interest and engagement in STEM (Boucher et al., 2017; Barrera et al., 2024). We contribute to this body of work by showing that presenting STEM fields in ways that emphasize their broader relevance can substantially improve women's persistence in STEM.

2 Background

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

Until 2005, this course was Java-based and focused on object-oriented programming and problem solving. The instructors identified several limitations of this course. First, its content was too simple for some students yet too challenging for others, and its pace did not accommodate varying skill levels. Second, and more importantly, because the course focused on object-oriented programming, its structure and curriculum did little to help students develop a richer understanding of CS as a discipline or to appreciate its broader contributions to other fields and society.

In 2006, in light of these limitations, the CS department replaced the existing course with a redesigned curriculum using Python, instead of Java, as the main programming language. The new curriculum still covered the basic programming skills necessary in an introductory course, but it moved away from focusing on object-oriented programming. Instead, the new curriculum incorporated a wide range of practical applications in science and engineering, demonstrating the importance of CS across other fields and emphasizing its relevance to real-world problem solving (Dodds et al., 2008; Alvarado, Dodds and Libeskind-Hadas, 2012).[1]

Introductory courses in certain STEM fields, such as CS, often create the perception that some students possess substantially more prior knowledge than others. Such impressions disproportionately affect female students and can undermine their confidence and interest in learning and continuing in the field (Fischer, 2017; Mouganie and Wang, 2020). To address this misconception, the redesigned course begins with hands-on assignments using a language invented by faculty in the department specifically for this course. This language is completely new to all students, and this approach therefore helps level the playing field and reduces the salience of pre-college experience.

In addition, the revised course offers two tracks designed to accommodate students with different levels of prior experience. Before entering the college, all admitted students take an assessment exam to evaluate their CS and programming knowledge. Based on the assessment results, students with little to no prior experience are placed in the standard section, while those with a demonstrated background are placed in the enrichment section. Both tracks cover the same core material, but the enrichment section engages with more advanced and challenging applications of the same foundational concepts. The split-track system keeps experienced students challenged without intimidating those new to CS. As a result, the design fosters a more inclusive learning environment for beginners, encouraging them to explore the discipline further. At the same time, it helps correct misconceptions among experienced students, particularly the belief that CS is only about programming.

During the reform period, the CS Department also implemented two complementary initiatives

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

aimed at increasing female students' engagement in CS: (a) expanding undergraduate research opportunities after students' first year, *available to both women and men*, with approximately 10 students selected annually, and (b) supporting women's participation in the Grace Hopper Celebration of Women in Computing conference, with about 5 students attending each year. To assess whether other college-wide initiatives might confound our estimates, we conducted interviews with CS faculty and staff from the Office of Institutional Research. All interviewees confirmed that the 2006 reform and accompanying initiatives were developed independently by the CS Department and were not part of broader administrative efforts to increase female participation in STEM at the college level. They also confirmed that instructor assignments for the redesigned course remained the same before and after the reform.

The reform applied to students entering the college in Fall 2006 and after; students who matriculated prior to Fall 2006 were unaffected. Because the curricular change, the split-track system, and the concurrent initiatives (i.e., the research assistantships and the Grace Hopper conference support) were introduced simultaneously, our estimate captures their combined treatment effect. However, the ancillary initiatives that targeted female students (i.e., Grace Hopper conference support) were small in scale. With an average female cohort size of 81.2 students post-reform, the additional initiatives reach only about 6.2 percent of female students. Their contribution to the estimated gender differential is therefore likely to be limited.

3 Data

3.1 Student Academic and Demographic Data

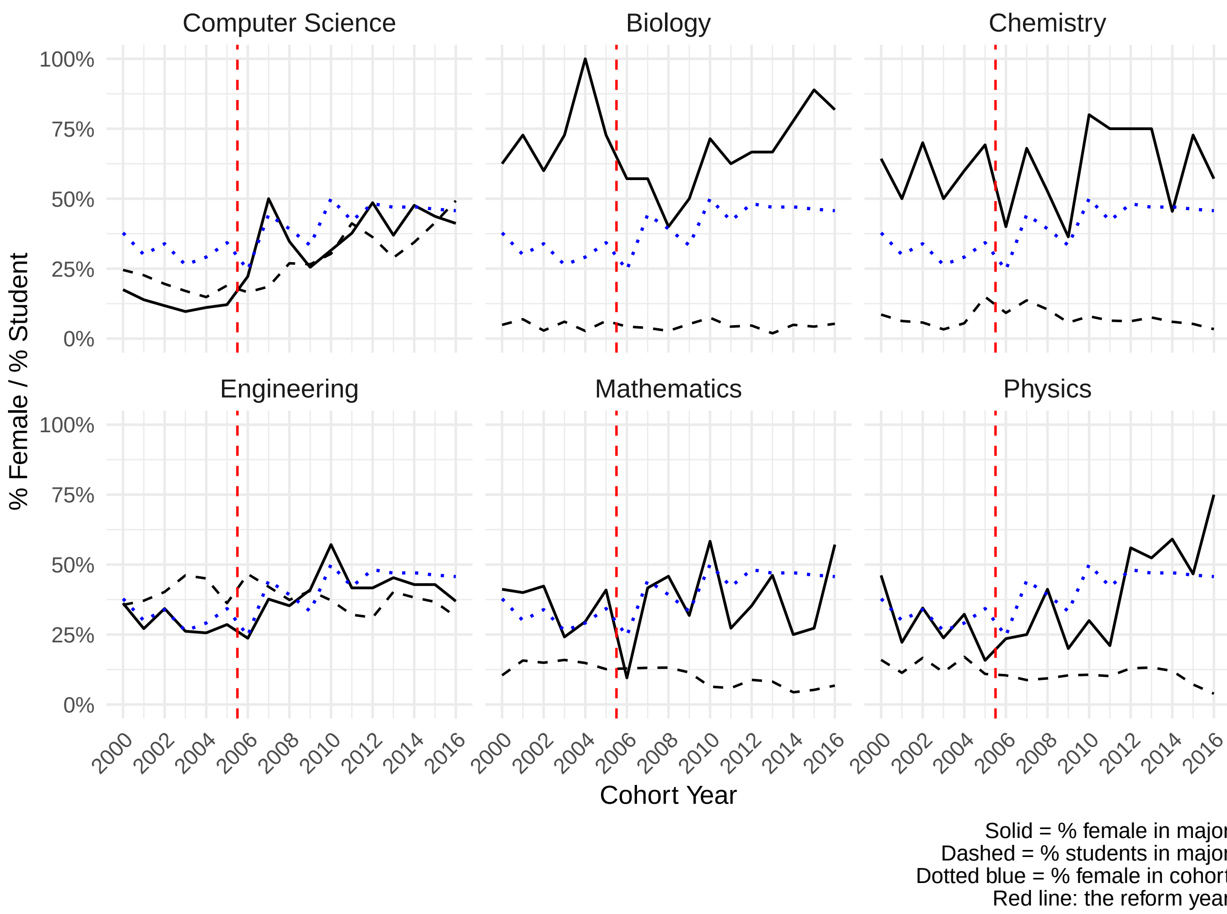
We obtain detailed student data at admission and graduation for all students in the 2000 to 2016 cohorts. Each entering cohort consists of 160 to 220 students. Information recorded at admission includes students' gender, race, SAT and/or ACT scores, other qualifications (SAT subject tests, advanced courses at high school, etc.), and their intended major at the time of admission. Information gathered at graduation includes students' major, cumulative GPA, major GPA, whether a student has dropped out without obtaining a diploma, and graduation year. In addition, we obtain academic records for all students in the introductory CS course and its subsequent optional advanced courses, including the semester each course was taken and the grades received.

The college offers joint majors in addition to single majors, and 460 or 14.7% of students pursued one of them during the sample period. 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. While a small fraction of students (135 or 4.3% of all students across the sample period) pursued a second major, we define majors based on students' primary major.

Figure 1 plots the evolution of the percentage of female (solid black) and all students (dashed black) across cohorts from 2000 to 2016 within each core major, along with the percentage of female students at the college (dotted blue). The red vertical dashed line indicates the timing of the 2006 curricular reform.

Biology and chemistry have consistently had a high female share throughout the period, with some dip in the reform year, although these majors enroll relatively few students, as shown in Appendix Figure A1. Mathematics and physics are more popular among female students than male students, although less so than biology and chemistry. Engineering remained one of the most popular majors throughout the period, and its female share closely tracks the overall college trend, showing no apparent shift associated with the reform. In contrast, before 2006, CS had been unpopular especially among female students. Following the reform, however, the share of female students in CS rose sharply, from about 15 to 20 percent to over 40 percent by 2016. The share of total students

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



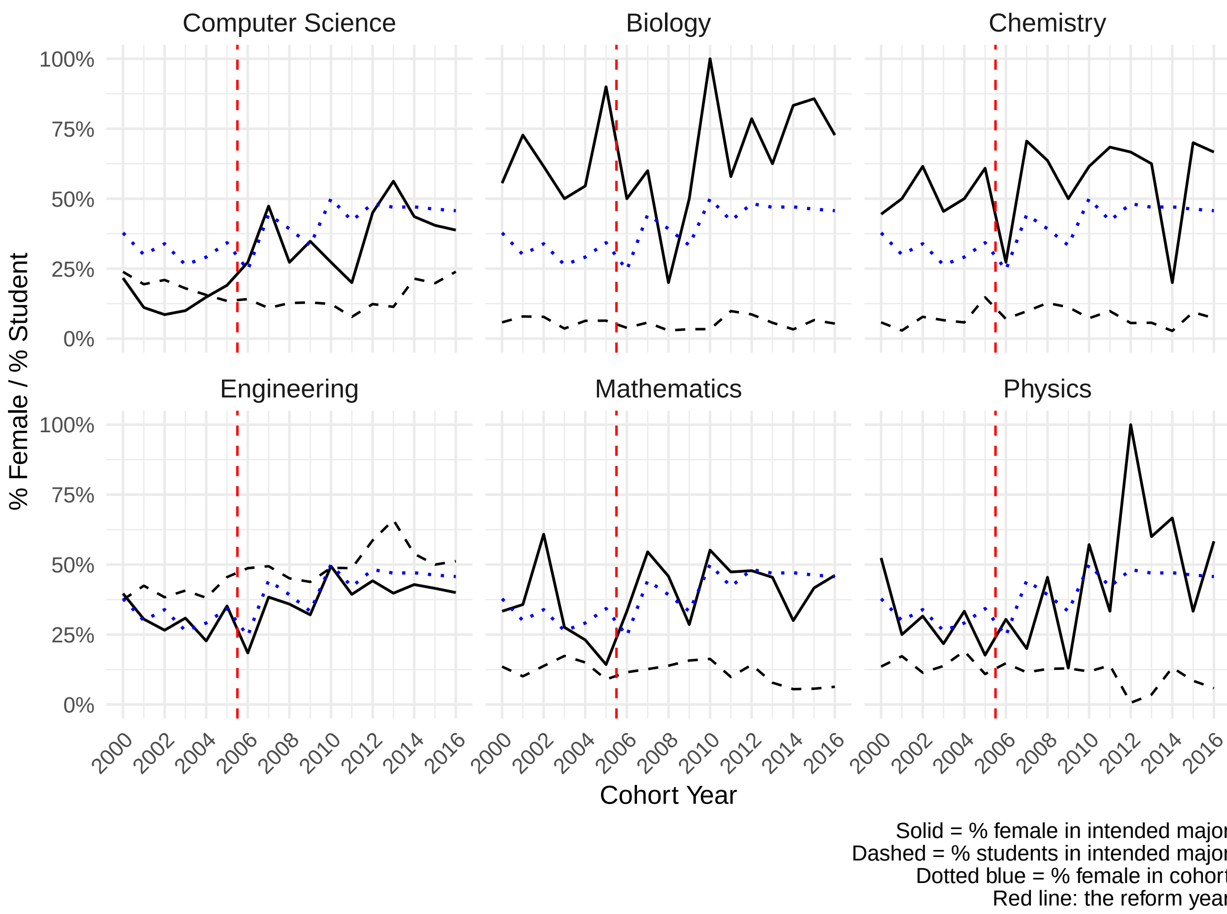
Notes: This figure presents the evolution of the percentage of female (solid black) and all students (dashed black) across cohorts from 2000 to 2016 within each core major, along with the percentage of female students at the college (dotted blue). The red vertical dashed line indicates the CS curriculum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

also rose after the reform, although not as much as the female share. This noticeable increase around the reform contrasts with the relatively stable trends observed in other STEM fields, confirming that the change reflects a CS-specific response rather than a broad institutional or cohort-wide shift.

Figure 2 presents the evolution of the percentage of female (solid black) and all students (dashed black) across cohorts from 2000 to 2016 within each core major they intended to pursue at the time of admission, along with the percentage of female students at the college (dotted blue). The red vertical dashed line marks the CS curriculum reform in 2006.

Before the reform, the female share of CS-intending students was around 15-20 percent and was

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 (solid black) and all students (dashed black) across cohorts from 2000 to 2016 within each core major they intended to pursue at the time of admission, along with the percentage of female students at the college (dotted blue). The red vertical dashed line marks the curriculum reform in 2006.

historically the lowest among all majors. Following the reform, the share of women who intended to major in CS noticeably increased to over 30% by 2016. By contrast, biology and chemistry maintained a high female share throughout the period. Engineering, mathematics, and physics had the lowest female shares, while the female shares, with physics trended upward starting around 2010. Appendix Figure A2 reports the corresponding counts by intended major.

3.2 Labor Market Earnings Data

To measure students' labor market outcomes, we obtained placement data from the Office of Advancement, which includes company names, job titles, and the start and end dates (if available) of post-graduation employment. Employment information is primarily collected via self-reports on students' alumni profiles. For students who do not update their profiles, the office manually verifies employment history using online platforms, LinkedIn, a widely used professional networking website that is broadly representative of college-educated individuals and white-collar professions (Amanzadeh, Kermani and McQuade, 2024). Economists have increasingly used LinkedIn data to study workforce composition, worker demographics, and earnings (Berry, Maloney and Neumark, 2024; Amanzadeh, Kermani and McQuade, 2024; Wheeler et al., 2022). The quality of our data is higher than that of conventional web-scraped LinkedIn data due to the manual review process.

Since the first position has the lowest percentage of missing observations, we focus on earnings at the start of the career (i.e., the first job post-graduation). To obtain earnings information for positions, we first verified company names by cross-referencing official company websites. We then linked job titles and the company's industry to the most similar Standard Occupational Classification (SOC) code. The median income associated with the corresponding SOC code in the Occupational Employment and Wage Statistics (OEWS) is assigned as the student's estimated earnings.[2] Excluding those who have attended graduate school, 93% of the observations with available earnings data had a start date within five years of graduation. Employment information is incomplete and missing for 47.0% of students in the sample, a rate slightly lower than prior studies using the same data source (Firoozi, 2025). While more students have missing data post-reform (55.1% compared to the pre-reform of 29.4%), there are no statistically or quantitatively significant differences by gender (see Appendix Table A1).

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

About 28.1% of students in the sample pursued graduate degrees. To estimate stipends for students entering graduate school, we scraped data from the PhD Stipends website,[3] which contains self-reported stipend information from graduate students. The median stipend reported for U.S. graduate programs in a given year was assigned to students entering graduate school that year. A potential concern is that pursuing a graduate degree typically results in lower earnings during the schooling period, and the share of students pursuing a graduate degree is substantially lower among CS and Engineering majors compared to other STEM disciplines.[4] We address this concern in Section 5 by examining earnings separately for graduate school attendees and non-attendees.

3.3 Summary Statistics

Table 1 presents summary statistics on the demographics and academic outcomes of male and female students in the 2000 to 2016 cohorts. Panel A reports variables related to students' decisions to major in CS. Panel B reports students' first-job salaries and graduate school enrollment. Panel C summarizes academic outcomes. Panel D presents pre-college academic characteristics measured at admission. Panel E summarizes the racial and ethnic composition of the sample by gender.

Compared to male students, female students show weaker interest in the CS major, with lower rates of majoring in CS (7 percentage points), lower intentions to major in CS at admission (6 percentage points), and an 8 percentage point lower likelihood of taking an optional advanced CS course. Note that the optional courses are not capped in the short run; any students who wish to take these advanced courses can do so. Panel B presents job outcomes, indicating that after graduation, female students have a slightly higher likelihood of attending graduate school (4 percentage points). Additionally, female students earn, on average, $5,770 less annually than male students. Panel C shows that, on average, female students have slightly lower cumulative GPAs

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

[4] In our sample, the percentage of students pursuing a PhD is 12.2% in CS, while it is 36.2% in biology, 65.9% in chemistry, 55.0% in physics, and 19.9% in engineering.

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 presents variables related to students' decisions to major in CS. Both the first and second optional CS courses are required for students who choose to major in CS. The first course serves as a prerequisite for the second, although students may place out of the first course and enroll directly in the second. Panel B presents student salaries at their first job and graduate school enrollment. Panel C summarizes academic outcomes. Panel D reports pre-college academic characteristics measured at admission. ACT scores are converted into SAT scores using the ACT/SAT concordance tables. Panel E summarizes the racial and ethnic composition of the sample. 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. Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

(0.04 points) and major GPAs (0.08 points) than male students.

Panel D details student characteristics at admission, showing that female students have slightly lower SAT math scores (12.03 points) and total scores (12.70 points).[5] Panel E presents the racial distribution of students, indicating that female students are more likely to be Asian (6 percentage points) and multi-race (2 percentage points), less likely to be Black (1 percentage point), Hispanic (2 percentage points), or Other race (4 percentage points).

4 Empirical Specification

We adopt an difference-in-differences approach to evaluate whether and to what extent the curricular reform affected female students' major choice and post-graduation outcomes relative to male students. Specifically, we estimate the following model:

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

Our primary outcomes of interest are: (a) a student's choice of majors, where $Outcome_i$ equals 1 if student i majors in CS, and 0 otherwise; (b) labor market earnings, where $Outcome_i$ is the natural logarithm of a student's annual salary at their first job after graduation; and (c) whether a student pursues a graduate degree after graduation, where $Outcome_i$ equals 1 if student i attends graduate school, and 0 otherwise. We also examine the effects on various academic outcomes.

$Female_i$ equals 1 if student i is female, and 0 otherwise. $\tau_{c(i)}$ represents the cohort fixed effects, which absorb any cohort-specific characteristics, including the female share.[6] We also add a set of student-specific academic and demographic characteristics X_i as controls, including race fixed effects, SAT math and verbal scores, and additional qualifications such as whether a student took SAT

[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).

[6]As shown in Table 1, nearly all students graduate on time in four years, and a student's entry year is aligned with their graduation year. Therefore, the cohort fixed effects in our specification absorb not only differences across entering cohorts but also any shocks that occur around the time students leave the college, including graduation-year labor-market conditions or institution-wide factors that vary by cohort.

subject tests or advanced high school courses. We interact X_i with a dummy variable indicating post-reform cohorts, $Post_{c(i)}$, to account for potential composition changes in post-reform cohorts and shifts in how they relate to outcomes after the reform. ϵ_i is an idiosyncratic error term. Standard errors are clustered at the cohort level to account for intra-cohort correlation (Abadie et al., 2023).

Our coefficients of interest are β_1^t ($t \geq 2006$), which capture the effect of the reform on female students' outcomes relative to male students in post-reform cohorts. The key identifying assumption is parallel trends: in the absence of the reform, female and male students' time trends would have evolved in the same way. While we cannot test it directly, the coefficients β_1^t ($t < 2006$), which capture differences in outcomes between female and male students in each pre-reform cohort relative to the baseline year, allow us to assess the plausibility of this assumption.

To obtain the average effect of the reform, we also estimate a version of equation 1. Specifically, we replace the cohort-by-female interactions, $\sum_{t=2000, t\neq 2005}^{2016} \beta_1^t \mathbb{1}[c(i) = t] \times Female_i$, with a single post-reform-by-female interaction, $Post_{c(i)} \times Female_i$:

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

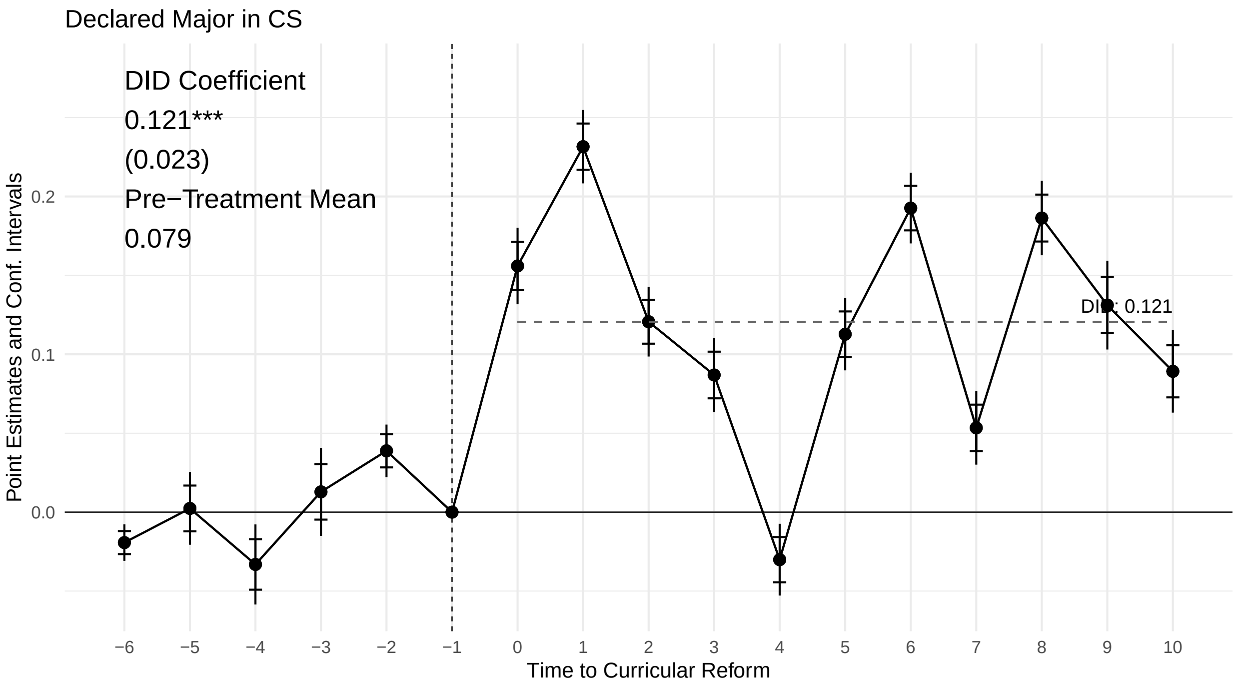
All variables are as defined in equation 1. We report β_1 along with the difference-in-differences plots.

We estimate both equations 1 and 2 via OLS. Because our treatment is binary, occurs in the same year for all treated units (non-staggered design), and includes a never-treated group, OLS provides consistent estimates (see, e.g., Baker et al., Forthcoming; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; 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 for 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 plots difference-in-differences estimates of the reform's effect on female students' probability of majoring in CS relative to men and to the baseline cohort. Note that the coefficients are relative to the year before the reform. The pre-reform path shows that the difference between female and male students remained relatively stable in the years leading up to the reform, consistent with the parallel trends assumption. Following the reform, the probability rose by roughly 12.1 percentage points on average.

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-Treated 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

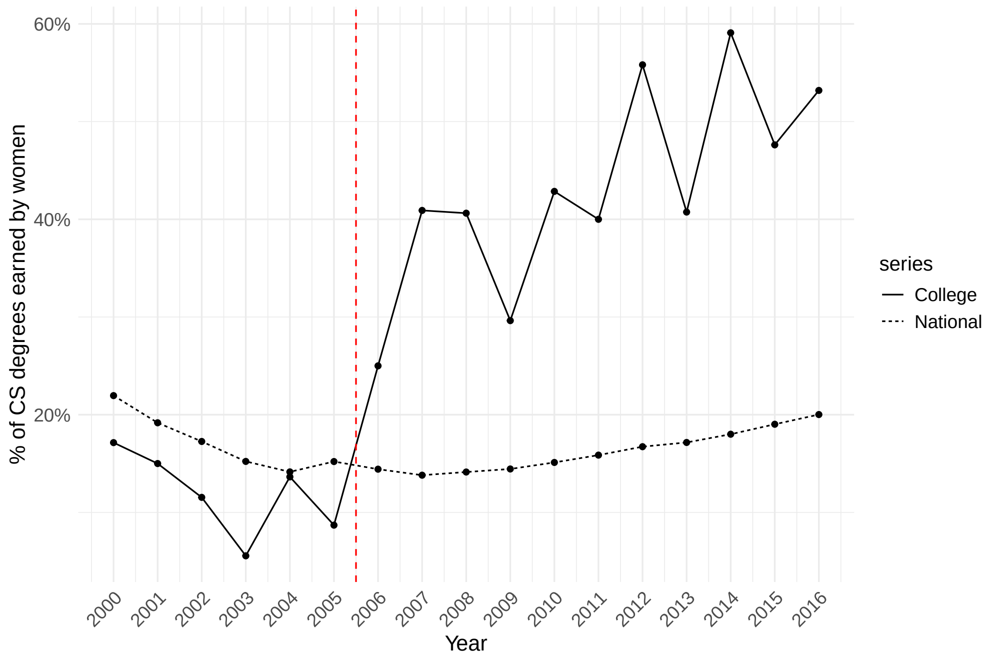
Academic Outcomes One concern about not covering foundational topics such as object-oriented programming in the introductory course is that it could harm academic outcomes in advanced classes. A related worry is that if major GPA falls after the reform, it may indicate that newly attracted students have less prior experience in CS, although this is not necessarily a negative outcome.

Table 2 presents DID estimates for various academic outcome measures. Columns (1) to (4) report results for all graduates, while columns (5) to (8) focus on CS graduates. Overall, there is no evidence that the reform negatively affected female students' academic performance or persistence compared to their male counterparts.

College vs. National Trend of CS Majors It is possible that national efforts to promote women's participation in CS contributed to changes in the female student composition over time. In Figure 4, we compare the percentage of CS degrees earned by women at the college to national trends using data from the Integrated Postsecondary Education Data System (IPEDS), maintained by the National Center for Education Statistics (NCES).[7] As shown in the figure, the share of CS degrees earned by women at the college consistently lagged behind the national average for

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



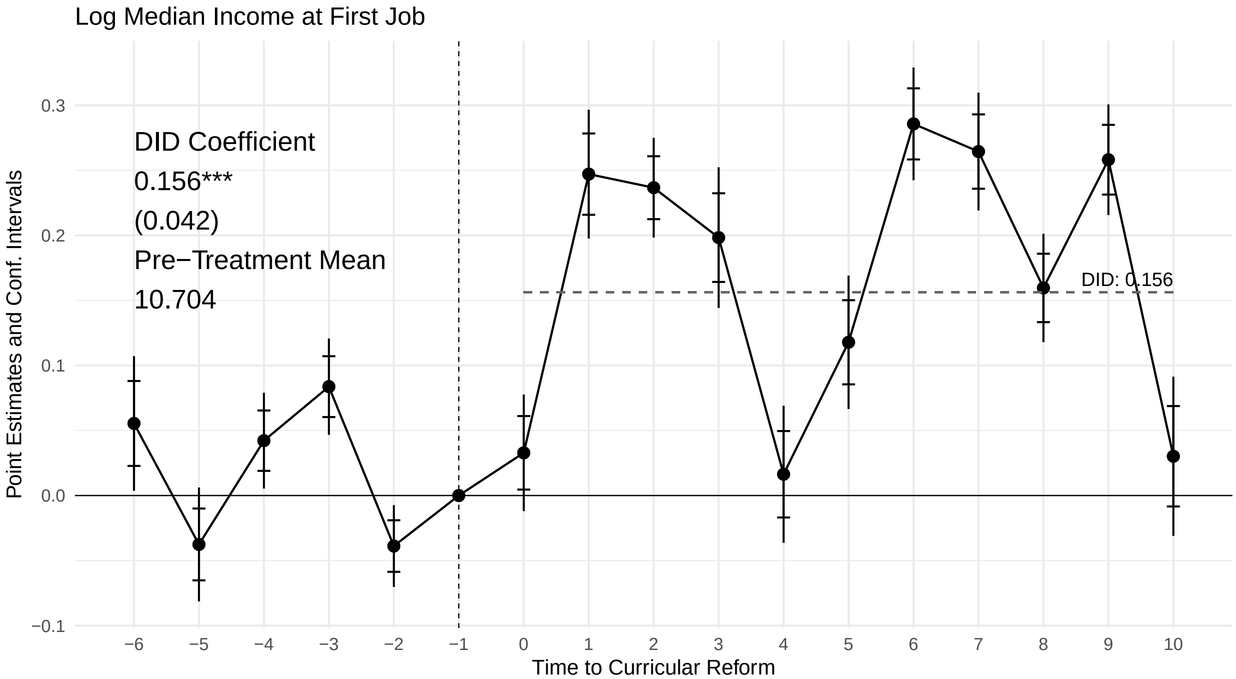
Notes: This figure plots the percentage of CS degrees earned by women at the college level (the solid line) and the national level (the dashed line) for cohorts entering in years 2000 to 2016. The data are from the Integrated Postsecondary Education Data System (IPEDS). We define CS degrees as those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

cohorts entering between 2000 and 2005. However, beginning with the 2006 cohort – the year of the curricular reform – the college's female representation in CS surpassed the national level and has generally trended upward, despite some year-to-year fluctuations. In contrast, female CS representation at the national level declined in the early 2000s and only gradually recovered. By 2016, the national share remained below its 2000 level, whereas the college's share had substantially increased.

5.2 Effects on Post-Graduation Outcomes

Labor Market Earnings Figure 5 presents the year-by-year impact of the curricular reform on female students' earnings at the first job. Note that the labor market analysis uses graduation-year earnings but plots effects by entry cohort. Thus, the 2006 coefficient is shown at 2006 even though the corresponding earnings are observed post-graduation. We present the results in this manner

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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

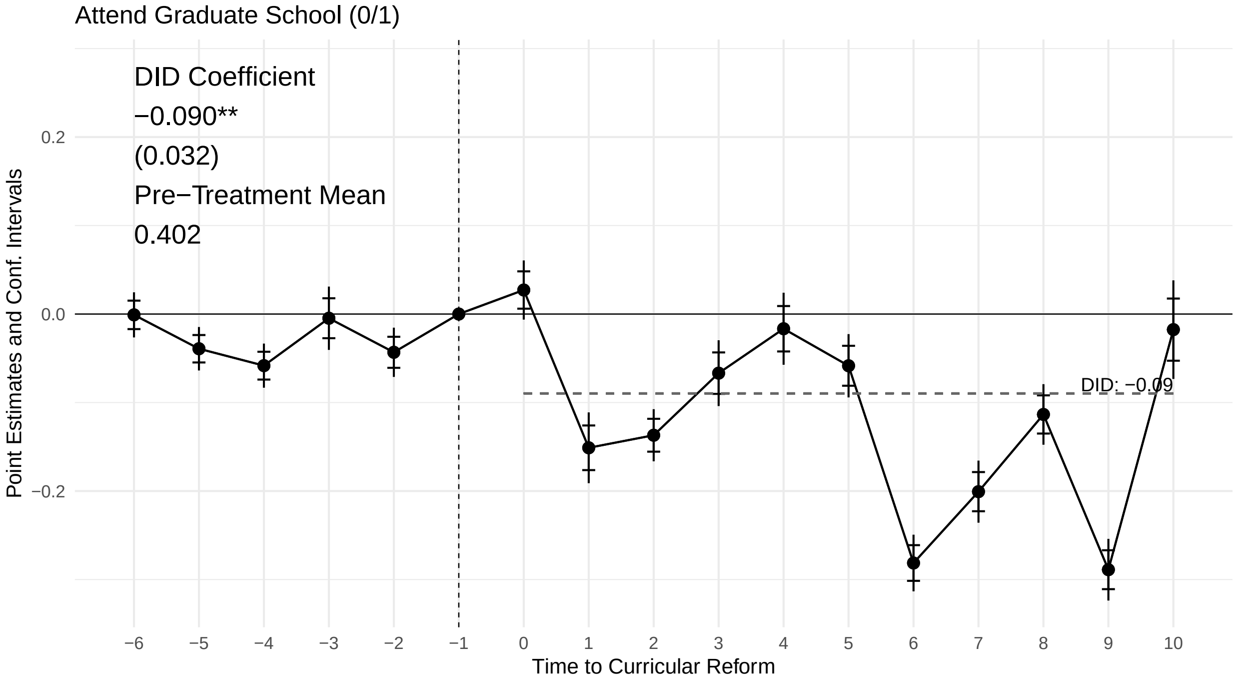
to ensure comparability across all outcomes. The pre-reform differences between female and male students are noisier than the differences in Figure 3, but do not exhibit any downward or upward pattern.

The figure shows that the reform increased women's median post-graduation earnings by approximately 16.9% ($e^{0.156} - 1 \approx 0.169$) relative to men. With a pre-treatment mean log(median income) for women of 10.704, the implied pre-reform median annual income among women is about $44,500 ($e^{10.704} = \$44,534$). Applying the 16.9% effect gives an earnings gain of roughly $7,526 for women after the reform ($0.169 \times \$44,534 = \$7,526$).

Note that because our earnings data is defined at the occupation category level, the effects observed in Figure 5 only capture occupational sorting. In fact, when we add fixed effects for occupation categories (SOC codes) of students' first job, the labor market earnings effect disappears

(Appendix Figure A6). Thus, these results indicate that the curricular reform significantly boosted early labor market earnings among female students due to improved occupational sorting.

Figure 6: Effects on Graduate School Attendance



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 Another important post-graduation outcome is whether students pursue graduate study. Figure 6 reports difference-in-differences estimates of the probability that female students enroll in graduate school around the reform. The figure shows that the reform decreased female students' probability of pursuing graduate study by 9 percentage points. An important caveat is that our data only contains students who pursue a graduate degree right after graduation. Therefore, the results exclude students who enter graduate school after spending time in the workforce.

One concern is that the earnings effect may be solely due to the drop in graduate school attendance rate among female students, as graduate school stipends are typically lower than a typical salary in the labor market. To address this concern, Column 1 of Appendix Table A2 presents heterogeneity in the earnings effect between graduate school attendees and non-graduate school attendees. The coefficient estimate on the interaction between female and post-reform dummies is 0.077 and marginally statistically significant at 10%, suggesting that those who entered the job market directly after graduation still experienced 8.0 percentage points ($e^{0.077} - 1 \approx 0.080$) earning increase relative to their male counterparts, which is about half the earnings gain in Figure 5.[8]

Thus, the results suggest that the reform increased female students' probability of majoring in CS without deteriorating their academic performance, and that the effect is not driven by national-level trends. The reform also increased female students' earnings in their first job through improved occupational sorting, and decreased the probability of pursuing graduate study immediately after graduation. About half of the earnings effect reflects reduced graduate school attendance, with the remainder driven by sorting into higher-paying occupations among labor market entrants.

5.3 Male Students' Outcomes

Our identification strategy relies on male students as the control group. Because the introductory course is mandatory for all students, men were also exposed to the redesigned curriculum. A potential concern is that the estimated effects on women may reflect changes in male students' outcomes in the opposite direction rather than genuine increases among women. Although descriptive, we address this concern by comparing male students' outcomes before and after the reform, controlling for all student-specific academic and demographic characteristics.

Table 3 reports results for our main outcomes. Male students' probability of majoring in CS increased by 8.9 percentage points, log median earnings increased by 0.165, and graduate school attendance decreased by 5.9 percentage points after the reform. Notably, these coefficients are in

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

Table 3: Male Students' Main Outcomes

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

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

the same direction as the effects observed for women. This suggests that our estimated effects on women do not reflect changes in male outcomes in the opposite direction; if anything, controlling for these male trends would yield even larger estimates of the reform's effect on women. Appendix Figure A3 plots the time trends and confirms no reversal around 2006.

Table 4: Male Students' 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)
Post	0.093*** (0.029)	0.050* (0.027)	-0.003 (0.021)	-0.016 (0.009)	0.091 (0.055)	0.084 (0.057)	0.016 (0.040)	-0.005 (0.033)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Pre-Treated 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	1900	1890	1823	1900	577	576	543	577

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

Table 4 reports results for academic outcomes. Male students' cumulative GPA and major GPA rose by 0.09 and 0.05 points after the reform, while their years to graduation and dropout rates remained statistically unchanged. Appendix Figure A4 plots the time trends and shows no significant deterioration. The small and positive post-reform coefficients suggest that the reform did not harm male students and, if anything, modestly improved their academic performance.

Thus, the results suggest that the reform did not affect male students in the directions opposite to women. If anything, male students experienced modest improvements in academic performance, while their major choices and post-graduation outcomes moved in the same direction as women's. These findings support the validity of using male students as the control group and indicate that the estimated effects on women reflect genuine gains rather than relative changes driven by deterioration in male outcomes.

6 Mechanisms

In this section, we investigate the mechanisms through which the curricular reform increased female students' probability of majoring in CS as well as the post-graduation outcomes.

6.1 Mechanisms for Major Choice

Regarding the increase in female students' probability of majoring in CS, there are three possible channels: (i) retention: improved retention among women who intended to major in CS at admission; (ii) switching: increased switching into CS among students who did not intend to major in CS at admission; and (iii) composition change: more women intending to major in CS at admission.

To investigate these three possibly channels, we augment 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 a dummy variable indicating whether a student i intended to major in CS at admission. Other variables are as defined in equation 2. We estimate this equation with and without fixed effects for students' intended major.

β_1 identifies the effect of the reform on CS-intending female students (retention) and β_2 the effect of the reform on non-CS-intending female students (switching). Adding intended major fixed effects shows us these effects net of composition change.

Table 5: Reform Effects by Intended Major at Admission

Outcome:	Major in CS (0/1)		Attend GS (0/1)		Log Median Income at First Job	
	(1)	(2)	(3)	(4)	(5)	(6)
Female × Post × Intend CS	0.250**	0.255**	0.029	0.036	0.021	0.011
	(0.101)	(0.102)	(0.122)	(0.128)	(0.162)	(0.170)
Female × Post	0.025	0.020	-0.082**	-0.093**	0.128**	0.141***
	(0.023)	(0.024)	(0.035)	(0.038)	(0.045)	(0.045)
Female	-0.074***	-0.067***	0.102***	0.092***	-0.200***	-0.182***
	(0.010)	(0.012)	(0.016)	(0.021)	(0.021)	(0.018)
Female × Intend CS	-0.156*	-0.164*	0.023	0.026	-0.026	-0.036
	(0.086)	(0.087)	(0.100)	(0.106)	(0.105)	(0.111)
Post × Intend CS	-0.095	-0.103	-0.036	-0.060	-0.054	-0.023
	(0.063)	(0.065)	(0.046)	(0.046)	(0.049)	(0.050)
Intend CS	0.570***		-0.102***		0.204***	
	(0.049)		(0.022)		(0.025)	
Linear combinations						
Female × Post × Intend CS	0.276***	0.275***	-0.053	-0.057	0.149	0.152
+ Female × Post	(0.092)	(0.091)	(0.110)	(0.112)	(0.149)	(0.152)
Female × Intend CS	-0.229***	-0.231***	0.125	0.118	-0.226**	-0.218*
+ Female	(0.078)	(0.077)	(0.087)	(0.091)	(0.104)	(0.109)
Cohort Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Intended Major FE		Y		Y		Y
Pre-Treated 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	3122	3122	1672	1672	1669	1669

Notes: This table presents OLS estimates of equation 3. The model is estimated for CS major dummy (columns 1 to 2), graduate school attendance dummy (columns 3 and 4), and log median income at the first job after graduation (columns 5 to 6). Columns 2, 4, and 6 include intended major fixed effects. Standard errors are clustered at the cohort-year level and are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5 presents OLS estimates of equation 3. In column 1, the coefficient on Intend CS is 0.57 and highly significant, indicating that before the reform, male students who intended to major in CS were 57 percentage points more likely to do so than those who did not. Among CS-intending students, however, women were 22.9 percentage points less likely than men to follow through on their intention – calculated as the sum of the coefficients on Female × Intend CS and Female.

Non-CS-intending women were 7.4 percentage points less likely than their male counterparts to major in CS, as shown by the coefficient on Female.

The triple interaction (Female × Post × Intend CS) is 0.25 and significant at 5%, indicating that the reform's effect on CS major choice was substantially larger for CS-intending women than for non-CS-intending women. The reform increased CS-intending women's probability of majoring in CS by 27.6 percentage points relative to men. In contrast, the coefficient on Female × Post is 0.025 and not significant, indicating that non-CS-intending women did not experience a differential change relative to their male counterparts. The coefficient on Post × Intend CS is negative but also insignificant, showing no change in CS major choice among CS-intending men after the reform. Column 2 adds intended major fixed effects with essentially identical results, ruling out composition changes as a driver.[9,10]

Thus, the effect observed in Figure 3 primarily comes from the retention channel: the reform improved persistence among female students who intended to major in CS at admission. There is little evidence that switching by non-CS-intending students or composition changes in entering cohorts contributed meaningfully to this effect.

6.2 Mechanisms for Post-Graduation Outcomes

Graduate School Attendance Columns 3 and 4 examine graduate school attendance. In column 3, the coefficient on Intend CS is -0.102 and highly significant, indicating that CS-intending male students were 10.2 percentage points less likely to pursue graduate study than non-CS-intending males – consistent with lower graduate school rates among CS majors. The coefficient on Female is

[9] Appendix Figure A5 corroborates this result: the overall effect falls by about half when intended major fixed effects are added to Figure 3. The effect attenuates with intended major fixed effects because the fixed effects absorb between-intended-major variation, and the effect is concentrated among CS-intending students who constitute a relatively small share (23–30%) of the sample.

[10] Figure 3 captures the policy-relevant effect one would expect from implementing the reform at another college with a similar composition of entering students, as it reflects the average effect across all students.

0.102, showing that non-CS-intending women were 10.2 percentage points more likely to attend graduate school than their male counterparts. The interaction Female × Intend CS is close to zero and not significant, implying that women were more likely to pursue graduate study regardless of intended major.

Interestingly, the decline in graduate school attendance among women after the reform is not concentrated among CS-intending students. The coefficient on Female × Post is -0.082 and significant at 5%, while the triple interaction (Female × Post × Intend CS) is near zero and insignificant. Similarly, the coefficient on Post × Intend CS is not significant. These patterns indicate that the reform reduced graduate school attendance among all women, not just those who switched into CS. The magnitude of the Female × Post coefficient (-0.082) is close to the difference-in-differences estimate in Figure 6. Results are quantitatively similar with intended major fixed effects in column 4, suggesting that composition changes do not drive the findings.

Thus, the drop in graduate school attendance after the reform is unlikely to reflect increased CS majoring among women. Because the effect appears immediately in the first post-reform cohort, one plausible explanation is that exposure to the redesigned course sparked women's interest in applying their skills in the workforce, leading them to enter the labor market rather than pursue graduate study. However, our data capture only first job placement, so we cannot determine whether these students eventually pursued graduate degrees or forgone this human capital investment altogether.

Labor Market Earnings Columns 5 and 6 examine log median income at the first job. In column 5, the coefficient on Intend CS is 0.204 and highly significant: before the reform, CS-intending male students earned 22.6% more than non-CS-intending males ($e^{0.204} - 1 \approx 0.226$), likely reflecting their higher probability of majoring in CS and lower rates of graduate school attendance. The interaction Female × Intend CS is close to zero and not significant, indicating that this CS-intending premium applied equally to women. However, women faced an earnings penalty: the coefficient on Female is -0.200, implying that non-CS-intending women earned 18.1% less than their male counterparts before the reform ($e^{-0.200} - 1 \approx -0.181$).

The reform increased women's earnings broadly, not just among CS-intending students. The coefficient on Female $\times$ Post is 0.128 and significant at 5%, indicating that women's post-graduation earnings rose by 13.7% relative to men ($e^{0.128} - 1 \approx 0.137$). The triple interaction is near zero and insignificant, meaning this gain did not differ between CS-intending and non-CS-intending women – the earnings benefits thus reflect broader gains to female students rather than a concentration among those who switched into CS. The coefficient on Post $\times$ Intend CS is also not significant, indicating no differential earnings change for CS-intending men. Results are robust to intended major fixed effects in column 6, ruling out composition changes as a driver.

Thus, the labor market earnings effects operate regardless of whether female students intended to major in CS at admission, and are therefore unlikely to be due to increased CS majors among them.

7 Conclusion

This paper studies whether a curricular reform in an introductory computer science (CS) course that emphasized the social relevance of the discipline affected female students' CS major choice and post-graduation outcomes. Using rich administrative data on academic outcomes and labor market placements, we find that the reform increased the probability that female students majored in computer science by 12.1 percentage points. This shift was driven primarily by greater retention of female students who intended to major in CS at admission. Importantly, these gains were not accompanied by any decline in academic performance as measured by GPA, dropout rates, and years to graduation.

Crucially, the reform also translated into improved labor market outcomes: it increased female students' earnings by 16.9 percent relative to their male counterparts, driven both by reduced graduate school attendance and by sorting into higher-paying occupations. Taken together, our findings suggest that curricular reform in gateway STEM courses can increase women's participation and improve their labor market outcomes.

Our analysis has some limitations. First, it focuses on a single STEM-focused liberal arts college. While the college also offers options to major in non-STEM subjects, effects may differ at universities where non-STEM majors are more widely available. Second, we estimate the combined effect of the redesigned introductory CS course and two complementary initiatives associated with it; although the initiatives are small-scale, we cannot separately identify their individual contributions or potential complementarities with the curriculum redesign. Third, our labor market outcomes capture early-career earnings. How these translate into longer-term outcomes remains an open question – especially whether those who chose not to pursue graduate study can acquire additional skills later in their careers. Nevertheless, we provide causal evidence that curricular reform can be an effective policy lever for narrowing gender gaps in STEM fields.

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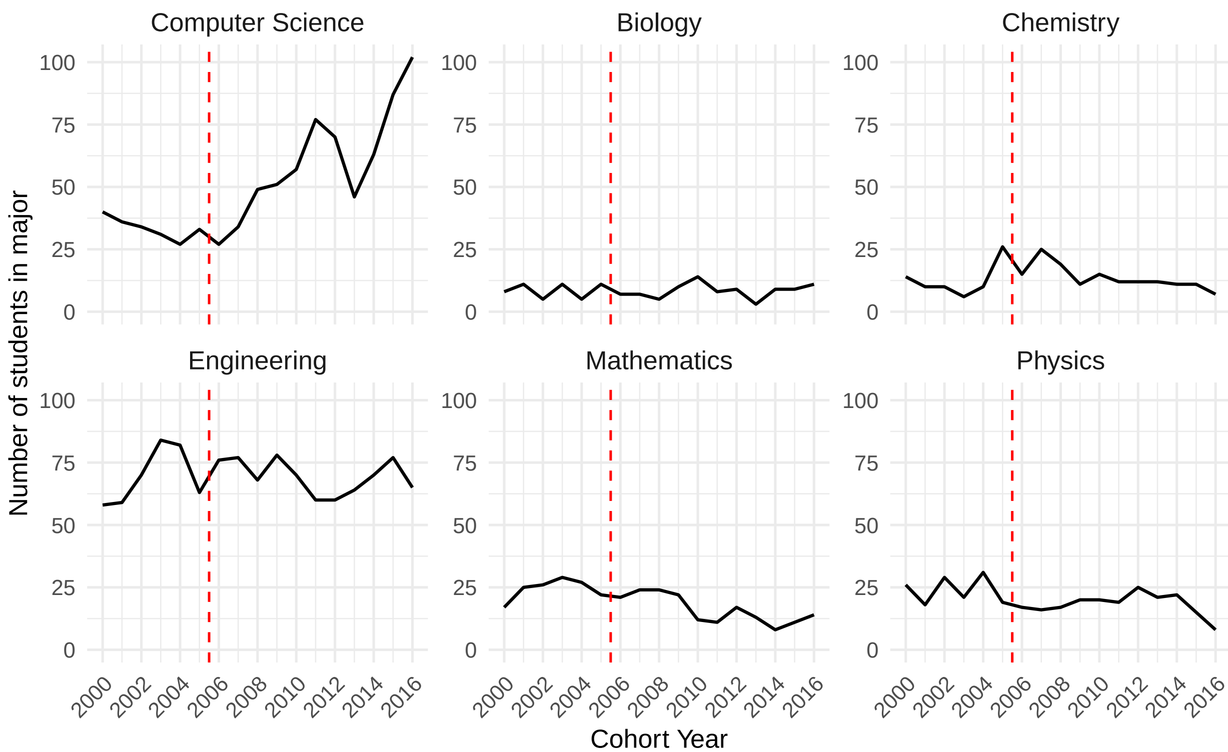
Appendix

A Additional Figures and Tables

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



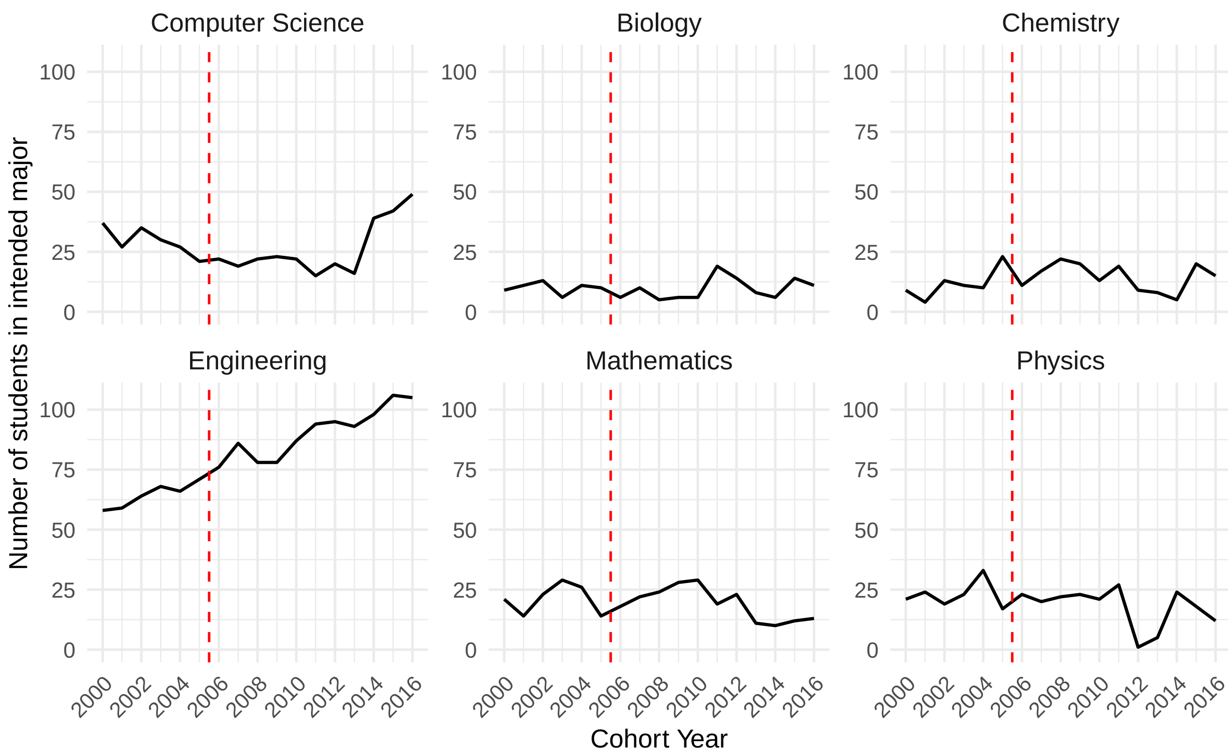
Notes: This figure presents the evolution of the number of students across cohorts from 2000 to 2016 within each core major. The red vertical dashed line indicates the CS curriculum reform in 2006.

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

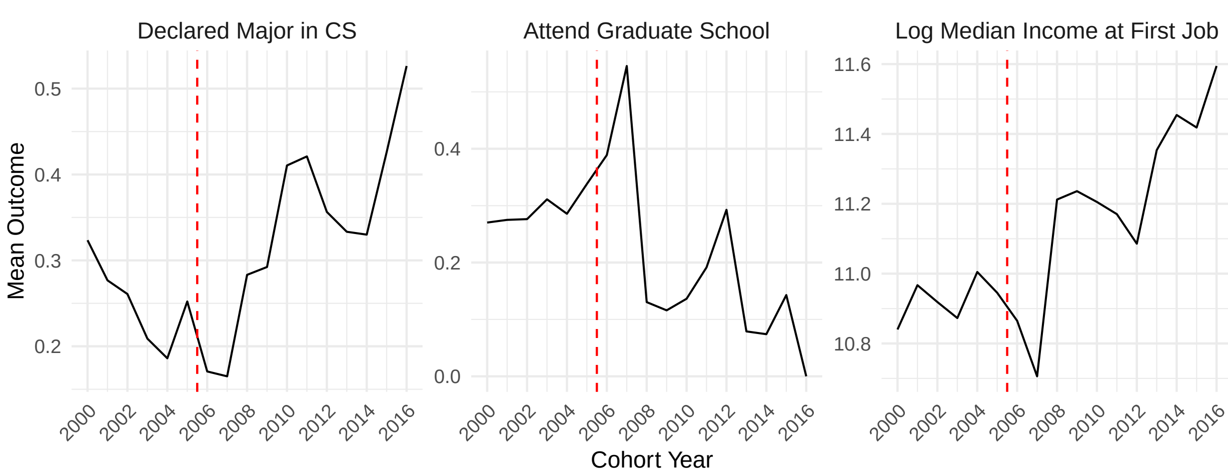
Notes: This table reports the percentage of students with missing placement data, by reform period, gender, and their interactions. All reported differences are tested using t-tests of mean differences. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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



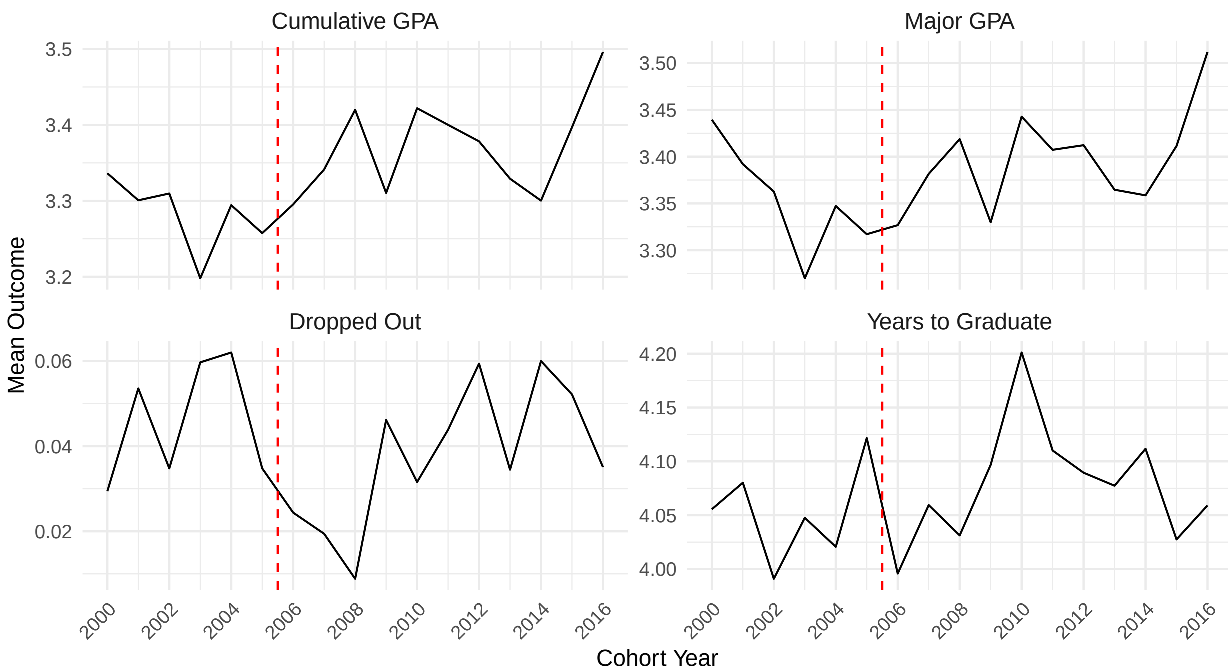
Notes: This figure presents the evolution of the number of students across cohorts from 2000 to 2016 within each core intended major. The red vertical dashed line indicates the CS curriculum reform in 2006.

Figure A3: Male Students' Main Outcomes over Time



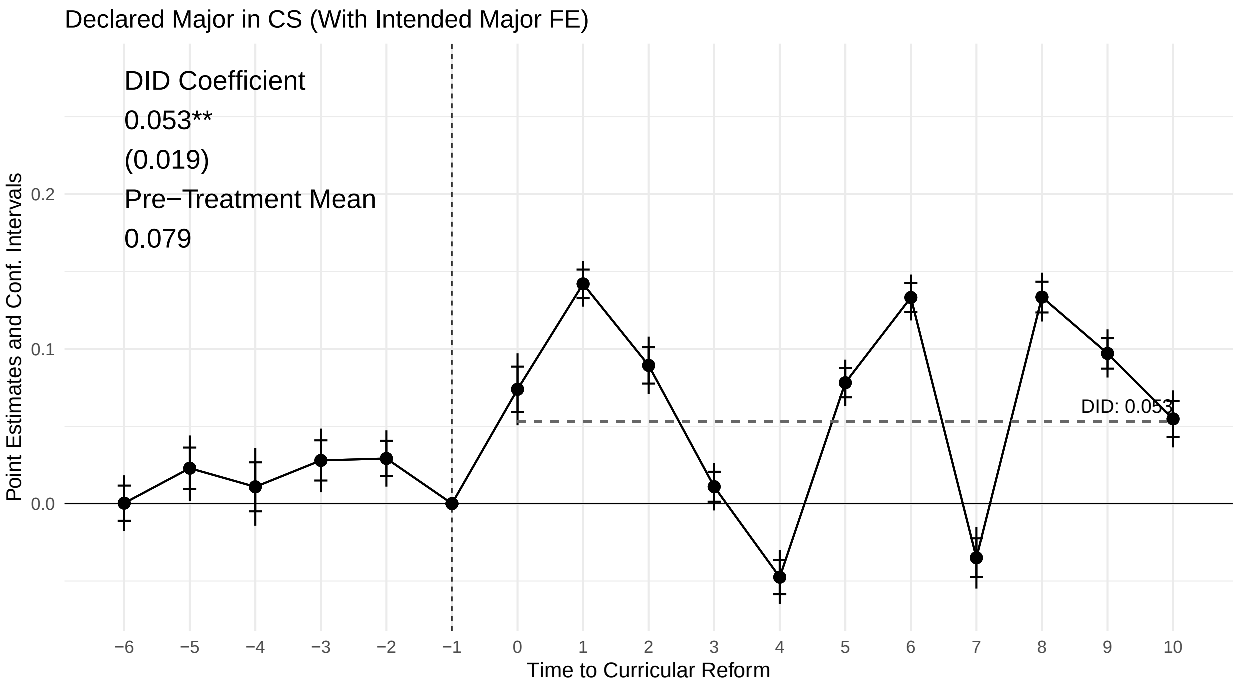
Notes: This figure plots the mean of our main outcomes, including CS major, log median income, and graduate school attendance among men over the study period (years 2000 to 2016), where the CS curriculum reform in 2006 is marked with a red dashed vertical line.

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 for 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

Outcome:	Log Median Income at First Job	
	(1)	(2)
Female × Post × GS Attendee	-0.058	-0.056
	(0.043)	(0.044)
Female × Post	0.077*	0.071*
	(0.043)	(0.040)
Female	-0.132***	-0.121***
	(0.038)	(0.036)
Female × GS Attendee	0.113***	0.116***
	(0.035)	(0.033)
Post × GS Attendee	-0.023	-0.020
	(0.038)	(0.037)
GS Attendee	-1.213***	-1.209***
	(0.029)	(0.030)
Linear combinations		
Female × Post × GS Attendee	0.019*	0.015
+ Female × Post	(0.011)	(0.013)
Female × GS Attendee	-0.019***	-0.004
+ Female	(0.005)	(0.008)
Cohort Year FE	Y	Y
Controls	Y	Y
Intended Major FE		Y
Pre-Treated Mean	10.704	10.704
Adj. R-squared	0.843	0.844
Observations	1669	1669

Notes: This table presents OLS estimates of equation 2, allowing the effect to vary by students' graduate school attendance 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.