Essays on Gender and Education

by

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ABSTRACT

This dissertation focuses on the reasons why men and women make different choices when it comes to investing in human capital. The common thread of all three essays is a focus on one particular dimension of the human capital investment decision: the choice of college major. I study gender differences in college major choice in three different contexts. The first, the dot-com crash, is a large negative shock to the relative payoffs of different college majors. The second, the transition to coeducation at former women's colleges, is a structural change in colleges. The third is long-run changes over time.

Chapter 1 studies the change in women's college major choices in response to a large, negative labor market shock, and how gender differences in STEM grades might lead women to have a stronger reaction to a labor market shock than men do. Although the dot-com crash had similar labor market effects for new graduates in engineering and computer science, it had different effects on who chose each major: women disproportionately left computer science, but not engineering. I investigate the mechanism behind the gender difference in reaction to the dot-com crash using administrative data on students from a four-year public university. At said university, the gender gap in grades (in favor of men) is larger in computer science than engineering. I estimate a structural model of major choice where students choose a major to maximize expected lifetime utility, conditional on grades, the labor market, and other factors. I find that if the distribution of grades had been the same in engineering and computer science, the gender difference in reaction to the dot-com crash would have been 33 to 42% smaller, suggesting that students reacted to the dot-com crash in accordance with their perceived comparative advantage. My results suggest that grades are an important component in retaining women in computer science degree programs. Universities hoping to encourage women to major in computer science should investigate the sources of gender gaps in STEM grades and work to help women improve their performance.

Chapter 2 studies the change in women's college major choices induced by the introduction of male peers. Though American women earn college degrees at higher rates than men, they are still under-represented in quantitative fields such as STEM and economics. Researchers have speculated gender differences in labor market decisions may originate

in part from psycho-social factors such as gender norms and competition, many of which become more relevant to women when they are in more male environments. We leverage a unique setting that generated variation in women's exposure to male peers: colleges that transitioned from women-only to coeducation. At such colleges, we observe a steady decrease in the share of women majoring in STEM over the decade following the transition to coeducation. This corresponds to a 17% decrease in the share of women majoring in STEM for a 10 percentage point increase in the male share of the graduating class. We find no evidence that the female share of faculty declines in response to the switch to coeducation, suggesting that our results are driven primarily by peer rather than by role-model effects. Our results suggest that women's human capital investments are affected by the gender mix of their fellow students and have implications for gender gaps in the labor market.

Chapter 3 studies long-run changes in men's and women's choices of college major over time, in particular whether a Schelling tipping pattern exists in the gender composition of college majors. Following Pan's (2015) model of tipping in occupations, I build a framework that can produce a tipping pattern in the gender composition of college majors. However, I find that no evidence of a tipping pattern in college major. By relaxing two assumptions in previous tipping models, I explain theoretically why tipping may not occur in this context. I test the modified framework and find that the lack of tipping is most likely explained by men facing only small utility costs of being in highly female majors.

CHAPTER I

Gender, Grades, and College Major During the Dot-Com Crash

1.1 Introduction

The dot-com crash was the largest shock to the high tech sector in recent memory, and it had large labor market effects for recent college graduates. As shown in Figure 1.1, computer science and engineering[1] had similar expected log starting salary in every year, and those salaries fell relative to the salaries of other majors from 2000 to 2003 before recovering in 2004. Although the shock to job prospects was the same for students in both majors, the dot-com crash had very different effects on students' willingness to enter engineering and computer science. Figure 1.2 shows the log number of men and women in the United States who completed degrees in computer science and engineering every year. Beginning with the class of 2005, who started college around 2001, there was a sharp drop in the log number of students earning computer science degrees, and the reaction was twice as large for women as for men. There was no decrease in engineering degrees after the dot-com crash, and only a small gender difference in the change in probability that students chose an engineering major after the crash. This is puzzling because computer science and engineering are similar fields and should, in theory, attract similar students. Furthermore, the crash did not have large effects on the gender difference in salary in either field, as shown in Figure 1.3.[2]

In this paper, I explore why the dot-com crash made computer science programs, but

[1]For the remainder of this paper, "engineering" refers to all engineering fields other than electrical and computer engineering, which are aggregated with computer science majors.

[2]Data in Figures 1.1 and 1.3 is provided by the National Association for Colleges and Employers *Salary Survey*. The gender difference in salary in engineering is due to differences in fields chosen by men in women within engineering: women are more likely to be chemical engineers (the highest paid engineering major) than men, and men are more likely to be civil engineers (the lowest paid engineering major) than women.

not engineering programs, significantly more male. I find that, at one large public university, the gender gap in grades (in favor of men) is larger in computer science courses than in engineering. To understand the role of grades in driving women out of computer science after the dot-com crash, I use administrative data on students and concurrent labor market data to estimate a structural model of college major choice conditional on GPA and the labor market for students who entered college between 1996 and 2005. I then simulate students' choices of majors when GPAs for computer science students have the same distribution as GPAs for engineering students. I find that if GPAs in computer science had the same distribution as GPAs in engineering, then the gender difference in reactions to the dot-com crash would have been 33 to 42% smaller. This suggests that students acted according to their perceived comparative advantage when choosing majors in the years after the dot-com crash. My results suggest that degree programs looking to attract and retain more women should examine their grading policy, and, if they find systematic disparities in men's and women's academic performance, they should investigate the source of those disparities. While I cannot rule out that women simply are not as good at computer science as men, it seems unlikely that the difference in gender gaps in computer science and engineering grades could be fully explained by gender differences in ability. It seems more likely that differences in the way that computer science and engineering teach and evaluate students are responsible for the larger gender gap in grades in computer science.

According to the IPEDS, computer science is the only STEM field that grew more male between 1980 and 2010, and the dot-com crash was one of the two largest events in that process.[3] All other STEM fields, including engineering, grew more female over the same period. This is puzzling because engineering and computer science are similar in terms of job market outcomes and the math ability required of students. Therefore, studying the differences between the two fields may provide insight into the gender gap in STEM as a whole. Furthermore, computer science is a quickly growing field that has had consistently good job prospects over the past several years.[4] The quick obsolescence of software used by professional computer scientists and engineers has created a constant need for new graduates of engineering and computer science programs, leading to the narrative that there is a shortage of qualified workers in these fields despite the explosive growth in computer science degree programs (Deming and Noray, 2018). For this reason, policy-

[3] As noted by National Academies of Sciences, Engineering, and Medicine (2018*a*), gender segregation in computer science increased during periods when the field was shrinking: the mid to late 1980s and the early to mid 2000s.

[4] The *Occupational Outlook Handbook* by the Bureau of Labor Statistics (2016) projects that opportunities for software developers will grow by 24% between 2016 and 2026, much faster than average. Other computer-related occupations have similar outlooks.

makers have expressed interest in expanding the supply of new computer science workers. Understanding the importance of grades to students' decisions to pursue computer science will be helpful for understanding how to push students of all genders to major in computer science.

This paper contributes to the literature on the interaction between gender, college major choice and labor market volatility by providing previously unavailable evidence on how selection into majors changes when the labor market is volatile. Previous work has shown that students' choice of major responds to labor market shocks, although women tend to care less about salary and more about nonpecuniary benefits than men (Long, Goldhaber and Huntington-Klein, 2015; Shu, 2016; Wiswall and Zafar, 2015*a*,*b*, 2018; Zafar, 2011, 2013). Furthermore, Blom, Cadena and Keys (2015) found that women are more likely than men to shift their choice of major during recessions to (typically male-dominated) degrees with better employment prospects, suggesting that women may be more sensitive to the labor market when choosing college major. However, these papers use retrospective data on major choice which does not include information on grades or other factors during college, which means they cannot examine how selection into majors changes during periods of labor market volatility. This paper also contributes to the literature on the effects of graduating in a recession (Kahn, 2010; Oreopoulos, von Wachter and Heisz, 2012). The major paper in this literature, Oreopoulos, von Wachter and Heisz (2012), finds that students who graduate in a recession suffer large losses to lifetime earnings because they start off their careers with lower-paying employers. My results suggest that students take action to mitigate the effects of graduating in a recession by changing their major to one with better career prospects, and that students who change their major will be the ones who have lower grades relative to other majors. This result is also consistent with the results of Blom, Cadena and Keys (2015).

This paper also contributes to the literature on gender, comparative advantage and STEM fields. Previous work suggests women are as well-prepared as men to study STEM subjects and better prepared than men to study non-STEM subjects, suggesting that women have comparative advantage in non-STEM fields (Breda and Napp, 2019; Card and Payne, 2017; O'Dea et al., 2018; Stoet and Geary, 2018). I add to this literature by providing a real-world test of whether students act according to comparative advantage during labor market shocks: during a negative shock to two STEM majors that have different gender gaps in grades, women were more likely to leave the major with a larger gender gap in grades. My results also suggest that comparative advantage could be at work within STEM fields: there is a smaller difference between women's performance in non-STEM and engineering coursework than their non-STEM and computer science coursework. This makes women less likely to choose computer science than other STEM fields, and caused them to be more sensitive to the dot-com crash.[5]

Finally, this paper contributes to the large literature on the gender gap in STEM majoring by using a novel strategy of comparing two similar STEM majors to show that grades explain a portion of the gender gap. Several papers have examined how academic performance affects women's choice to enter and continue in quantitative majors, with mixed results (Ahn et al., 2019; Astorne-Figari and Speer, 2019; Goldin, 2015; Kugler, Tinsley and Ukhaneva, 2017). Other proposed explanations include, but are not limited to, gender differences in math SAT scores (Turner and Bowen, 1999), preparation in non-STEM fields (Card and Payne, 2017), tastes for majors and for non-pecuniary benefits in the labor market (Wiswall and Zafar, 2018; Zafar, 2013), and role model and peer effects (Carrell, Page and West, 2010). Additionally, most work on the gender gap in STEM is conducted during periods of stable relative demand for majors, whereas this paper can study the interaction of the gender gap in STEM with labor market volatility.

The rest of the paper proceeds as follows. Section 1.2 discuss the data used. Section 1.3 describes the computer science program at the studied university. Section 1.4 describes a dynamic structural model of college major choice over a student's college career. Section 1.5 presents the estimated model parameters and the results of two simulated counterfactual scenarios – one where students in computer science had the same distribution of grades as students in engineering, and one where the dot-com crash did not happen. Section 1.6 provides discussion of my results. Section 1.7 describes robustness checks. Section 1.8 concludes.

1.2 Data

I use three sources of data to estimate the model. Data on students' choices and performance is from administrative data on students at a four-year public university with a prestigious computer science program, which I will refer to as The University. Contemporaneous data on salaries for college graduates by major is provided by the National Association of Colleges and Employers (NACE). Data on salaries for college dropouts and unemployment is from the Outgoing Rotation Group of the CPS (CPS-ORG).

[5]Other recent work suggests that women underperform their expectations (measured by outside GPA) by more than men in introductory STEM courses. The exception is lab- and project-based courses, which suggests women may be at a particular disadvantage in college-level exams in STEM (Koester, Grom and McKay, 2016; Matz et al., 2017).

1.2.1 Student sample

My student sample is first-time undergraduates who entered The University between 1996 and 2005.[6] The sample is limited to students in the College of Liberal Arts and the College of Engineering, which are the two largest colleges. The data includes information on all courses taken, major declared in each semester, student demographic data, grades, and AP credits for all students in all years, with SAT scores and other admissions data for students who entered in 2000 and later.

Trends in computer science degree production at The University moved similarly to the national trends. Figure 1.4 shows the log number of computing degrees awarded to men and women nationally and at The University. The dot-com crash had a similar effect on the gender balance of computer science degrees at The University as it did for degrees nationally.

1.2.2 Labor market returns

Contemporaneous data on salaries for college graduates by major is taken from the NACE *Salary Survey* from 1995 to 2010. This is the only yearly salary data by major in the 1990s that has a large sample of computer science students.[7] The survey reports the mean and median salaries of graduates by major at over 250 colleges and universities, as well as the means by gender. The career center at the The University directs students who ask about what salary they can expect to earn in a particular major to the NACE salary survey, which means that this data is the same as the data that students had available to them at the time. Average log salary for individuals without a college degree is calculated using the CPS-ORG.

Yearly unemployment data by major in a large sample is generally not available before 2009.[8] I therefore use yearly unemployment rates in related occupations to each major from the CPS-ORG.

[6]In 2006, the computer science department began to make an effort to recruit female students to computing programs. IPEDS shows a sharp uptick in the female share of computer science graduates beginning in 2010. For this reason, I exclude cohorts entering in 2006 and later.

[7]There are only a small number of computer science majors in each SIPP survey, and only a small share of those are female.

[8]While this data is available every other year from the National Survey of Recent College Graduates, that survey is was not run between 2000 and 2002, which means it skips the dot-com crash.

1.3 Computer science at The University

1.3.1 The computer science major

There are three steps to a degree at The University. Students first take the prerequisite courses for the major. They then declare a major in computer science, which most students do at the end of sophomore year, and take their upper-level computer science courses. Students then graduate and enter the workforce.

I aggregate four majors into one "Computer Science" group: two computer science majors, computer engineering, and electrical engineering.[9] One computer science major is for students in the College of Liberal Arts and the other is for students in the College of Engineering. These two majors have the same core course requirements,[10] and students are advised that the programs are the same difficulty. Computer engineering and electrical engineering are both in the College of Engineering only. The College of Engineering version of the computer science major opened in the Fall 2000 semester, which made computer science more available to students.[11]

Computer science and engineering have a similar set of prerequisites, including a writing course, three calculus courses, one programming course,[12] and a certain number of science courses.[13] Students who are serious about majoring in computer science also take a second semester of programming, which the faculty consider to be the gateway course to the computer science major.

1.3.2 The effects of the dot-com crash at The University

Although the dot-com crash decreased the probability of becoming a computer science major by more for women than men, the crash did not drive students away from completing the set of prerequisites to the computer science or engineering degree. Instead, the

[9] All of these majors are in the same department, and the first two years of coursework are similar.

[10] The College of Liberal Arts requires at least a C in calculus 1, 2, and 3, two semesters of programming, discrete math, and two science courses before students declare the major. Students needed a 2.7 average across those courses before 2003 and a 2.5 in 2003 and later. While the College of Engineering requires fewer courses before declaring a major, students must pass the same set of courses with at least a C to use them as prerequisites. It is unclear whether the GPA cutoff applied to students in the College of Engineering, but the College of Engineering reserved the right to restrict which students can enter certain majors. Transferring between colleges required a C in the same set of requirements.

[11] Computer science in the College of Engineering mostly drew students from computer engineering at first. By 2005 the College of Engineering version was both the more popular and the more female of the two computer science majors.

[12] Prospective computer science majors who entered before 2000 took a different course than prospective engineering majors, but the course for non-majors could fulfill the requirement for computer science.

[13] College of Engineering students took two physics courses and one chemistry course, with labs. College of Liberal Arts computer science students took eight credits of any natural science courses.

crash disproportionately drove women away from declaring a first major in computer science. The crash did not have a large effect on the gender balance of engineering programs.

Figure 1.5 shows the log number of men and women at each stage of the computer science major and engineering majors by the year of entry to The University.[14] There was only a small decrease in the log number of women who took engineering and computer science prerequisites and a small increase in the log number of men who took those prerequisites in the cohorts who entered The University after the dot-com crash.[15] The increase for men begins with students who started college in 2003 to 2005, which may not be directly related to the dot-com crash. The effects of the crash on the computer science major were much larger later in college: the crash decreased the number of female students who declared a computer science major and who finished a computer science major by proportionally more than the number of male students at each stage, beginning with students who entered college between 2001 and 2002. This was not the case for engineering, where the log number of men and women who declared and finished majors in engineering increased by about the same amount for men and women who entered college between 2000 and 2002. While there is a slight increase in the number of men, relative to women, who chose engineering beginning in 2004, the difference is not nearly as dramatic as it is for computer science.

Figure 1.5 also shows that the dot-com crash increased attrition from computer science by more for women than men. The difference between the log number of students taking courses and declaring a major is the proportion of students who leave the computer science pipeline at the stage of declaring the computing major. The dot-com crash widened this gap for both men and women, indicating that the dot-com crash increased attrition for both men and women, but the gap widened by much more for women than for men. Similarly, the difference between the log number of students declaring a computing major and finishing a computing degree is the proportion of students who leave the computing pipeline at the stage of declaring the computing major. The dot-com crash did not widen this gap for men, but it did widen this gap by a small amount for women, indicating that the dot-com crash increased attrition at late stages of the degree for women only.[16]

[14] Note that the line for taking prerequisites is the same within genders.

[15] The effects of the crash on taking *any* computer science course is similar to the effects on declaring a major and finishing a major. However, the full set of prerequisites indicates students who were serious about the computer science major. Appendix A.6 has more details.

[16] Regression analysis of attrition at each stage can be found in Appendix A.6.

1.3.3 Grades and gender in computer science and engineering

In my sample, women earn lower average grades than men in all STEM fields, but the gender grade difference is largest in computer science. Table 1.6 shows the average grades, in grade points, by gender in the gateway courses in mechanical engineering and computer science, where the gateway course refers to the first core course for a major.[17] The average woman in the computer science gateway course earned a 2.64, whereas the average man earns a 2.92, a difference of 28% of a grade point. The average woman in the mechanical engineering gateway course earned a 2.75, whereas the average man earns a 2.84, a difference of 9% of a grade point. Women who are interested in STEM but sensitive to grades may therefore prefer engineering to computer science. The larger grade differences in computer science persisted through college and led to a lower in-major GPA at graduation for women in computer science than women in engineering.

1.4 Structural model

I construct and estimate a structural model of college major choice in order to understand how students select into different majors conditional on academic performance. A structural model is the ideal tool for this analysis because it allows me to run a policy simulation where I make grades in computer science have the same distribution as grades in engineering. The structural model also allows me to find where students who would have chosen computer science before the crash went. Neither of these are possible in reduced form analysis.

To match the stages described in Section 1.3.2, students choose their major in a three-stage Roy-style process. Students are forward-looking, and they choose majors to maximize their expected lifetime utility. The utility of a major is partly deterministic and partly stochastic, and the deterministic portion is based on academic performance, the labor market, and other factors that will be described in the next section. Intuitively, when the dot-com crash shocked the computer science labor market, some students who were close to the margin of choosing computer science before the crash changed to other majors. Because there was a larger proportional decrease in women's computer science majoring after the dot-com crash, women must have been more clustered around the margin of choosing computer science than men. My goal in this paper is to find what characteris-

[17] Students usually take both of these courses as sophomores. The computer science course is the second programming class described in Section 1.3.1. Mechanical engineering is the largest non-computing engineering major at The University, and the course is titled "Introduction to Mechanical Engineering." Gender differences in grades in the mechanical engineering gateway are similar for the other engineering gateway courses.

tic, captured in the deterministic portion of utility, led women to be clustered around the margin.

The order of events is as follows. In period 1, freshmen arrive on campus, observe the labor market for every major, and form expectations about the labor market and their future academic performance. Students next realize their taste shocks for each choice of "track," or prerequisites, and choose their track. Students then take their first two years of coursework and realize their period 1 grades. Period 2 begins at the end of sophomore year. Students observe the labor market and their period 1 grades and then update their expectations about the labor market and future academic performance. Students next realize their taste shocks for each potential first major and either choose their first major or drop out permanently. Students then take their final two years of coursework and realize their period 2 grades. Period 3 begins during senior year. Students observe the labor market and update their labor market expectations. Student then realize their taste shocks for each potential final major and either graduate with their final major or drop out of college. After graduating college or dropping out, students permanently enter the labor market and then work until retirement.

1.4.1 The utility of a college major

Students choose majors in three stages. In period 1, students choose a track of prerequisite coursework. In period 2, students choose their first major or drop out. In period 1, students graduate with a degree in their final major or drop out. In each stage, students' goal is to maximize the expected present discounted value of lifetime utility. In the final period, students work until retirement.

During period 1, students enter college, observe the information they have available to them, form expectations about the labor market and their future performance in each major, and choose a track of introductory coursework. Their choice set $\mathcal{C}$ includes Pre-Engineering/Computer Science, Pre-Science, and Non-STEM.[18] After making their period 1 choice, students take two years' worth of coursework in their chosen track. Students may choose any period 2 and 3 major regardless of the track they choose in period 1. However, choosing a major that is not related to a track imposes a cost in future periods.

Students choose their track to maximize their expected lifetime utility, conditional on their demographic variables and the AP credits they earned while in high school.[19] Student

[18]Tracks are defined based on the prerequisites for each major. See Appendix Section A.1.1 for details.

[19]SAT and ACT scores are only available for students who started in 2000 and later. In a robustness check, I estimate the model only for students who entered in 2000 or later and have either SAT or ACT scores available. Details can be found in Appendix A.7.1.

i of gender g's problem in period 1 is

$$\max_{c \in \mathcal{C}} \left\{ \alpha_{10c}^{g} + \alpha_{11c}^{g} AP_i + \alpha_{12c}^{g} X_i + \alpha_{13c}^{g} Post_i + \varepsilon_{1ic}^{g} + \beta \mathbb{E}\left[V_2^g(s_{i2}) \right| s_{i1}, c] \right\}$$

For the rest of this section, I suppress the g superscripts, but all parts of the model are estimated separately by gender. β is the discount factor, which is set to 0.95. s_{i1} is the period 1 state space, which includes student's earned AP credits AP_i,[20] cohort of entry to college, and demographic information X_i.[21] AP credits enter the value function as individual indicator variables for earning credit in each exam. Having particular AP credits directly reduces the cost of choosing a particular track by lowering the number of courses students must complete. AP credits also capture major-specific taste and ability. $Post_i$ is an indicator variable that is equal to 1 if the student entered The University in 2001 or later, which captures change in students' average tastes for major j that could have occurred due to the dot-com crash.[22]. The track-specific taste shock ε_{1ic} is i.i.d Type 1 Extreme Value. $\mathbb{E}\left[V_2(s_{i2})|s_{i1}, c\right]$ is the expected future value of track c.

During period 2, students observe their period 1 grades, update their expectations about the labor market and their future grades, and declare their first major or drop out. Students' choice set $\mathcal{M}$ includes Computer Science, Engineering, Science, Business, Humanities/Social Sciences/Other, and dropping out (D).[23] Students who drop out enter the labor market permanently and get two extra years of the labor market payoff of a major. After making their period 2 choice, students who did not drop out take their final two years' worth of coursework in their chosen first major.

Students choose their first major to maximize their expected lifetime utility, conditional on their choices and performance in period 1. The student's problem is

$$V_2(s_{i2}, c^*) = \max_{j \in \mathcal{M}} \left\{ V_{2j}(s_{i2}) + \beta \mathbb{E}\left[V_3(s_{i3}) \right| s_{i2}, j] \right\}$$

[20] AP credits used include calculus, physics, biology, chemistry, English, economics, and history. Computer science is not included because the requirements for accepting AP credit in computer science relaxed substantially in 2000, likely in order to reduce the strain on the capacity of the computer science program, and before the relaxation of the constraint very few students were able to place out of introductory programming. However, there was a similar gender difference in reaction to the dot-com crash in terms of taking the AP Computer Science exam.

[21] The included demographic variables are race, ethnicity, international status, in-state residency, and average IRS family income in a student's home ZIP code for domestic students. IRS data on average family income in home ZIP code is imputed from 1998 to 2001 using linear interpolation.

[22] This could have occurred because of salient signals like the collapse of superstar firms, as described in Choi, Lou and Mukherjee (2019). Another possibility is that something about the available jobs in different fields, like nonpecuniary benefits, may have changed, as described in Wiswall and Zafar (2018)

[23] See Appendix A.1 for a full list of majors in each category.

where

$$V_{2j}(s_{i2}, c^*) = \begin{cases} \alpha_{20j} + \alpha_{21j,c^*} T_{i1,c^*} + \alpha_{22j,c^*} G_{i1,c^*} + \xi_{2j,c^*} + \alpha_{23j} X_{i2} + \alpha_{24j} Post_i + \varepsilon_{2ij} & j \neq D \\ V^{LM}(D, T+2) + \varepsilon_{2iD} & j = D \end{cases}$$

s_{i2} is the student's period 2 state space, which includes the period 1 state space s_{i1}, the period 1 choice of track c^*, realized in-track GPA from period 1 coursework[24] T_{i1,c^*}, and realized overall GPA from period 1 coursework G_{i1,c^*}. The contribution of T_{i1,c^*} and G_{i1,c^*} to the payoff of a major depends on the combination of c^* and period 2 major, as performance in a particular track provides different information about performance in different majors. AP credits no longer enter the value function because they no longer directly change the costs of pursuing a major. Students also realize a major-specific cost of each period 1 choice of track ξ_{2j,c^*}.[25] $Post_i$ once again controls for changes in students' tastes for majors caused by the dot-com crash, and is now equal to 1 if the student chose their first major in 2001 or later. $V^{LM}(D, T+2)$ is the labor market value of dropping out before declaring a major, which includes two extra years of labor market experience. $\mathbb{E}\left[V_3(s_{i3}) | \, s_{i2}, j\right]$ is the expected future value of first major j. The student's taste shock ε_{2ij} is i.i.d. Type 1 Extreme Value and is independent of the period 1 taste shock.

During period 3, students observe the labor market and their performance in their last two years of classes, update their beliefs about the labor market, and decide whether to keep their first major and graduate, change their major and graduate, or drop out.[26] Students have the same choice set as they did in the previous period.

Students choose their final major to maximize expected lifetime utility, conditional on their previous choices and performance in period 2. The student's problem is

$$V_3(s_{i3}) = \max_{j \in \mathcal{M}} \left\{ V_{3j}(s_{i3}) + \beta \mathbb{E}\left[V^{LM}(j, T)\right] \right\}$$

[24]For Pre-Engineering/CS, the track GPA is the GPA in calculus, physics, chemistry, and any computing or engineering coursework. For Pre-Science, the track GPA is the GPA in all science and math coursework. For Non-STEM, the track GPA is the GPA in non-STEM courses.

[25]Technically speaking, ξ_{jc} can be positive, as we might expect it to be for the computer science major and the pre-engineering/CS track. This represents a switching cost which is specific to each period 1 track. For identification, I leave out $c =$Non-STEM.

[26]Students who did not graduate within seven years are considered to have dropped out of college.

where

$$V_{3j}(s_{i3}) = \begin{cases} \alpha_{30j} + \alpha_{31j} M_{ij_2} + \alpha_{32j}^{N} G_{ij_2} + \alpha_{33j} X_{i3} + \alpha_{34j} Post_i + \xi_{3jc^*} + \varepsilon_{3ij} & j = j_2^*, j \neq D \\ \alpha_{30j} + \alpha_{32j}^{S} G_{ij_2} + \alpha_{33j} X_{i3} + \alpha_{34j} Post_i + \xi_{3jc^*} + C_j + \varepsilon_{3ij} & j \neq j_2^*, j \neq D \\ V^{LM}(D, T+1) + \varepsilon_{3iD} & j = D \end{cases}$$

s_{i3} is the student's state space period 3, which includes the period 2 state space s_{i2}, the student's period 2 choice j_2^*, the student's realized in-major GPA from their period 2 major M_{ij_2}, and the student's realized cumulative GPA from period 2 G_{ij_2}. The contribution of GPA to the utility of a major depends on whether the student is switching majors.[27] The student's in-major GPA is only realized if the student chose major j in period 2 and therefore only enters the value function if the student is not changing majors. $Post_i$ controls for changes in students' tastes for majors caused by the dot-com crash and is now equal to 1 if the student chose their final major in 2001 or later. ξ_{3jc^*} is a major-specific cost of choosing final major j conditional on having chosen track c, capturing the cumulative cost of multiple switches or the benefit of switching back to an original choice. C_j is a major-specific cost of switching into major j. $\mathbb{E}\left[V^{LM}(j,T)\right]$ is the expected labor market value of a major, which will be described in the next section. $V^{LM}(D, T+1)$ is the labor market value of dropping out, which includes one extra year in the labor market. The student's taste shock ε_{3ij} is i.i.d. Type 1 Extreme Value and is independent of the period 1 and 2 taste shocks.

1.4.2 Labor market value of a college major

After college, students enter the labor force and work for T years. Students form their beliefs on the labor market during freshman year and update them based on labor market information from their sophomore and junior years. Students assume that shocks to starting salary are permanent, and they update their beliefs about the distribution of starting salary draws accordingly.[28] I construct $\mathbb{E}\left[V^{LM}(j,T)\right]$ using calibrated variables from NACE, the CPS-ORG, and the ACS. The rest of this section will describe how I calibrate lifetime earnings.

[27]Ideally, the contribution of GPA would depend on the pair of first and final majors chosen. Unfortunately, because there are certain pairs of majors for which no switches occurred during the sample period, those coefficients are not identified. The same issue exists for switching costs.

[28]Clark (2015) found that during the dot-com crash period, students treated the dot-com crash as more persistent than it actually proved to be, and having students treat the shock as permanent was a better fit than rational expectations. In a robustness check, I test what happens when salary and unemployment rates follow an AR(1) process. Details can be found in Appendix A.8.1.

The labor market payoff of a major depends on employment and salary conditional on employment. The present discounted value of the student's lifetime earnings is

$$\mathbb{E}\left[\sum_{\tau=0}^{T}\beta^{\tau}\left(\mathbb{1}(U_{ij\tau}=1)u(b_{i\tau})+\mathbb{1}(U_{ij\tau}=0)u(Y_{ij\tau})\right)\right]$$

where β is the discount rate, $b_{i\tau}$ is the value of not working in period s, $U_{ij\tau}$ is a 0/1 variable representing unemployment, and $Y_{ij\tau}$ is salary for major j in period τ. I set $u(b_{i\tau})=0$ and set $u(Y_{ij\tau})=\log(Y_{ij\tau})$.[29] I also assume that salary and unemployment are independent.[30] I calculate the present discounted value of lifetime income for major j using

$$V^{LM}(j,T)=\sum_{\tau=1}^{T}\beta^{\tau-1}\left(1-P(U_{ij\tau}=0)\right)\mathbb{E}\left[\log\left(Y_{ij\tau}\right)\right]$$

where the discount factor β is set to 0.95 and T, the number of years the student works, is set to 12.[31]

Log earnings depend on experience and a draw of log starting salary. I model the wage generation process for a student in major j who graduated in year t_0 as

$$\log Y_{i\tau}=\gamma_{1j}exp_{i\tau}+\gamma_{2j}exp_{i\tau}^{2}+\theta_{ij,t_0}^{Y} \tag{1.1}$$

θ_{ij,t_0}^{Y} is the student's stochastic draw of log starting salary, which incorporates labor market shocks and an error term for salary. I assume that θ_{ij,t_0}^{Y} is independent of students' taste shocks for tracks and majors ε. $exp_{i\tau}$ is potential experience, which is equal to $age_\tau-22$ for college graduates and $age_\tau-20$ for college dropouts.[32] Table 1.1 reports the calibrated

[29] My model does not include non-pecuniary benefits to careers in different majors, which Wiswall and Zafar (2018) found are important. Ryoo and Rosen (2004) and Deming and Noray (2018) also found that engineers tend to move into management later in their careers, which could be part of the non-pecuniary benefit of a particular major. While I cannot measure a major's nonpecuniary benefit, the effect of labor market shocks on nonpecuniary benefits of particular majors or career paths could be a worthwhile area for future research. My model also does not include payment in stock options.

[30] This assumption would hold if, for example, unemployment caused by the dot-com crash was the result of company closures rather than laying off the worst performer at every company. While that may not have been true for the labor market itself, it seems plausible for new graduates.

[31] T is a relatively low value because I wanted to avoid additional bias that could result from women's differential attrition from the labor market by major. However, I find that the results are not especially sensitive to choice of T (see Appendix A.9) and that students in the Wiswall and Zafar (2015*a*) survey do not seem to plan to differentially select out of the labor market based on their choice of major (see Appendix A.4).

[32] The use of potential experience opens the issue of how women's labor supply choices might affect the labor market returns to a major. If women's labor supply choices affect the labor market returns of every major in the same way, then women's fertility plans will not bias the estimates. Note that we care only about students' expectations over future labor supply, not the real choices students will make. Sufficient conditions

parameters. The expected log salary of a student who graduated in major j in year t_0 is therefore

$$\mathbb{E}\left[\log Y_{i\tau}\right] = \tilde{\gamma}_{1j} exp_{i\tau} + \tilde{\gamma}_{2j} exp_{i\tau}^2 + \mathbb{E}\left[\theta_{ij,t_0}^{Y,g}\right]$$

where $\tilde{\gamma}_{1j}$ and $\tilde{\gamma}_{2j}$ are students' expected returns to potential experience.

I calibrate $\tilde{\gamma}_{1j}$ and $\tilde{\gamma}_{2j}$ using data on earnings by major from the 2009-2016 ACS.[33] I estimate the following equation using least squares:

$$\log Y_{ij} = \tilde{\gamma}_{1j} exp_{i\tau} + \tilde{\gamma}_{2j} exp_{i\tau}^2 + \xi_{j\tau} + \xi_s + \zeta Z_i + e_{ij}$$

$\xi_{j\tau}$ is a major-by-year fixed effect, which controls for labor market shocks, and ξ_s is a fixed effect for state of residence. Z_i is a set of controls for gender, race, ethnicity, and marital status. The estimated values of $\tilde{\gamma}_{1j}$ and $\tilde{\gamma}_{2j}$ are reported in Table 1.1.

I calibrate $\mathbb{E}\left[\theta_{ij,t_0}^{Y}\right]$ from the NACE data for college graduates and the CPS-ORG data for college dropouts. I assume that students know the distribution of starting salary draws for the most recent cohort of graduates and have unbiased beliefs about $\mathbb{E}\left[\theta_{ij,t_0}^{Y}\right]$.[34] I also assume that starting salary does not differ by gender.[35] I assume that salary is distributed log-normally. For college graduates, I calculate[36]

$$\mathbb{E}\left[\theta_{ij,t_0}^{Y}\middle| exp_{ij} = 0\right] = \sum_{k \in j} \omega_k \log(\text{median salary}_{k,t_0})$$

where ω_k is a weight equal to the proportion of each major k within major group j.[37] For college dropouts, I calculate $\mathbb{E}\left[\theta_{D,t_0}^{Y}\right]$ using the mean starting salary for individuals between the ages of 20 and 24 with some college education who are employed and not

for this are that (1) the returns to experience are the same across all majors and (2) women's fertility and future labor supply plans while in college are the same no matter what major they choose. Evidence on (2) is given in Appendix A.4; in short, women's expectations over future labor supply do not vary much by prospective majors, although women may expect they would be more likely to be out of the labor force at ages 30 and 45 if they dropped out of college.

[33]This introduces an additional assumption that labor market returns to potential experience do not change over time and do not differ by gender.

[34]While many studies, including Wiswall and Zafar (2015*b*), find that students tend to overestimate earnings, this will not bias my estimation unless students systematically overestimate log earnings by more in one major than others.

[35]McDonald and Thornton (2007) found that in the NACE data, 95% of the gender difference in average salary could be explained by differences in major. I choose to pool men and women for two reasons. First, not all institutions report student gender to NACE, and those that do seem to be in the lower end of the salary distribution; graduates of The University are likely to be on the higher end of the salary distribution given the quality of the institution. Second, median salary is not reported by gender, which means it is harder to get a clean estimate of expected log salary.

[36]I use this method because the NACE data provides only means and the 25th, 50th, and 75th percentiles. Details on the calculation of moments of the distribution of log salary are contained in Appendix A.5.

[37]A complete list of each major k in each group j can be found in Appendix A.1.

enrolled in school.[38] All mean salaries are adjusted to 2010 dollars using the CPI.[39] Students expect that shocks to starting salary are permanent and that θ^Y is not affected by experience, so that

$$\mathbb{E}\left[\theta^Y_{ij,t_0+\tau}\middle| exp_{ij}=\tau\right]=\mathbb{E}\left[\theta^Y_{ij,t_0}\middle| exp_{ij}=0\right]$$

For college graduates, I set $P(U_{ij\tau})$ equal to the unemployment rate among individuals age 22 to 26 who list occupations related to major j in year τ in the CPS-ORG and who are in the labor market. I assume that students know the unemployment rate in each major. For college dropouts, I use the unemployment rate among college dropouts between the ages of 20 and 24 who are in the labor force and not enrolled in school.

1.4.3 Production functions for GPA

Students take courses between the period 1 and period 2 decision and between the period 2 and period 3 decision. Grades are realized just before students make their period 2 and period 3 choices. Because future GPA is part of the continuation value for periods 1 and 2 and is the major portion of the transition of the state space over time, the estimation of future GPA is part of students' decision process in periods 1 and 2. I assume that students know the grade production function and have rational expectations over grades. In the rest of this section I will describe the grade production functions.

1.4.3.1 The production function for period 1 grades

In period 2, grades have evolved from the initial state space, which contains information on the period 1 choice, earned AP credits and demographic information, including average family income by ZIP code of residence. As the processes are likely to be somewhat different for men and women, they are estimated separately by gender.

The production function for period 2 overall GPA G_{ic2} and in-track GPA T_{ic2}, conditional on choosing track c, takes the following form:

$$G_{ic1}=\phi_{0c2}+\phi_{1c2}AP_i+\phi_{2c2}X_i+\delta^G_{s2}+\delta^G_{t2}+u_{i2}$$
$$T_{ic1}=\theta_{0c2}+\theta_{1c2}AP_i+\theta_{2c2}X_i+\delta^T_{s2}+\delta^T_{t2}+v_{i2}$$

[38] These estimators are unadjusted for race and gender for consistency with the NACE data.

[39] One potential problem with this estimation of earnings can occur if students understand that labor market returns to a major come from a Roy-style model of major choice. Because the NACE does not adjust for ability, I am unable to control for this in my regressions. If students recognize that graduates of a particular major have higher major-specific ability, and if major-specific ability has different average effects for different majors, then there is a chance that my estimates of the labor market returns to different majors could be biased in a way that might affect my results. In Appendix A.4, I use survey data from Wiswall and Zafar (2015*a*) to put a sign and magnitude on the potential bias that could result.

AP_i is a vector of AP credits, and X_i is a vector of demographic variables. δ_{s2}^{G} and δ_{s2}^{T} are state of residence fixed effects and δ_{t2}^{G} and δ_{t2}^{T} are cohort fixed effects. I assume that $(u_i^{12}, v_i^{12}) \sim \mathcal{N}(0, \Sigma_{12})$. I assume that (u_{i2}, v_{i2}) are independent of ε and θ_{ijt_0}.[40]

1.4.3.2 The production function for period 2 grades

In period 3, grades evolve from the period 2 state space, which contains information on choices in periods 1 and 2, period 2 grades, earned AP credits, and demographic information. The grade production function is again allowed to fully vary by gender in order to allow for gender differences in the grade production process.

The production function for period 3 overall GPA G_{ij3} and in-track GPA M_{ij3}, conditional on choosing major j, takes the following form:

$$G_{ij2} = \phi_{0j} + \phi_{1j} AP_i + \phi_{2j} X_i + \phi_{3j}^{c^*} G_{i1} + \phi_{4j}^{c^*} T_{i1,c^*} + c_j^M S_j + \delta_{j,c^*}^{G} + \delta_s^G + \delta_t^G + u_{i3} \quad (1.2)$$

$$M_{ij2} = \theta_{0j} + \theta_{1j} AP_i + \theta_{2j} X_i + \theta_{3j}^{c^*} G_{i1,c^*} + \theta_{4j}^{c^*} T_{i1,c^*} + c_j^M S_j + \delta_{j,c^*}^{G} + \delta_s^M + \delta_t^M + v_{i3} \quad (1.3)$$

G_{ic2} is the realized period 2 overall GPA and T_{ic2} is the realized period 2 in-track GPA. The coefficients on the period 2 GPAs vary based on the track chosen in period 1 to account for the different information that each track provides for each major. Similar to the previous section, AP_i is a vector of AP credits, δ_t^G and δ_t^M are cohort fixed effects, and δ_s^G and δ_s^M are state of residence fixed effects. S_j is an indicator of switching majors from periods 2 to 3, which allows changing majors to affect grades as well as utility. δ_{j,c^*}^{G} and δ_{j,c^*}^{M} are major-specific fixed effects for the period 1 choice of track. I assume that $(u_{i3}, v_{i3}) \sim \mathcal{N}(0, \Sigma_{23})$. I assume that (u_{i3}, v_{i3}) are independent of ε, $\theta_{ijt_0}^{Y}$, and (u_i^{12}, v_i^{12}).

1.4.4 Identification

As is standard in multinomial logit models, the utility parameters of each major can only be identified in relative terms. For this reason, I will estimate the model from differences in utility. In period 1, I will set Non-STEM to be the outside option. In periods 2 and 3, dropping out will be the outside option.

Utility is identified separately from grade expectations by changes in the difference in the expected labor market value of a major from the expected labor market value of dropping out. The dot-com crash decreased this value for all majors, but the largest decrease was for computing majors. The change in the rank order of majors helps to identify the

[40] To simplify estimation, I break the domain of the normal distribution into 10 values and calculate the expected future value over a 10 by 10 grid of combinations of possible error terms.

utility of different majors.

1.4.5 Estimating the model

I estimate the model separately for men and women using maximum likelihood and backwards induction. Estimating the model separately by gender allows me to examine gender differences in preferences over both labor market returns and factors like grades. In period 1, I use a multinomial logit model, meaning that ε_{1i} i.i.d. Extreme Value Type 1. In periods 2 and 3, I use a nested logit model where all majors other than dropping out are grouped together. This means that ε_{2i} and ε_{3i} are i.i.d. Generalized Extreme Value. The implication of this functional form is that the unobserved portion of students' preferences over majors other than dropping out are uncorrelated.

In order to simplify computation, the maximum likelihood estimation is performed in two steps in periods 1 and 2. I first estimate the parameters of the grade production process, then use those to calculate the expected future utility of each major.[41] I also assume that the error terms on salary are independent of the error terms on grades and utility, and that the error terms on grades and utility in each period are not serially correlated.

1.5 Results

1.5.1 Model fit

When considering the effect of the grade distribution on the gender difference in reactions to the dot-com crash, we care about the gender difference in the change in computer science majoring due to the dot-com crash. In this section, I discuss how well my model fits that difference in differences under the true grade distribution. My estimation targets the share of men and women who choose each major before and after the crash in each period. My estimation does not target the difference in differences.

Table 1.2 compares the actual and predicted shares of men and women who chose computer science before and after the crash.[42] The "Before" students entered The University between 1996 and 2000, while the "After" students entered The University between 2001 and 2005. My model does not perfectly predict the shares of men and women who

[41] Rust and Phelan (1997) and Rothwell and Rust (1997) show that the coefficient estimates from this two-step process are consistent. Standard error estimates from this two-step process are not consistent, although the standard error estimates from a full information maximum likelihood estimation would be. I therefore bootstrap the standard errors for the coefficients on grades and AP credits.

[42] Appendix Figure A.1 shows the shares of men and women choosing computer science year-by-year. Appendix Table A.1 reports the shares of men and women who chose every major.

choose computer science in each period because when predicting shares in the later periods, I substitute the prediction for previous periods into the variable for previous periods' choices. However, it does a good job in predicting the differences in differences, especially in periods 1 and 2.

Panel A of Table 1.2 reports the shares of men and women who chose the Pre-Engineering/CS track. The model predicts these shares nearly exactly for both men and women. The model also exactly fits the percent change in share of students choosing each track in period 1. The third line of Panel A reports the difference in differences, which again fits exactly.

Panel B of Table 1.2 reports the shares of men and women who chose a first major in computer science. The model underpredicts the percentage change in the share of men and women choosing computer science after the dot-com crash,but predicts the difference in differences well. After the dot-com crash, the share of women choosing a first major in computer science dropped by 52.5% and the share of men choosing a first major in computer science dropped by 27.3%. My model predicts a drop of 37.2% for women and 11.2% for men. The model also overpredicts the share of women choosing computer science both before and after the crash. However, the model predicts a 26.1 percentage point difference in differences, which is very similar to the 25.3 percentage point difference in differences in the data.

Panel C of Table 1.2 reports the shares of men and women who chose a final major in computer science. The model predicts the share of women choosing computer science well, but considerably underpredicts the share of men choosing computer science.[43] The model predicts a 54.8% drop in women's computer science majoring after the crash, compared to 57.7% in the data, whereas it predicts a 20.1% drop for men, compared to a 29.4% drop in the data. The model predicts a difference in differences of 34.7 percentage points, as compared to 28.3 percentage points in the data.

1.5.2 Are women more sensitive to grades and academic background than men?

Prior research has indicated that women may care more about grades than men, especially in STEM coursework (Ahn et al., 2019; Astorne-Figari and Speer, 2019; Goldin, 2015; Kugler, Tinsley and Ukhaneva, 2017; Rask, 2010). If women are more sensitive to grades than men, the gender difference in reactions to the dot-com crash would be larger than what would be caused just by differences in grades. I therefore examine the estimated coefficients on grades in the value function for majors. A larger coefficient on a variable means that that variable is relatively more important than the labor market value of a ma-

[43]The underprediction for men is tied to grade expectations: when men have perfect foresight over grades, the share of men choosing computer science is much higher.

jor; in other words, students respond more strongly to that variable when deciding on a major. Focusing on computer science and engineering majors, I find no systematic gender difference in sensitivity to grades in period 2. While women tend to have larger coefficients on grades than men in period 3, the differences are not statistically significant.[44]

Table 1.3 reports the estimated coefficients on grades in periods 2 and 3. Panel A reports those coefficients for period 2, where the contribution of grades to the value function depends on the period 1 choice. Focusing just on the computer science major and the pre-Engineering/CS track, which is the most common track choice for computer science majors, there are some interesting patterns. Women who chose the pre-Engineering/CS track have a large negative coefficient on their in-track GPA and a large positive coefficient on their overall GPA, whereas men who chose the pre-Engineering/CS track have small positive coefficients on both GPAs. The gender difference in coefficients is statistically significant. This suggests that women who moved from the pre-Engineering/CS track to a first major in computer science may have been negatively selected on their in-track grades, whereas men were somewhat positively selected on their in-track grades. This is not true for the first major in engineering, where men and women have very similar coefficients on both GPAs if they chose the pre-Engineering/CS track.

Panel B of Table 1.3 reports grade coefficients for period 3. In period 3, students only get value from the in-major GPA if they chose that major in period 2, and the value students get from their cumulative GPA depends on whether they switch majors. I again focus on computer science and engineering majors. In both computer science and engineering, women's coefficient on in-major GPA is larger than men's, but the coefficients are not statistically significantly different. For women who are not switching majors, the coefficient on cumulative GPA is negative, whereas men's is positive, but the difference is again not statistically significant. Men and women have similar coefficients on cumulative GPA if they are not changing majors.

It is also worthwhile to consider whether men and women make different choices in period 1 based on their academic backgrounds. If women with a less strong academic background in STEM are less likely to choose either STEM track than similar men, that could directly influence the decision to enter computer science. Table 1.4 reports the coefficients on AP credits in period 1. Women often have larger coefficients than men on AP credits that are directly related to the track they are considering – for instance, women considering the pre-Engineering/CS track have larger coefficients than men on having AP credit for both semesters of calculus. However, the differences are typically not statistically

[44]Unlike Goldin (2015), I do not find that women are more sensitive to dropping down one letter grade in either of the first two programming classes; see Appendix A.3.1.

significant.

Overall, I find that women who chose the most related track to computer science care more about their grades than similar men when choosing computer science, but not engineering. I also find only suggestive evidence that women care more about their grades than men in the final period, or that there is a stronger relationship between women's AP credits and early coursetaking.

1.5.3 How did grades affect students during the dot-com crash?

As I described in Section 1.3.3, there is a larger gender gap in grades in computer science than engineering. In this section, I simulate what major choices would have been during the sample period if computer science grades had the same distribution of engineering grades. This test is useful because it might be possible for universities to bring their computer science grade distribution in line with their engineering grade distribution by changing teaching or evaluation methods; completely closing gender gaps in STEM grades, on the other hand, is probably not possible if the effort is only made by a single university.

I simulate in-major grades using the period 2 in-major grade production function described in Equation 1.3. Students's in-major GPA in computer science is calculated using

$$\tilde{M}_{i2,CS} = \theta_{0,ENG} + \theta_{1,ENG}AP_i + \theta_{2,ENG}X_i + \theta_{3,ENG,c^*}G_{i1,c^*} + \theta_{4,ENG,c^*}T_{i1,c^*} + c^M_{ENG}S_{CS} + \delta^G_{ENG,c^*} + \delta^M_s + \delta^M_t + \tilde{v}_{i3}$$

The error term $\tilde{v}_{i3}$ is calculated using the difference between students' realized and expected in-major GPA in the major they actually chose, which preserves the actual realized grade shock. Cumulative GPA for computer science is recalculated using the simulated computer science GPA and holding coursework choices and grades outside of computer science at their actual level. Expectations over future in-major and cumulative GPAs are recalculated in the same manner.

Table 1.5 reports the share of students who chose the Pre-Engineering/CS track, a first major in computer science, and a final major in computer science, as predicted by the model with the true grade distribution and the simulated distribution. The table also reports the changes induced by the simulation to the change in computer science majoring due to the crash and the difference in differences. Panel A reports the simulation results for period 1, Panel B reports the results for period 2, and Panel C reports the results for period 3.

Grades had little effect on the difference in reactions to the dot-com crash in period

1. There is a very small increase in men's choosing the pre-Engineering/CS track after the crash due to the simulated grades, but the change is so small that it does not affect men's percentage change in an economically significant way. There are no changes for women. The lack of changes from the simulated grades may make some sense here because students who choose the Pre-Engineering/CS track tend to become either computer science or engineering majors. The simulation only changes grades for computer science majors, and we might expect that giving computer science students the grade distribution for engineering would primarily draw students from engineering.

Grades explain part of the difference in reactions to the dot-com crash in period 2. Under the real grade distribution in computer science, 3.1% of women and 11.8% of men in my model choose computer science as a first major before the dot-com crash and 1.9% of women and 10.5% of men choose computer science after the dot-com crash, which is a decrease in the probability of choosing computer science of 37.2% for women and 11.2% for men. Under the counterfactual grade distribution, 4.5% of women and 15.6% of men choose computer science as a first major before the dot-com crash and 3.3% of women and 13.9% of men choose computer science after the dot-com crash, which is a decrease in the probability of choosing computer science of 26.6% for women and 11.4% for men. The simulation therefore made women considerably less sensitive to the dot-com crash, but barely affected men's reaction to the crash. The difference in men's and women's reaction to the dot-com crash narrowed by 41.6%, a large change.

Grades explain a smaller part of the difference in reactions to the dot-com crash in period 3. Under the real grade distribution in computer science, 2.1% of women and 7.0% of men in my model choose computer science as a first major before the dot-com crash and 1.0% of women and 5.6% of men choose computer science after the dot-com crash, which is a decrease in the probability of choosing computer science of 54.8% for women and 20.1% for men. Under the counterfactual grade distribution, 3.7% of women and 12.1% of men choose computer science as a first major before the dot-com crash and 2.1% of women and 9.5% of men choose computer science after the dot-com crash, which is a decrease in the probability of choosing computer science of 44.3% for women and 21.2% for men. The simulation therefore made women considerably less sensitive to the dot-com crash and made men slightly more sensitive to the crash. The difference in men's and women's reaction to the dot-com crash narrowed by 33.4%, also a large change.

1.5.4 Where did students go instead of computer science?

It is also instructive to consider what majors students chose instead of computer science after the dot-com crash. I ran a counterfactual experiment where the 2001 recession did not disproportionately affect computer science and engineering majors. To do this, I froze salaries and unemployment rates for computer science and engineering majors relative to the levels for drop outs from 2000 to 2007, as shown in Figure 1.7, and set $Post_i = 0$ for all students. I then predicted which tracks and majors students chose in the absence of the dot-com crash. The simulation results suggest that the dot-com crash largely pushed both men and women toward STEM majors other than computer science, though women were pushed more toward science majors and men more toward engineering majors.

Surprisingly, the dot-com crash seems to have driven a similar number of men and women out of computer science. Figure 1.8 report the percentage change in the share of students choosing each track, first major, and final major. The crash did not have large effects on the probability that either men or women chose the Pre-Engineering/CS track. Women who entered college between 1996 and 2000 were 9.5% less likely to choose a first major in computer science and 25.1% less likely to choose a final major in computer science than they would have been in the absence of the dot-com crash. Men in the same cohorts were 7.4% less likely to choose a first major in computer science and 26.2% less likely to choose a final major in computer science.[45] Women who entered college between 2001 and 2005 were 32.5% less likely to choose a first major in computer science and 61.1% less likely to choose a final major in computer science. Men in the same cohorts were 25.0% less likely to choose a first major in computer science and 54.8% less likely to choose a final major in computer science. While the decrease in computer science majoring is generally slightly smaller for men, the results are much more similar than would have been suggested by Section 1.3.2 and my previous results. The explanation may be found in Table 1.6, which reports the share of men and women who chose each track, first major, and final major both with and without the dot-com crash. Panels B and C suggest that in the absence of the crash, women's growth in the computer science major would have slowed down and possibly slightly reversed, whereas men would have continued to enter computer science in the absence of the crash.

The crash pushed both men and women toward majoring in non-computing STEM fields and away from business.[46] Men were pushed more toward engineering and women were pushed more toward science, especially as a final major. Women who entered The University after the dot-com crash were 18% more likely to choose a first major in engineering and 48.7% more likely to choose a final major in engineering than they would have been in the absence of the dot-com crash. These same women were 11.4% more likely to

[45] Note that the majority of students in these cohorts had made decisions about their first major before the crash, while a large number had not yet made decisions about their final major.

[46] The shift away from business was perhaps unsurprising given that the crash seems to have decreased the compensation for business students relative to other majors.

choose a first major in science and 61.7% more likely to choose a final major in science. Men in the same cohorts were 25.3% more likely to choose a first major in engineering, 108% more likely to choose a final major in engineering, 15.9% more likely to choose a first major in science, and 53.0% more likely to choose a final major in science than they would have been in the absence of the dot-com crash. Both men and women were driven away from majoring in business, with slightly larger effects for women, and women were pushed less to the humanities and social sciences, less to drop out early in the degree, and more to drop out late in their degree.

1.6 Why does computer science have a large gender grade gap?

In previous sections, I established that there is a larger gender grade gap in computer science at The University than they do in engineering, and that the difference in gender grade gaps across fields explains part of the gender difference in reactions to the dot-com crash. This suggests that students reacted to the dot-com crash in accordance with what they perceived to be their comparative advantage. My results suggest that retention of women in computer science (and probably all majors) is tied to grades.

It is not clear that students' reactions to the dot-com crash were efficient, because gender differences in grades may not accurately reflect gender differences in ability to be a good computer scientist. While I cannot rule out that gender differences in ability drive all gender differences in grades, it seems unlikely given the differences in gender grade gaps across fields. Computer science and engineering require similar baseline ability in math and science, and the two fields teach broadly similar skills.[47] Factors like effort, course content, and role model and peer effects, among others, also help determine grades, and may affect women differently from men.

Universities hoping to improve diversity in their computer science programs should look for gender differences in computer science grades and attempt to remove those disparities. My findings suggest that they can start by looking for differences between computer science and non-computing engineering programs. One potential difference between the two fields is how courses are evaluated. Computer science courses at The University assign grades based on exams and machine-graded coding assignments, which leaves little room for skills other than programming.[48] In contrast, most engineering courses have a lab component or large group project. Engineering grades are therefore more likely to reflect

[47]Gender differences in SAT Math scores typically do not explain gender differences in STEM majoring or performance in STEM classes (Koester, Grom and McKay, 2016; Matz et al., 2017; Turner and Bowen, 1999).

[48]Machine grading of programming assignments was instituted at The University to deal with capacity challenges related to the dot-com boom.

writing and social skills than computer science grades.[49] If all three skills are important in the labor market for both computer scientists and engineers, computer science grades could be a biased signal of ability to be a good professional computer scientist, and the signal may be more biased for women. Social skills in particular have become more important in the labor market over the past several decades, especially in math-intensive jobs (Deming, 2017). Adolescent girls tend to both have better social skills and value social skills more than boys, and there is evidence that the growing demand for social skills can explain part of the increase in women's employment in highly paid occupations over the same period (Cortes, Jaimovich and Siu, 2018; Merrell and Gimpel, 1998; Tan, Oe and Le, 2018). If social skills are indeed a component of labor market productivity that is overlooked by computer science grades, then adding a group project component to computer science courses could help encourage women to major in computer science.[50] While other interventions may also successful, I suggest this one because it is within the control of the university, advocated for by experts in computer science education,[51] and potentially beneficial for all students, not just women.

1.7 Robustness checks and alternative specifications

1.7.1 Curricular changes

A major curricular change occurred in The University's computer science program during the sample period. In Spring 2000, the introductory programming course for prospective computer science majors was changed from a very technical "bottom-up" class to a more traditional "top-down" programming course.[52] Students were also given more choices in which higher level courses fulfilled requirements. Given the timing of the curricular change, there is concern that curricular changes could confound the effect of the dot-com crash.

[49]This is consistent with a finding women underperform, relative to their GPA in other classes, by more than men in STEM lecture courses, but not in lab courses (Koester, Grom and McKay, 2016; Matz et al., 2017). These differences are not explained by gender differences in test scores or course-taking. I am able to reproduce the underperformance result for the first two programming courses; see Appendix A.3.1.

[50]A report by the National Center for Women and Information Technology suggests that collaboration in courses can help retain women. However, collaboration on student projects requires monitoring to ensure that students do not cheat. (See https://www.ncwit.org/resources/how-do-you-retain-women-through-collaborative-learning/how-do-you-retain-women-through; accessed 2-25-2020). Computer science programs at top universities often explicitly discourage collaboration because it is difficult to monitor students when work is graded by machine.

[51]DuBow et al. (2016) provides an overview of the current best practices for retaining women in computer science, including promoting collaboration in class.

[52]A traditional course existed throughout the entire sample period for non-majors.

I used IPEDS data for universities with the top 25 computer science programs in the 2018 *US News and World Report* to evaluate the impact of similar changes at other universities on the female share of computing degrees during periods of relatively stable labor demand. I collected data on curricular changes in the computer science, computer engineering, and electrical engineering programs from archived department websites on the Wayback Machine. Exposure to a less technical introductory programming course did not affect the female share of a graduates. The more flexible upper-level curriculum was correlated with a lower female share of graduates, but only if the curriculum change occurred the same year as graduation. Because this curricular change occurred in 2001, the relevant affected class would be students who started their senior year in 2001; this paper has found that the students most affected by the dot-com crash were freshmen and sophomores in 2001. I therefore conclude that these curricular changes did not create the gender difference in reaction to the dot-com crash at The University. Further details are available in Appendix A.2.

1.7.2 Adding ability measures to the value of majors

Major-specific ability is known to be highly correlated with college major choice (e.g. Wiswall and Zafar, 2015*a*). While I have data on AP credits earned for all students, I only have SAT and ACT scores (which are probably a better ability measure) for students who entered in 2000 and later. Furthermore, AP credits are not included in the value function in later periods, but they may be worth using because they likely proxy for major-specific ability. I therefore run two robustness checks in this section: I estimate my model for students entering in 2000 and later using SAT scores, and I estimate my model with indicators for all earned AP credits in the value function in all periods.

1.7.2.1 SAT scores

In one robustness check, I add both SAT Math and SAT Verbal scores into the value function in every period. Controlling for SAT scores changes many coefficients on AP scores in period 1, including a few changed signs. However, the differences are generally not statistically significant. Controlling for SAT scores does not switch the sign on most GPA variables, and in many cases the GPA coefficients are larger in magnitude when controlling for SAT scores. These differences are also generally not statistically significant. Further details are available in Appendix A.7.1.

1.7.2.2 AP scores in all periods

In another robustness check, I use AP credits in the value function in all periods. Keeping AP credits in the value function does not systematically change the coefficients on grades, and most changes are relatively small. However, the coefficients on grades for women choosing computer science tend to be slightly lower in magnitude than in the main specification. Further details are available in Appendix A.7.2.

1.7.3 Alternative specifications of the labor market

1.7.3.1 Transitory labor market shocks

In one robustness check , I allow students to believe that labor market shocks are transitory. To do this, I let the unemployment rate and the average log salary in a major to follow an AR(1) process. When labor market shocks are transitory, women's coefficients on grades tend to be smaller in magnitude. Men's grade coefficients change somewhat but there is no systematic pattern to the changes. Full details are available in Appendix A.8.1.

1.7.3.2 Estimating the utility of unemployment

Typically, we think that students, especially women, do not pay much attention to salary when choosing a major (Zafar, 2013). It is therefore surprising that the reaction to the dot-com crash was so large. This raises concerns that the possibility of being unemployed after college loads onto grades. I therefore ran a robustness check where I estimate the value of unemployment $u(b_i)$ in my model rather than setting it to 0. There are only small, statistically insignificant changes in coefficients on grades from the main specification. Full details are available in Appendix A.8.2.

1.7.4 Sensitivity to calibrated parameters

In an additional robustness check, I estimate the model with different values of the discount rate β and time to retirement T. As a general rule, the coefficients on grades in the value function for the computer science major rise a small amount when β or T rises. This most likely reflects the fact that raising either β or T raises the value of the labor market, and the coefficients on grades must therefore rise slightly to preserve the relative sizes of the effects of changes in grades and changes in salary. Further details can be found in Appendix A.9.

1.8 Conclusion

This paper provides evidence on the importance of gender differences in grades to the gender gap in computer science majoring. I found that the dot-com crash made the computer science major much more male, nationally and at a four-year public university with a prestigious computer science program. However, even though the dot-com crash had similar labor market effects on new graduates in engineering, which is a similar major and should attract similar students, engineering majors did not become significantly more male after the crash. Computer science also has a larger gender grade gap (in favor of men) than engineering or other STEM fields. To learn whether gender differences in grades drove gender differences in reactions to the dot-com crash, I estimated a structural model of major choice where students choose a major to maximize their expected lifetime utility, conditional on the labor market, their grades, and other factors.

I find that if computer science and engineering have the same distribution of grades by gender, the gender difference in the change in computer science majoring after the dot-com crash would have 41.6% smaller at the time of choosing a first major and 33.4% smaller at the time of graduation. I also find that the dot-com crash increased the probability that both men and women would major in engineering and natural sciences, with smaller increases in the humanities and social sciences, and decreased the probability that both men and women would major in business. The patterns of substitution provide further evidence that there is something about engineering majors which make them more attractive to women than computer science, even though on the surface the two majors seem similar. These results provide evidence that grades are an important part of how students choose majors, as women substituted to majors where the gender gap in grades was smaller.

My results suggest that students react to crashes in labor demand for a particular major in accordance with what they perceive to be their comparative advantage. Students who expected to have the lowest payoff of computer science were the ones who substituted away from computer science after the dot-com crash. Because of the large gender gap in grades in computer science, women were more likely to be in the group of students with the lowest payoff of computer science. This result suggests that retention of women in computer science (and probably all majors) depends on the distribution of grades. Universities hoping to improve diversity in their computer science programs should look for gender differences in computer science grades and attempt to remove those disparities. My findings suggest that they can start by looking for differences between computer science and non-computing engineering programs. While it is unlikely that action on the part of universities alone can close gender gaps in STEM grades, it may be possible to bring computer science more in line with engineering.

While I explain a sizeable portion of the difference in men's and women's change in computer science majoring in the years following the crash, more than half is still unexplained. Alternative mechanisms that could be explored include role model effects, peer effects, and risk aversion. The dot-com crash may also have disproportionately affected the types of computer science jobs that were most popular with women or changed the nonpecuniary benefits available in different jobs. Comparing computer science and engineering programs during the dot-com crash would be an interesting way to validate the contributions of each of these factors to gender differences in computer science majoring.

An open question is how grades contribute to the payoff of a major. Grades reflect many different factors, from ability to effort to how courses are evaluated, and it is not clear exactly how (or if) grades affect a student's future prospects in the labor market, or how students *expect* grades to affect their job prospects, especially in a volatile labor market. Students likely also have a psychological benefit of getting high grades, but it is again unclear how large this benefit is. The effect of grades on job prospects during recessions is therefore a worthwhile avenue for future research, as is the question of whether the gender gap in grades in computer science represents a difference in women's ability to be good professional computer scientists.

1.9 Tables

Table 1.1: Calibrated parameters of earnings

Discount rate: β	0.95					
Lifespan: T	12					
Unemployment value: $u(b_{i\tau})$	0					
Experience parameters	*CS*	*Eng.*	*Sci.*	*Bus.*	*Other*	*Dropout*
$\tilde{\gamma}_1$	0.062	0.060	0.076	0.057	0.057	0.068
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$\tilde{\gamma}_2$	-0.0012	-0.0012	-0.0014	-0.0011	-0.0011	-0.0011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Source of experience parameters is the 2009-2017 American Community Survey from IPUMS-USA (Ruggles et al, 2019). Two-digit majors not offered at The University were dropped. Regression was run only for individuals with some college or a bachelor's degree only. Regression specification includes controls for demographic variables, state fixed effects, year fixed effects, and major fixed effects. Potential experience is calculated using age - 20 for some college individuals and age - 22 for bachelor's degree holders.

Table 1.2: Comparing Actual and Predicted Shares of Computer Science Majoring

	Shares in Data			Predicted Shares		
	Before	After	% Change	Before	After	% Change
Period 1 (Pre-Engineering/CS Track)						
Women	0.149	0.120	−23.5	0.149	0.120	−23.5
Men	0.343	0.321	−6.7	0.344	0.322	−6.7
Difference			−16.8			−16.8
Period 2 (First major in CS)						
Women	0.024	0.011	−52.5	0.031	0.019	−37.2
Men	0.132	0.096	−27.3	0.118	0.105	−11.2
Difference			−25.3			−26.1
Period 3 (Final major in CS)						
Women	0.024	0.010	−57.7	0.021	0.010	−54.8
Men	0.131	0.092	−29.4	0.070	0.056	−20.1
Difference			−28.3			−34.7

Notes: Table reports shares of students in data and model prediction that major in computer science, before and after the crash. “Before” refers to entering The University between 1996 and 2000; “after” refers to entering The University between 2001 and 2005.

Table 1.3: Women's and Men's responses to grades

	Women					Men				
	C.S.	Eng.	Sci.	Bus.	Hum./SS	C.S.	Eng.	Sci.	Bus.	Hum./SS
					Panel A: Period 2 (first majors)					
In-Track GPA										
× Pre-Science	7.27	3.44	-0.73	0.42	-1.31	2.19	1.25	0.08	1.18	-0.82
	(2.3)	(0.77)	(0.44)	(0.53)	(0.43)	(0.53)	(0.46)	(0.38)	(0.37)	(0.34)
× Pre-Eng./CS	-3.41	2.05	-0.44	-0.27	-1.55	0.78	1.54	0.61	0.22	-0.88
	(0.87)	(0.44)	(0.53)	(0.57)	(0.46)	(0.24)	(0.22)	(0.32)	(0.29)	(0.22)
× Non-STEM	16.63	9.84	8.15	-6.6	1.63	1.36	1.06	5.07	-3.6	0.37
	(2.2)	(1.3)	(0.68)	(0.84)	(0.6)	(0.58)	(0.59)	(0.58)	(0.52)	(0.48)
Overall GPA										
× Pre-Science	-2.12	-5.27	0.85	0.3	1	-2.83	-1.67	-0.26	-1.76	0.18
	(2.6)	(0.97)	(0.6)	(0.72)	(0.58)	(0.64)	(0.57)	(0.5)	(0.52)	(0.47)
× Pre-Eng./CS	7.8	0.36	3.54	0.4	3.3	0.86	0.06	0.47	0.84	1.19
	(1.6)	(0.85)	(0.92)	(1)	(0.87)	(0.36)	(0.33)	(0.4)	(0.45)	(0.32)
× Non-STEM	-10.78	-1.83	-7.16	5.84	-1.92	-2	-1.34	-4.71	3.27	-1.13
	(1.6)	(0.97)	(0.68)	(0.91)	(0.63)	(0.59)	(0.59)	(0.55)	(0.56)	(0.49)
					Panel B: Period 3 (final majors)					
In-Major GPA	8.36	5.24	2.85	3.29	-1.76	4.13	2.96	2.34	2.71	-0.71
× No Switch	(1.7)	(0.73)	(0.32)	(0.61)	(0.34)	(0.48)	(0.46)	(0.45)	(0.47)	(0.38)
Overall GPA	-5.29	-0.98	0.72	1.68	5.68	0.41	1.55	1.26	1.12	4.38
× No Switch	(2.5)	(0.84)	(0.46)	(0.81)	(0.37)	(0.6)	(0.55)	(0.54)	(0.58)	(0.38)
Overall GPA	4.74	3.78	4.45	4.62	3.48	4.66	3.47	4.1	3.91	3.17
× Switch	(0.72)	(0.43)	(0.25)	(0.29)	(0.26)	(0.28)	(0.29)	(0.25)	(0.2)	(0.2)

Notes: Multinomial logit coefficients describing men's and women's responses to grades when choosing majors in periods 2 and 3. Standard errors are in parentheses. Standard errors were calculated using a bootstrap with 500 repetitions. The outside option in periods 2 and 3 is permanently dropping out of college. Additional controls included are the log of the average income in student's ZIP code of residence, race/ethnicity, and indicators for being an international student, in-state residency, and entering The University via the College of Liberal Arts.

Table 1.4: Women's and Men's responses to AP credits

	Women		Men	
	Pre-Eng./CS	Pre-Science	Pre-Eng./CS	Pre-Science
Calculus 1	0.33	0.21	0.03	-0.11
	(0.094)	(0.062)	(0.058)	(0.056)
Calculus 2	0.43	1.07	0.15	1.42
	(0.19)	(0.089)	(0.096)	(0.07)
English	-0.32	-0.07	-0.3	-0.27
	(0.084)	(0.05)	(0.058)	(0.05)
Economics	-0.69	-0.22	-0.05	-0.24
	(0.23)	(0.12)	(0.1)	(0.095)
Biology	0.049	0.999	-0.157	0.973
	(0.12)	(0.059)	(0.074)	(0.052)
History	-0.703	0.009	-0.455	-0.292
	(0.16)	(0.055)	(0.065)	(0.055)
Chemistry	-0.02	1.09	0.2	0.3
	(0.19)	(0.11)	(0.079)	(0.069)
Foreign Language	0.22	0.11	0.18	0.47
	(0.37)	(0.15)	(0.25)	(0.17)
Physics	-0.03	0.21	1.04	0.23
	(0.32)	(0.13)	(0.12)	(0.097)

Notes: Estimated multinomial logit coefficients for stage 1 of structural model. Standard errors in parentheses. Standard errors were calculated using a bootstrap with 500 repetitions. Results are estimated separately for men and women, relative to Non-STEM. Estimation also includes controls for race, log average income in ZIP code of residence, in-state residency, international status, entering The University via the College of Liberal Arts, and estimated continuation value. Fields with multiple exams (e.g. foreign language, economics) represent having at least one credit in any exam in that group. Where an IB exam exists, credit gained from that exam is combined with the AP exam into a single indicator. Credit for AP Computer Science includes the placement exam for computer science.

Table 1.5: Shares of students choosing computer science with actual and counterfactual grades

	Women			Men			
	Before	After	% Change	Before	After	% Change	Diff-in-Diff
			Period 1 (Pre-Engineering/CS Track)				
Model (Actual Grades)	0.149	0.120	-19.0	0.344	0.322	-6.2	-12.8
Model (Counterfactual Grades)	0.149	0.120	-19.0	0.346	0.324	-6.2	-12.8
% Change from Simulation			0			0	0
			Period 2 (First major in computer science)				
Model (Actual Grades)	0.031	0.019	-37.2	0.118	0.105	-11.2	-26.1
Model (Counterfactual Grades)	0.045	0.033	-26.6	0.156	0.139	-11.4	-15.2
% Change from Simulation			28.5			-2.0	41.6
			Period 3 (Final major in computer science)				
Model (Actual Grades)	0.021	0.010	-54.8	0.070	0.056	-20.1	-34.7
Model (Counterfactual Grades)	0.037	0.021	-44.3	0.121	0.095	-21.2	-23.1
% Change from Simulation			-19.1			5.7	-33.4

Notes: Table reports shares of students that major in computer science before and after the crash, as predicted by the model with both students' actual grades and counterfactual grades. "Before" refers to entering The University between 1996 and 2000; "after" refers to entering The University between 2001 and 2005.

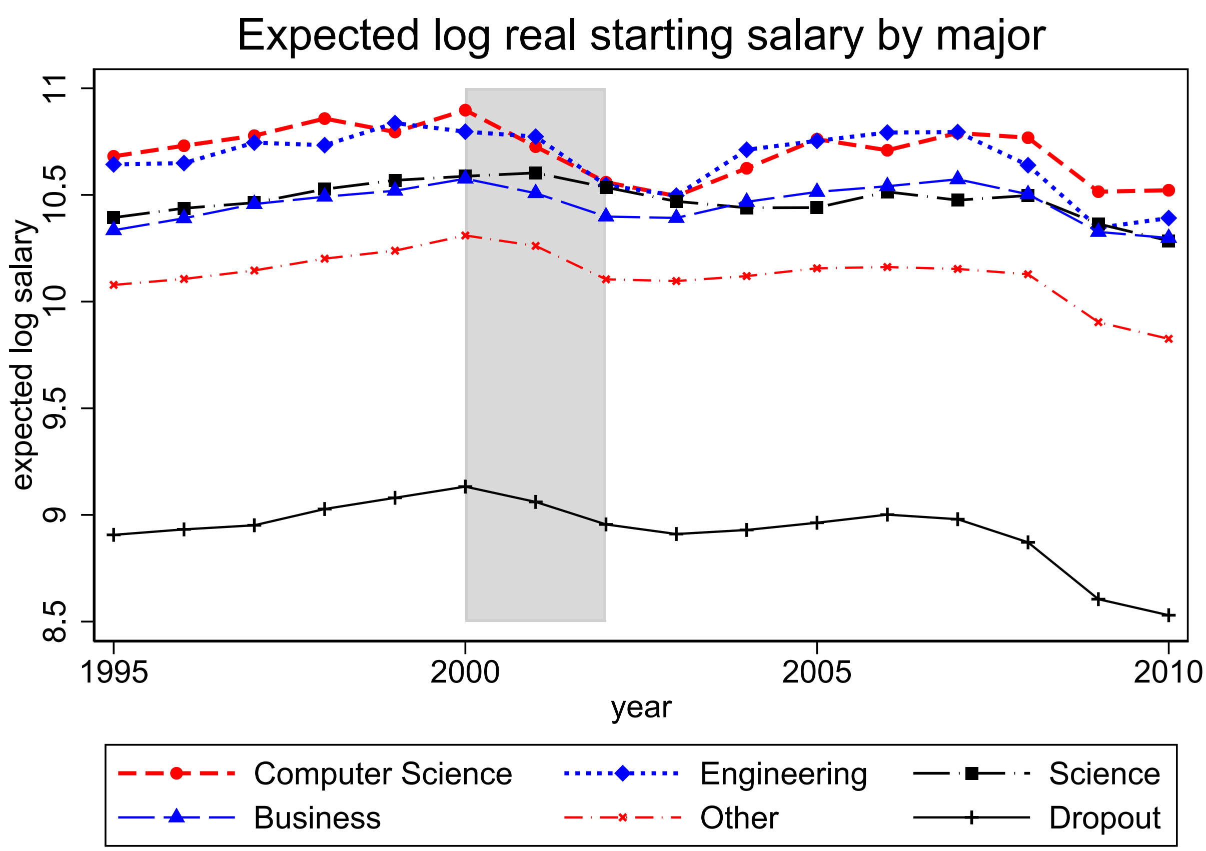
Table 1.6: Shares of each major with and without the dot-com crash

	Women						Men					
	With Crash			Without Crash			With Crash			Without Crash		
Major	Before	After	% Change	Before	After	% Change	Before	After	% Change	Before	After	% Change
Panel A: Period 1												
Non-STEM	0.625	0.658	5.1	0.625	0.638	2.1	0.482	0.494	2.5	0.482	0.487	0.9
Pre-Eng./C.S.	0.149	0.120	−23.5	0.149	0.121	−23.2	0.344	0.322	−6.7	0.344	0.333	−3.3
Pre-Science	0.227	0.222	−2.3	0.227	0.241	6	0.174	0.183	5.1	0.174	0.180	3.5
Panel B: Period 2												
Drop out	0.020	0.011	−47.7	0.021	0.014	−32.5	0.033	0.020	−38.5	0.034	0.022	−35.6
C.S.	0.031	0.019	−37.2	0.034	0.028	−15.9	0.118	0.105	−11.2	0.128	0.140	9.6
Eng.	0.102	0.092	−9.9	0.099	0.078	−20.9	0.201	0.210	4.5	0.192	0.168	−12.6
Science	0.091	0.125	37.1	0.088	0.112	26.6	0.088	0.118	33.3	0.086	0.102	18.6
Bus.	0.090	0.087	−3	0.097	0.142	46.9	0.171	0.173	1.2	0.181	0.239	32.2
Hum./SS	0.666	0.666	0	0.661	0.625	−5.5	0.387	0.373	−3.7	0.381	0.330	−13.2
Panel C: Period 3												
Drop out	0.043	0.036	−16.2	0.038	0.028	−25.3	0.093	0.064	−31	0.087	0.063	−27.6
C.S.	0.021	0.010	−54.8	0.028	0.025	−12.9	0.070	0.056	−20.1	0.094	0.123	30.3
Eng.	0.086	0.085	−1.3	0.081	0.057	−29.1	0.180	0.223	24	0.156	0.107	−31.5
Science	0.044	0.061	38.8	0.033	0.038	15	0.065	0.076	17	0.054	0.050	−6.7
Bus.	0.032	0.052	59.9	0.037	0.109	195	0.128	0.189	47.4	0.144	0.310	115.5
Hum./SS	0.773	0.756	−2.2	0.783	0.743	−5.1	0.464	0.392	−15.5	0.465	0.347	−25.3

Notes: Table reports shares of students that choose each major among "before crash" cohorts (1996-2000 entrants) and "after crash" cohorts (2001-2005 entrants) with and without the dot-com crash. Simulation of choices without the crash was constructed by freezing log salary and the unemployment rate, relative to those for college dropouts, from 2000 to 2007 and setting $P(U_j) = 0$ for all students. Shares with crash reproduce results reported in Table 1.2.

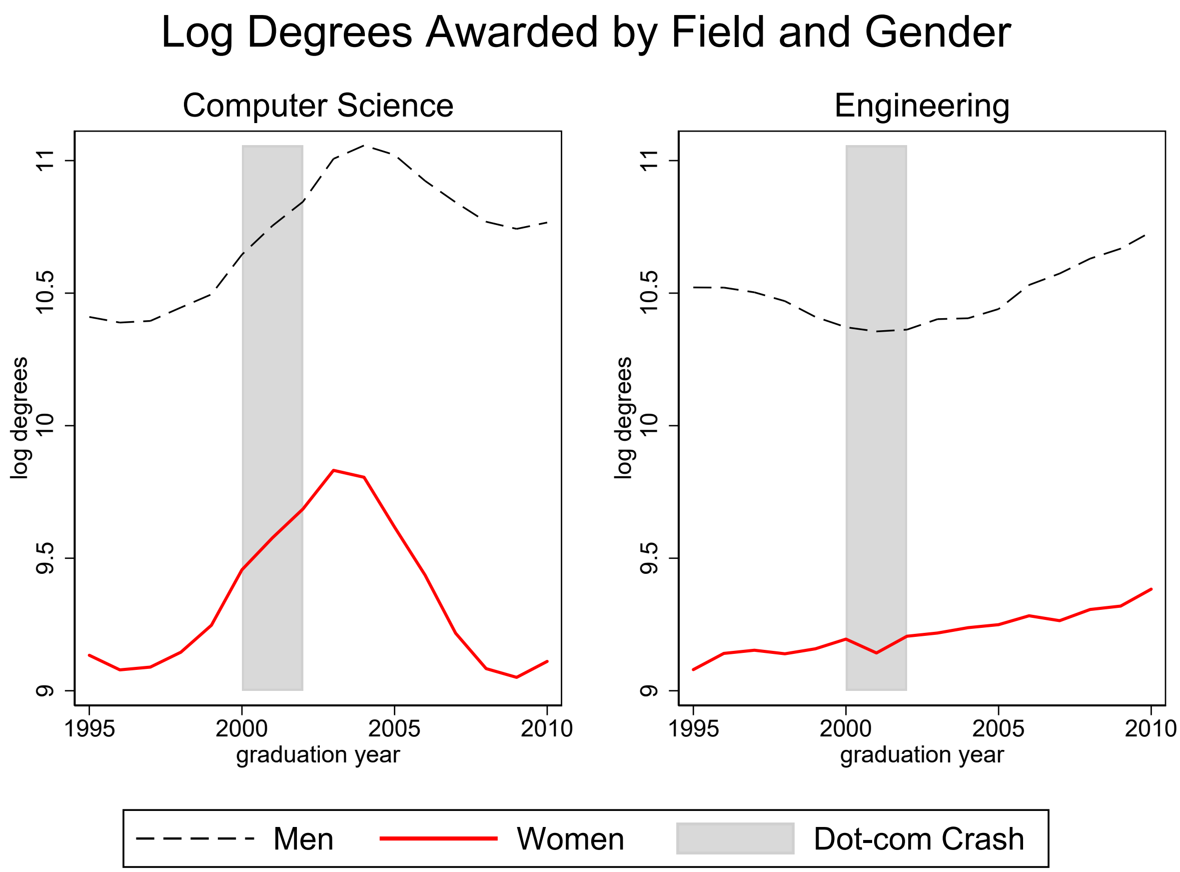
1.10 Figures

Figure 1.1: The effect of the dot-com crash on salaries by major



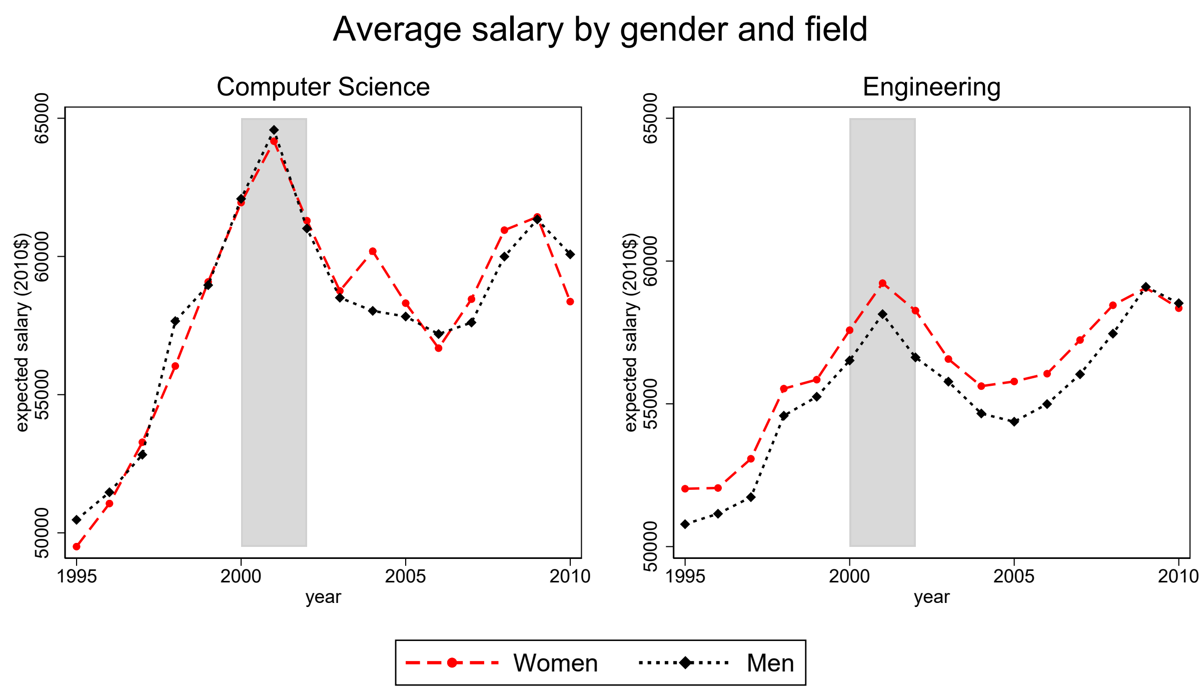
Notes: Data source is the *Salary Survey* by the National Association of Colleges and Employers (salary for graduates by major) and the CPS Outgoing Rotation Group (salary for drop-outs, unemployment in related occupations to major). Expected log salary is calculated using $(1 - P(\text{unemployed}) \times \log$ median salary. All salaries were converted to 2010$ using the CPI. Major groups in the *Salary Survey* are aggregated up using a weighted average, with weights based on representation in the NACE. Majors not offered at The University are excluded.

Figure 1.2: Log computing and engineering degrees awarded in the US



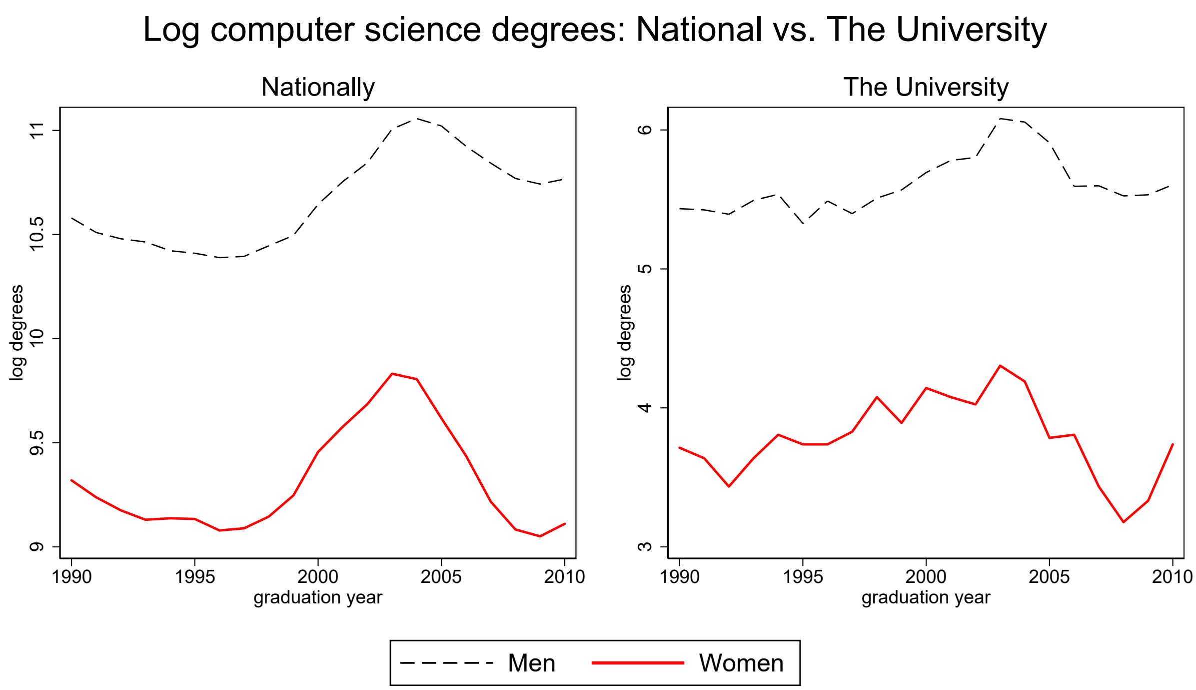
Notes: Integrated Postsecondary Educational Data System, National Center for Education Statistics. "Computer science" refers to computer science, computer engineering, and electrical engineering. Data measures number of completed degrees by year, major, and gender.

Figure 1.3: Computer science and engineering salaries by gender



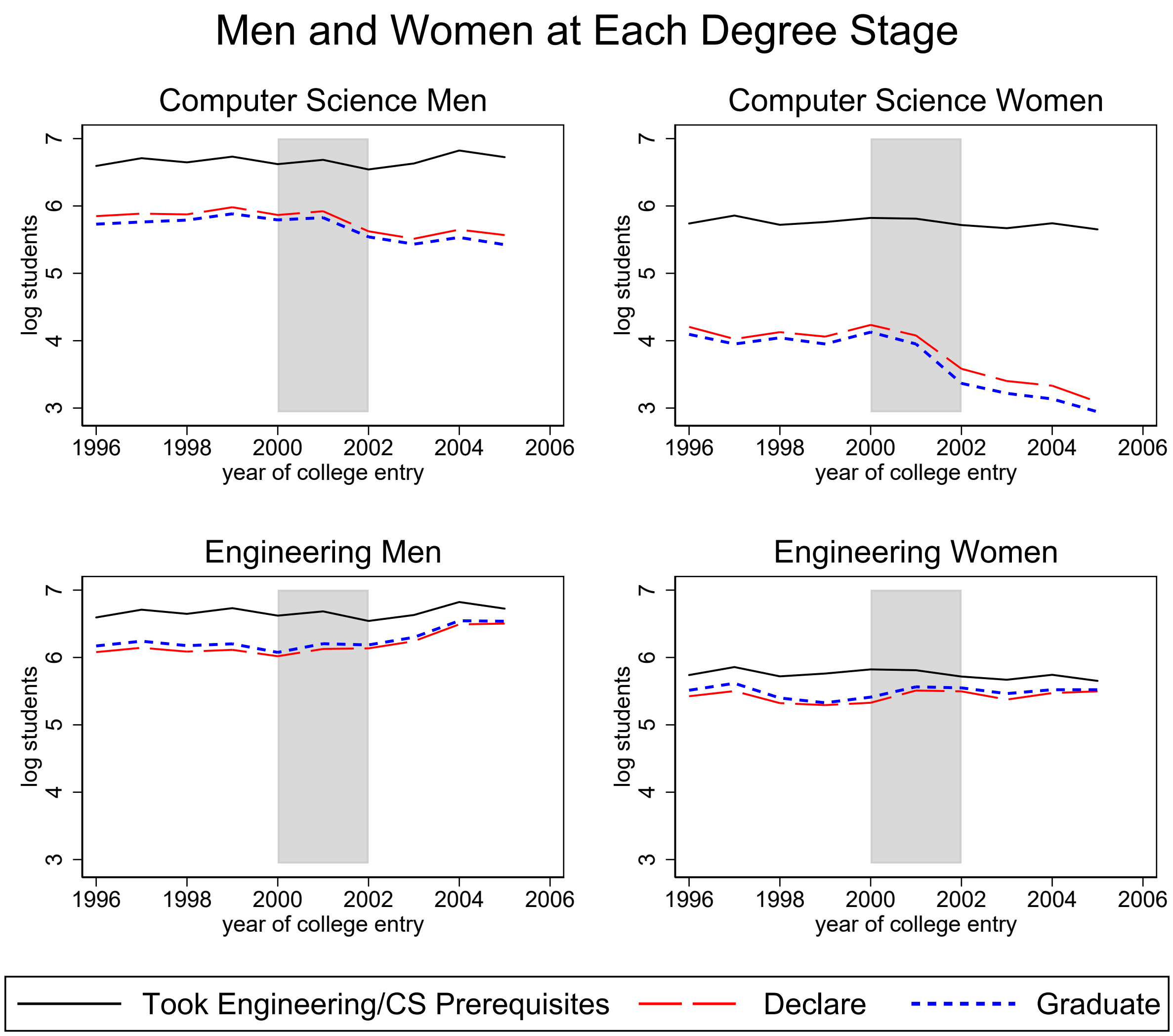
Notes: Data source is the *Salary Survey* by the National Association of Colleges and Employers. Graph shows mean salary for graduates by major and gender. Expected log salary is calculated using $(1 - P(\text{unemployed}) \times \log$ median salary. All salaries were converted to 2010$ using the CPI. Major groups in the *Salary Survey* are aggregated up using a weighted average, with weights based on representation in the NACE. Majors not offered at The University are excluded.

Figure 1.4: Log degrees awarded to men and women, nationally and at The University



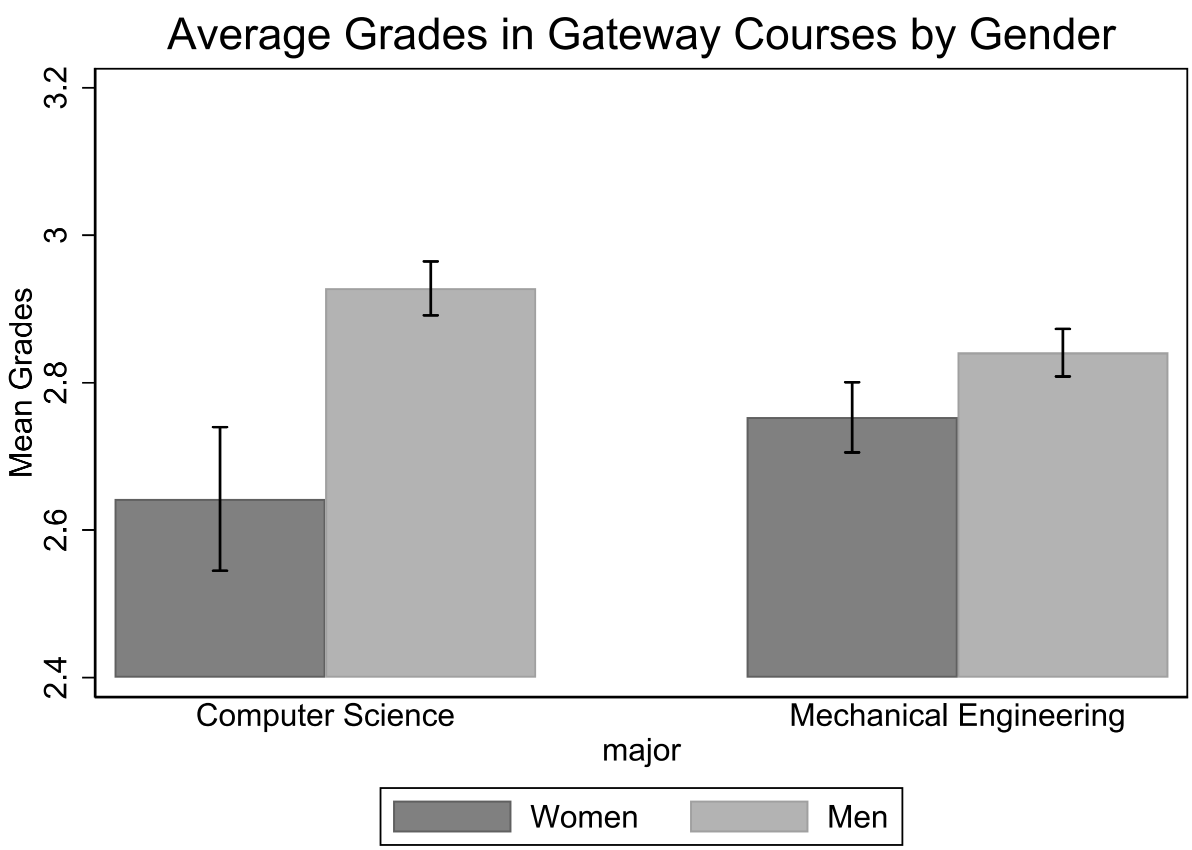
Notes: Data from Integrated Postsecondary Educational Data System (IPEDS) at the National Center for Education Statistics (NCES) showing number of bachelor's degrees awarded by gender in computer science and engineering at all four-year US institutions offering federal student aid. Data measures number of completed degrees by year, major, and gender.

Figure 1.5: Log women and men at stages of the computer science degree



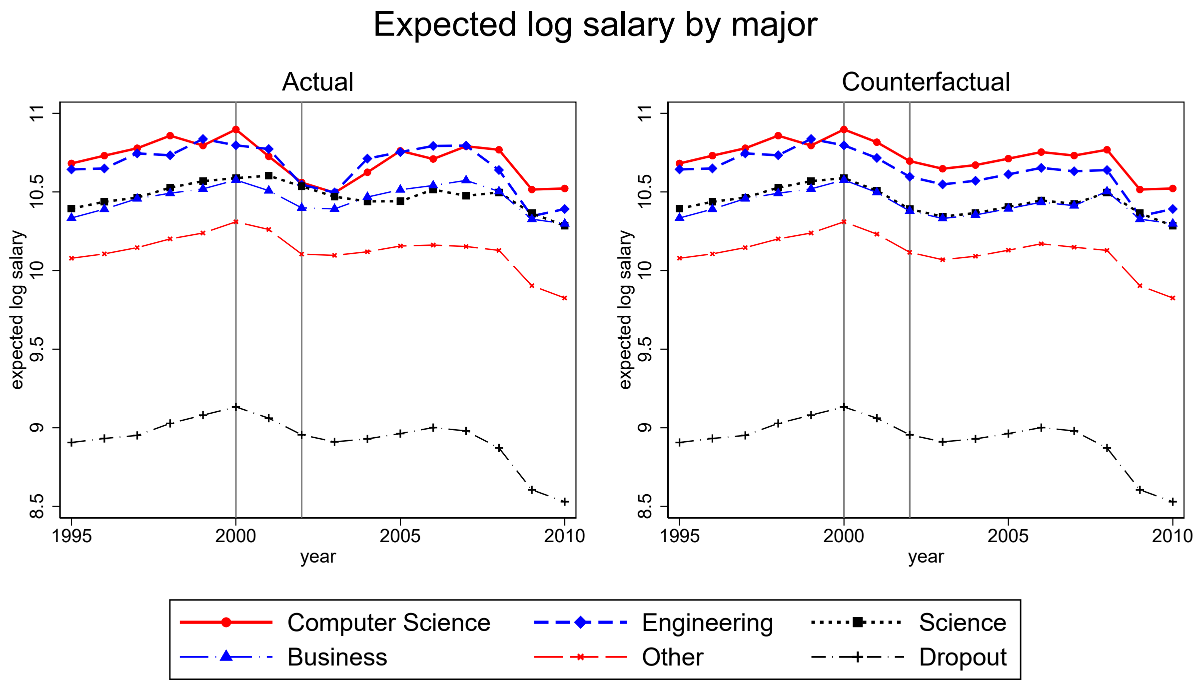
Notes: Source is administrative data on students at The University who entered between 1996 and 2005. "Took Engineering/CS Prerequisites" refers to following the pre-Engineering/CS track as described in Appendix A.1 and is the same line for computer science and engineering graphs. "Declaring a major" refers to declaring a computer science, computer engineering, or electrical engineering major at any point in college. "Graduating" means completing a bachelor's degree in computer science, computer engineering, or electrical engineering.

Figure 1.6: Average grades by gender in gateway courses in engineering and computer science



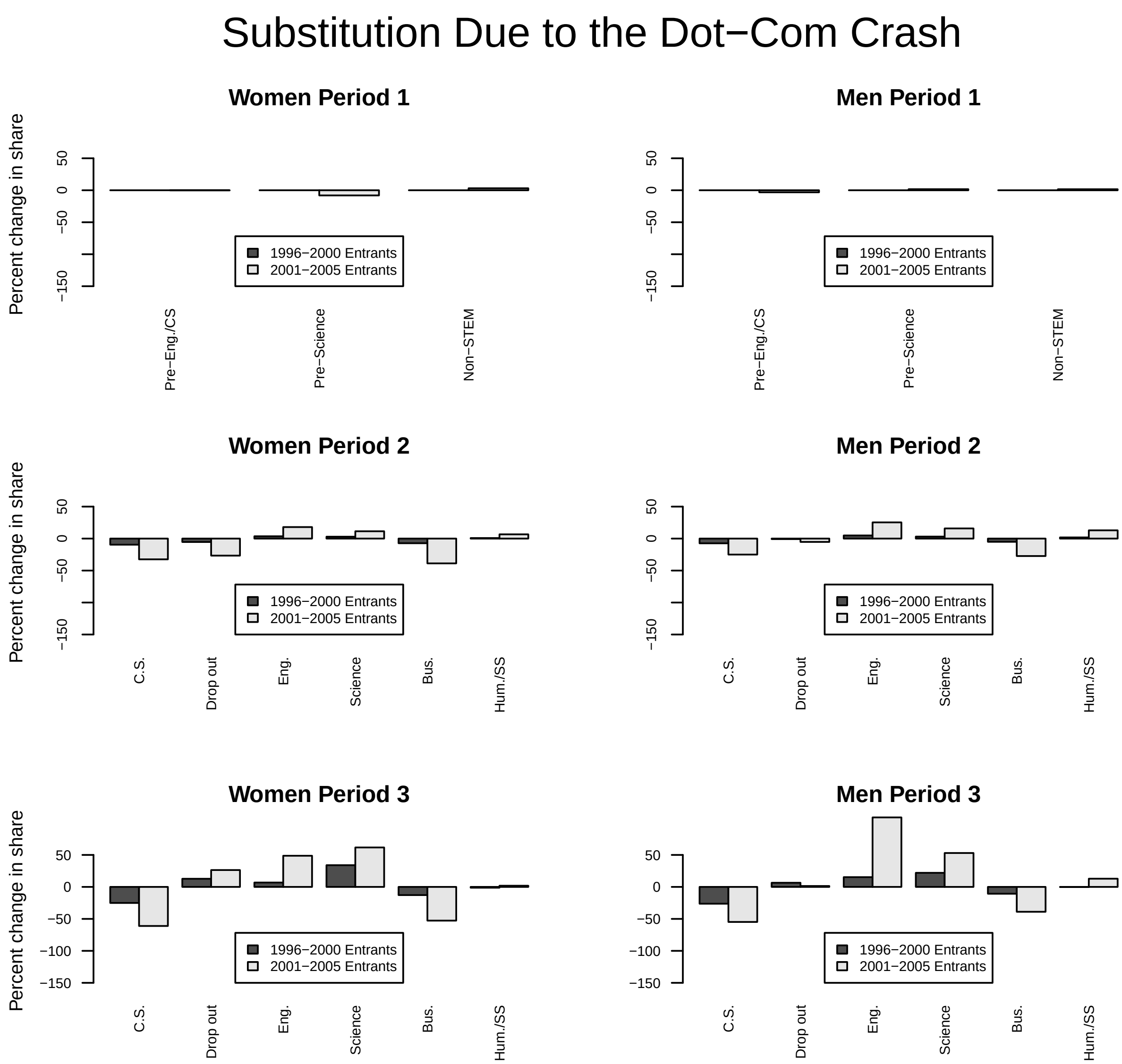
Notes: Source is administrative data on students at The University who entered between 1996 and 2005. Bars represent 95% confidence interval.

Figure 1.7: Expected log salary by major, with and without the dot-com crash



Notes: Data source is *Salary Survey*, National Association of Colleges and Employers (salary), and Outgoing Rotation Group of Current Population Survey (unemployment by related occupation). All starting salaries are converted to 2010$ using CPI. Expected log starting salary is calculated using $(1 - \text{unemployment})(\mathbb{E}[\log \text{salary}])$, with $\mathbb{E}[\log \text{salary}]$ calculated based on moments of log-normal distribution, as described in appendix. Unemployment calculated for all workers in related occupations to each major. Utility of being unemployed normalized to zero. Counterfactual graph freezes the difference between salaries for drop-outs and salaries for computer science graduates at the 2000 level between 2000 and 2007.

Figure 1.8: Change in share of majors chosen due to dot-com crash



Notes: Figure shows changes in shares of majors chosen when dot-com crash is removed, as percentage of the same shares in the model with the dot-com crash. Simulation of choices without the crash was constructed by freezing log salary and the unemployment rate, relative to those for college dropouts, from 2000 to 2007 and setting $Post_i = 0$ for all students.

CHAPTER II

When Sarah Meets Lawrence: The Effect of Coeducation on Women's Major Choices

From a work with Ariel J. Binder, Dana Shaat, and Brenden Timpe

2.1 Introduction

In 2016, women earned 57% of all baccalaureate degrees awarded in the United States, but only 37% of degrees awarded in STEM fields.[1] While women have achieved or exceeded parity in some STEM-related fields, they lag far behind men in the highest-paying fields of physical and computer sciences, math, and engineering, as well as in some quantitative social sciences such as economics (Barone, 2011; Kahn and Ginther, 2017). The gender gap in STEM majoring is partially responsible for inequality in the labor market: the gender wage gap remains large among the college-educated (Blau and Kahn, 2017; Goldin, 2014), and the gender difference in achievement of STEM degrees accounts for a substantial portion of this gap (Sloane, Hurst and Black, 2019).

A leading explanation for the gender gap in STEM majoring emphasizes gender differences in preferences for quantitative coursework and careers (e.g. Shapiro and Sax, 2011; Wiswall and Zafar, 2015*a*; Zafar, 2013).[2] Economists, drawing on a long tradition in the psychology literature, have increasingly speculated that these taste differences may originate in part from psycho-social factors rather than traditional explanations like compar-

[1]These statistics are from the Integrated Postsecondary Education Data System (IPEDS). STEM includes life sciences, physical sciences, science technology, mathematics and statistics, engineering and engineering technology, and computer science.

[2]Another explanation emphasizes gender differences in quantitative course-taking and test performance that emerge in adolescence (e.g. Ceci et al., 2014; Ceci, Williams and Barnett, 2009; Kahn and Ginther, 2017). This is not our direct focus here, although we comment throughout on how our research design and results might inform this perspective as well.

ative advantage (Akerlof and Kranton, 2000; Bertrand, 2011). For instance, women may have an aversion to competition (Gneezy, Leonard and List, 2009; Niederle and Vesterlund, 2007, 2008), be subject to social norms that only men should be breadwinners (Bertrand, Kamenica and Pan, 2015; Bursztyn, Fujiwara and Pallais, 2017), or anticipate a need to enter a flexible job that allows them to support a family (Wiswall and Zafar, 2018). Though many of these factors have been analyzed in laboratory settings, little real-world evidence exists on how they shape the gender gap in quantitative major completion. As observed major choices reflect economic as well as psycho-social factors, separately identifying one from the other remains an important challenge in the literature.

This paper offers new evidence that psycho-social factors affect the gender gap in quantitative major choice. Our approach is to recognize that many such factors have greater relevance in shaping women's major choices when more male peers are present. We leverage a unique setting that generated variation in women's exposure to male peers: the decline of women's colleges in the United States. While women's colleges numbered in the hundreds in the early 1960s, many have since transitioned to co-education. Goldin and Katz (2011) argued that institutions responded differently to rising national demand for co-education, according to plausibly exogenous institutional variables. They observed that "many of the aggregate factors that have been regarded as important do not appear to have mattered greatly for the precise timing of institutional switching"[3] (p. 412). This suggests, and our econometric tests fail to falsify, that the differential timing of women's colleges' transitions to co-education induced plausibly random variation in the shares of women's potential peers that were men.

We use this variation across time and institutions in a difference-in-difference research design to estimate the effect of changes in the gender composition of a college or university on women students' decisions to major in lucrative fields such as STEM. We estimate a series of event-study specifications that flexibly measure changes in major choice within a school after the switch to coeducation, and across schools that made the switch at different times and with different patterns of integration of men. Our event-study regressions are estimated on a sample of 1,013 baccalaureate institutions, 79 of which were women's institutions that transitioned to co-education at varying times since 1966. This sample is drawn from a database we construct by linking together newly collected data on the years former single-sex institutions became coeducational with administrative data on institutions of higher education in the United States, yielding an unbalanced panel of information that spans the years 1966-2016 and the near-universe of baccalaureate institutions. Our administrative data contains baccalaureate degrees awarded by field of degree and gender, as

[3]These factors included the Second World War, business cycles, and Title IX (Goldin and Katz, 2011).

well as information on institutional characteristics such as institutional finances, number of male and female full-time faculty, and fall semester enrollment.

We find that the switch to coeducation altered the distribution of majors chosen by female students at former women's colleges. The share of women earning STEM degrees fell steadily over the first decade after the transition to coeducation, with the effect growing as men continued to enter. Over that first decade, coeducation induced a 24% decrease in the share of women who graduated with STEM degrees. We estimate that every 10-percentage-point increase in the male share of a graduating class induced by transition to coeducation decreases the share of women earning a STEM degree by 1.11 percentage points. Coeducation induced statistically significant decreases in the share of women majoring in math, the physical sciences, and the biological sciences, as well as economics. We see a corresponding increase in the share of women choosing health majors.[4] In an effort to explore role-model effects as a possible channels, we examine the effect of coeducation on the gender-mix of faculty. We find no evidence that the faculty at former women's colleges became more male over the ten years after the switch to coeducation.

The effect of coeducation on STEM majoring at newly coeducational institutions could operate through two channels: coeducation could change both women's interest in STEM majors conditional on attending an institution (a "majoring effect") and women's interest in attending an institution in the first place (a "selection effect"). Our estimates of the effect of coeducation on the share of women majoring in STEM are a combination of these two effects. While we remain agnostic on how coeducation might affect selection into institutions, the literature on the effect of psycho-social factors on women's labor market choices suggests that the attractiveness of a STEM major will decrease in response to the entrance of men to classes and campus life. Regardless of the channel through which the effect of coeducation on women's STEM majoring operates, our results suggest that when men are present at an institution, women become less likely to choose a traditionally male-dominated field at that institution.

The paper proceeds as follows. The next section summarizes related literature and our contribution. Section 2.3 briefly narrates the rise and fall of women's colleges in the United States. Section 2.4 describes the hypothesized effects of the transition to coeducation on women's incentives to attend an institution and major in STEM at that institution. Section 2.5 describes our data and sample. Section 2.6 lays out our research design and presents tests of its internal validity. Section 2.7 presents our main event study results. Section 2.8 verifies our main result using a synthetic control design. Section 2.9 works to rule

[4]The vast majority of degrees categorized under health majors are in nursing or allied health fields rather than pre-professional degree programs.

out an important alternative explanation, which is that STEM fields are more capacity-constrained than non-STEM fields. Section 2.10 discusses the broader implications of our results and concludes the paper.

2.2 Related literature and contribution

The rich literature on the gender gap in college STEM majoring has examined many proposed explanations over the years. While gender differences in math ability (Turner and Bowen, 1999), STEM grades[5] (Astorne-Figari and Speer, 2019; Goldin, 2015), high school course-taking (Card and Payne, 2017) and many other student characteristics all contribute to gender differences in college major choice, they only account for a small portion of the gap in STEM majoring. Heterogeneous preferences for majors are the primary determinant of college major choice and a driving factor of the gender gap in STEM majoring (e.g. Wiswall and Zafar, 2015*a*; Zafar, 2013). Recent work has attempted to tease out exactly *which* preferences are behind the gender gap in STEM, with findings suggesting that gender differences in preferences for flexible jobs matter more than gender differences in risk aversion or patience (Patnaik et al., 2020; Wiswall and Zafar, 2018). We contribute to this literature by providing evidence that psycho-social factors such as gender roles also play a role in creating gender differences in preferences for majors.

A long-standing psychology literature finds that gender roles are created by childhood interaction with adults. While young boys and girls are psychologically very similar, large differences emerge with age and in laboratory contexts meant to resemble real-world performance environments (Hyde, 2005). As children grow older, they associate science more strongly with men (Miller et al., 2018).[6] Other research links gender differences in STEM majoring to gender differences in academic performance that begin in childhood (Ceci et al., 2014; Ceci, Williams and Barnett, 2009; Joensen and Nielsen, 2015; Stoet and Geary, 2018). The literature on stereotype threat suggests that reminders that women underperform and are underrepresented in STEM can damage women's performance on STEM exams (Murphy, Steele and Gross, 2007; Nguyen and Ryan, 2008; Spencer, Steele and Quinn, 1999; Steele, 1997).[7] However, stereotypes about women's STEM ability are mediated by exposure to female professors (Dasgupta and Asgari, 2004).

[5] See also Chapter I.

[6] Relatedly, "professional role confidence," or confidence in one's ability to be a successful professional in the field, is a major driver of the gender gap in attrition from college engineering programs Cech et al. (2011).

[7] Women who are place less importance on their gender identity may be affected less by stereotype threat (Schmader, 2002).

Economists have come to acknowledge that psycho-social factors can cause gender differences in labor market and educational preferences (Bertrand, 2011). A common trait among these psycho-social factors, which we exploit in this paper, is that they are more likely to influence women's behavior if men are present. In the Akerlof and Kranton (2000) model of the economics of identity, women experience a psychological penalty for acting outside of gender norms. Identity costs may come into play if women believe that STEM is a "man's job" or that only men should be breadwinners (Bertrand, Kamenica and Pan, 2015). Refusal to adhere to traditional gender norms is also costly on the marriage market (Bursztyn, Fujiwara and Pallais, 2017), which may lead women to avoid male-dominated majors when men enter their potential peer group. Other researchers have studied women's willingness to compete. Laboratory experiments consistently find that women's willingness to compete and aptitude in competition are lower when competing against men than when competing only against other women (Booth, Cardona-Sosa and Nolen, 2014; Gneezy, Niederle and Rustichini, 2003; Niederle and Vesterlund, 2007, 2008). Economists have also found that women are more willing to choose STEM majors when they see female role models doing the same (Bottia et al., 2015; Carrell, Page and West, 2010; Kofoed and McGovney, 2019). Our paper contributes to a growing interest among labor and education economists to extend this evidence to real-world educational contexts. We provide evidence that college women are more likely to choose traditionally male-dominated fields when their potential peer group is more female.

In an educational context, costs of bucking traditional gender norms that are larger when more men are present will manifest as a gendered peer effect. Previous researchers have found conflicting results on the effects of female peers on women's persistence in male-dominated activities.[8] Researchers have documented substantial positive effects of high-performing female peers (Mouganie and Wang, 2020) and younger sisters (Brenøe, 2017) on girls' choice to pursue science tracks in high school, but have also found that a higher proportion of female peers in high school reduced women's college STEM majoring (Brenøe and Zölitz, 2020). In higher education, a higher proportion of female peers reduced the gender gap in attrition from the first co-educational class at West Point (Huntington-Klein and Rose, 2018) and improved women's chances of degree completion within 6 years in STEM doctoral programs (Bostwick and Weinberg, 2018). However, exposure to more female peers made women at a Dutch business school less likely to choose male-dominated majors (Zölitz and Feld, 2018).[9] Our paper documents substantial causal

[8]Other literature has looked at male-coded behaviors. For instance, girls who attend single-sex high schools are more competitive and less risk averse than girls who attend coeducational high schools (Booth and Nolen, 2012*a*,*b*; Booth, Cardona-Sosa and Nolen, 2014).

[9]Also related to these two strands of literature is the work of Kunze and Miller (2017), which documented

effects of exposure to female peers on women's STEM majoring in more general American collegiate contexts than prior work.

Finally, our work revitalizes an older literature on the educational roles played by women's colleges. Early observational studies found that graduates of women's colleges were likelier to achieve professional prominence (measured as appearing in the *Who's Who of American Women*) and to enter math, science or medical professions (e.g. Tidball, 1980, 1989). Attending a women's college also raises occupational prestige and income earned post-graduation (Riordan, 1994). Women at women's colleges report more satisfaction with most educational aspects of the college experience and feeling more supported in their education endeavors relative to women at co-educational institutions (Kinzie et al., 2007; Miller-Bernal, 1993; Smith, 1990).[10] Most related to our paper is a case study of a former women's college which found a decrease in the number of women choosing traditionally male-dominated majors and occupations after that college transitioned to co-education (Billger, 2002). Our paper provides a comprehensive study of the effect of coeducation on women's STEM majoring at a much more diverse group of institutions.

2.3 Women's colleges and the transition to coeducation

Women's colleges have been a part of higher education in the United States since 1836. Their footprint grew until its peak in the early 1960s,[11,12] then plummeted over the next several decades as competition in higher education rose and more women opted out of majors like home economics, food science, and education, which had been the staples of many early women's colleges. Thirty-four women's colleges (and only three men's colleges) remain today.

An institution's decision to transition to co-education involved the input of several groups of stakeholders: currently enrolled students, alumnae and alumnae organizations, faculty associations, the president and other high-ranking members of the administration, and the board of trustees (Goldin and Katz, 2011; Miller-Bernal and Poulson, 2004). Coeducation was potentially extremely costly to an institution, as transitioning to co-education

that having a woman boss mitigates the gender gap in promotion, but having more woman peers (in one's own workplace at one's own grade level) may exacerbate this gap.

[10]Dasgupta and Asgari (2004) found that students at a women's college were less likely to form negative stereotypes about women's STEM ability than female students at a coeducational college, but that the effect was mediated by the presence of female professors. Also related is evidence that single-sex classes within a coeducational university improve women's performance (Booth, Cardona-Sosa and Nolen, 2018).

[11]Goldin and Katz (2011) provide a comprehensive summary of the drivers of the switch to coeducation.

[12]Historians have pinned the 1960 population of women's colleges between 233 and 315 (Harwarth, Maline and DeBra, 1997).

risked upsetting alumnae and losing out on donation dollars. Transition also required the construction of new dorms, classrooms and public spaces, and the hiring of new faculty. On the other hand, transition was likely to expand enrollment and thus bring in more tuition revenue. And as high-achieving students increasingly came to prefer coeducation to single-sex learning environments, transition may have ensured the continued enrollment of quality students of all genders. Thus, the decision to transition to co-education depended on a number of subjective variables, including the size, preferences and political will of the alumnae network and the perceptions, preferences and political wills of the faculty, administration and board of trustees. These variables, in turn, depended on a number of idiosyncratic factors, or on decisions taken long before the pressure for co-education mounted (e.g. the college's date and location of opening; the nature of institutional control—public, private, Catholic, non-religious; and the personality and ideals of the president).

The change to coeducation generally did not come about due to the preferences of students already attending. Indeed, the possibility of switching to co-education was not often a popular one among already-enrolled students and alumni, who saw women's colleges as a place where women were "the focus of *all* the attention and *all* the opportunities" (Smith College, 2019). Trustees often pushed the reform through despite resistance from students and alumni. This launched a series of important changes that included admitting male undergraduates, expanding the ranks of male faculty, and adding men's sports teams (The Economist, 1987).

The politics underlying transitions to co-education were unpredictable, and comparable institutions likely experienced quasi-random variation in the existence and timing of transition to co-education. No matter the reason why colleges became coeducational, the final decision was generally made by college trustees and implemented by the next academic year, which allowed men to apply immediately. Our empirical research design, described in Section 2.6, seeks to leverage this exact variation.

2.4 Hypothesized effects of transition to coeducation on women's college and major choices

Our theoretical framework is based on a Roy model of college and major choice, where students choose a college and then a major to maximize their expected lifetime utility conditional on their own characteristics.[13] A high school senior first chooses a college to attend from a set of coeducational and women-only institutions. Once she arrives, she

[13] See Appendix B.1 for a more formal model.

will choose whether to study a STEM major or a non-STEM major. The student only fully realizes the payoff of each major at her chosen institution once she arrives.

If institution i transitions to coeducation, the effect on STEM majoring at i could operate through two channels: a change in the attractiveness of i as a whole (a "selection effect") and a change in the relative attractiveness of a STEM major at i (a "majoring effect"). In other words, changes in the composition of the student body may produce a decrease in women's STEM majoring, and women who continue to attend i may also change from STEM to non-STEM majors. While we remain agnostic on the effect of coeducation on the value of i for the average woman, the literature described in Section 3.2 suggests that the value of a STEM major at i will decrease in response to the entrance of men to classes and campus life. Our estimates of the effect of coeducation on the share of women majoring in STEM are a combination of the majoring effect and the selection effect. Regardless of the channel through which the effect of coeducation on women's STEM majoring operates, our results suggest that when men are present at an institution, women become less likely to choose a traditionally male-dominated field at that institution. Decomposing the magnitude of these two effects is a worthwhile avenue for future research.

2.5 Data on colleges and coeducation

2.5.1 Institution-level data

Our results rely on data from the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). IPEDS collects data from all institutions of higher education in the United States who participate in federal financial assistance programs. Many schools participate voluntarily even if they do not accept federal financial assistance, so the coverage of U.S. higher education—certainly baccalaureate-degree-granting institutions—is nearly universal.

IPEDS and HEGIS provide information from 1984–2016 and 1966–1983, respectively, on the number of degrees awarded by year, institution, major, and gender.[14] We use these data to construct a measure of the share of graduates of gender G that earn a degree in concentration c at institution i in graduation year t. We denote this variable as $s^G_{c,it}$:

$$s^G_{c,it} = \frac{\sum_\mu D^G_{\mu,it} \times \mathbb{1}(\mu \in c)}{\sum_\mu D^G_{\mu,it}}. \tag{2.1}$$

[14]The digitized version of the HEGIS data is not available in 1970, though we hope to add that to future versions of this work.

In this expression, $D^G_{\mu,it}$ is the number of degrees in major μ earned by graduates from institution i, in year t, and of gender G. It is important to note that the data only provide a measure of degrees awarded: we do not observe individuals who matriculate but do not finish their degrees, and we do not observe the time to completion for those who finish their degree. As a result, we cannot investigate these intermediate channels of degree progress.

Our outcome of interest is the share of women graduates earning degrees in STEM fields (or $s^W_{STEM,it}$). Because our primary interest is in the selection of women into majors that are traditionally male-dominated, we define STEM to include engineering, computer science, life and physical sciences, and mathematics.[15,16]

HEGIS and IPEDS also provide information on institutional characteristics that may be related to an institution's capacity to produce STEM majors, in particular, the number of male and female full-time faculty. The faculty data begins in the 1971-72 academic year, but the survey was not run in every year.[17] We use the faculty data to establish whether the faculty at women's colleges became more male after the transition to coeducation, which might be a second channel through which the effect of coeducation operated. IPEDS and HEGIS also provide information on institutional finances and fall semester enrollment beginning with the 1968-69 academic year.

2.5.2 Hand-collected data on dates of transition to co-education

Critical to our analysis is information on the gender status of each institution in each year. We construct a data set containing this information via the following procedure.[18] We identify all institutions that awarded over 90% of their degrees to women in the first year they they are observed in the IPEDS/HEGIS data. Because of concerns about response rates at institutions that entered the data after the transition to IPEDS, we restrict our sample to HEGIS-participating institutions that began offering four-year degrees before 1987.[19] For each of these institutions, we gathered information on whether it was once

[15]The vast majority of liberal arts colleges in our sample do not offer programs in architecture or engineering, and few offer business, health programs or computer science. We exclude health from STEM because it is a traditionally female field.

[16]Appendix B.2.2 provides a complete list of major names and codes contained in our STEM definition and in our other groups of majors.

[17]The faculty survey was run intermittently throughout the 1970s and the early 1980s. Beginning in the mid 1980s, the survey was run every other year before becoming a yearly survey in the 1990s.

[18]A full list of former women's colleges found in the HEGIS/IPEDS data using this procedure can be found in Appendix Table B.1. The table also includes notes on complications with the switch to coeducation, where possible.

[19]The HEGIS data covers all institutions of higher education in the United States, with "institutions of higher education" defined by Title IV of the Higher Education Act. When NCES transitioned to IPEDS, the

a women's college and, if so, the date of transition to coeducation from the institution's website, the "Every Woman's Guide to Colleges and Universities," or other online sources.[20] In total, the full data includes 219 institutions that were women-only in the first year they were observed,[21] 135 of which transitioned to coeducation. The data also includes 1,657 institutions which were coeducational in the first year they were observed and 228 institutions which were men only in the first year they were observed.

We dropped a set of institutions where the transition to coeducation was a gradual process rather than a single event.[22] This include cases in which two single-sex colleges or universities merged (6 institutions), cases where a women's college was absorbed by a partner or coordinate college (12 institutions), institutions that awarded more than ten degrees per year to men before the official date of transition to coeducation where we were unable to verify that said men did not attend traditional undergraduate classes (11 institutions),[23] and institutions where men were admitted as commuter students before they were admitted as residential students (9 institutions). For balance, we omit institutions that closed fewer than nine years after the transition to coeducation (12 institutions). We also omit institutions that did not award any STEM degrees to women in the year they entered the data (26 institutions), as they likely did not have STEM programs to begin with. As many of these criteria overlap, we are left with a sample of 79 institutions that switched to coeducation.

Finally, for further balance, we omit institutions that were in the data for less than 15 years (359 institutions) from the control group. We also omit the U.S. Service Schools (8 institutions), institutions that were men's colleges in the first year we observe them (258 institutions), coordinate colleges (18 institutions), institutions where no women were awarded STEM degrees in the first year we observe them (876 institutions),[24] and for-profit institutions (52 institutions). This leaves us with a total of 25 institutions that were always

sample was expanded to include many more institutions. For information about response rates, see the ICPSR documentation for study 2220, which is the IPEDS financial data for fall 1987. The documentation discusses concerns about response rates and imputation for institutions which enter the data after the transition to IPEDS.

[20] Over 90% of our transition dates were found on *.edu* websites.

[21] For some institutions not picked up in our original sample, we rely on the classification made by HEGIS. This means that some institutions which were classified as coordinate rather than single sex are excluded from our total of 266.

[22] Appendix B.4.3 includes a more thorough breakdown of our sample.

[23] Our sample includes institutions where more than ten degrees per year were awarded to men before the official date of transition to coeducation if we could verify the existence of a coeducational adult education (night) program. See Appendix B.4.2 for more information.

[24] Several institutions that were originally men's colleges transitioned to coeducation program-by-program, often establishing a nursing or teaching program before allowing women into academic programs. STEM programs were often the last to open to women.

women's colleges and 909 institutions that were always coeducational.

2.5.3 Summary statistics

Table 2.1 presents descriptive statistics of our sample of switchers, always women's colleges, and always coeducational colleges. The three types of schools are relatively similar in the share of women choosing STEM in the first year they enter the data. The switchers are similar to the always women's colleges in terms of total enrollment in the first year available, the female share of degrees awarded and of total enrollment in the first years those are available, and the number of graduate degrees awarded in the first year those are available. All public women's colleges eventually switched to coeducation, but the switchers sample is still 92% private institutions, whereas only 57% of our always coeducational schools are private. Sixty percent of our switchers were at some point affiliated with the Catholic church, compared to 24% of the always women's colleges and 6% of the always coeducational colleges. And finally, switchers are much less selective than the always women's colleges, and possibly slightly more selective than the always coeducational sample.

Figure 2.1 documents the distribution of the year of transition to coeducation at women's colleges in our sample. The modal transition date is between 1969 and 1971, before the passage of Title IX in 1972.[25] Although Title IX undoubtedly had large effects on the environment for women in higher education,[26] it is unlikely that it was a driver of the transition to coeducation at the majority of the institutions in our sample.

As men joined the student body at former women's colleges, their presence was felt disproportionately in traditionally "male" disciplines. Figure 2.2 reports the distribution of majors chosen by men from years 1 to 5 and 6 to 10 after the transition to coeducation. During both intervals, business was the most popular major among men, followed by social

[25]Our sample has switch dates that are more concentrated in the late 1960s and early 1970s than our full data on former women's colleges. A number of institutions that changed to coeducation in the 1980s and 1990s either closed shortly thereafter, did not have STEM programs in 1966, or had large numbers of male graduates before their official date to coeducation. However, the fact that the modal transition date is in the late 1960s does not change.

[26]Rim (2020) provides a review of the changes induced by Title IX in addition to an analysis on the effects of women's enrollment in male-dominated graduate and professional programs. Title IX did prohibit discrimination in admissions at undergraduate public institutions, but that did not apply to private undergraduate colleges. Title IX did apply to other programs at private institutions if the institution received federal money, including student aid grants. However, until 1987, Title IX only applied to the program receiving federal money, rather than the entire institution (see pg. 8 and footnote 15 of Rim (2020)). We also believe that, aside from student aid grants, federal money was not a large driver of decisions at former women's colleges in our sample, the vast majority of which were small private colleges – direct federal appropriations were very unlikely, and the median total expenditure on research per year is $0 (according to the IPEDS finance data).

sciences (including economics) and STEM. During the later interval, business grew more popular and social sciences grew less popular.

2.6 Empirical strategy

We exploit variation in the timing of women's colleges' conversion to coeducation to study its effect on plausible determinants of women's major choices, as well as on women's major choices themselves. Because we expect individuals' major choices to evolve dynamically in response to this change in the gender mix of the student body, our main results rely on the following event-study specification:

$$Y_{it} = \theta_i + W_i \sum_{k=-5}^{10} \beta_k 1\left(k = t - t_i^*\right) + \delta_{r(i)t} + \psi_{c(i)t} + \varepsilon_{it} \tag{2.2}$$

where Y_{it} is an outcome of interest, θ_i is an institution fixed effect, $\delta_{r(i)t}$ is a set of region-by-year fixed effects that account nonparametrically for differential trends across regions of the United States, and $\psi_{c(i)t}$ is a set of institutional control-by-year fixed effects, where institutional control is measured at the first year we observe the institution and differentiates between public, Catholic private, and other private colleges.[27] As shown in Table 2.1, women's colleges in 1966 were more likely to be private and religiously affiliated than colleges that were coeducational in 1966. Like the region-by-year effects, these variables control nonparametrically for differential movements in women's STEM majoring behavior by institutional control.

The coefficients of interest are expressed in vector β_k.[28] The indicator W_i is equal to 1 for schools that switched from female-only to co-education during our sample period. Conceptually, this means that we include institutions that did not convert to co-education during the sample period in the control group . Inclusion of these institutions improves precision by contributing to the estimation of our fixed effects and other covariates.

The key identifying assumption is that, conditional on our fixed effects and covariates, *there is no unobserved determinant of outcome Y_{it} that is correlated with institutions' transition from a female-only student body to co-education.* While this assumption is funda-

[27]When estimating this model, we also experimented with adding various state-level labor demand controls, such as yearly unemployment rates for all prime-age individuals, yearly unemployment rates for 18-25-year-olds, and average wage ratios between STEM- and non-STEM-related occupations. The results proved robust to these controls. See Appendix Figure B.2. Our results are also robust to the inclusion of different sets of fixed effects; see Appendix Figure B.1

[28]We set $\beta_{-1} = 0$. Institutions that did not transition to co-education during the sample period are assigned an event time of -1.

mentally impossible to verify, we are able to provide some evidence consistent with unconfoundedness. Our event-study specification allows us to estimate β_k before the reform; a series of coefficients that depart significantly from a flat pre-trend would be suggestive of differential trends that would violate our key identifying assumption.

Our main outcome of interest is the share of graduating women who earned a degree in a given field c, as defined in Equation 2.1. For these estimates, because there is a lag between the time men join a former all-women's campus and the time the affected students graduate, we define our outcome variable as $s^W_{ci,t+3}$. This decision reflects three factors. First, the male share of the student body at former women's colleges increased slowly at first, as we will show in Section 2.7.1. Second, male entering freshmen would have had comparatively little interaction with upperclasswomen. And third, students who are within two years of graduation may not have time to change majors.[29] Our choice of outcome variable thus takes the conservative approach of coding cohorts as "treated" beginning with those who were three years away from graduation at the date of the transition to coeducation.

To explore the mechanisms behind the effects we estimate, we regress the male share of female students' potential peers and the female share of potential instructors using equation 2.2. We do not directly observe either of these objects, but we can construct reasonable proxies using the HEGIS/IPEDS data. We measure the male share of potential peers for a woman graduating in year t from institution i as the share of total degrees awarded to men (or s^M_{it}):

$$s^M_{it} = \frac{\sum_\mu D^M_{\mu,it}}{\sum_\mu D^M_{\mu,it} + \sum_\mu D^W_{\mu,it}} \tag{2.3}$$

Similarly, we measure the female share of potential instructors as the share of faculty that are female in the woman's graduation year. These measures are institution-level and are thus "potential" in nature: they do not reflect endogenous choices of women to construct male- or female-dominant social groups, within their institution, in response to an influx of men.

In all specifications, we cluster standard errors at the institution level. Our preferred specifications are weighted by the total number of degrees earned by women at the institution-year level. However, the results do not substantially change if we do not weight the regressions (Solon, Haider and Wooldridge, 2015).

[29] Hsu (2018) notes that students who have invested a lot of time into a degree generally take the fastest path to graduation based on the course requirements they have fulfilled, even in cases of low match quality between student and major.

As described in Section 2.4, the switch to coeducation may alter female students' behavior and college experiences in several dimensions. The most direct consequence is a change in the gender mix of male students. The effect through this channel, Section 2.4's majoring effect, is our primary theoretical object of interest. However, to the extent that tastes for a particular major are correlated with preferences for a female-only college environment, the switch to coeducation may manifest as a change in the institution students choose to attend, and therefore the composition of the student body—Section 2.4's selection effect. Our administrative data on degree attainment by sex and field does not allow us to directly disentangle these two channels. As a result, our estimates are best interpreted as "intent-to-treat" effects of the change in the gender mix of a college.

2.7 Results

We present our results with three different control groups: all schools that fit the criteria outlined in Section 2.5.2, the colleges that were coeducational throughout that period ("always coed" colleges), and the colleges that were women-only throughout that period ("always women's" colleges). We also present results for a slightly different sample: colleges with less than 5,000 students enrolled in the fall of 1968 (the first year for which enrollment data is available from HEGIS) or the first year we observe the institution, whichever is earlier.[30] As a general rule, the results when using the always coed colleges were the same as the results for the full sample. The results on STEM majoring when using the always womens colleges as a control and when using the sample of smaller schools only are slightly smaller than the results for the main sample, but the difference is not statistically significant.

2.7.1 The effect of coeducation on the determinants of STEM majoring

Figure 2.3 reports the effect of the switch to coeducation on the male share of graduates, using estimates from Equation 2.2. Beginning with the first cohort of juniors who were exposed to coeducation, there is a gradual increase in the male share of the graduating class. At the ninth year after the transition to coeducation, the male share of the graduating class had risen by 23 percentage points relative to the control group in most samples. The rise was slightly smaller when only women's colleges are used as a control group, where the relative increase in the male share of the graduating class nine years

[30]The largest switcher in our sample, Texas Women's University, had slightly more than 5,000 students enrolled in fall 1968.

after the transition to coeducation had risen by 17 percentage points. However, there are no statistically significant differences between the four samples.

Figure 2.4 reports the effect of the switch to coeducation on the female share of faculty, using estimates from Equation 2.2. Kaplan (1978) notes that the faculty of Vassar College became more male after the transition to coeducation. However, we do not find that this was true across the board within ten years of the transition to coeducation. We find no statistically significant effect of coeducation on the female share of faculty, and if anything, the point estimates suggest there may have been an increase in the female share of faculty at newly coeducational institutions. We therefore conclude that there is no evidence to suggest that positive effects of female role models at newly coeducational institutions were lessened by the switch to coeducation, at least not in the short term. There are again no statistically significant differences between the specifications with different control groups.

To provide evidence in favor of our identifying assumption, we test whether β_{-5}, β_{-4}, β_{-3}, and β_{-2} are jointly different from zero for the effect of coeducation on the male share of graduates and the share of women majoring in STEM, and we test whether β_{-4}, β_{-3}, and β_{-2} are jointly different from zero for the female share of faculty. The reason for the shorter pre-trend for faculty is the lack of data from the years before the switch. The results of these tests are displayed in Panel A of Table 2.2. We find evidence of a pre-trend in the entry of men to women's colleges, which we attribute to the fact that many women's colleges admitted a small number of men to adult education programs in advance of the switch to coeducation. However, we do not find evidence of a pre-trend on the female share of faculty.

Based on these results, the effects of the transition to coeducation at former women's colleges were likely the effect of an increase in the male share of peers rather than a decrease in the female share of faculty role models.

2.7.2 The effect of coeducation on women's STEM majoring

Figure 2.5 reports the effect of the switch to coeducation on the share of women who major in STEM, using estimates from Equation 2.2, and Table 2.3 reports the average share of women choosing each major at time -1 at the switcher institutions. Beginning at time 0, with students who were sophomores the year of the switch to coeducation, there is a sustained decrease in women's STEM majoring at newly coeducational institutions. By time 5, the share of women majoring in STEM had fallen by 1.9 percentage points, or 22% of the share of women choosing STEM the year before the transition to coeducation. By time 9, the share of women majoring in STEM had fallen by 2.7 percentage points, or 32%. The effect of coeducation is smaller when comparing these institutions to women's colleges only or when only considering schools with fewer than 5,000 students during the 1968-1969 academic year, but the differences are not statistically significant.[31]

To provide evidence in favor of our identifying assumption, we test whether β_{-5}, β_{-4}, β_{-3}, and β_{-2} are jointly different from zero. The results of these tests are displayed in Panel B of Table 2.2. We do not find evidence of a pre-trend on the share of women graduating with STEM degrees.

As noted by Kahn and Ginther (2017), more quantitative STEM programs have more trouble recruiting women than less quantitative STEM programs. This lines up with the number of women who actually complete these degrees. In 1980, women earned 42% of biological science degrees, 23% of physical science degrees (28% of chemistry degrees and 12% of physics degrees), 42% of math degrees, 30% of computer science degrees, and 30% of economics degrees in the United States. In 2016, women earned 56% of biological science degrees, 39% of physical science degrees (57% of chemistry degrees and 19% of physics degrees), 40% of math degrees, 18% of computer science degrees, and 32% of economics degrees in the United States. In 1980, women earned 50% of bachelor's degrees, and in 2016, women earned 57% of bachelor's degrees – meaning, the less quantitative STEM fields, biology and chemistry, have now achieved parity, but the more quantitative fields of physics, math, and economics experienced less progress, and computer science is considerably *less* female than it was in 1980.[32] For this reason, we think it is important to examine the effect of coeducation by field — were women more likely to substitute away from more quantitative fields?

Figure 2.6 reports the effect of the switch to coeducation on the share of women who major in biological sciences, physical sciences, and math, as well as economics, which is not included in our definition of STEM but is a highly male-dominated field. All reported results are from the main sample in Figure 2.5. As reported in Table 2.3, at time -1, the most popular of these majors among women at switcher institutions was the biological sciences, followed by math, the physical sciences, and economics. The female share of these majors falls relative to the level at time -1 by the largest number of percentage

[31] The difference between samples is likely due to the average availability of engineering in different control groups. Appendix Figure B.7 reports the estimates of Equation 2.2 when the dependent variable is just the share of women majoring in engineering. The gradual decrease in engineering in the main sample and using the always coeducational institutions as a control group is likely due to larger growth of engineering in the control group rather than a causal effect of coeducation. The effect on engineering is also much smaller when comparing the switchers to only women's colleges, where the effect is near zero, and using only the smaller schools, where the effect is halfway between the main sample and the women's colleges. Women's colleges rarely have engineering programs, and smaller schools are less likely to have engineering programs.

[32] The backwards progress in computer science is a well-known issue in the field and occurred during periods when the major became less popular overall. See Chapter I or National Academies of Sciences, Engineering, and Medicine (2018*b*).

points in biological sciences. We also see large drops in the share of women majoring in economics, math, and the physical sciences.[33] However, economics sees the largest drop in share of women majoring in the field relative to the share of women who chose each field at time -1, with chemistry, biology, and math having similar decreases relative to their popularity before the transition to coeducation.

The effect of coeducation on the math major seems to begin slightly earlier than the effect of coeducation on the other majors, perhaps having an effect on students who were further along in their degrees than students who chose other STEM fields. Though the point estimates of β_{-4}, β_{-3}, and β_{-2} seem to be similarly sized to each other, they are all somewhat above zero. Additionally, the large positive spike in STEM majoring at time -5 seems to come entirely from the math major. We believe the large upward spike in math majoring at time -5 is due to a historical decline in math majoring in the late 1960s and early 1970s associated with the end of the Space Race and nationwide changes in the structure and focus of the math major (Tucker, 2013). This decline may have been larger at women's colleges, as other colleges may have only recently allowed women into their math programs.[34] However, we believe that, given the lack of changes from time -4 to -2, coeducation still had a large effect on math majoring. As a robustness check, we also test the effect of coeducation on STE fields, and we find a similar (but slightly smaller) effect to our STEM results. Those estimates are reported in Appendix Figure B.11.

To summarize the previous paragraphs, and to help understand what majors women substituted to, we estimate an overall difference-in-difference coefficient for the effect of coeducation on the share of women majoring in STEM, our three individual STEM fields, social sciences (including economics), economics, health, and education. These estimates are reported in Table 2.4. The table also reports the share of women who chose each major at time -1. Columns 1 through 6 report the effects of coeducation on STEM and the social sciences,[35] including the effects of coeducation on specific fields. Column 1 reports the effect of coeducation on the share of women majoring in STEM in the nine years following the transition to coeducation. The results suggest that coeducation induced a 2.1 percentage point, or 24%, decrease in the share of women majoring in STEM on average over the nine years following the transition to coeducation. Columns 2 through 4 report the effect of coeducation on the share of women majoring in biological sciences, physical

[33] The effect on the physical sciences is driven by chemistry, which is also the most common physical science field chosen by women at time -1.

[34] We also check whether this could have been the result of a changing definition of the math major, for instance a change from including math education in math to separating the two majors.See Appendix B.2.3 for more details on math vs. math education.

[35] Economics is included in the social sciences.

sciences, and math respectively. Coeducation induced a 0.67 percentage point (17%) decrease in the share of women majoring in the biological sciences, a 0.31 percentage point (25%) decrease in the share of women majoring in the physical sciences, and a 0.55 percentage point (19%) decrease in the share of women majoring in math. Columns 5 and 6 report a 2.1 percentage point (13%) decrease in the share of women majoring in the social sciences as a whole and a 0.41 percentage point (55%) decrease, though only marginally significant, in the share of women majoring in economics. Columns 7 and 8 report the effects of coeducation on traditionally female-dominated fields: health professions[36] and education. Coeducation induced a 3.85 percentage point (30%) increase in the share of women majoring in health professions and a 1.97 percentage point (8%) increase, though not statistically significant, in the share of women majoring in education.[37]

2.7.3 Interpreting the intent-to-treat effect

As discussed in section 2.6, our estimated effects on women's choice of major are best interpreted as intent-to-treat effects of the switch to coeducation on institutions' production of female STEM majors (and majors of other disciplines). These estimates can be difficult to interpret because they capture the effect on major choice net of all margins of response to the switch to coeducation — including the effect on the gender composition of the student body, which itself responds dynamically to the reform.

To construct a more easily interpretable estimate, in this section we conduct a rescaling exercise by dividing the ITT estimate in each event-year by the corresponding estimated effect on the share of the graduating class that is male and dividing the new estimate by the share of women choosing STEM majors at time -1. We then construct a 95% confidence interval using the 2.5th and 97.5th percentile of this rescaled estimate from a block bootstrap routine with 500 replications. We also calculate a difference-in-difference version of the rescaled effect in a similar manner. Under a stronger set of assumptions, this exercise can be interpreted as a semielasticity of major choice with respect to the gender

[36]While pre-professional fields like pre-medicine and pre-dentistry are included in this code, they generally make up a very small share of the students at a given college that are reported as health majors. The vast majority of students reported as health majors hold degrees in nursing or allied health.

[37]Appendix Figure B.6 reports the event study estimates of the effect of coeducation on the share of women majoring in education, humanities, social sciences (including economics), psychology, health, and business. We see large decreases in both social science and business majoring. However, as discussed in Section 2.5.3, only 22 of our switcher institutions awarded at least one business degree to a woman in the first year we observe said institution; 71 awarded at least one business degree to a man in that year. We therefore think that, at baseline, the business program was limited to adult education students in many cases, although many institutions likely opened that program up to women at some point during our sample period. That said, though potentially problematic, the effect of coeducation on business majoring is striking. We also see an increase in health and a smaller increase in education.

composition of women's peers at the level of the institution.[38] However, we interpret it more conservatively as a summary statistic of the effect of coeducation on women's choice of major.

Figure 2.7 reports the rescaled effect of coeducation on women's STEM majoring. We find that the rescaled effect is relatively stable over time, and the average rescaled effect, which is captured by the difference-in-difference estimate, is -0.174. This magnitude can be interpreted in the following way: when the male share of the graduating class increases by ten percentage points, the share of female graduates who earn STEM degrees decreases by 17.4% percent.

We calculate a similar estimate for all majors. The three majors with statistically significant negative estimates of the rescaled effect of coeducation are economics, STEM, and social sciences other than economics, from most negative to least. Home economics and business have negative estimates that are not statistically significant, and the humanities, psychology, and art have estimates close to zero. From smallest to largest, the majors with positive rescaled effects of coeducation are education, other,[39] and health. Education and health, notably, are the most female majors, and other includes social work, another very female major. We therefore conclude that co-education pushed women out of traditionally male-dominated majors (economics, STEM, and, in the 1960s and 1970s, social sciences) and pushed women into traditionally female-dominated majors (education and health).

2.8 Robustness check: the synthetic control method

The estimates described above rely on the assumption that our event-study specification produces unbiased estimates of the counterfactual scenario in which our "treated" group of women's colleges had not converted to coeducation. Our event-study estimates and balance tests provide suggestive evidence in support of our key identifying assumption that there are no unobserved determinants of the share of women majoring in STEM that are correlated with colleges' switch to mixed-gender classes. However, this assumption is fundamentally unverifiable.

[38]Specifically, under the key identifying assumption laid out in section 2.6 and the additional assumption that our estimates of β_k are driven solely by the male share of one's peers, the rescaling exercise in this section will recover a local average treatment effect of gender composition on major choices. While this assumption is is consistent with the results of section 2.7.1, as well as the tests in sections 2.9, we do not have a way of testing it more directly. We interpret the results in this section as a suggestive exercise to quantify the influence of male peers on the choice of quantitative fields of study.

[39]"Other" includes agriculture, forestry, law, trades/vocational, military science, library science, multi/interdisciplinary majors, theology and religious vocations, protective services, and public administration and social services.

This section evaluates the sensitivity of our results to our choice of a comparison group of colleges. As discussed in Section 3.2, many U.S. women's colleges converted to coeducation in response to increasing demand for mixed-sex education and competition among institutions. To the extent that these unobserved variables affect female students' choice of major, there is some risk that our comparison group of schools – which presumably were less affected by these forces – do not give rise to the ideal counterfactual for women's choice of major at schools that switched.

As a robustness check for our main results, we use the synthetic control method to estimate the effect of switching to coeducation on women's choice of major. The synthetic control method offers a data-driven procedure by which we can construct a control group that matches our treatment group, based on pre-treatment characteristics.

We follow the guidance of Ferman, Pinto and Possebom (2020) and, for our main specification, construct a synthetic control group by matching on the entire set of pre-treatment outcome variables. We see this as an obvious baseline approach that reduces concerns about specification searching and, in cases where with sufficiently lengthy pre-periods, reduces the bias of the synthetic control estimator (Abadie, Diamond and Hainmueller, 2010; Kaul et al., 2018). The disadvantage of this approach is that we run the risk of overfitting, particularly for our early-switching schools with few observed pre-treatment periods. To assuage these concerns, we again follow Ferman, Pinto and Possebom (2020) and report estimates from three other specifications. For our main estimates of the effect on STEM using our baseline specification, we conduct inference by randomly reassigning treatment status and estimating the effect of the transition to coeducation on the placebo institutions (Abadie, Diamond and Hainmueller, 2015). If our estimated effect is either below the 2.5th percentile or above the 97.5th percentile of placebo effects, the effect is statistically significant.

One additional complication of our setting is that we have multiple "treated" schools rather than the single treated unit that is more common in synthetic control settings. We depart from the standard case in two ways to incorporate this feature into the method. First, we group schools that switched to coeducation in the same year so that the "treated" groups are effectively school-cohort combinations; this adjustment reduces both computational burden and noise. Second, we construct a synthetic control group separately for each cohort of treated schools and then average the effects by year relative to the switch (Acemoglu et al., 2016; Cavallo et al., 2013).

Figure 2.9 reports the results of the synthetic control estimation. The synthetic control result is similar in magnitude to our event study results, with a roughly 2 percentage point decrease in the share of women majoring in STEM by five years after the transition to coeducation and a 3 percentage point decrease by nine years after the transition to coeducation. The synthetic control results also remove the spike in STEM majoring at time -5. We also calculate a "difference-in-difference" estimate by averaging the post-treatment coefficients and subtracting them from the average pre-treatment coefficients; the estimate of -0.02 is an outlier in the distribution of placebo effects, with a p-value of 0.007. This estimate is almost identical to the one we obtain in our event-study model, as reported in Table 2.4.

Figure 2.10 reports estimates from our robustness checks. The first specification replicates the estimates from Figure 2.9. The second specification uses only the second half of pre-treatment outcomes as matching variables, rather than the full pre-period. The third specification uses a five-year average of the pre-treatment period, a five-year average of the ratio of total PhD and professional degrees to bachelor's degrees, and the share of *all* students at a school that majored in humanities, social science, physical science, and business in the year before the reform. Finally, the fourth specification replaces the bachelor's-degree shares from event-year -1 with those same shares for the last half of the pre-period.

While these robustness checks are generally noisier than our baseline estimates, the results are relatively consistent across specifications. Our estimates of the effect on STEM change very little; the difference-in-difference estimate for our robustness checks are slightly smaller than the baseline estimate, ranging from -0.014 to -0.018. Similarly, we find the share of women majoring in physical science fell by about $0.003 - 0.004$, a drop of around $24 - 32\%$. Our estimates of the effect on biology and economics are less robust, although the magnitudes are similar to our event-study estimates. We again see particularly large effects on economics — our baseline specification suggests a 33 percent drop — although the pre-trends we see in some specifications may suggest we should interpret this estimate cautiously.

2.9 Ruling out capacity constraints as an explanation

One potential threat to our identification would be if newly coeducational colleges had larger capacity constraints in STEM majors than in non-STEM majors. One might worry that, if STEM was both more costly for colleges and more popular among men, women might be more crowded out of STEM majors than non-STEM majors after the transition to coeducation. To rule out this possibility, we examine how the log number of degrees in each STEM field changed and how that change correlated with the cost of each STEM field. If capacity constraints were the only explanation for why women were less likely to get STEM degrees after the transition to coeducation, we would see an inverse correlation between the expense to colleges of offering different fields and the growth in those fields after the transition to coeducation.

We propose a difference in differences exercise to understand the correlation between the change in the size of different fields and the cost of those fields. For each quantitative field or traditionally female-dominated field μ at school i during year t, we estimate

$$\log(Degrees)_{it\mu} = \theta_{i\mu} + W_i Post_{it}\gamma_\mu + \delta_{r(i)t\mu} + \psi_{c(i)t\mu} + \varepsilon_{it\mu} \tag{2.4}$$

$\log(Degrees)_{it\mu}$ is the log number of degrees in μ awarded to both male and female students graduating from school i in year t. Our coefficient of interest is γ_μ: the effect of the switch to coeducation on the log number of degrees awarded in field μ. As before, W_i is an indicator of being a women's college that switched to coeducation. $Post_{it}$ is an indicator that school i has already switched to coeducation. $\theta_{i\mu}$, $\delta_{r(i)t\mu}$, and $\psi_{c(i)t\mu}$ are year, region-by-year, and control-by-year fixed effects, similar to our event study specification. We then rank the size of γ_μ in order of the cost of providing each field as described in Hemelt et al. (2018).[40]

The most expensive field commonly offered at the institutions in our sample is nursing, followed by education. The most expensive STEM field is physics, followed by chemistry, biology, economics, and math.[41] Figure 2.11 reports the estimates of γ_μ for each of these fields, in order from most expensive to least expensive. If capacity constraints were the only factor responsible for changes in the share of women choosing each field, we would expect that the most expensive fields would grow the least and the least expensive fields would grow the most. In that case, the difference-in-difference coefficients would get larger (less negative or more positive) as the cost of offering the field decreased. This is not the case: there does not appear to be any relationship between cost and the change in the log number of degrees awarded by field. We therefore conclude that capacity constraints were not the only driver of women's substitution away from STEM after the transition to

[40]Hemelt et al. (2018) rank fields of study by cost relative to the English major. They establish that costs vary widely by field, and interestingly, both math and economics are cheaper to offer than English (and many other non-STEM majors). The variance in costs of offering different fields is largely explained by differences in class size and faculty pay — economics and math are cheaper because they often have very large classes.

[41]Nursing is the second most expensive field ranked by Hemelt et al. (2018), and education is the fourth most expensive. The two most expensive STEM fields are electrical engineering (which is the most expensive field) and mechanical engineering (which is the third most expensive field). The vast majority of colleges in our sample do not offer engineering, so we omit electrical and mechanical engineering from our analysis. Computer science is also more expensive than physics. However, most of our sample switched to coeducation in the early 1970s, when computer science was just beginning to be offered as a degree (and before most small liberal arts colleges would have had a computer science program). Given the huge changes to the field of computer science, we are not confident that its place in the rank order of costs has been stable since 1966.

coeducation at former women's colleges.

2.10 Conclusion

This paper provides new evidence of the effect of the peer gender composition on women's choice of major, a consequential decision that can affect the career trajectory and earnings potential of a student for decades to come. By exploiting the change in the gender mix of students at historically female-only colleges, we find that the subsequent increase in male students has significant effects on women's likelihood of majoring in the life sciences, physical sciences, mathematics, and economics. Our analysis suggests that the reduction in women's STEM majoring is driven by an increase in potential male peers rather than a decrease in opportunities to interact with female faculty role models. These findings do not appear to be driven by supply-side factors such as capacity constraints. Overall, these findings suggest that interaction with male peers discourages women from pursuing careers in STEM and that "non-cognitive" factors, including but not limited to gender identity, stereotype threat, aversion to competition, and pressure to conform to gender norms, could contribute substantially to the persistence of gender gaps in the labor market.

The introduction of coeducation at a formerly all-female institution could drive women at the institution from majoring in STEM in two ways. The first is that coeducation decreases the payoff of a STEM major, relative to other majors, for all women, lowering women's STEM majoring conditional on the decision to attend the institution. The second is that coeducation also decreases some women's interest in the institution itself. If there is a correlation between preferences for STEM majoring and preferences for attending a women's college, changes in the enrollment decision could also change the share of an institution's female graduates who earn STEM degrees. We find either scenario (and the combination of the two) interesting: the first suggests a direct effect of gender composition on women's desire to major in a quantitative field, whereas the second suggests a correlation between interest in STEM and interest in attending a women's college. We believe that an attempt to disentangle the two channels is an interesting avenue for future research. We also believe that a parallel study on the effects of coeducation on former men's colleges would be an interesting counterpoint to this study.

2.11 Tables

Table 2.1: Descriptive statistics

	Switchers	Always Women	Always Coed
STEM share of women	0.12	0.11	0.10
in first year available	(0.047)	(0.035)	(0.129)
Total enrollment	1190.80	1292.76	5081.28
in first year available	(907.539)	(581.615)	(6338.532)
Female share degrees	1.00	1.00	0.46
in first year available	(0.016)	(0.008)	(0.148)
Female share of enrollment	0.95	1.00	0.44
in first year available	(0.172)	(0.019)	(0.140)
Graduate degrees awarded	10.52	12.16	161.95
in first year available	(25.467)	(30.127)	(398.090)
Private	0.92	1.00	0.54
	(0.267)	(0.000)	(0.499)
Catholic	0.61	0.24	0.06
	(0.491)	(0.436)	(0.230)
1972 Barron's rating	3.94	3.36	4.19
	(0.732)	(1.114)	(0.843)
Selective (1972)	0.19	0.48	0.12
	(0.395)	(0.510)	(0.330)
Observations	79	25	909

Notes: Descriptive statistics of schools that switched to coeducation, schools that remained women's colleges, and schools that have been coeducational since long before 1966. 1969 is the first year of availability for enrollment and financial data. Graduate degrees refers to masters, doctoral, and professional degrees. Barron's ratings are first available in 1972 and do not exist for all schools. "Selective" refers to a Barron's rating of 1, 2, or 3. Standard deviations are in parentheses.

Table 2.2: F-statistics for pre-trends in event study regressions

	F statistic	p-value
Determinants of STEM Majoring		
Male share of graduates	9.528	3.31e-06
Female share of faculty	1.315	0.268
Women's STEM Majoring		
STEM share of women	1.785	0.148

Notes: Results of F-test of joint significance of β_{-5}, β_{-4}, β_{-3}, and β_{-2} from estimates of Equation 2.2 with each dependent variable.

Table 2.3: Average share of women choosing each major at time -1

Field	Share of women
STEM	0.086
	(0.046)
Biological sciences	0.040
	(0.026)
Physical sciences	0.012
	(0.020)
Chemistry	0.011
	(0.019)
Physics	0.001
	(0.002)
Math and Computer Science	0.031
	(0.026)
Math and Statistics	0.029
	(0.020)
Computer Science	0.002
	(0.015)
Engineering	0.000
	(0.000)
Social Sciences	0.162
	(0.104)
Economics	0.007
	(0.018)
Business	0.060
	(0.112)
Health	0.123
	(0.176)
Education	0.244
	(0.205)
Humanities	0.137
	(0.095)
Psychology	0.060
	(0.074)

Notes: Table shows the average share of women choosing STEM, each STEM major, and economics at time -1 at schools in switcher sample. Math includes statistics and applied math. Physical sciences includes chemistry, physics, astronomy, and earth sciences. Computer science includes information science. We exclude baccalaureate programs in agriculture, architecture, law, library science, military science, multi/interdisciplinary, public administration, vocational and technical fields, and visual and performing arts from this table, but those students are included in the denominator.

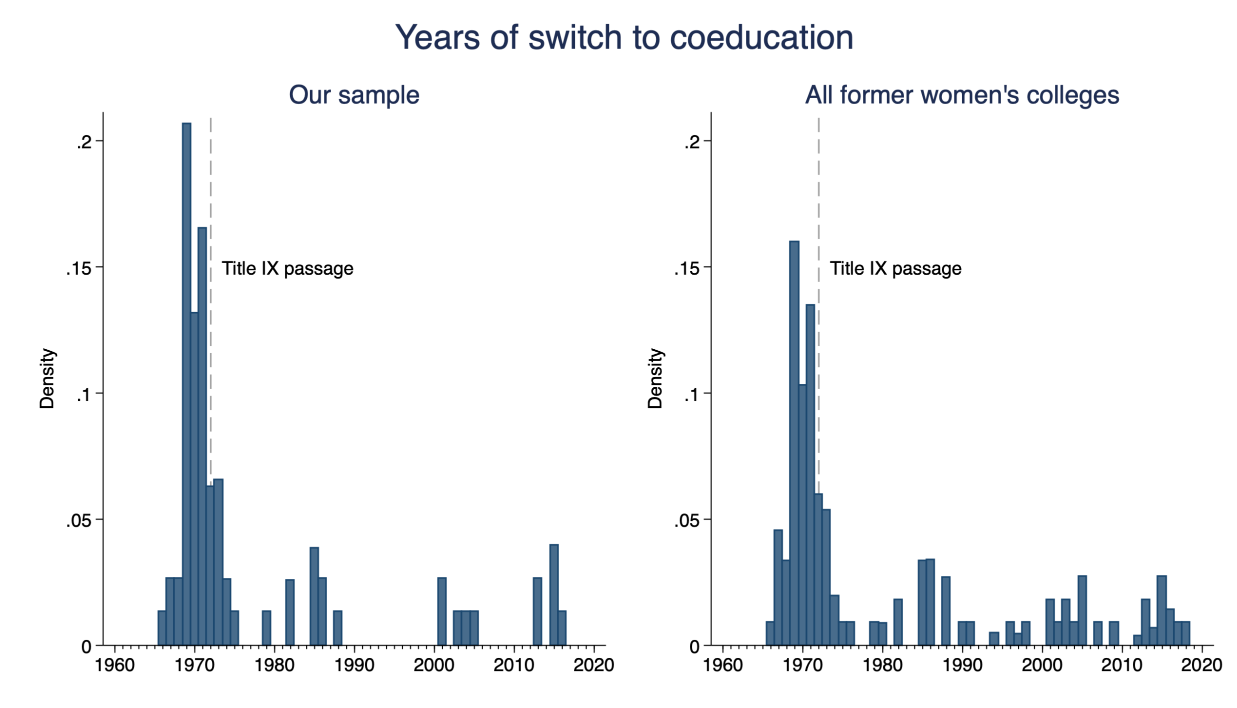
Table 2.4: Effects of coeducation on share of women choosing a field

	(1) STEM	(2) Biological Science	(3) Physical Science	(4) Math	(5) Social Science	(6) Economics	(7) Health	(8) Education
Switcher $\times$ Post	-0.0205***	-0.00667**	-0.00312***	-0.00546***	-0.0214***	-0.00410*	0.0385**	0.0197
	(0.00457)	(0.00270)	(0.000865)	(0.00206)	(0.00821)	(0.00232)	(0.0168)	(0.0126)
Observations	47,973	47,973	47,973	47,973	47,973	47,973	47,973	47,973
R-squared	0.785	0.698	0.536	0.489	0.705	0.696	0.718	0.806
Mean at time -1	0.0851	0.0397	0.0126	0.0285	0.161	0.00743	0.127	0.236

Notes: Each column shows difference-in-difference estimates obtained by estimating equation 2.2, with event-time constrained to a binary indicator of before or after reform, with dependent variable specified. Standard errors are robust to arbitrary intraclass correlation within institution and across years.
*** p<0.01, ** p<0.05, * p<0.1

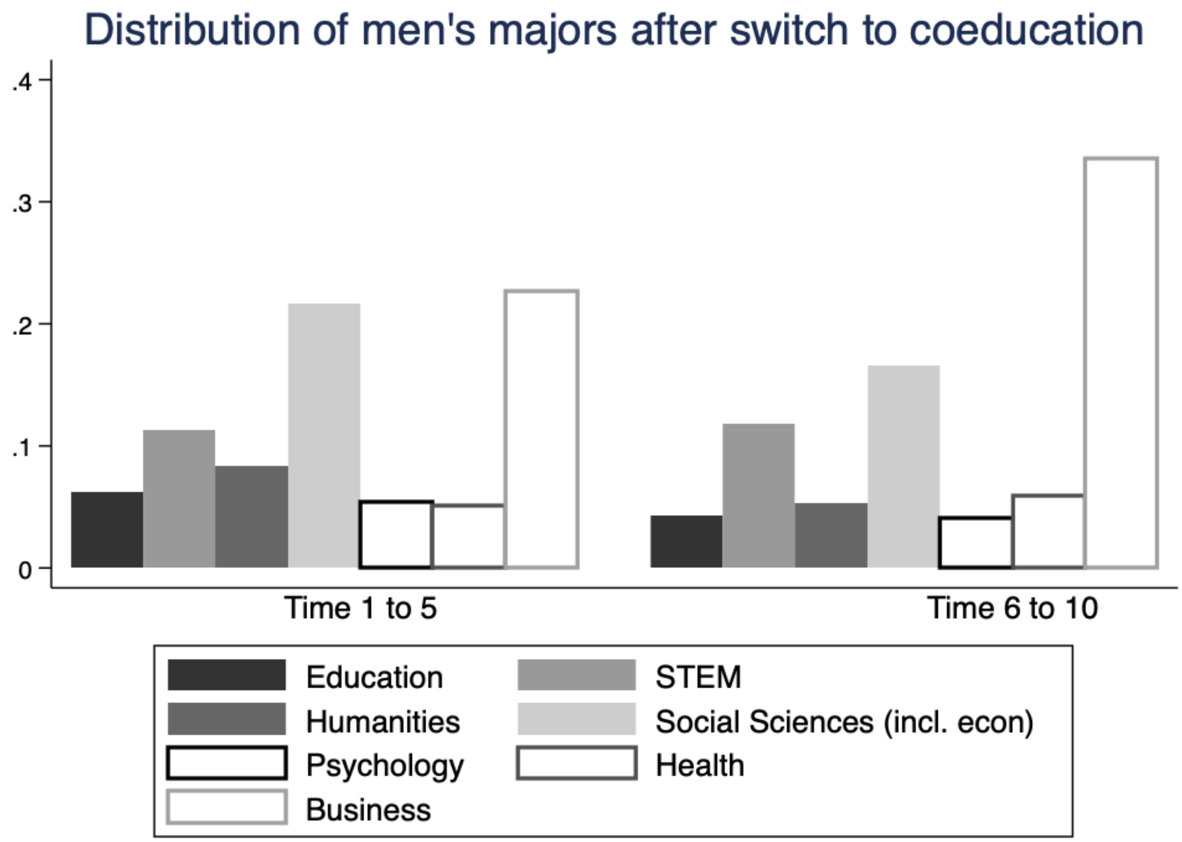
2.12 Figures

Figure 2.1: Distribution of the year of switch to coeducation



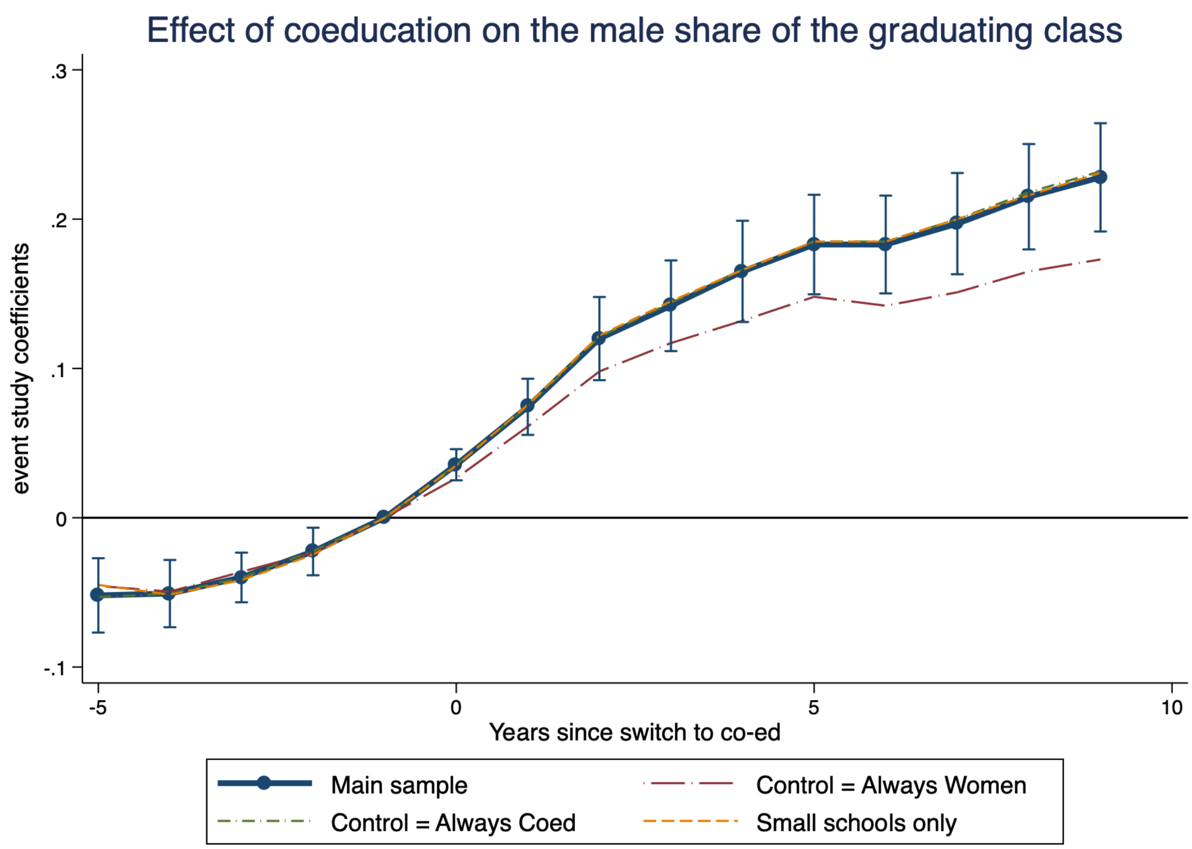
Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS), linked to hand-collected data on the years that former women-only institutions switched to coeducation.

Figure 2.2: Distribution of men's major choices after the switch to coeducation



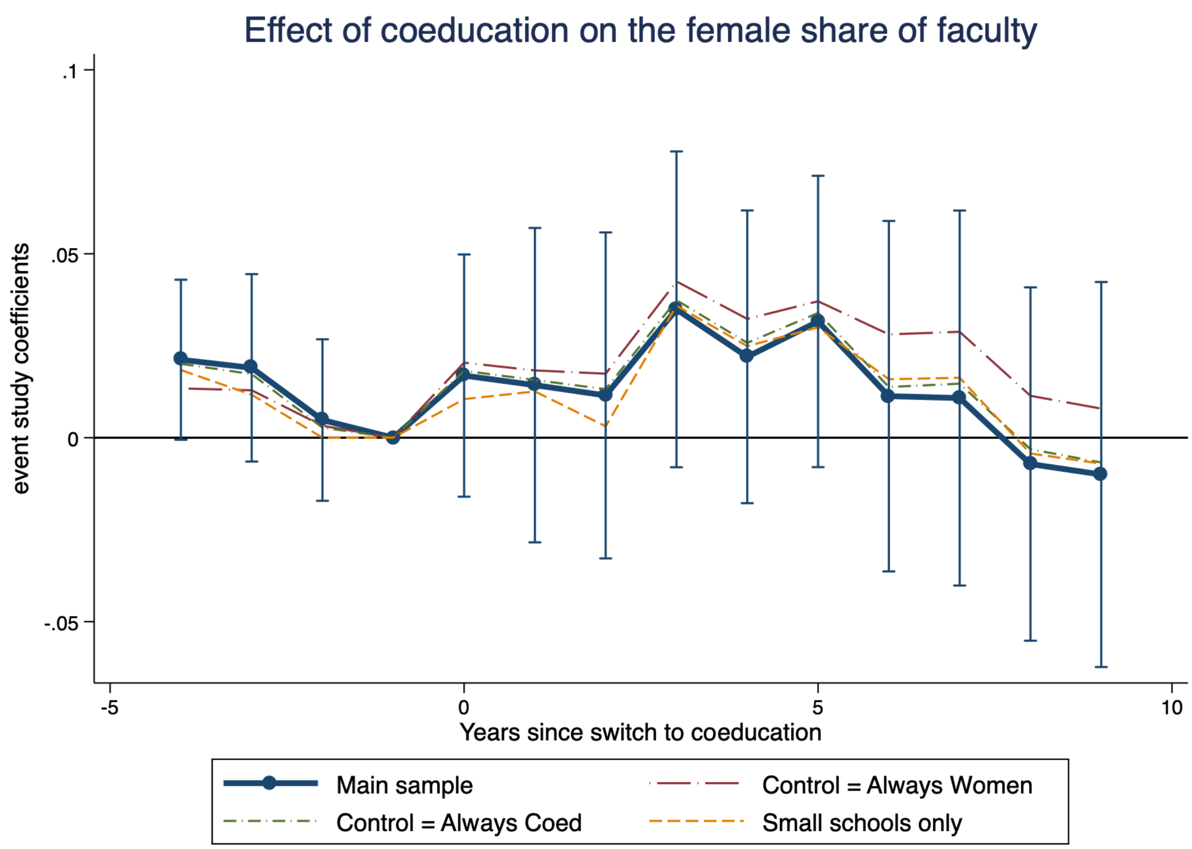
Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from $1966-1969$ and $1971-2016$ in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS), linked to hand-collected data on the years that former women-only institutions switched to coeducation. The size of each bar is calculated using $\frac{\sum_i \sum_{t=t_1}^{t_2} N_{ijt}^{men}}{\sum_j \sum_i \sum_{t=t_1}^{t_2} N_{jit}^{men}}$ where N_{ijt}^{men} represents the number of men at college i choosing major j at time t years after the transition to coeducation. Excluded categories of majors include agriculture, architecture, law, library science, military science, multi/interdisciplinary, public administration, vocational and technical fields, and visual and performing arts.

Figure 2.3: The effect of becoming coeducational on the male share of graduates



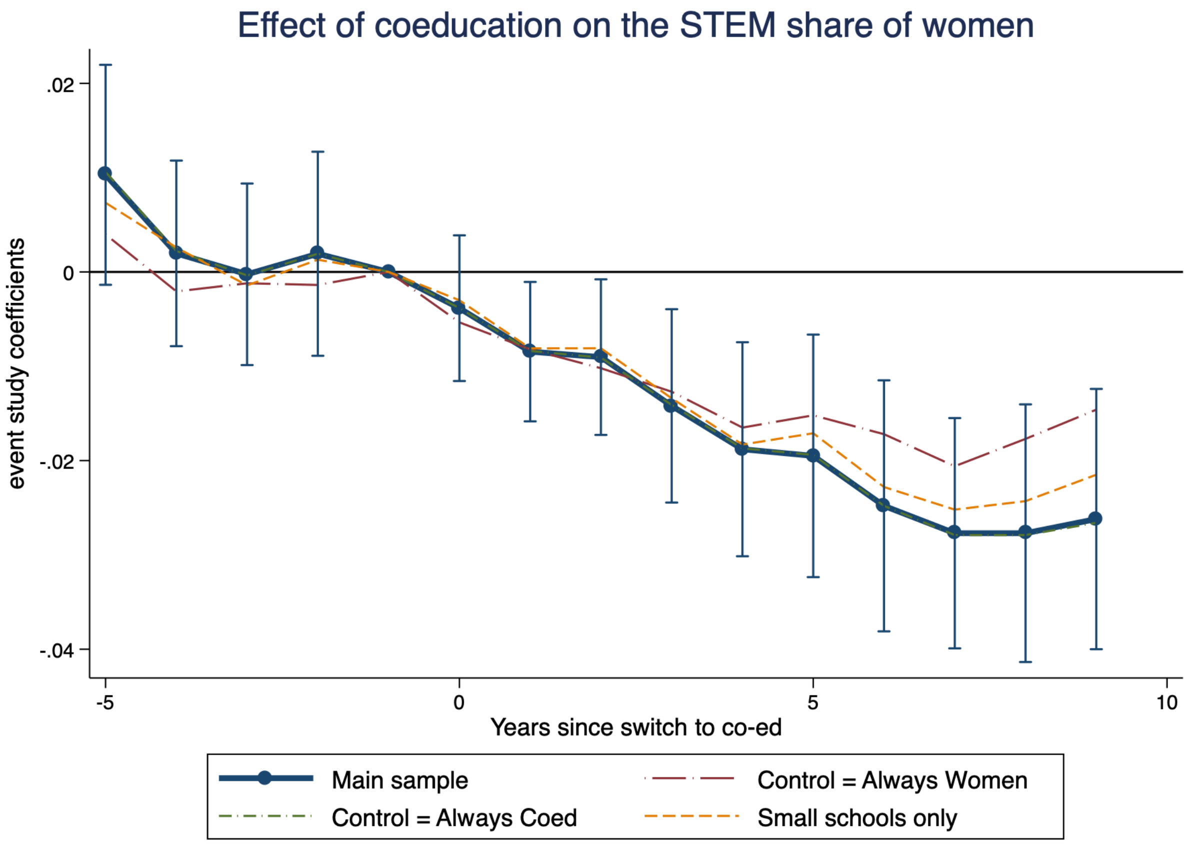
Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2. Standard errors are clustered at the institution level.

Figure 2.4: The effect of becoming coeducational on the male share of full-time faculty



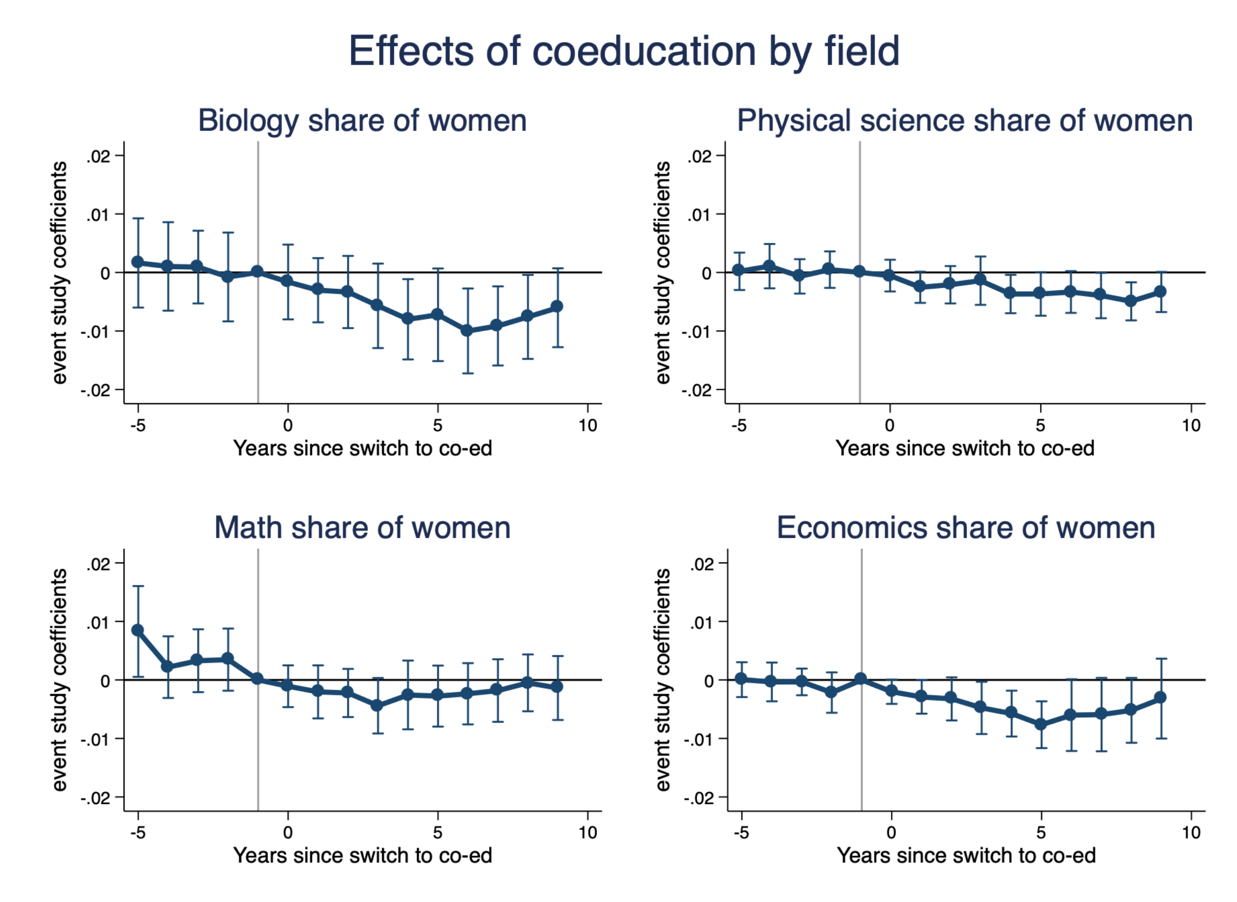
Notes: Data is drawn from records of the number of full-time faculty in the fall semester from 1971-2016 (with gaps) in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2. Standard errors are clustered at the institution level.

Figure 2.5: The effect of becoming coeducational on the STEM share of degrees awarded to women



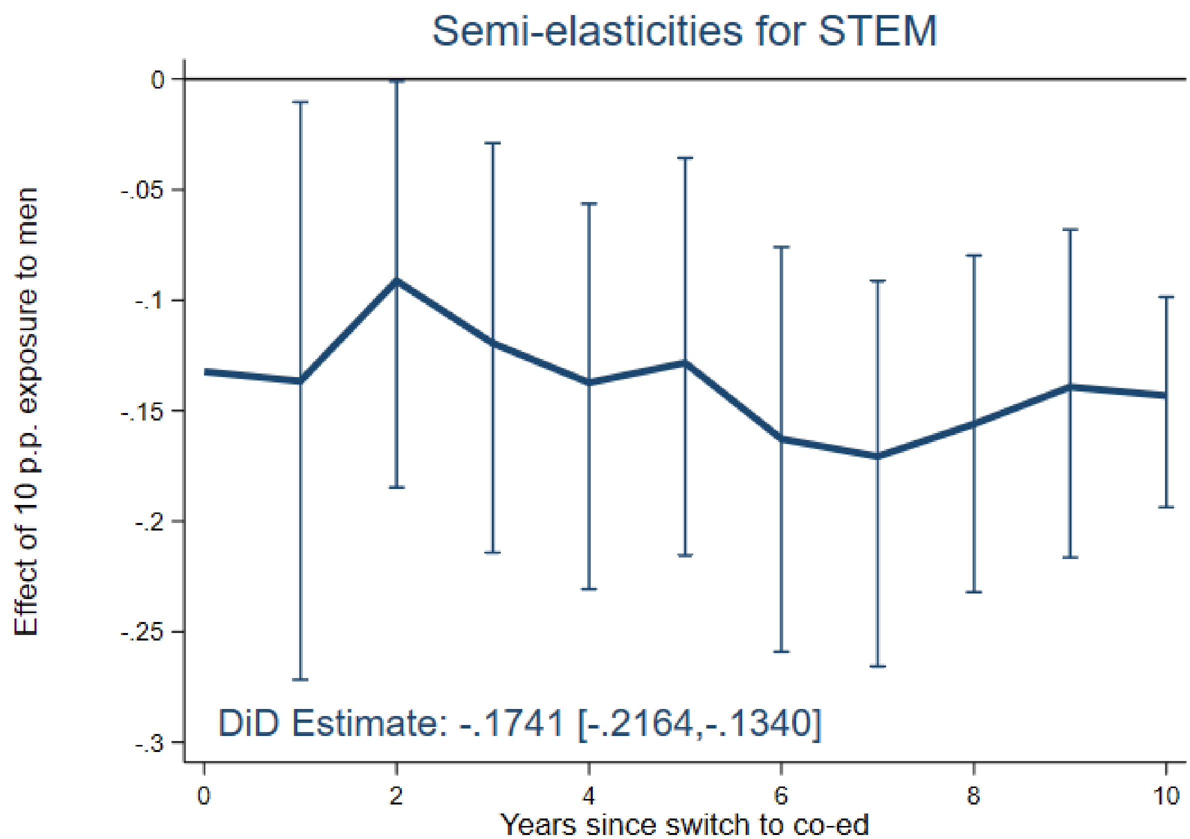
Notes: STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2. Standard errors are clustered at the institution level.

Figure 2.6: The effect of becoming coeducational on the STEM share of degrees awarded to women



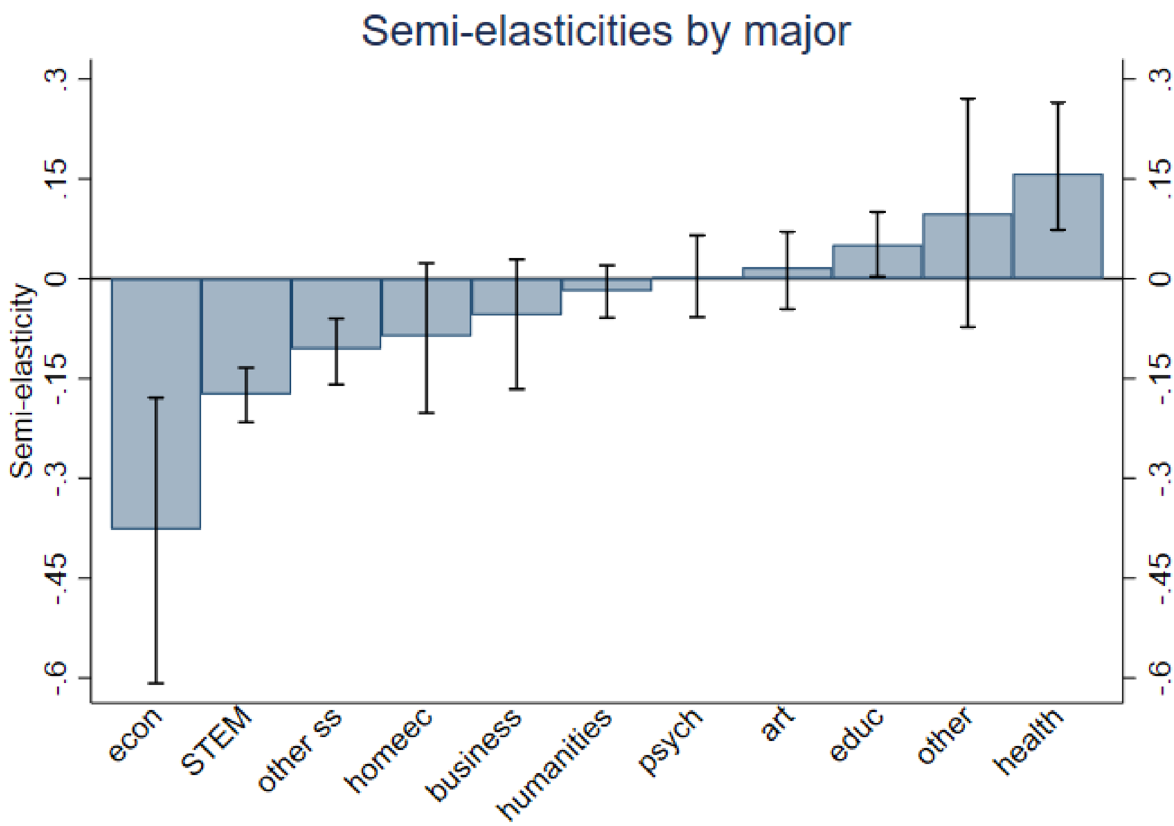
Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2. Standard errors are clustered at the institution level.

Figure 2.7: The rescaled effect of exposure to men on women's STEM majoring



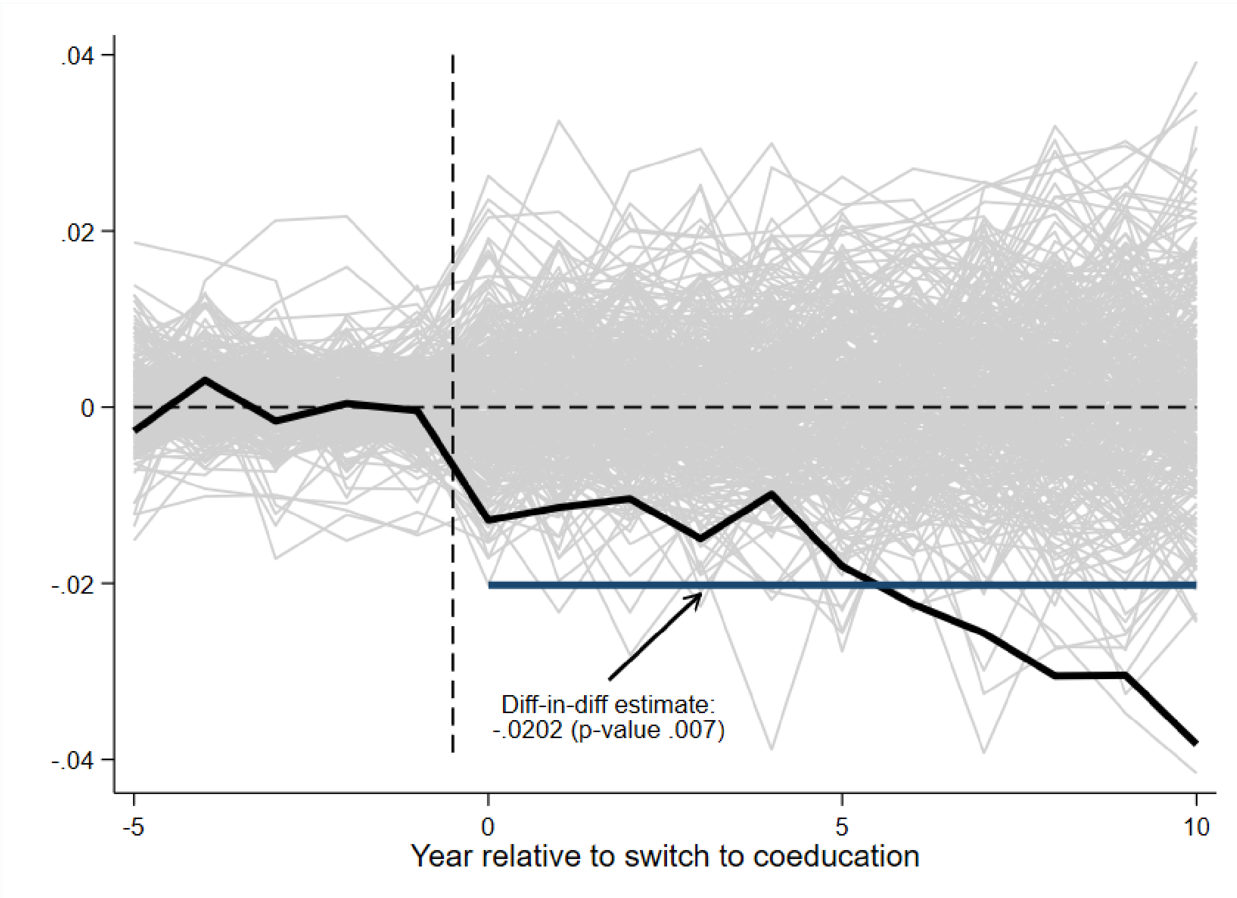
Notes: Plot shows the estimated effect of a cohort's share male on female students' propensity to graduate with a STEM major, with the college's conversion from all-female to co-education used as an instrument for the share male. Estimates are constructed by regressing the share of women majoring in STEM on equation 2.2, and scaling estimates of β_s by the event-study estimates obtained from running the same regression with the share male as the outcome variable. Ninety-five percent confidence intervals are obtained using a block bootstrap with 1,000 replications, clustering at the institution level. STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS).

Figure 2.8: The rescaled effect of general exposure to men on every major



Notes: Plot shows the estimated effect of a cohort's share male on female students' propensity to graduate with eacj major, with the college's conversion from all-female to co-education used as an instrument for the share male. Estimates are constructed by regressing the share of women majoring in each major on the difference-in-difference version of equation 2.2, and scaling those estimates by the difference-in-difference estimate obtained from running the same regression with the share male as the outcome variable. Estimates are then divided by the share of women choosing each major at time -1 to construct a semi-elasticity and then multiplied by 10 to calculate the effect of a 10 percentage point increase in the male share of the graduating class. Ninety-five percent confidence intervals are obtained using a block bootstrap with 500 replications, clustering at the institution level. STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS).

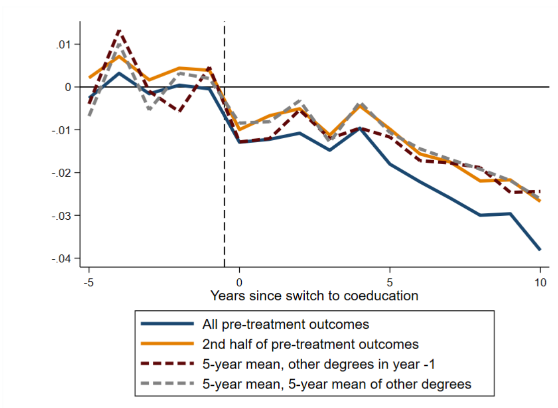
Figure 2.9: The effect of becoming coeducational on the STEM share of degrees awarded to women in synthetic control specification



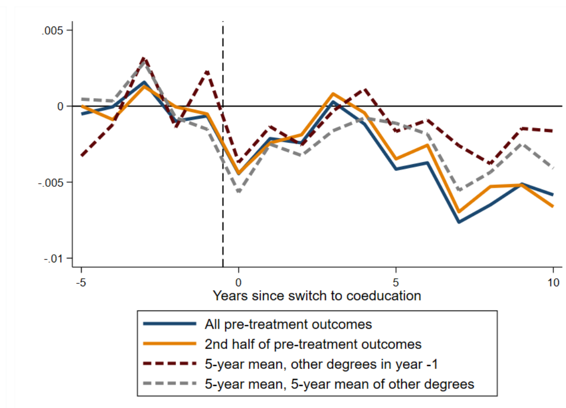
Notes: STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Sample is limited to schools with no missing years of data, and the treatment group is limited to schools that switched between 1969 and 2009. Figure shows estimates from synthetic control method in which synthetic control is chosen by matching on all pre-treatment outcomes, separately for each cohort of former women's college "switching" schools, and calculating the aggregate effect by average across cohorts by year relative to the switch. Grey lines report results of randomization inference procedure with 306 replications.

Figure 2.10: Synthetic control estimates using alternate specifications and majors

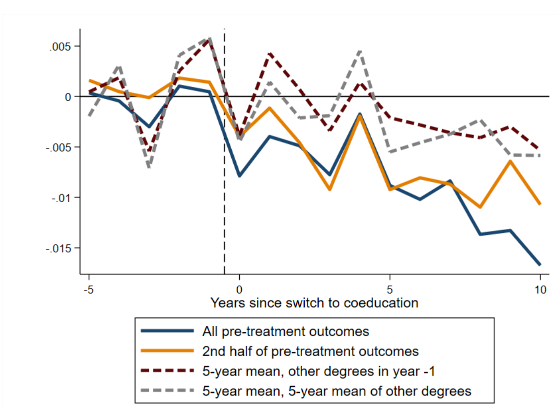
(a) STEM



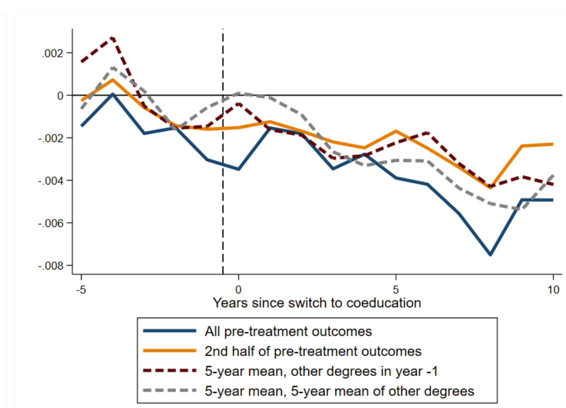
(b) Physical science



(c) Biology

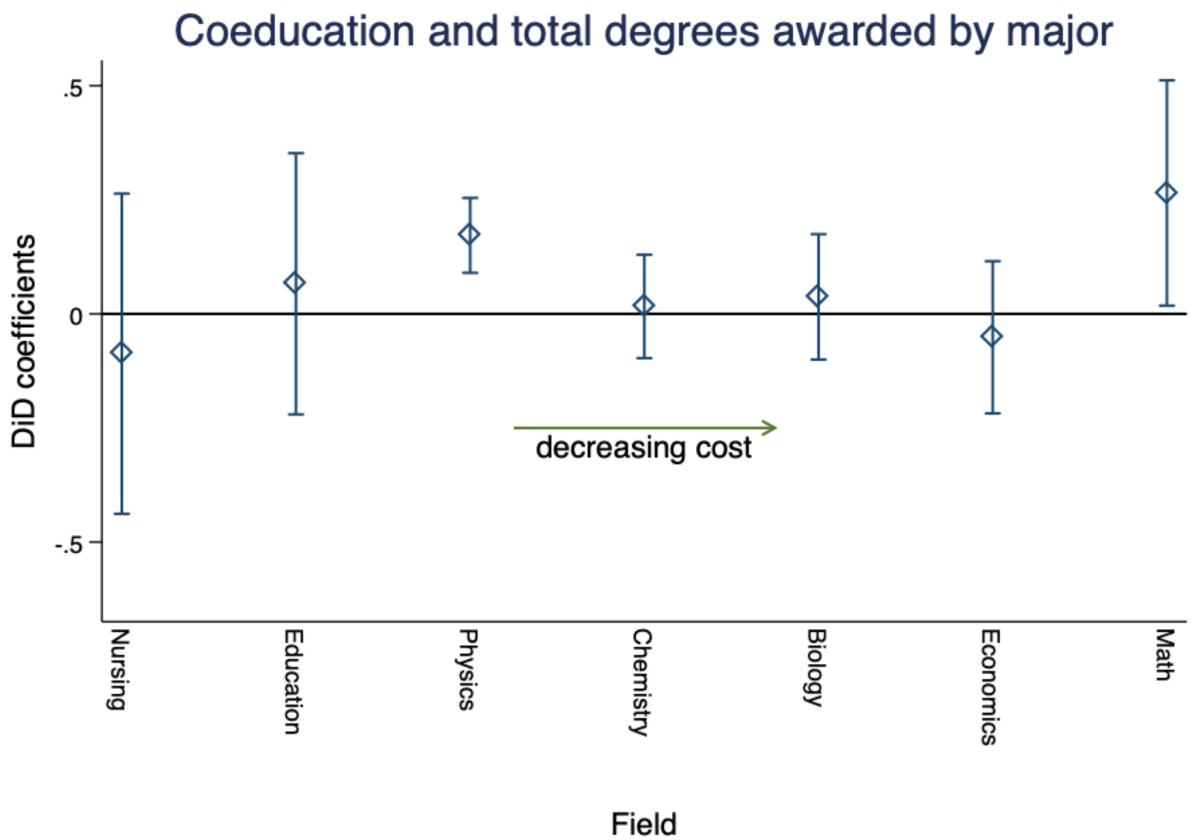


(d) Economics



Notes: STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Physical science degrees include chemistry, physics, geology, and other closely related fields. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Sample is limited to schools with no missing years of data, and the treatment group is limited to schools that switched between 1969 and 2009. Figure shows estimates from synthetic control method in which synthetic control is chosen by matching on all pre-treatment outcomes, separately for each cohort of former women's college "switching" schools, and calculating the aggregate effect by average across cohorts by year relative to the switch.

Figure 2.11: Difference-in-difference coefficients for effect of coeducation on log number of degrees awarded by field



Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of γ_f from equation 2.4 ranked in order of cost of field estimated in Hemelt et al. (2018).

CHAPTER III

How Tipping Models May Fail: Gender and College Major Choice

3.1 Introduction

It is well-known that men and women tend to choose different majors in college. Policy makers are particularly concerned about the lack of women's representation in science, technology, engineering, and mathematics (STEM) fields. In 2016, women earned 57% of bachelor's degrees in the United States, but only 37% of STEM bachelor's degrees.[1] Women who hold STEM degrees are also considerably more likely to work in healthcare fields and education than men who hold similar degrees (Beede et al., 2011). Many women who work in STEM fields believe that the gender gap in STEM is created by cultural conditions that make the field unfriendly to women rather than gender differences in interest in math and science (Frieze et al., 2004; Society of Women Engineers, 2016).

Following long tradition in the psychology and sociology literature, economists have come to acknowledge that gender identity plays a role in preferences over college major (Akerlof and Kranton, 2000).[2] Intuitively, choosing a college major that is more consistent with stereotypes about the opposite gender imposes a cost, and such costs influence decisions. Previous research has found compelling evidence that gender identity costs influence labor market decisions. In particular, Pan (2015) uses the concept of the identity cost to create a model of gender tipping in occupation. Intuitively, as women enter the labor market, certain occupations receive larger relative shocks to the labor supply of women. Once the female share of an occupation becomes large enough, the occupation "tips" and men rapidly exit the occupation.

[1]These statistics are from the Integrated Postsecondary Education Data System (IPEDS).
[2]See also Chapter II.

This paper studies whether a tipping pattern also exists in the gender composition of college majors. It is interesting to study gender tipping of college major in its own right, not just as an extension of tipping in occupations. For one thing, it seems worthwhile to try to get women into majors with a higher expected wage. Even accounting for differences in industry and occupation that different majors prepare graduates for, choice of college major plays a part in the gender wage differential (Brown and Corcoran, 1997). Just based on this factor, there is substantial policy interest in understanding what factors affect college major choice. Though expected future wages and beliefs about ability play a role, college major choice is primarily determined by heterogeneous tastes for difference majors (Wiswall and Zafar, 2015*a*; Zafar, 2013). Tastes for majors are potentially influenced by gender identity. College major therefore may exhibit a tipping pattern with regards to gender. If gender identity costs do play a role in college major choice, then there are policy recommendations associated with ameliorating costs associated with gender identity, such as making sure that there are role models and networking opportunities available for students in majors that are traditionally dominated by the opposite gender. Much of the policy interest is aimed at getting women into majority-male majors, as the majority-male majors tend to be better paid. However, it is worthwhile to study why men might rapidly exit majors that look like they will become majority female, as those men will tend to gravitate toward more male majors and possibly crowd out women who would otherwise enter.

The time path of college major choice is also suggestive of the possibility of a tipping pattern. The time path of the gender composition of certain college majors using administrative data on completed degrees suggests there could be a tipping pattern like Pan (2015) finds for occupations. If there is tipping, the male share of a major at a school will drop sharply after it reaches a particular critical value, the tipping point. In such a case, the time path of a major will look like an inverted S-shape. Figure 3.1 compares the share of men graduating with bachelor degrees in four majors nationwide to the share of men graduating with bachelor degrees nationwide. In 1966, psychology graduates were approximately 60% male. That share began to fall sharply in 1970, when the male share had fallen to approximately 45%, and continued falling rapidly until the early 1980s, eventually leveling off at a male share of approximately 25% – far below the male share of all graduates. Biology exhibits a similar, though less dramatic, pattern. The male share in 1966 was approximately 70%, above the male share of all majors. In the early 1970s, beginning when the male share was still approximately 70%, the male share began to rapidly fall, eventually leveling off at approximately 40% – also below the male share of graduates. Contrast those to mechanical engineering, which never fell below 85% male, and

English, which began at approximately 35% male. Changes in the male share of graduates in both of those majors roughly track the change in male share for all majors. It seems that mechanical engineering never fell to a large enough share of women to switch to a mostly-female equilibrium, and English had already reached a mostly-female equilibrium by the beginning of the data in 1966.

Given the time path of college major choice and the fact that occupations tip, it is surprising that I do not find gender tipping in choice of college major. I set up a framework based on the tipping models of Card, Mas and Rothstein (2008) and Pan (2015) and test that framework using methods based on Card, Mas and Rothstein (2008). I explain my finding that tipping does not occur by relaxing two assumptions made in the previous papers: I allow majors to grow and women to experience a cost of being in a major that is too "male." Relaxing these assumptions reveals that tipping may not happen if a major is sufficiently large or if identity costs to men are sufficiently small. I find that in the case of college major, it seems that tipping does not occur because the identity cost to men of being in too "female" a major is too small. My findings seem to be more consistent with a model of smooth changes in the female share from 0 to 1 than with the sudden, complete segregation described by Schelling (1971) and Card, Mas and Rothstein (2011). The first part of my contribution to the literature is therefore in expanding the tipping model to explain theoretically why it may not apply to college major, despite applying to occupation. In the conclusion I will also explore possible explanations for how tipping can occur in occupations but not college major.

The second part of my contribution is to the literature on how gender identity affects choice of college major. There is a large body of suggestive evidence that there might be a gender identity component to choice of college major, especially for women who enter very "male" majors. Carrell, Page and West (2010) find that having female professors in introductory math and science classes in college leads female students to perform better, take more math and science courses, and declare majors in math and science. This suggests that role models and gender identity can affect women's beliefs and preferences toward field of study. The psychology literature on stereotype threat suggests that when women are primed to expect gender differences in performance on math exams, their performance tends to suffer (Spencer, Steele and Quinn, 1999). However, women who are less feminine-identified may perform more closely to men (Schmader, 2002). Both of these suggest that gender identity may influence beliefs about performance in different fields. My project is more related to how gender identity affects men's preferences over college major, which is less studied but could be equally important to explaining why gender gaps exist in choice of college major. My finding that tipping does not occur suggests that gender identity is likely not important to men in choosing college major and may weaken the overall case for the importance of gender identity to the choice of college major for both men and women.

The paper is organized as follows. Section 3.2 describes the historical dynamics of occupational and college major choice. Section 3.3 describes a model of gender tipping in college major. Section 3.4 describes my empirical strategy for testing for tipping in college major. Section 3.5 describes the data I use to test for tipping. Section 3.6 discusses my results. Section 3.7 discusses why tipping fails in the context of college major choice. Section 3.8 concludes.

3.2 Gender and the dynamics of college majors

Tipping in occupations occurred against the background of women entering the labor force in greater numbers following the Second World War. Women tended to concentrate in particular occupations, especially clerical occupations, and some of those occupations changed from being almost entirely male to almost entirely female (Pan, 2015). Differences in the initial female share of occupations existed for many reasons, including widespread gender discrimination in hiring, especially in early periods, and restrictions on married women's holding jobs in several occupations.

Over the period of my study, which will begin in 1971, women's college attendance and graduation increased dramatically relative to men's. By the 1980s, women were more likely to go to college than their male peers (Goldin, Katz and Kuziemko, 2006). Similarly to occupations, women tended to enter certain majors, like health and education, earlier than others. Many universities which were originally open only to men became coeducational in a slow, major-by-major process. In many cases, male-only universities opened women's degree programs in nursing and education. These universities opened more and more programs to women throughout the 1960s and early 1970s, many in reaction to the passage of Title IX. However, not all universities had these restrictions on women, and differences in the existence of restrictions on women's majoring, and the timing of lifting such restrictions, may explain part of why the initial female share varies across majors and institutions in the same year. Variance in initial shares could also be due to differences in social norms about what women should study across years and geographic areas.

3.3 A model of gender tipping

I construct a model of future labor supply for men and women conditional on expected future wage and the female share of the major. This model is based on that of Card, Mas and Rothstein (2008) and Pan (2015). I make two modifications to the previous two models. First, I allow women to experience a utility cost to being in a heavily male major. Second, I explicitly account for the growth of programs by imposing a market clearing condition for the size of a major at a school rather than normalizing the size of the major. In the remainder of this section, I will describe the conditions which produce tipping behavior, which is characterized by rapid exit of men from a major at a particular school once the female share increases past a "tipping point."

Let n_s^m and n_s^w represent the number of men and women in some major at school s. The female share of this major at school s is

$$f_s = \frac{n_s^w}{n_s^m + n_s^w}$$

I define the inverse future labor supply equations $e_s^m(n_s^m, f_s)$ and $e_s^w(n_s^w, f_s)$ as the expected future wage necessary to induce the marginal man or women into that major given female share f_s.

Two assumptions on the shape of e_s^m and e_s^w are necessary to produce tipping behavior. The first is that labor supply is upward-sloping – that is, $\frac{\partial e_s^m}{\partial n_s^m} > 0$ and $\frac{\partial e_s^w}{\partial n_s^w} > 0$. The second assumption involves costs to gender identity. I assume that men experience a convex cost of being in a major that is too "female," meaning that

$$\frac{\partial e_s^m}{\partial f_s} \geq 0; \frac{\partial^2 e_s^m}{\partial f_s^2} > 0$$

The assumption that men experience a convex cost of being in a female major seems reasonable in light of the framework developed by Akerlof and Kranton (2000). They describe situations where people in occupations that do not fit with traditional gender roles, especially women in highly male occupations, may feel out of place and ambivalent about their work. Although men's gender identity is not highly studied, it seems that such logic should carry to allowing men to experience costs to identity from being in a highly female college major given that there is a link between college major and occupation.

Unlike Pan (2015) and Card, Mas and Rothstein (2008), I also allow women to experience a convex cost of being in a major that is too "male,"meaning that

$$\frac{\partial e_s^w}{\partial(1-f_s)} \geq 0; \frac{\partial^2 e_s^w}{\partial^2(1-f_s)} \geq 0$$

The second equation implies that $\frac{\partial e_s^w}{\partial f_s} \leq 0$.[3] Allowing women to experience identity costs

[3]Both Pan (2015) and Card, Mas and Rothstein (2008) assume that their "minority" group has no identity

of being in a highly male major makes sense in light of the existing literature on gender identity and college major, in particular Carrell, Page and West's (2010) finding that putting female professors in introductory STEM courses improves women's grades in those courses and raises the likelihood that female students declare STEM majors, even though female professors in such classes have no effect on men's performance or major-declaring behavior.

Employers have preferences over graduates of different colleges. This means that e_s^m and e_s^w may vary across schools. Unlike Pan (2015) and Card, Mas and Rothstein (2008), I impose a market clearing condition here rather than normalizing the size of majors. This is so that I can explicitly account for the growth of a major within my model.[4] I let q_s represent the quantity of graduates of a particular major at school s demanded at the equilibrium wage. By market clearing, it must be that $n_s^m + n_s^w = q_s$. I can therefore rewrite $n_s^m = (1 - f_s)q_s$ and $n_s^w = f_s q_s$. I can also rewrite the inverse labor supply equations as $e_s^m((1 - f_s)q_s, f_s)$ and $e_s^w(f_s q_s, f_s)$. Totally differentiating the inverse labor supply equations with respect to f_s finds that

$$\frac{de_s^m}{df_s} = -\frac{\partial e_s^m}{\partial n_s^m} q_s + \frac{\partial e_s^m}{\partial f_s} \tag{3.1}$$

and

$$\frac{de_s^w}{df_s} = \frac{\partial e_s^w}{\partial n_s^w} q_s + \frac{\partial e_s^w}{\partial f_s} \tag{3.2}$$

The size of the identity cost relative to the upward slope of the labor supply curves will determine the shapes of inverse labor supply curves, which determine the existence of tipping behavior.

I assume that employers are indifferent between employing new male and female graduates,[5] and that both male and female graduates enter national labor markets, so that the equilibrium wage in each major does not vary by school that the student graduated from.

cost for illustrative purposes, but claim that the analysis will still go through if there is a small identity cost for the minority group. Neither paper explicitly accounts for the minority group's identity cost or explores the restrictions on the minority group's identity costs that must be placed in order for tipping to occur. My model does allow women's identity cost to be zero, so the analysis in the two previous papers can still hold under mine.

[4]Note that both Pan (2015) and Card, Mas and Rothstein (2008) acknowledge that occupations and neighborhoods tend to grow over time, and Pan (2015) accounts for it in her empirical work.

[5]This assumption is plausible, especially in more recent years, because gender wage differences within occupations tend to be related to gender differences in experience in the workforce and demand for family friendly amenities (Goldin, 2014), which generally require spending time in the workforce. In particular, McDonald and Thornton (2007) found that 95% of the gender pay gap for new college graduates comes from different choices of major.

Therefore, an equilibrium with $f_s \in (0, 1)$ requires that

$$e_s^m((1 - f_s)q_s, f_s) = e^w(f_s q_s, f_s)$$

If a major is entirely male ($f_s = 0$), it must be that

$$e_s^m(q_s, 0) \leq e^w(0, 0)$$

and if a major is entirely female ($f_s = 1$), it must be that

$$e_s^w(0, 0) \geq e^w(q_s, 1)$$

Figure 3.2 depicts a case where tipping exists. The blue line represents e_s^m and the red lines represent e_s^w. Equilibria occur at the values of f_s where $e_s^w = e_s^m$ and at $f_s = 1$. Diamonds represent stable equilibria, and circles represent unstable equilibria. The highest level of e_s^w represented in the figure has three equilibria: A, B, and C. A and C are stable. B is unstable – positive shocks to women's future labor supply cause the marginal man at B to need a higher expected future wage to stay in the major, and he therefore exits, pushing the female share up. This repeats until the female share reaches 1.

Positive shocks to women's future labor supply cause e_s^w to lower, as women will now need a lower expected future wage to be willing to enter. As e_s^w lowers, the share of women in the integrated equilibrium rises smoothly until e_s^w is tangent to e_s^m. The point of tangency, which occurs at f^*, is the stable integrated equilibrium with the highest possible female share. Any further positive shocks to future female labor supply will leave only the fully-female equilibrium. I therefore refer to f^* as the "tipping point" – shocks to future labor supply that increase the female share f_s past f^* will cause men to rapidly exit the major, and the major at school s will become completely female.

The existence of this tipping pattern requires restrictions on the shape of the inverse labor supply functions. The identity cost to men of being in a "female" major must be large enough to make e_s^m steeper than e_s^w at high levels of f. Formally, there must exist some $f \in (0, 1)$ such that

$$\frac{\partial e_s^m}{\partial n_s^m} q_s \Big|_{f_s = f} < \frac{\partial e_s^m}{\partial f_s} \Big|_{f_s = f}$$

for all $f > F$. In such a case, e^m will first be decreasing in f_s as we walk down the labor supply curve. e^m will eventually begin to increase as the identity cost overtakes the effect of walking down the labor supply curve. The identity cost to women must also be relatively small. A necessary condition for tipping is that e^m is steeper than e^w at both high and low values of f_s, or

$$\left.\frac{de_s^w}{df_s}\right|_{f_s=1} < \left.\frac{de_s^m}{df_s}\right|_{f_s=1} \tag{3.3}$$

$$\left.\frac{de_s^w}{df_s}\right|_{f_s=0} < \left.\frac{de_s^m}{df_s}\right|_{f_s=0} \tag{3.4}$$

This requirement can be interpreted as men experiencing a substantially larger utility cost of being in a highly female major than women's utility cost of being in a highly male major.[6] Section 3.7 discusses the implications of relaxing either Equation 3.3, Equation 3.4, or both.

3.4 Empirical strategy

3.4.1 Key empirical insights of the tipping model

The model depicted in Figure 3.2 assumes that there are steady increases in women's future labor supply for a particular field of study. This assumption seems reasonable, as women's entry to college has steadily increased relative to men over the past several decades (Goldin, Katz and Kuziemko, 2006). However, women have been disproportionately entering certain majors over others during the sample period,[7] which suggests that there have been major-specific shocks to women's future labor supply. Majors with different initial female share f_s will react to these shocks differently.

For majors with female share f_s below the tipping point f_s^*, small shocks in relative female future labor supply will lead to smooth changes in the location of the integrated equilibrium share of women. If r is the maximum shock to women's future labor supply that a major can face, then majors with $f_s \in [0, f^* - r)$ will have $E[\Delta f_s | f_s] = g_1(f_s)$, where g_1 is a smooth function. Majors with f_s above the tipping point f_s^* have already begun the process of tipping. These majors therefore have $E[\Delta f_s | f_s] = g_2(f_s)$, where g_2 is positive and large, and $\lim_{\varepsilon \to 0^+} g_2(f_s^* + \varepsilon) - g_1(f_s^* - \varepsilon) > 0$. Majors with f_s below but close to the tipping point f_s^* – that is, majors with $f \in [f_s^* - r, f_s^*)$ – may or may not experience tipping behavior dependent on the size of the shock to future female labor supply.

Assuming that r is small, I can specify $E[\Delta f_s | f_s] \approx \mathbb{1}(f_s < f_s^*) g_1(f_s) + \mathbb{1}(f_s \geq f_s^*) g_2(f_s)$, which is discontinuous at f^*. Testing for tipping relies on testing for a discontinuity in the

[6]Note that this restriction allows for a point of tangency f^* for e_s^m and e_s^w to be very close to 1. In such a case, tipping does technically occur, but the break size will be small because there is very little room for the female share to increase.

[7]For example, as shown in Figure 1, women entered psychology and biology more quickly than average during the sample period, whereas they entered engineering less quickly than average.

expected change in share at the tipping point f^*.

3.4.2 Empirical strategy

My dependent variable is the change in the male share of graduates from major i at school s at time t, calculated as

$$D_{ist} = \frac{n^m_{is(t+\Delta t)}}{q_{is(t+\Delta t)}} - \frac{n^m_{ist}}{q_{ist}}$$

I study the male share because it makes more intuitive sense in the context of studying identity costs to men: if the female share increases past the tipping point, then all men will exit. I look at changes in the male share over both one year and five years, as one year might not be long enough for a major to adjust.[8] The previous section suggests that the change in share $E[\Delta f_{is}|f_{is}]$ is a smooth function of the female share f_{is} on either side of the tipping point f^*. In each year, I implement a search for a candidate tipping point f^* as detailed in the next section, then test for a break in the change in the male share around that tipping point. I then use ordinary least squares to estimate

$$D_{is} = h(f_{is} - f^*) + \delta \mathbb{1}(f_{is} > f^*_{is}) + X_{is}\beta + \theta_s + \varepsilon$$

Here, $h(f_{is} - f^*)$ is a quartic in the distance of a major from the tipping point. X_{ist} is a set of program characteristics, including the expected entry level wage of a graduate from that major, the program size, the total number of bachelor's graduates from the school, and a fixed effect for the broad category the major fits into.[9] θ_s is an institution fixed effect. The parameter of interest δ measures the size of the break in the change in share around the tipping point; a negative, large and statistically significant estimate of δ indicates that college major does in fact exhibit tipping behavior.[10] I calculate candidate tipping points, nationally, regionally, and by school, but all observations are pooled to calculate the size

[8]Note that D_{ist} represents the change in the male share $\Delta(1 - f_s)$ rather than the change in the female share Δf_s. I make this change to allow for greater ease of interpretation – looking at changes in the male share means we are looking at rapid exit of men from majors that reach a critical female threshold rather than rapid entry of women after majors reach a certain critical female threshold. Given that $\Delta(1 - f_s) = -\Delta f_s$, the analysis follows through in exactly the same way as described in previous sections, but we are looking for a jump *down* in $\Delta(1 - f_s)$ at f^* rather than a jump up, as the previous section would suggest.

[9]Broad category of major here refers to engineering vs. life sciences vs. social sciences, and other similar groupings.

[10]I run the analysis both using and not using weights by the size of the major; reported results do not include weights, but including weights does not substantially change the results. The results are robust to several differences in specification, including the exclusion of different controls for pre-period characteristics of majors and schools and allowing coefficients to vary on either side of f^*.

of the break.

Based on the structural break literature, I can ignore sampling error in the location of break points (Bai, 1997, e.g.). I therefore do not adjust standard errors to account for sampling error in f^*. However, the structural break literature finds that when the same sample is used to calculate both the break point and the size of the break, estimates of the break size δ have a nonstandard distribution (Leamer, 1978). Therefore, standard hypothesis tests will reject too often. Following Card, Mas and Rothstein (2008), to deal with this problem I use a fraction of the sample, randomly assigned, to calculate the size of the break.[11] Because the samples are independent, the estimate of δ will have a standard distribution. I cluster standard errors by institution.

3.4.3 Searching for tipping points

I search for a tipping point using a version of Card, Mas and Rothstein's (2008) fixed point method. This method takes advantage of the implication of the tipping model that

$$E[\Delta f_s | f_s < f^*] \leq E[\Delta f_s] \leq E[\Delta f_s | f_s > f^*]$$

In other words, when the female share of a major is equal to the tipping point, the female share should be changing at the same rate as the change in the female share of college graduates overall. I calculate the tipping point separately in each year, and I calculate tipping points on a national and regional[12] basis. In each year, I model the difference between the change in male share for a major and the overall change in the male share as

$$D_{is} - E[D_{is}|g] = R(f_{is})$$

where g indicates which group the tipping point is measured for (all observations, a geographic region, or school), $E[D_{is}|g]$ is the overall change in male share for group g, and R is a smooth function of f_{is}, here defined as a quartic. If g is not national, R is modeled separately for each group. The tipping point f^* is the real root of R between 0 and 1.[13]

[11] When the tipping point is calculated nationally and regionally, I use $\frac{1}{3}$ of the sample, randomly assigned, to calculate the size of the break. The other $\frac{2}{3}$ is used to calculate the candidate tipping point. When the tipping point is calculated by school, I use $\frac{1}{5}$ of the sample to calculate the size of the break and $\frac{4}{5}$ of the sample to calculate the candidate tipping point. The reason for splitting the sample differently when calculating by school is that calculating the tipping point is a data-hungry process; for reasons of sample size, I need to devote a larger portion of the sample to calculating the tipping point.

[12] "Regional" here is defined using the OBE (Office of Business Economics) Region in the NCES data.

[13] In the cases where R has two real roots between 0 and 1, the root where R has a more negative slope is chosen.

3.4.4 Identifying when tipping does not occur

In the case where there is no tipping, we expect to see either a break size of zero ($\hat{\delta} = 0$) or a nonexistent tipping point ($f^* = 0$). A break size of zero is straightforward to estimate, whereas a nonexistent tipping point is slightly more complicated. The tipping point $f^* = 0$ in the case where R has no real roots between 0 and 1. This indicates that there is no tipping pattern to the gender composition of college majors, at least in that year and group. When g is either a region or a school, rather than national, I test for the size of the break δ using only those groups that have $f^* > 0$.

3.5 Data

I use administrative data on the number of male and female graduates by major, level, and institution between 1971 and 2014 from the Higher Education General Information Survey (HEGIS) and the Integrated Postsecondary Educational Data System (IPEDS), both collected by the National Center for Education Statistics. The data is reported for the near-universe of degree-granting institutions in the US as part of federal requirements for the provision of federal student aid. Major codes were based on the four-digit 1990 Classification of Instructional Programs.[14] Majors with $f < 0.01$ and $f > 0.99$ were trimmed to avoid effects being driven by extreme majors, and in the main part of the analysis, majors with under 20 students were dropped.

Data on expected wage is constructed on a national level, as it is not clear that new college grads enter a local labor market and there is no finely-grained data available on average wage by major and institution. I construct expected wage based on the US Decennial Census from 1960, 1970, 1980, 1990 and 2000 and the American Community Survey from 2001-2015. The ACS collected data on college major starting in 2009. I construct a distribution of occupation by major for men in the ACS between 2009 and 2015 and then take weighted averages of the male hourly average wage by occupation in each year.[15]

[14]Classification of majors changed multiple times over the sample period. The bridging of four-digit major codes across various iterations of the CIP system was done using crosswalks available from the NCES. When possible, bridging of codes from HEGIS to CIP was done using crosswalks provided by the NCES. Where a bridge did not exist in the crosswalk, matching was done based on similar major names between HEGIS and the CIP system. If two majors ever were combined into one code, I treated them as if they were combined for the entire sample period. Majors were only included if they existed in the entire sample period. Majors coded as "other" and broad categories such as "Humanities or Sciences" were excluded.

[15]1950 occupation coding was used to ensure consistency of occupational classification across all years. This construction inherently assumes that the occupational distribution by major is constant in all years. While this assumption is likely too strong, data on major in earlier years does not have detailed enough classification to construct the distribution in earlier years. The average wage by occupation was constructed

3.6 Evidence of a lack of tipping behavior in college majors

Based on the model of tipping presented in Section 3.3, if there is tipping, we should see a break in the average change in the male share at a particular value of the female share f. Figure 3.3 presents binned scatterplots of the average five-year change in the male share against the female share in five-year periods. If there is tipping, in every plot we would expect to see an obvious break point in the average five year change in the male share. Just to the right of the break, the average change in the male share should be dramatically lower than it is just to the left of the break. In Figure 3.3, there is no obvious break point where the five year change in the male share drops in any of the five-year periods. Graphically, this indicates that we should not expect to find evidence of tipping. Similar plots of the change in male share over one year are presented in Figure 3.4. Once again, there is no obvious negative break in the change in the male share. In the rest of this section, I present formal evidence that while tipping by gender seems to occur in occupations, it does not appear to occur in college majors. I test one-, five-, and ten-year changes in the male share of majors and allow tipping points to be national and regional.

Table 3.1 presents the results when tipping points and break sizes are calculated on a national scale. Columns 2-4 look at one-year changes in the male share. When looking at one-year changes, the fixed point procedure returns a tipping point of 0 for nine different years. Even when tipping points are greater than zero, the break sizes in all years are very close to zero. Based on the fact that tipping points are zero in nearly half of the years studied and the fact that break sizes are small, it seems that there is no tipping occurring over a one-year period, or if there is, that we need more precision in the estimate of the tipping point.

We might expect that tipping requires some adjustment time. I therefore also consider five-year changes. Columns 5-7 of Table 3.1 look at five-year changes in the male share. When looking at five-year changes, the fixed point procedure returns a tipping point of 0 in nine years, and in years where the tipping point is nonzero, there is . This again suggests that tipping is not occurring, or that we need more precision in the estimate of the tipping point to see it.

Finally, in order to replicate Pan (2015), I consider ten-year changes. Columns 8-10

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using men aged 22-65 with a college degree or higher, then constructing a Mincer wage equation

$$\log \text{wage}_{iot} = \alpha + \beta \text{Ed}_i + \gamma_1 \text{exp}_i + \gamma_2 \text{exp}_i^2 + \theta_t + \zeta_o$$

where Ed_i is a series of indicator variables for having a master's, doctoral or professional degree, exp_i is potential experience, θ_t is a year fixed effect and ζ_o is an occupation fixed effect. The experience and education terms were then subtracted out to find an occupation's average entry-level wage.

of Table 3.1 look at ten-year changes in the male share. Once again, nine years return no tipping point, and in years with nonzero tipping points, break sizes are close to zero, suggesting that tipping does not occur in college majors.

In order to provide further precision, I also consider whether tipping occurs when tipping points are allowed to vary by Census region. This might occur if there are region-specific differences in the cost to men of being in a highly female major. Table 3.2 looks at one-year changes when tipping points are calculated at a regional level and regions with nonzero tipping points are pooled to estimate the break size. Column 1 notes the fraction of regions in which the tipping point is equal to zero, and Column 2 notes the average tipping point in regions where the tipping point is greater than zero. While there is at least one region with a non-zero tipping point in each year, all regions have nonzero tipping points in all but fourteen years. Perhaps more importantly, there are only two years with a statistically significant break: 1972 and 1973. In these years, there is a small but statistically significant negative break: majors with a female share above their tipping points had a decrease in the male share that was 3.6 percentage points larger than majors just below the tipping point in 1972, and 5.0 percentage points larger in 1973. In these years, the average tipping point in the regions with non-zero tipping points was 0.35 in both years, which is in line with Pan (2015). Overall, however, the results in Table 3.2 are not strong enough to indicate that tipping is occurring in college major over the course of one year, at least not for the entire period.

I also allow tipping points to vary by region when changes are estimated over five years. These results are presented in Table 3.3. Column 1 notes the fraction of regions in which the tipping point is equal to zero, and Column 2 notes the average tipping point in regions where the tipping point is greater than zero. While there is at least one region with a non-zero tipping point in each year, all regions have nonzero tipping points in ten years. There is no year in which there is a statistically significant negative structural break. Once again, this evidence suggests that tipping does not occur.

Finally, I allow tipping points to vary by region when changes are estimated over ten years.olumn 1 notes the fraction of regions in which the tipping point is equal to zero, and Column 2 notes the average tipping point in regions where the tipping point is greater than zero. While there is at least one region with a non-zero tipping point in each year except 1977, all regions have nonzero tipping points in only eleven years, and the only year with a statistically significant negative break size is 1975.

3.7 Why tipping may fail

3.7.1 Theory-based explanations

The necessary conditions for tipping described in Equations 3.3 and 3.4 may fail in three ways:

1. Neither men nor women have sufficiently strong identity costs – Equation 3.3 is violated
2. Only women have strong identity costs – Equations 3.3 and 3.4 are both violated
3. Both men and women have strong identity costs – Equation 3.4 is violated

Figure 3.5 depicts a situation consistent with case 1. In this case, e_s^m is monotonically decreasing[16] – for all values of f_s,

$$\frac{\partial e_s^m}{\partial n_s^m} q_s \geq \frac{\partial e_s^m}{\partial f_s}$$

As in the model described in Section 3.3, e_s^w is monotonically increasing. As a result, there is only one equilibrium, and positive shocks to female future labor supply will cause f_s to increase smoothly.

Monotonicity in e_s^m could occur either because q_s is large or because $\frac{\partial e_s^m}{\partial f_s}$ is small for all values of f_s. If monotonicity occurs because q_s is large, then tipping only occurs at smaller schools. Tipping behavior should also go away as majors within a school grow. If monotonicity occurs because the utility cost to men of being in female majors is relatively small, we would not expect a major of any size to experience tipping. If the utility cost to men of being in female majors shrinks over time, tipping points will rise over time and tipping behavior might disappear entirely.

Figure 3.6 depicts a situation consistent with case 2.[17] This implies that women have sufficiently strong identity costs of being in a highly male major to make e_s^w U-shaped, and men have sufficiently small identity costs to make e_s^m close to monotonic. In such a case, we could potentially tipping in the opposite direction than studied in this paper – when enough men enter a major, women rapidly exit. The analysis is similar to that in Section 3.3. In Figure 3.6, diamonds represent stable equilibria. Positive shocks to male future labor supply lead to steady decreases in the female share until the female share reaches

[16] As long as Equation 3.3 does not hold and Equation 3.4 holds, this analysis follows even if e_s^m and e_s^w are not actually monotonic in f_s.

[17] As in the previous section, as long as neither Equation 3.3 nor Equation 3.4 holds, this analysis follows.

f^*, which is the tipping point. Any further shocks to male future labor supply will cause a divergence to a completely male equilibrium. In this case, positive shocks to women's future labor supply could also produce smooth movements of the female share f, but f would not be able to fall below f^* except in the case of $f = 0$.

Figures 3.7 and 3.8 depict a situation consistent with case 3, where both men and women have identity costs that are strong enough to make their inverse future labor supply curves U-shaped. In this case, there will be no stable equilibrium where a major has both men and women. Figure 3.7 depicts a major with these shapes of future labor supply curves which receives a positive shock to women's future labor supply. Diamonds represent stable equilibria and circles represent unstable equilibria. Before the shock, there are three equilibria, A, B, and C. A and C, where $f_s = 0$ and 1 respectively, are stable equilibria. B is an unstable equilibrium. After a positive shock to future female labor supply, the marginal man at B will require a larger expected future wage to be willing to stay in the major. He will therefore exit, pushing the female share up. This will lead to a divergence of the major to the completely female equilibrium. After the shock, there are again three equilibria, A, D, and E. A and E are stable equilibria, and D is unstable.

Figure 3.8 depicts the same major when it receives a positive shock to men's future labor supply. Before the shock, there are three equilibria, A, B, and C. A and C, where $f_s = 0$ and 1 respectively, are stable equilibria. B is an unstable equilibrium. After a positive shock to future male labor supply, the marginal woman at B will require a larger expected future wage to be willing to stay in the major. She will therefore exit, pushing the female share down. This will lead to a divergence of the major to the completely male equilibrium. After the shock, there are again three equilibria, C, D, and E. C and D are stable equilibria, and E is unstable.

I can distinguish between the three cases based on the distribution of female share f across all majors. If we are in case 1, we should see smooth movements of the female share from 0 to 1, and may see any value of the female share. If we are in case 2, we should see a mass point at $f = 0$. There must also exist some value f^* such that there are no observations with $f \in (0, f^*)$. If we are in case 3, there is no stable integrated equilibrium, so we should see only mass points at $f = 0$ and $f = 1$. Figure 3.9 shows the distribution of female shares over a five-year period. While there are mass points at $f = 0$ and $f = 1$, there is positive density at all values of f, indicating that we are seeing case 1.

3.7.2 Testing for the reason tipping fails

Based on Equation 3.1, there are two possibilities for the reason why e_s^m might be shaped as described in case 1 in the previous section. The first is that the identity cost to men of being in a highly female major is relatively small. The second is that a program is large. If tipping only occurs in the smallest programs, my previous analysis may fail to pick it up. Therefore, it is necessary to test whether tipping is not occurring because men's identity costs are small or because the average program is large.

To test this, I break programs into quintiles by total number of graduates in each year. I then re-run my analysis for both one and five year changes.[18] The results from the analysis of quintiles 1 and 5 for one year changes are reported in Table 3.5. Columns 1-3 report the tipping point, break size, and standard error for the smallest quintile of programs, and columns 4-6 report the same for the largest quintile of programs. The smallest quintile is slightly more likely than the largest to have a nonzero tipping point. However, in the years where the tipping point is nonzero the smallest quintile is no more likely than the largest to have a nonzero estimate of δ. The results from the analysis of quintiles 1 and 5 for five year changes are reported in Table 3.6. Columns 1-3 report the tipping point, break size, and standard error for the smallest quintile of programs, and columns 4-6 report the same for the largest quintile of programs. Once again, while the smallest quintile is more likely than the largest to have a nonzero tipping point, in the years where the tipping point is nonzero the smallest quintile is no more likely than the largest to have a nonzero estimate of δ. Finally, Table Table 3.7 reports similar results by quintile for ten-year changes. In most years, I find a tipping point of zero in both quintiles.[19] Based on these results, it seems that the lack of tipping behavior in the gender composition of college majors occurs because identity costs matter less in the choice of college major, at least to men.

3.8 Conclusion

This paper explores the dynamics of gender segregation of college majors, with the conclusion that the gender segregation of college majors occurs differently from the gender segregation of occupations. Pan (2015) found that there are discontinuities in the flows of men into college majors that follow a Schelling tipping pattern. Using an approach similar to that of previous papers, I find no evidence that there are similar discontinuities in the flows of men into different college majors. I expand and test the tipping model of Card, Mas and Rothstein (2008) and Pan (2015) to explain why tipping may not occur in this context, finding that the lack of gender tipping in college majors is most likely because men do not experience sufficiently high costs to being in "female" majors. The model also

[18] I have also tried directly controlling for the size of the program and interactions of program size and female share within the fixed point equation R described in Section 3.4, with similar results.

[19] The results for quintiles 2-4 for one and five year changes can be found in Appendix Tables C.1, C.2, and C.3.

implies that tipping may become less important as majors grow.

It is puzzling that gender tipping does not occur in college major when it has been shown to occur in occupations. In fact, given that we could see graduates of particular majors as a flow into a stock of workers in particular occupations, we might expect college majors to be *more* volatile in their gender composition. The simplest explanation is that tipping only occurs in occupations that do not require college degrees. If tipping is large enough in occupations that do not require college degrees, then that may cover up the fact that tipping is not occurring in occupations that do. This explanation is supported by the facts that Pan (2015) finds that tipping points are lower and, except from 1980-1990, breaks around the tipping point are larger in blue-collar occupations than in white-collar occupations. She also finds less evidence of tipping in later decades than in earlier, which could be occurring as college attendance rises. However, Goldin, Katz and Kuziemko (2006) find that college attendance collapsed in the 1970s and picked back up again in the 1980s. If the reason for the difference between my findings and Pan's (2015) is that occupations requiring college education do not tip, we should see more occupational tipping from 1970-1980 than 1960-1970, which is not the case. Therefore, while a lack of tipping in highly-educated occupations may explain some of the lack of tipping in college majors, it is unlikely to be the whole story.

Perhaps the more compelling explanation is that in colleges, the men who leave tipped majors would have to go somewhere else in a college. Tipping in state-wide occupational labor markets is probably an aggregation of interactions that occur across hundreds of small offices within a state. Men who do not want to work with women can move to a new office in a role where they don't have to interact with women as often, or they can move into management within the same office. The cost of transferring colleges is much higher than the cost of changing jobs, so the majority of men who leave a major because the do not want to interact with women will have to find a new major within the same college. Men who have a high enough cost of interacting with women to be willing to pay such a cost would probably sort into colleges with low female shares in the first place. Given that, it might be reasonable to test for tipping within the entire student body of colleges, though to avoid deliberate manipulation of the female share by the admissions department, such an analysis would have to be limited to less selective schools.

3.9 Tables

Table 3.1: Tipping points and break sizes when tipping points are national

	$\Delta t = 1$ year			$\Delta t = 5$ years			$\Delta t = 10$ years		
Year	f^*	Break	s.e.	f^*	Break	s.e.	f^*	Break	s.e.
1971	0.047	0.000	0.000	0.000	–	–	0.000	–	–
1972	0.000	–	–	0.000	–	–	0.029	0.000	0.000
1973	0.040	0.000	0.000	0.027	0.000	0.000	0.037	0.000	0.000
1974	0.047	0.000	0.000	0.044	0.000	0.000	0.036	0.000	0.000
1975	0.030	0.000	0.000	0.045	0.000	0.000	0.045	0.000	0.000
1976	0.045	0.000	0.000	0.000	–	–	0.044	0.000	0.000
1977	0.046	0.000	0.000	0.046	0.000	0.000	0.046	0.000	0.000
1978	0.000	–	–	0.047	0.000	0.000	0.000	–	–
1979	0.070	0.002	0.006	0.008	0.000	0.000	0.041	0.000	0.000
1980	0.000	–	–	0.000	–	–	0.000	–	–
1981	0.000	–	–	0.049	0.000	0.000	0.000	–	–
1982	0.000	–	–	0.020	0.000	0.000	0.056	0.013	0.024
1983	0.826	−0.014	0.007	0.044	0.000	0.000	0.055	0.015	0.029
1984	0.000	–	–	0.095	−0.006	0.013	0.053	−0.004	0.033
1985	0.000	–	–	0.048	0.000	0.000	0.113	−0.003	0.015
1986	0.956	0.000	0.000	0.066	0.000	0.015	0.056	0.012	0.030
1987	0.037	0.000	0.000	0.052	0.012	0.043	0.052	0.085	0.065
1988	0.095	−0.001	0.006	0.054	−0.020	0.030	0.032	0.000	0.000
1989	0.068	0.007	0.007	0.040	0.000	0.000	0.069	0.008	0.017
1990	0.068	−0.001	0.008	0.163	−0.009	0.012	0.095	0.018	0.014
1991	0.961	0.000	0.000	0.000	–	–	0.096	−0.013	0.015
1992	0.109	−0.001	0.006	0.000	–	–	0.044	0.000	0.000
1993	0.047	0.000	0.000	0.037	0.000	0.000	0.049	0.000	0.000
1994	0.041	0.000	0.000	0.115	−0.014	0.012	0.000	–	–
1995	0.051	−0.008	0.036	0.061	−0.024	0.023	0.048	0.000	0.000
1996	0.134	−0.001	0.006	0.000	–	–	0.001	0.000	0.000
1997	0.058	0.002	0.011	0.028	0.000	0.000	0.180	−0.007	0.014
1998	0.096	0.002	0.006	0.000	–	–	0.221	0.007	0.011
1999	0.051	0.000	0.000	0.000	–	–	0.220	−0.020	0.011
2000	0.048	0.000	0.000	0.866	0.000	0.010	0.883	0.016	0.011
2001	0.884	0.005	0.004	0.872	0.003	0.009	0.000	–	–
2002	0.000	–	–	0.972	0.000	0.000	0.000	–	–
2003	0.855	−0.006	0.004	0.987	0.000	0.000	0.000	–	–
2004	0.051	0.010	0.036	0.031	0.000	0.000	0.000	–	–
2005	0.000	–	–	0.096	0.000	0.012			
2006	0.953	0.000	0.000	0.026	0.000	0.000			
2007	0.214	−0.006	0.004	0.047	0.000	0.000			
2008	0.061	−0.002	0.008	0.168	0.001	0.010			

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Regions are defined according to the Office of Business Economics's definitions in the NCES files, excluding the US Service Schools and Outlying Regions. Observations with $f < 0.05$ or $f > 0.95$ are excluded. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size. Ten-year breaks cannot be estimated past 2003 due to the nature of the data.

Table 3.2: Tipping points and break sizes: Tipping points regional, $\Delta t = 1$ year

	Tipping Points		Breaks over 1 year	
	(1)	(2)	(3)	(4)
Year	Proportion zero	Mean of Non-zero	Break size	s.e.
1971	0.5	0.050	0.011	0.0309
1972	0.25	0.353	−0.036	0.0049
1973	0.25	0.345	−0.050	0.0065
1974	0.25	0.049	–	–
1975	0.25	0.065	−0.010	0.0087
1976	0.5	0.048	−0.035	0.0404
1977	0	0.112	−0.001	0.0050
1978	0.25	0.061	−0.006	0.0095
1979	0.25	0.072	0.003	0.0070
1980	0	0.033	−0.014	0.0223
1981	0.5	0.068	0.012	0.0111
1982	0.75	0.418	0.012	0.0048
1983	0	0.685	−0.017	0.0043
1984	0	0.485	−0.010	0.0040
1985	0.25	0.754	0	0.0030
1986	0.25	0.670	−0.023	0.0047
1987	0.5	0.079	−0.009	0.0106
1988	0.25	0.072	−0.013	0.0082
1989	0	0.522	−0.003	0.0035
1990	0	0.070	−0.003	0.0070
1991	0.5	0.157	−0.001	0.0067
1992	0.25	0.084	−0.003	0.0069
1993	0.25	0.388	−0.017	0.0040
1994	0	0.085	−0.004	0.0080
1995	0.25	0.106	−0.011	0.0064
1996	0	0.101	−0.003	0.0064
1997	0.5	0.064	0.003	0.0106
1998	0.25	0.046	0.028	0.0215
1999	0.25	0.090	0.006	0.0072
2000	0	0.260	−0.011	0.0038
2001	0	0.478	−0.007	0.0030
2002	0	0.323	0.001	0.0028
2003	0.25	0.703	−0.002	0.0024
2004	0.25	0.236	−0.001	0.0035
2005	0.25	0.373	−0.017	0.0039
2006	0.5	0.138	−0.004	0.0067
2007	0	0.274	−0.016	0.0036
2008	0	0.486	−0.008	0.0029

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Regions are defined according to the Office of Business Economics's definitions in the NCES files, excluding the US Service Schools and Outlying Regions. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points were calculated by region, and all regions were pooled to calculate break size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size. Standard errors are clustered by institution.

Table 3.3: Tipping points and break sizes: Tipping points regional, $\Delta t = 5$ years

	Tipping Points		Breaks	
	(1)	(2)	(3)	(4)
Year	Proportion zero	Mean of Non-zero	Break size	s.e.
1971	0.5	0.005	–	–
1972	0	0.005	–	–
1973	0.25	0.004	–	–
1974	0.75	0.005	–	–
1975	0.5	0.003	–	–
1976	0.75	0.005	–	–
1977	0.25	0.007	0.005	0.0324
1978	0.5	0.006	–	–
1979	0.25	0.011	−0.032	0.0606
1980	0.75	0.001	–	–
1981	0.75	0.014	−0.015	0.0791
1982	0.25	0.044	−0.024	0.0169
1983	0	0.029	0.010	0.0171
1984	0	0.013	−0.027	0.0766
1985	0	0.086	0.002	0.0119
1986	0.25	0.045	0.018	0.0157
1987	0	0.082	−0.014	0.0123
1988	0.25	0.057	−0.009	0.0171
1989	0.75	0.038	−0.013	0.0378
1990	0.25	0.041	0.010	0.0190
1991	0	0.033	−0.016	0.0194
1992	0.25	0.018	0.007	0.0529
1993	0.25	0.041	0.022	0.0216
1994	0.5	0.109	0.008	0.0142
1995	0	0.037	−0.005	0.0169
1996	0.25	0.041	−0.007	0.0211
1997	0	0.110	−0.010	0.0127
1998	0.25	0.026	−0.016	0.0423
1999	0	0.052	−0.005	0.0174
2000	0.25	0.089	−0.023	0.0170
2001	0	0.411	−0.006	0.0059
2002	0.25	0.331	−0.010	0.0064
2003	0.5	0.035	−0.030	0.0310
2004	0.75	0.026	–	–
2005	0.5	0.126	0.012	0.0124
2006	0.25	0.045	0.012	0.0160
2007	0.25	0.090	−0.009	0.0111
2008	0.5	0.002	–	–

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Regions are defined according to the Office of Business Economics's definitions in the NCES files, excluding the US Service Schools and Outlying Regions. Observations with $f < 0.01$ or $f > 0.99$ are excluded to avoid effects driven by extreme majors; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points were calculated by region, and all regions were pooled to calculate break size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size. Standard errors are clustered by institution.

Table 3.4: Tipping points and break sizes: Tipping points regional, $\Delta t = 10$ years

	Tipping Points		Breaks	
	(1)	(2)	(3)	(4)
Year	Proportion zero	Mean of Non-zero	Break size	s.e.
1971	0.25	0.005	–	–
1972	0.5	0.002	–	–
1973	0.5	0.003	–	–
1974	0.5	0.00	–	–
1975	0.75	0.258	−0.044	0.0147
1976	0.25	0.084	−0.017	0.0139
1977	1	0	–	–
1978	0	0.054	0.014	0.0164
1979	0.25	0.017	−0.028	0.0273
1980	0	0.034	0.011	0.0184
1981	0.5	0.048	0.009	0.0222
1982	0.25	0.031	−0.011	0.0238
1983	0	0.071	0.021	0.0169
1984	0	0.060	0.014	0.0162
1985	0	0.062	−0.038	0.0177
1986	0	0.053	0.013	0.0165
1987	0.25	0.037	0.017	0.0226
1988	0	0.059	−0.009	0.0184
1989	0.25	0.114	−0.021	0.0161
1990	0.25	0.059	−0.013	0.01810
1991	0.25	0.038	−0.023	0.0234
1992	0.5	0.076	0.002	0.0211
1993	0.25	0.035	−0.014	0.0272
1994	0.25	0.087	−0.020	0.0154
1995	0.25	0.153	−0.004	0.0144
1996	0	0.082	−0.017	0.0150
1997	0	0.1183	0.002	0.0142
1998	0.25	0.052	0.015	0.0250
1999	0	0.102	0.030	0.0161
2000	0.25	0.449	−0.011	0.0075
2001	0.25	0.368	−0.016	0.0081
2002	0	0.060	−0.012	0.0189
2003	0.5	0.523	−0.018	0.0086

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Regions are defined according to the Office of Business Economics's definitions in the NCES files, excluding the US Service Schools and Outlying Regions. Observations with $f < 0.01$ or $f > 0.99$ are excluded to avoid effects driven by extreme majors; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points were calculated by region, and all regions were pooled to calculate break size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size. Standard errors are clustered by institution.

Table 3.5: Tipping by quintile of program size for quintiles 1 and 5, $\Delta t = 1$ years

	Quintile 1			Quintile 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0.916	0	0	0.023	0	0.004
1972	0	0	0	0	0	0
1973	0	0	0	0	0	0
1974	0	0	0	0	0	0
1975	0.939	0	0	0	0	0
1976	0	0	0	0	0	0
1977	0	0	0	0	0	0
1978	0.992	0	0	0	0	0
1979	0	0	0	0	0	0
1980	0	0	0	0	0	0
1981	0	0	0	0	0	0
1982	0	0	0	0.011	0	0
1983	0	0	0	0	0	0
1984	0	0	0	0.876	0.004	0.006
1985	0.977	0	0	0	0	0
1986	0	0	0	0	0	0
1987	0.997	0	0	0	0	0
1988	0	0	0	0	0	0
1989	0	0	0	0	0	0
1990	0	0	0	0	0	0
1991	0	0	0	0.926	0.002	0.005
1992	0.012	0	0	0	0	0
1993	0	0	0	0	0	0
1994	0	0	0	0	0	0
1995	0	0	0	0	0	0
1996	0	0	0	0	0	0
1997	0	0	0	0	0	0
1998	0	0	0	0	0	0
1999	0	0	0	0	0	0
2000	0	0	0	0	0	0
2001	0.969	0	0	0	0	0
2002	0	0	0	0	0	0
2003	0	0	0	0.435	0.004	0.003
2004	0	0	0	0.552	0.000	0.002
2005	0	0	0	0.971	0.007	0.007
2006	0	0	0	0	0	0
2007	0	0	0	0	0	0
2008	0.976	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

Table 3.6: Tipping by quintile of program size, $\Delta t = 5$ years

	Quintile 1			Quintile 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0.954	0	0	0.007	0	0
1972	0	0	0	0.002	0	0
1973	0.085	0.178	0.238	0.003	0	0
1974	0.086	−0.032	0.237	0	0	0
1975	0.993	0	0	0	0	0
1976	0	0	0	0	0	0
1977	0.065	0	0	0	0	0
1978	0.080	0	0	0	0	0
1979	0	0	0	0	0	0
1980	0	0	0	0	0	0
1981	0	0	0	0	0	0
1982	0.078	0	0	0.846	−0.016	0.014
1983	0	0	0	0.895	−0.024	0.013
1984	0.087	0	0	0	0	0
1985	0.076	0	0	0.006	0	0
1986	0.086	−0.091	0.170	0	0	0
1987	0	0	0	0.010	0	0
1988	0	0	0	0	0	0
1989	0	0	0	0	0	0
1990	0	0	0	0.006	0	0
1991	0.076	0	0	0	0	0
1992	0.086	−0.085	0.225	0	0	0
1993	0.064	0	0	0	0	0
1994	0.037	0	0	0	0	0
1995	0.073	0	0	0.015	0	0
1996	0.074	0	0	0.011	0	0
1997	0	0	0	0	0	0
1998	0	0	0	0.011	0	0
1999	0	0	0	0.017	0.005	0.066
2000	0.083	0	0	0.004	0	0
2001	0	0	0	0.411	−0.002	0.007
2002	0	0	0	0.101	−0.001	0.014
2003	0	0	0	0.012	0	0
2004	0	0	0	0.999	0	0
2005	0.087	0	0	0.119	0.032	0.013
2006	0	0	0	0.098	−0.001	0.013
2007	0	0	0	0.121	0.011	0.012
2008	0	0	0	0	0	0
2009	0	0	0	0	0	0
2010	0.075	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

Table 3.7: Tipping by quintile of program size, $\Delta t = 10$ years

	Quintile 1			Quintile 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0	0	0	0	0	0
1972	0	0	0	0	0	0
1973	0	0	0	0	0	0
1974	0	0	0	0	0	0
1975	0	0	0	0	0	0
1976	0	0	0	0	0	0
1977	0	0	0	0	0	0
1978	0	0	0	0	0	0
1979	0	0	0	0	0	0
1980	0	0	0	0	0	0
1981	0	0	0	0	0	0
1982	0	0	0	0	0	0
1983	0	0	0	0	0	0
1984	0	0	0	0	0	0
1985	0	0	0	0	0	0
1986	0	0	0	0	0	0
1987	0	0	0	0	0	0
1988	0	0	0	0	0	0
1989	0	0	0	0	0	0
1990	0	0	0	0	0	0
1991	0	0	0	0	0	0
1992	0	0	0	0	0	0
1993	0	0	0	0	0	0
1994	0	0	0	0	0	0
1995	0	0	0	0	0	0
1996	0	0	0	0	0	0
1997	0	0	0	0	0	0
1998	0	0	0	0	0	0
1999	0	0	0	0.289	−0.001	0.011
2000	0	0	0	0.448	−0.004	0.008
2001	0	0	0	0	0	0
2002	0	0	0	0	0	0
2003	0	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth−order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

3.10 Figures

Figure 3.1: Share of men in certain majors nationwide based on HEGIS and IPEDS data

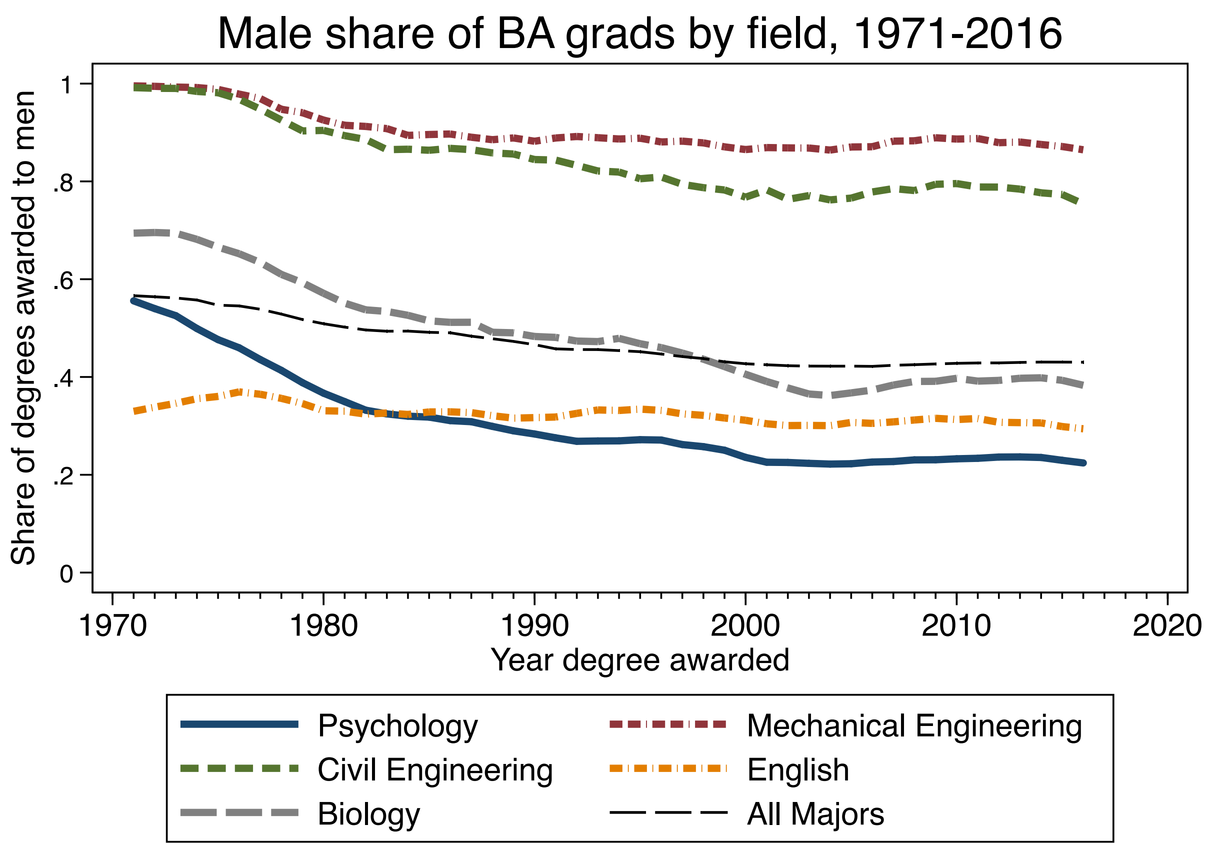


Figure 3.2: A model of tipping in college major

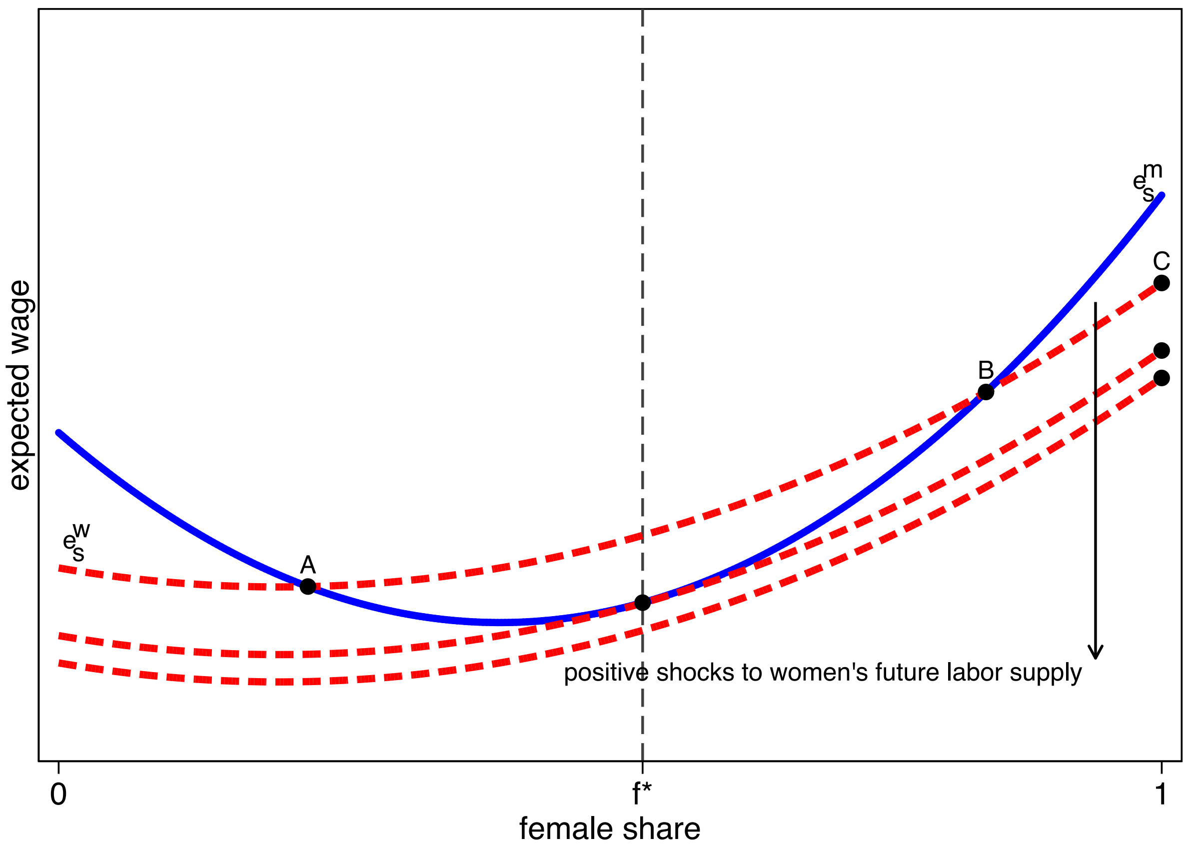
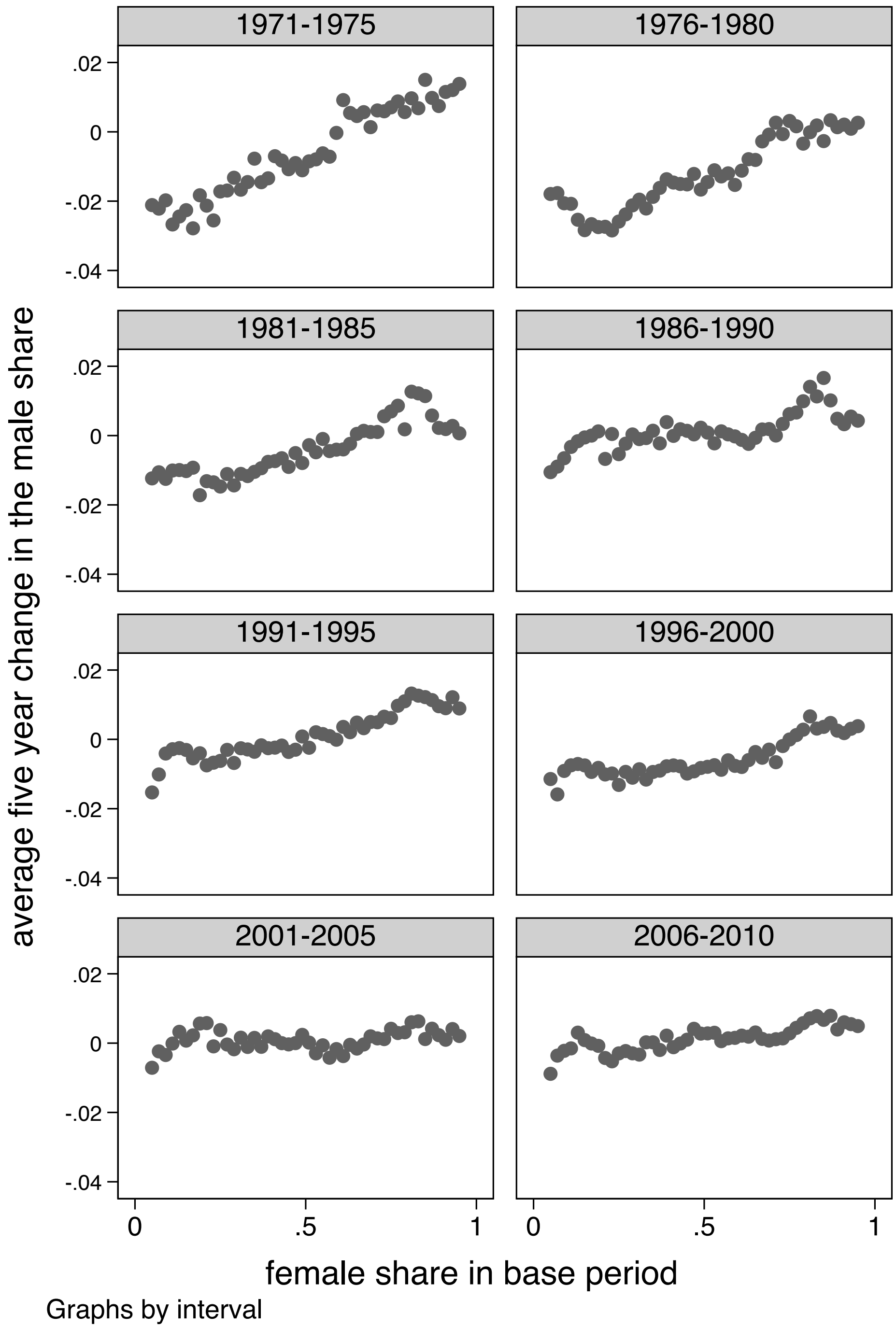
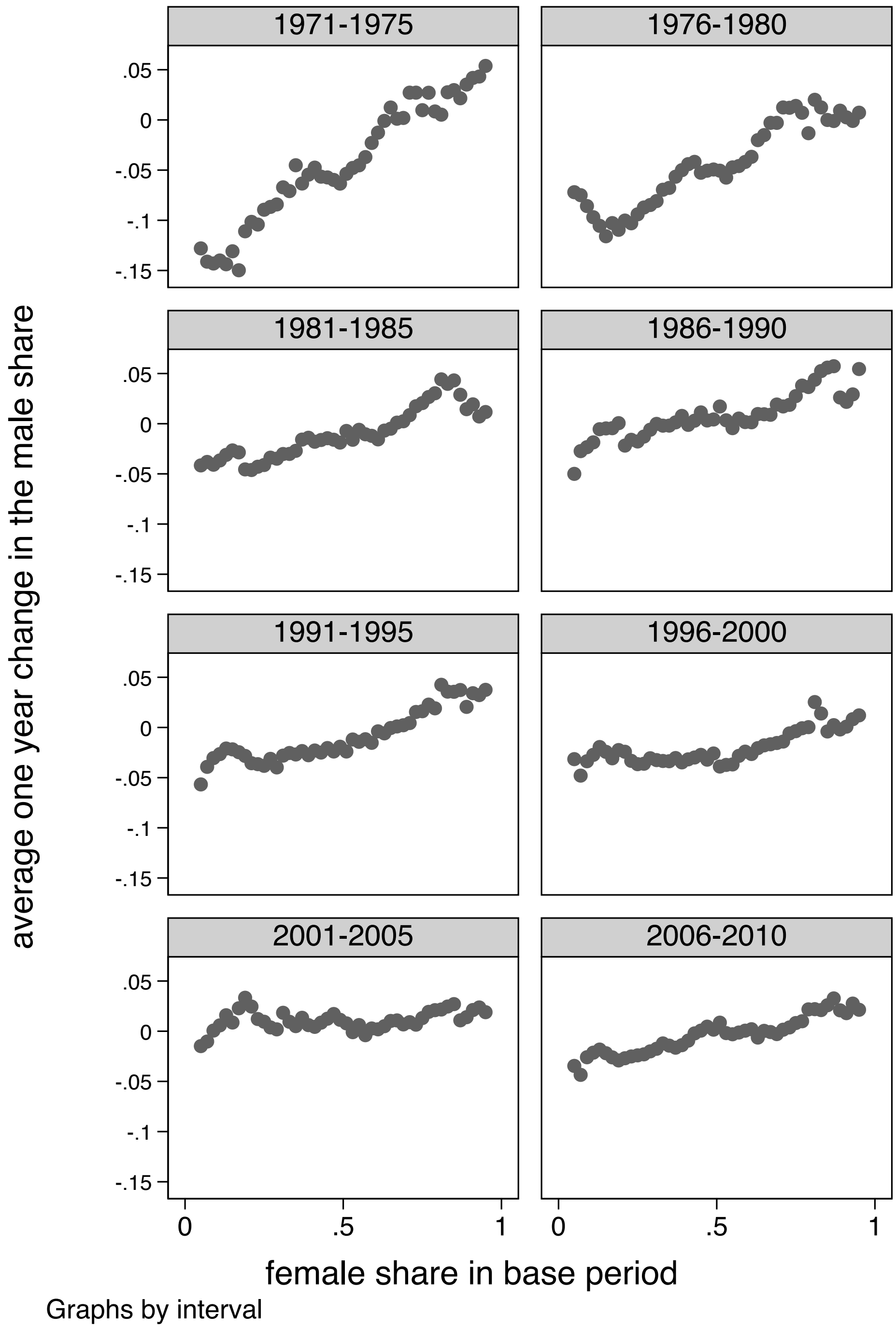


Figure 3.3: Average five year change in male share vs. female share in base period



Notes: Observations are a three-year moving average of the female share in a major×institution cell, grouped into bins of size 0.02. Only schools that are coeducational in the base period are included. Observations are weighted by the total number of graduates in that year.

Figure 3.4: Average one year change in male share vs. female share in base period



Notes: Observations are a three-year moving average of the female share in a major×institution cell, grouped into bins of size 0.02. Only schools that are coeducational in the base period are included. Observations are weighted by the total number of graduates in that year.

Figure 3.5: Future labor supply functions that do not produce tipping behavior - Case 1

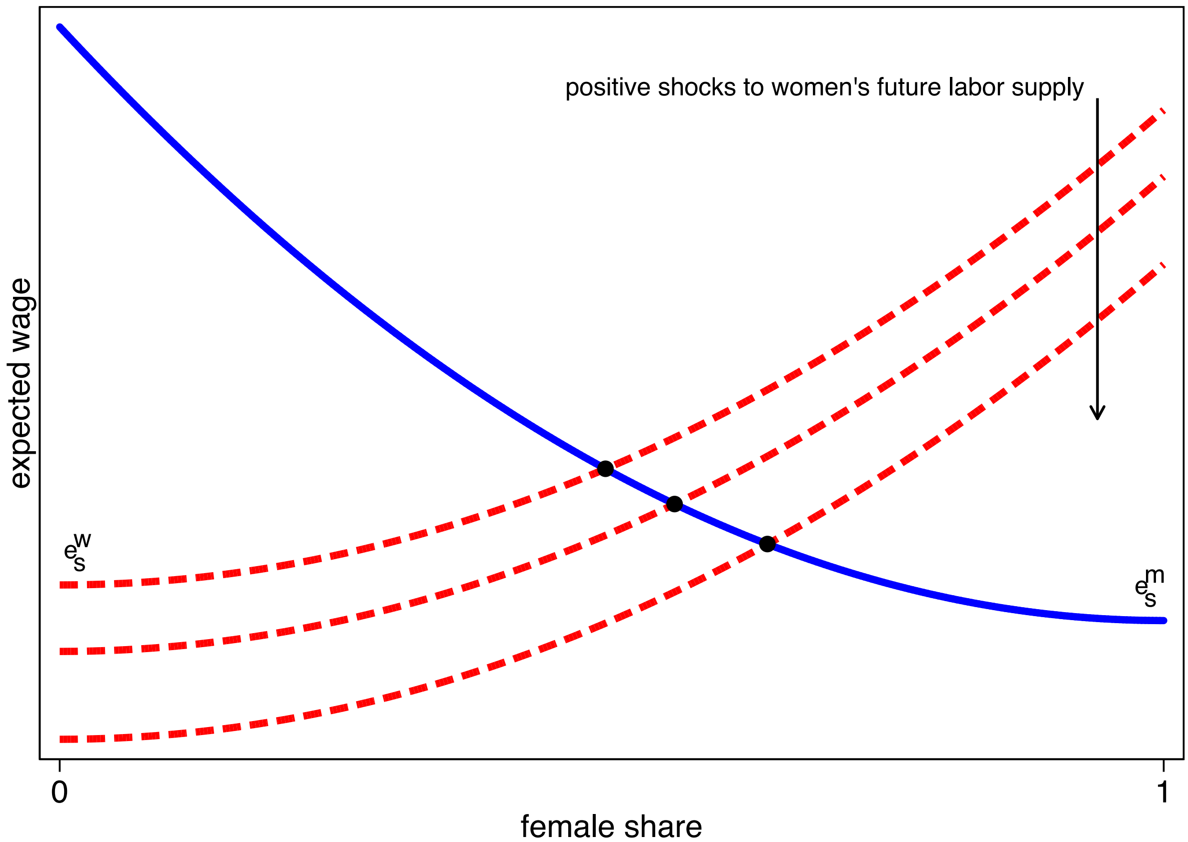


Figure 3.6: Future labor supply functions that do not produce tipping behavior - Case 2

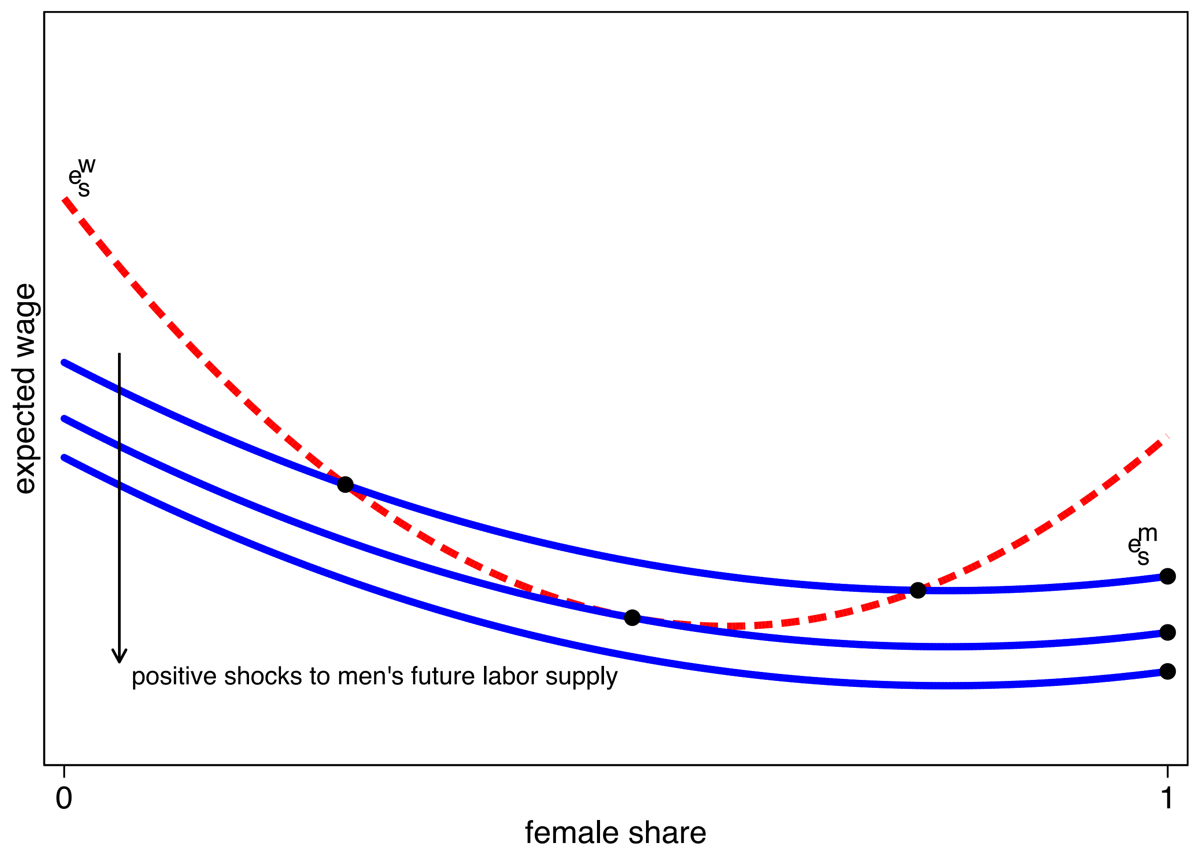


Figure 3.7: Future labor supply functions that do not produce tipping behavior - Case 3 with shocks to women's future labor supply

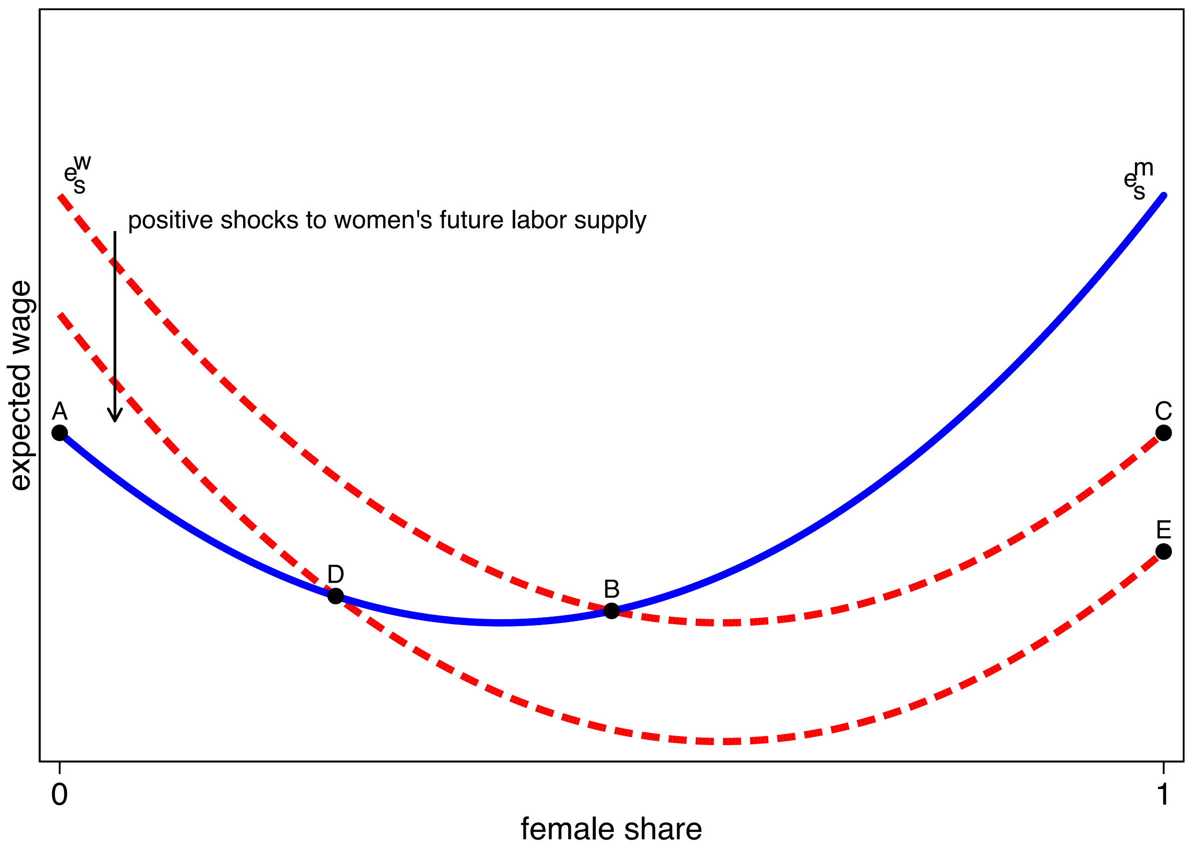


Figure 3.8: Future labor supply functions that do not produce tipping behavior - Case 3 with shocks to men's future labor supply

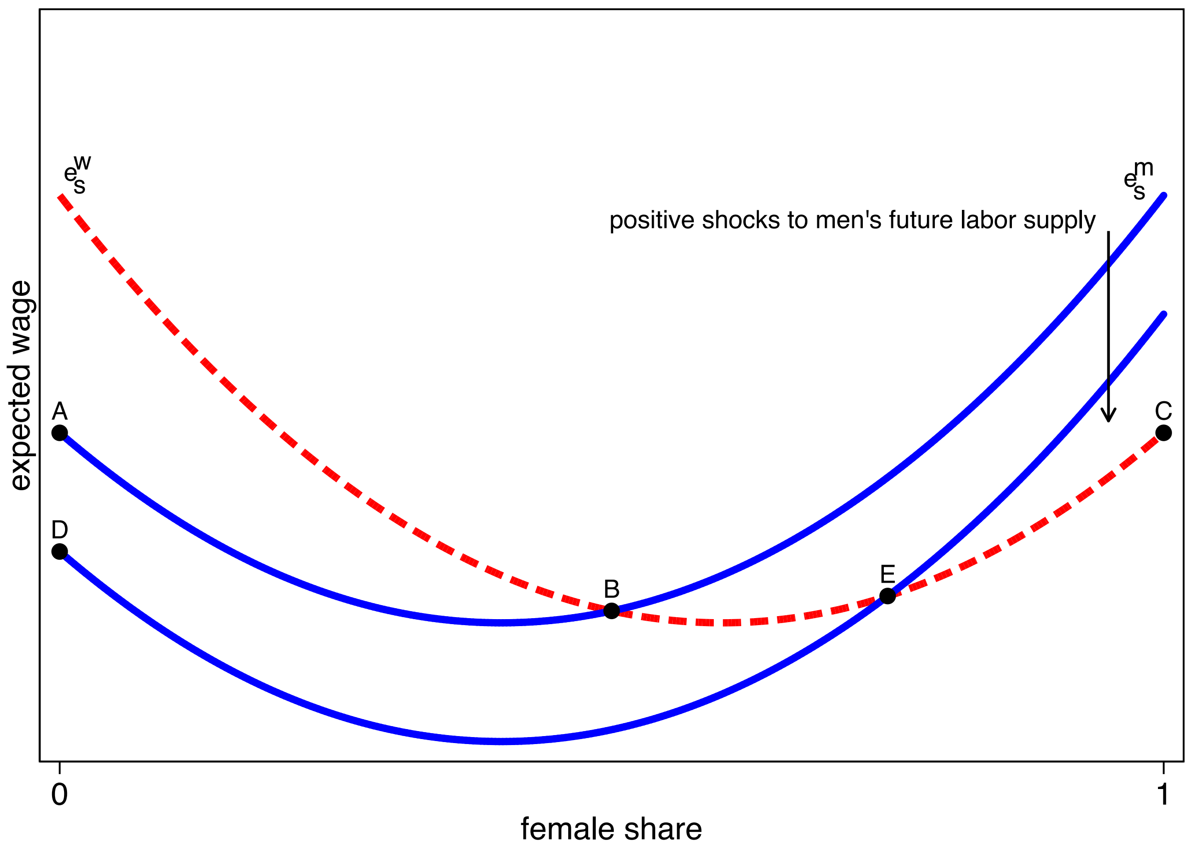
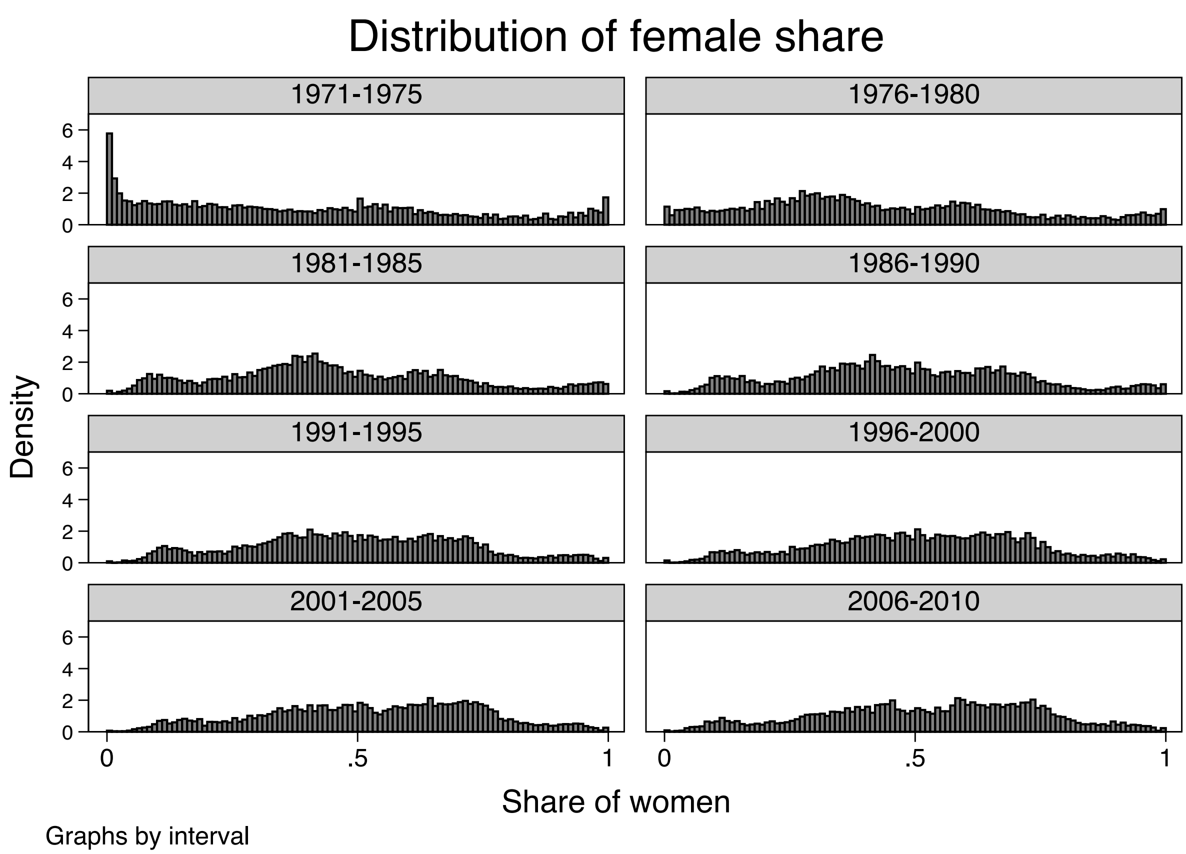


Figure 3.9: Histograms of female share of major over five-year intervals



Notes: Observations are completions of men and women at the major×institution level. Shares are a three-year moving average. This figure includes only coeducational institutions. Observations are weighted by size of the major×institution cell.

APPENDIX A

Chapter I Supporting Material

A.1 Data construction and definitions

A.1.1 Period 1: Coursework tracks

In period 1 of my model, students choose a track of coursework c to maximize expected lifetime utility. There are three track options: Pre-Engineering/Computer Science, Pre-Science, and Non-STEM. These options are based on the prerequisites for various degrees at The University. Students must complete all of these prerequisites by the end of their fourth semester to be placed in a particular coursework track.

Because many computing majors enter The University through the College of Engineering, their coursework tracks are aggregated into the Pre-Engineering/Computer Science track. College of Engineering students must take three semesters of calculus, two semesters of physics, and one semester of chemistry courses as part of their general education requirements. In 2000, engineering students also became required to take a programming course. Prospective computer science students who enter The University through the College of Liberal Arts are required to take three semesters of calculus, two science courses, two programming courses, and one discrete math course before declaring the major. To match these pre-requisites and to capture students who were planning to be engineering or computer science majors but dropped out halfway through the prerequisites, I have defined the pre-Engineering/CS track to require that students take at least one semester of calculus on campus within the first two semesters at college, plus one semester of either physics or chemistry and one programming or engineering course within the first four semesters on campus. Students can substitute AP credits for the physics or chemistry requirements. The in-track GPA for pre-Engineering/CS students is their GPA over calculus, computing, and engineering coursework.

Science majors are housed in the College of Liberal Arts.[1] Most science majors require coursework in physics, chemistry, and calculus, and life sciences majors require coursework in biology as well.[2] To match this, the Pre-Science track requires students to either take one semester of calculus on campus within the first two semesters or to have AP credit that places them out of both calculus 1 and 2. Students must also take an introductory course in physics, biology, chemistry, or statistics within the first four semesters. Students who meet the requirements of both the Science and Business tracks are assigned based on the field in which they have taken a larger number of credits.

Non-STEM majors are housed in the College of Liberal Arts. While these majors often require calculus and statistics, the requirements are generally less onerous than those of the STEM majors. Students are classified as Non-STEM if they do not meet the requirements of either the Pre-Engineering/CS track or the Pre-Science track.

A.1.2 Periods 2 and 3: Groups of majors

Majors are aggregated into groups for the purpose of this analysis. This section lists majors that are part of each group.

My sample is students who entered through the College of Liberal Arts and the College of Engineering. The College of Business, College of Dentistry, and College of Nursing do not accept students as freshmen and therefore require a cross-campus transfer from the College of Liberal Arts. Some students also transfer to other colleges that do accept freshmen, such as the College of Kinesiology, the College of Education, and the College of Fine Arts. While very few students transfer into freshman-accepting colleges, students who do are coded into the appropriate group based on subject matter. Students can also transfer between the College of Liberal Arts and the College of Engineering. Typically, cross-campus transfers require completing prerequisites; cross-campus transfers to the College of Engineering must meet all prerequisites for engineering majors, which are covered by completing the pre-Engineering/CS track.

Computing Computer science, computer engineering, electrical engineering

Engineering Aerospace engineering, biomedical engineering, civil and environmental engineering, chemical engineering, nuclear engineering, engineering physics, industrial

[1] Note that health sciences have been classified as "Non-STEM." This is because health majors at The University typically do not have to take calculus or extensive science coursework outside of their departments. The health majors are not especially popular among my sample – kinesiology majors are admitted into the College of Kinesiology, and nursing and dental hygiene are most common among transfer and second degree students.

[2] One exception is statistics, which like computer science requires students to take calculus and introductory programming.

and operations engineering, materials science and engineering, mechanical engineering, space and climate science, naval engineering

Science Chemistry, biological sciences, physics, astronomy, neuroscience, mathematics, statistics, environmental and earth science

Business Business, economics, sports management (for students who transferred to College of Kinesiology)

Humanities/Social Sciences/Other Humanities (foreign languages, area studies, international studies, classics, religious studies, philosophy, English, group studies, linguistics), social sciences (anthropology, psychology (including cognitive science and biopsychology), political science, sociology, history, and other social science), communications, public administration, nursing, dental hygiene; for students who transferred into the relevant colleges, art, architecture, education, kinesiology

A.1.3 First time and transfer students

My data does not directly identify transfer students before 2002. I define a first-time undergraduate as an undergraduate student who entered The University with less than one semester (18 credit hours) of transfer credit, excluding AP and IB credits, who does not have transfer credit for introductory composition. Spring entrants and students in second degree programs in nursing and dental hygiene were also excluded.

A.2 Curricular changes during the sample period

During the sample period, The University went through one major curricular change for computing degree programs, which affected students who declared a computer science major in Spring 2001 and later.[3] This curricular change consisted of two parts: a major change to the structure of the introductory programming course, making the course less technical, and a diversification of upper level courses that could fulfill requirements. If curricular changes in computing programs disproportionately drove away women, then that will present a threat to my analysis. Curricular changes are generally binding only on students who declare their major in or after a particular semester, but older students can elect to switch to the new curriculum. That means that changes that are likely to make

[3]There was also one minor curricular change, which allowed more flexibility in upper-level electives taken and required a senior project. This seems to have been a change for the entire College of Engineering and is unlikely to have significantly affected students' majoring behavior. In particular, the senior project seems to have been meant to line up with accreditation requirements.

a major harder to finish will probably not affect more senior students, but changes that make a major easier to finish (especially in terms of later classes)

In order to empirically analyze the gendered effects of these curricular changes, I look at similar changes at peer institutions. I use data from the Integrated Postsecondary Education Data System (IPEDS) on the log number of degrees awarded to men and women between 1985 and 2016 at institutions ranked within the top 25 for computer science by *U.S. News and World Report* in 2019. Information on institutions' curriculum in computing majors was gathered from archived versions of department websites on the Wayback Machine (archive.org). The more technical version of introductory programming depends on a textbook that was written in 1995 and published in 1999, so the beginning of the Wayback Machine does not constrain the start of my sample of universities. Information on upper level required courses is not available on the Wayback Machine for most universities before 1997, and it is not available for any university before 1994. The analysis of peer institutions therefore begins with the first academic year archived by the Wayback Machine or with the starting year of the first curriculum archived by the Wayback Machine.

I run the following regression to understand the effects of similar curricular changes at peer institutions to The University.

$$fshare_{stk} = \beta_0 + \beta_1 Expose_{stk} + \xi_s + \zeta_k + \eta_t + \varepsilon_{stk} \tag{A.1}$$

$fshare_{stk}$ represents female share of bachelor's degrees awarded in major $k \in \{CS, CS, EE\}$ at school s in year t . $Expose_{stk}$ is an indicator variable for whether a student was exposed to a particular curriculum. I run the regression with four different versions of the exposure variable, representing exposure to the change in freshman, sophomore, junior, or senior year.[4] ξ_s is a school fixed effect, controlling for the average level of the computing gender gap within a school. ζ_k is a program fixed effect, controlling for the average gender gap by type of computing program (computer science, computer engineering, and electrical engineering). η_t is a year fixed effect, controlling for the evolution of the computing gender gap over time.

A.2.1 Introductory Programming

Over the course of the sample period, there were three introductory programming courses offered at The University. In every year, at least two of these were available to students. In my main analysis, I aggregated these into one "introductory programming" course.

[4] Each year is approximated based on four-year graduation.

The first course, Introduction to Computing (CS 112), was offered from 1995 to 2000.[5] CS 112 was a highly technical, "bottom-up" course that began with understanding how computers actually work and then moved to programming. Interviews with the professor who taught CS 112 and students who took CS 112 suggest that previous programming experience was not particularly helpful in this course, as the course covered material that is generally not covered in traditional programming coursework. Students who planned to become computing majors were encouraged to take CS 112 because it was the best preparation for core coursework, especially in computer science, but other programming coursework and a placement test were both accepted.

The second course, Introduction to Programming (CS 110), was offered throughout the sample period. CS 110 is a traditional introductory programming course. CS 110 is generally taught in one or more high-level programming languages.[6] While the languages CS 110 is taught in do occasionally change,[7] the substance of the material and the concepts taught are broadly the same. Before 2000, CS 110 was meant for students who wanted to learn programming but who were not intending to become computing majors. After the curricular change, all students from the College of Liberal Arts who wanted to take introductory programming took CS 110.

The third course, Introduction to Programming for Engineers (Engineering 100), was offered beginning around 1997 and became required for all engineering students by the fall of 2001. In the early years of Engineering 101, students who took the course and then became computing majors were required to take a bridging course; by fall 2000, that requirement had gone away. Engineering 100 teaches many of the same concepts as CS 110, as well as some skills necessary for modeling in mathematics and physics. The class is typically split between MATLAB and a high-level programming used in industry. Beginning in roughly 1999, students from the College of Engineering who wanted to take programming but who did not intend to be computing majors took this course. Beginning in 2000, all College of Engineering students who wanted to take programming took this course. Beginning in 2001, all College of Engineering students took this course.

Four of the top 25 universities for computer science at some point instituted a course similar to CS 112 as an introductory programming course. At some, but not all, of these universities the course was required for electrical and computer engineering students but not for computer science students.[8] Two universities discontinued the course. Information

[5] CS 112 was eliminated because of the departure of the professor who taught it.

[6] Currently, the course is taught primarily in C++ and Python, with some exposure to other languages when appropriate.

[7] Changes to the language of introductory programming courses are very common and tend to occur in response to trends in languages used in industry.

[8] Additionally, several universities instituted a similar course in the sophomore year. Those universities

on whether a university instituted a similar course is based on whether an introductory computer science or computer engineering course used a particular textbook in their introductory course. This information was provided by one of the authors of the textbook and confirmed using archived versions of university websites on archive.org. The first edition was published in 1999, and no university other than The University used it before then.

Table A.2 reports the estimated coefficients of Equation A.1 for *not* having an introductory programming course in the style of CS 112. The coefficient of interest is for No CS 112. This coefficient is identified from changes in whether a course similar to CS 112 was required for computer science, computer engineering, or electrical engineering students within a particular institution and major. My results show that there is no effect on the female share of a major from removing a requirement similar to CS 112 in the sophomore, junior, or senior years. This makes sense because the course is typically taken by freshman. There is a marginally significant positive coefficient on the removal of CS 112 for freshman year, which suggests that, if moving to a less technical introductory programming course has any effect on the female share of a computing field, it makes the field *more* female. This works in the opposite direction from the effects of the dot-com crash and therefore is not likely to be a confounder.

A.2.2 Diversification of upper-level electives

The other major portion of the 2001 curricular change was a diversification in the upper-level courses that computer science majors were required to take. Students who declared before Spring 2001 were required to take either Operating Systems (OS) or Compilers, which are among the most difficult upper-level electives offered in most computer science departments.[9] From Fall 2001 on, students chose from a list of several different options for electives. Computer engineering students went through the same curricular change. Electrical engineering students never were required to take either course. Intuitively, this means that a computer science or computer engineering degree at The University became somewhat easier to achieve.

This diversification of the computer science and computer engineering curriculum was relatively common among the top 25 universities for computer science. Eight of the top 25 schools removed a similar requirement, either that students take OS or that they choose

are coded as not requiring CS 112, as starting with the bottom-up approach after having basic programming knowledge is a separate experience from having a bottom-up version as the first course.

[9] OS is a considerably more popular course as it has much more applicability to computer science as used in industry. The course is still very popular despite not being required.

between OS and one or two other courses, between 1997 and 2017. Six of the top 25 schools still require students to take OS. I began my analysis of peer institutions with the academic year of the earliest archived version of computing curricula on the Wayback Machine, as it is likely that institutions coded as never requiring OS simply removed the requirement earlier.

Table A.3 reports the estimated coefficients of Equation A.1 for relaxing the requirement that students take OS. The coefficient of interest is for No OS. Removing the OS requirement from a computing program did not change the female share of graduates from that program unless the change occurred during a cohort's senior year. If the change occurred during a cohort's senior year, removing the requirement for OS tends to decrease the female share of a department's graduates by 1.1 percentage points. This could be because women are more likely to plan ahead, and the removal of OS allows students who have either failed the course or not planned ahead soon enough to take the course on time to finish a computing degree more easily. Because the change at The University occurred in 2001, only seniors in 2001 should have been affected. The dot-com crash primarily affected students who were underclassmen in 2001. Therefore, the relaxing of the requirement for OS is not likely to be a confounder.

A.3 Replicating other results about grades and gender

It is important to check whether the previous results about grades that I cite hold in my sample as well. I first check whether women are more likely to drop out of computer science courses conditional on a B than men, as Goldin (2015) found in economics classes. I also check the Koester, Grom and McKay (2016) and Matz et al. (2017) result that women underperform in STEM relative to men and underperform their GPA outside of those classes by more than men.

A.3.1 Differential responses to letter grades by gender

Looking directly at men's and women's responses to GPAs could potentially mask responses to getting Bs in early coursework. For this reason, I directly examine attrition conditional on grades in first computer science classes. Figure A.2 shows the relative probability that women chose computing majors conditional on each letter grade in introductory programming. The dark bars represent students who entered before the dot-com crash, while the light bars represent students who entered after the crash. The left panel shows first majors, the period 2 choice, and the right panel shows final majors, the period

3 choice. If, as Goldin (2015) found with economics coursework, the probability of choosing a computing major fell by more than men conditional on earning a lower letter grade, we would expect to see that each bar would be shorter than the one to its left, and if the dot-com crash increased women's sensitivity to poor grades, the dropoff would be steeper. This is in fact not the case; women's probability of choosing computing as either their first or final major does not seem to be systematically related to their grades in introductory programming.

Figure A.3 shows the relative probability that women chose computing majors conditional on each letter grade in programming 2, as that may be a more critical course for actually indicating what it is like to be a computer scientist. Once again, there does not seem to be a systematic dropoff in the probability that women choose computing majors based on each successive grade, although it should be noted that before the crash there did seem to be a dropoff in probability within broader letter grades, both for first and final major– for instance, the relative probability that women in the 1996 to 2000 cohorts who earned a B had a lower probability, relative to their male peers with the same grade, than women in those cohorts who earned a B+. However, this effect did not exist for cohorts after the crash. Women who entered The University between 2001 and 2005 had a pretty flat probability, relative to men, of declaring a first major in computing conditional on each lower grade, and there is no clear pattern for final majors.

It is difficult to say why pattern of attrition found by Goldin (2015) in economics coursework does not exist in my context. It should be noted, however, that in the late 1990s programming was not a required course for majors outside of computing, engineering, and some mathematics and statistics concentrations, whereas economics is a required course for students in many different majors. It is possible that the difference lies in actual course-taking: perhaps women are more likely than men to avoid a course where they expect to get a B or below. Women tend to get lower grades than men in STEM coursework. Koester, Grom and McKay (2016) found that STEM courses at the University of Michigan tend to impose "grade penalties" on students, meaning the average student will tend to earn a grade in that course that is lower (in grade point terms) than their GPA outside the course. They also found that, outside of lab coursework, the penalty is larger for women than for men. It is possible that a combination of the gender difference in expected grades and women's greater sensitivity to grades could have deterred women from taking computing coursework in the first place.[10]

[10] Whether the gender difference in grade penalties is because women are underperforming in the course relative to men or because they take easier other coursework should not make a difference– if women care more than men about pulling their GPA down, then women will still be more likely than men to avoid courses that impose a grade penalty. It might not even matter whether students know about the gender difference

A.3.2 Women's underperformance in STEM courses

Koester, Grom and McKay (2016) and Matz et al. (2017) discuss gender differences in grades in STEM courses at the University of Michigan and five universities in the Big Ten Academic Alliance, respectively. They find that STEM courses tend to impose what they refer to as "grade penalties" for all students, meaning that a student's grade (in grade point terms) in a course is generally below the student's GPA over all other courses taken before or concurrently with that course. Generally, if a course imposes a grade penalty, that course "grades harder" than other courses and may in fact be more difficult than other courses. Both papers find that STEM courses tend to impose grade penalties on students, and that lecture courses in STEM tend to impose significantly larger grade penalties on women, which they refer to as "gendered performance differences." Both papers also find that while lab courses in STEM do tend to impose grade penalties on students, lab courses do not tend to have gendered performance differences. Both papers suggest that the differences in gendered performance differences across types of STEM classes are related to differences in how courses are evaluated, and their results cannot be explained by differences in ability or the set of courses taken by men and women.

I find that these same gendered performance differences existed at The University in introductory programming and programming 2[11] during my sample period. Figure A.4 plots students' course grade in introductory programming against their GPA in other courses taken either before or during the same term as introductory programming. Figure A.5 plots the same for programming 2. Both figures are residualized on a set of controls: term-by-course fixed effects, AP credits, an indicator for college of entry, and demographic variables for introductory programming, and term fixed effects, AP credits, an indicator for college of entry, and demographic variables for programming 2. Conditional on a particular GPA outside of each course, women generally earn a lower grade in each course than similar men.

It is possible that gendered performance differences could occur because women take easier courses[12] outside of programming rather than a true performance difference conditional on a student's characteristics. To analyze whether this is occurring, I again follow Matz et al. (2017). I calculate the average difference between course grade and GPA in all courses in my sample, which I refer to as the "average grade difference" of the course. I then calculate the average of the average grade differences among courses that students took before introductory programming and the courses students took before programming

in grade penalties.

[11] These courses are described more in Appendix A.6.

[12] Or, more likely, courses that grade "less hard."

2. Results are reported in Table A.4. Women who take introductory programming and programming 2 do tend to have lower grade penalties in their non-programming courses than men, but the difference is much smaller than the grade penalty imposed by either class.

A.4 Potential bias from ability and labor force exit

It is reasonable to be concerned that unobserved major-specific ability or women's expected selection out of the labor force could bias the earnings estimation process. Because the multinomial logit model and the nested logit model are identified from differences relative to an outside option, if the average bias is the same in all majors, then overall it will cancel out. There is also a possibility that students understand that the choice of majors is a Roy-style process, and that the average reported salary for graduates of one particular major is going to be biased up because those students have the highest ability in that major.[13]

To understand how ability and work expectations could bias my estimate of labor market value, I turned to the data from Wiswall and Zafar (2015*a*), which they have made available. From here on, I will refer to Wiswall and Zafar (2015*a*) as WZ. They collected subjective expectations data on both work probability and earnings at ages 30 and 45.[14] Data was also collected on various characteristics, including demographics, family background, GPA, SAT scores, and subjective beliefs about students' own ability in a particular major. Note that a disadvantage of this data is that there are only 488 respondents, meaning that it might be hard to find statistically significant effects.

There is evidence in the data that students sort into majors[15] based on ability.[16] Table A.5 shows students' average expected ability rank among all graduates with a particular major, with 100 the highest, by the student's current major. Business and economics students have the highest average ability in economics and business, engineering and computer science students have the highest average ability in engineering and computer science, natural science students have the highest ability in natural science, and humanities

[13]It should be noted that Wiswall and Zafar (2015*a*) and Wiswall and Zafar (2015*b*) suggest that students at prestigious institutions tend to overestimate the salary they can expect in each major.

[14]WZ collected data on students' expectations in four major groups (Engineering and Computer Science, Natural Sciences, Economics, Humanities/Other Social Sciences) and non-graduation. These groups are similar to my groups, although computer science is combined with engineering. It is reasonable to assume that computer science probably has coefficients that are similar to engineering.

[15]WZ's sample is made up of freshmen, sophomores, and juniors, so this is major choice at the beginning and middle of college.

[16]This is of course consistent with plenty of prior research, most notably Arcidiacono (2004).

and other students have the highest average ability in humanities and other. Note, however, that students do not necessarily pick the major for which they have the highest ability - the average engineering student actually reports higher ability in both natural science and humanities/social sciences than in engineering.

Looking at expected earnings in a particular major by the major students have already declared, it is less clear whether there is a systematic relationship between the major a student has actually declared and their expected earnings conditional on each major. However, it is clear that there are differences in what students would expect to earn in a particular major based on the major they have already declared. Table A.6 shows average expected log earnings at ages 30 and 45 in each major by the major students have declared. Notably, natural science and business/economics majors have higher expected earnings in engineering at age 30 than engineering majors do. There are several other similar examples.

Looking at expected work probabilities in a particular major by the major students have already declared, I can draw a similar conclusion: students' expected probability of not working is not entirely independent of major. Table A.7 shows average nonwork probability at ages 30 and 45 in each major conditional on the major students have already declared. It seems that, on average, students expect a higher probability of nonwork at age 30 if they pick a humanities major. At age 45, however, there seems to be much less variation in expected nonwork probability across majors conditional on the majors that students have already chosen. Even at age 30, the differences are not statistically significant, suggesting that there is little if any bias in nonwork probability due to ability.

In order to test whether and how ability factors into expected earnings and nonwork, I ran regressions of the form

$$\log(\mathbb{E}\left[Y_{ijt}\right]) = \gamma_j^Y A_{ij} + X_{it}\beta^Y + \varepsilon_{ij}^Y \tag{A.2}$$

for earnings[17] and

$$F^{-1}(\mathbb{E}\left[N_{ijt}\right]) = \gamma_j^N A_{ij} + X_{it}\beta^Y + Z_{it}\delta^N + \varepsilon_{ij}^N \tag{A.3}$$

for nonwork. A_{ij} here refers to a ranked ability in major j. X_{it} is demographic characteristics and Z_{it} is probability of being married and of having no children at the relevant ages. $F(\cdot)$ is the logit CDF. The goal here is to see whether or not major-specific ability factors into earnings and nonwork expectations and, if so, to get a benchmark on the size of the bias we might expect in the expected future earnings equation.

[17] Students were asked to estimate their earnings conditional on working full time.

If ability does factor into earnings and nonwork, there would be bias in expected present discounted value of future earnings of the size

$$\gamma^Y (\mathbb{E}[A_{iMt}|M] - A_{iMt}) \tag{A.4}$$

for expected log earnings and

$$\gamma^N (\mathbb{E}[A_{iMt}|M] - A_{iMt}) \tag{A.5}$$

for the inverse CDF of nonwork.[18] This bias can be ignored if the average size of the bias in all majors is equal, as it will difference out in the estimation process.

Table A.8 displays the results of the earnings regression. Panel A contains results for expected earnings at age 30 while Panel B contains results for expected earnings at age 45. At both ages, conditional on demographics, there are positive and statistically significant effects of ability on expected earnings in natural sciences, business and economics, and dropping out. This suggests that my estimates of expected earnings using the process outlined in the early sections will likely be biased.

Table A.8 displays the results of the nonwork regression. Panel A contains results for expected nonwork probability at age 30 while Panel B contains results for expected nonwork probability at age 45. All coefficients are probit coefficients. Major-specific ability is only statistically significant in the humanities at age 30, which might be a graduate school effect. By age 45, it seems that there is only minimal effect of ability on nonwork, so there may not be much bias to be concerned about.

Based on these regressions, I would conclude that there is likely ability bias in my estimated earnings expectations. There might be ability bias in my estimated nonwork probabilities, but it is less likely. I will therefore calculate the likely size of the bias in earnings that is due to differences in ability only. To do this, I ran a bootstrap estimation of Equation A.4 with 10,000 repetitions.[19] The results are in Table A.10. It looks like, at both ages, there is positive bias on estimated earnings due to sorting into majors on ability.

[18] Therefore, the bias on the probability of nonwork would be

$$F\left(\gamma^N \mathbb{E}[A_{iMt}|M] + X_{it}\beta^N + h^N(exp_{it}) + Z_{it}\delta^N + \theta^N_{Mt}\right) - F\left(\gamma^N A_{iMt} + X_{it}\beta^N + h^N(exp_{it}) + Z_{it}\delta^N + \theta^N_{Mt}\right)$$

[19] Note that I cannot estimate bias for dropouts using this data, as I do not have data on students who drop out.

A.5 Constructing the salary distributions of each major

To construct the labor market returns of particular majors, I use (proprietary) data on average starting salary by major collected by the National Association of Colleges and Employers (NACE) and salary data from the Outgoing Rotation Group of the Current Population Survey (CPS-ORG) from 1995 to 2010.[20] The NACE data provides average and median salaries for college graduates specific major, with both pooled and gender-specific averages. Data from the CPS-ORG is used to calculate salary statistics for college drop-outs and unemployment probabilities for college drop-outs and college graduates in related occupations to each major. I calibrate returns to experience and grades using survey data from Wiswall and Zafar (2015*a*) (WZ). All mean salaries are adjusted to 2010 dollars using the CPI.

My main specification assumes that salaries are log-normally distributed and that grades, experience, and shocks to the starting position of salaries affect the mean of log salary.

To calculate starting salary, I denote the year τ salary of individual i of gender g who graduated (or dropped out and entered the labor market) in year t_0 with a degree in general major[21] j with $Y_{ij\tau}$. I assume that

$$\log Y_{ij\tau} = \theta_{jt_0} + \gamma_{1j}(\tau - t_0) + \gamma_{2j}(\tau - t_0)^2$$

where

$$\theta_{jt_0} \sim \mathcal{N}\left(\mu_{j,t_0}, \sigma^2_{jt_0}\right)$$

$\tau - t_0$ is the number of years of labor market experience individual i has. μ_{jt} is the expected log starting salary for a student who graduated in year t_0 in major j with exactly average overall and in-major GPAs. Here, I assume that students' salary trajectory over their career is entirely determined by their starting position in the labor market, and that students do not expect that their grades will affect starting salaries.[22] I also assume that the variance of

[20]NACE surveys colleges and universities to collect data on actual salary offers given to graduating students by major. The NACE data is particularly valuable in this case because the Career Center at the studied university directs students who ask about the salary of a particular college major to NACE publications, suggesting that it might be more accurate for estimating college students' expectations than data from national labor market surveys. NACE data is also net of any differences in experience or promotions that might not be observable in labor market survey data.

[21]"General major" here refers to a major in the choice set of my model: Computing, Engineering, Science, Business, and Other. NACE data contains information on specific majors, such as mechanical engineering, chemical engineering, and civil engineering. The specific majors corresponding to each general major are outlined in Appendix A.1. Specific majors in the NACE that are not offered within the College of Engineering, the College of Liberal Arts, and the College of Business are not included in these calculations.

[22]Or, more accurately, that the effect of grades on starting salaries is absorbed linearly into the value of each major.

log salary is the same for men and women, and that the pooled distribution of men's and women's log salaries is also normally distributed. Finally, I assume that θ_{jt_0} is independent of error terms in the grade production function and in the value function.

A.5.0.1 Calculating μ for college graduates

To calculate the labor market value of majors, all I need is $\mathbb{E}\left[\theta_{jt_0}\right] = \mu_{j,t_0}$. To calculate consistent estimators of μ_{jt} for college graduates, I need a formula for the μ_{jt} using the means and medians of specific majors, which will be aggregated into the average for all specific majors in a general major such as Engineering or Science. I assume that the distribution of log salaries for general major j is a weighted average of the distribution of log salaries in specific majors $k \in \mathcal{K}_j = \{1, ..., K_j\}$. I assume that

$$\theta_{kt_0} \sim \mathcal{N}\left(\mu_{j,t_0}, \sigma^2_{jt_0}\right)$$

The properties of the normal distribution mean that

$$\mu^g_{jt} = \sum_{k=1}^{K_j} \omega_k \mu^g_{kt} \tag{A.6}$$

where ω_k is the weight of major k and $\sum_{k=1}^{K_j} \omega_k = 1$. The weights are calculated from the representation of each major in the NACE data.

Because log salaries are normally distributed, salaries are distributed log-normal. I calculate $\mu_{jt,\text{pooled}} = \sum_{k=1}^{K_j} \omega_{k,\text{pooled}} \mu_{kt,\text{pooled}}$, where $\mu_{kt,\text{pooled}}$ is the log of the median salary for major k in the pooled distribution and the weights $\omega_{k,\text{pooled}}$ are calculated .[23] Similarly, when I need expected salary rather than expected log salary, I calculate the expected salary in major j using the weighted average of mean salaries of majors within $\mathcal{K}_j$ in the pooled distribution.

A.5.0.2 Calculating μ and σ for college drop-outs

For college drop-outs, where $j = DO$, I calculate consistent estimators of μ_{jt_0} in each year using the mean of individual log wage and salary income for workers between the ages of 20 and 24 with some college education.[24]

[23] This follows from the property that the median of a log-normal distribution is $\exp(\mu)$.
[24] These estimators are unadjusted for race for consistency with the NACE data.

A.6 The dot-com crash and the computing pipeline

In order to understand how to encourage women to persist in computing majors even in the face of transitory labor market shocks, it is important to understand when women are likely to substitute away from computing majors. Different policies may be helpful in encouraging entry to computer science programs and encouraging attachment to those programs. At The University, the dot-com crash both decreased women's entry to the computing pipeline and increased women's attrition from the pipeline after entry.

A common framework for understanding the gender gap in STEM is that of the "leaky pipeline." In a leaky pipeline framework, women are less likely to take the first step toward a STEM program, and proportionally more women than men leave the pipeline at each step. For students at The University, there are three steps on the pipeline of a computing degree: taking relevant coursework, declaring the major, and completing the degree. The following is a regression analysis of the graphical analysis conducted in Section 1.3.2.

To better understand which stages of the major choice process were most affected by the dot-com crash, I performed a logit difference-in-difference regression on the probability of choosing a computing major at each stage. The regression specification is

$$Y_{it} = F\left(\beta_0 + \beta_1 Post_{it} + \beta_2 Female_{it} + \beta_3 Post_{it} \times Female_{it} + X_{it}\gamma + \zeta_t + \varepsilon_{it}\right)$$

where X_{it} are demographic controls and ζ_t are cohort fixed effects.[25] $Post_{it}$ refers to entering The University in 2001 or later.[26] Y_{it} is an indicator representing four different outcomes: ever taking any computing course, ever taking second semester programming, ever declaring a computing major, and completing a computing degree. I model two different processes: overall changes at every stage and attrition. For overall changes at each stage, every regression was estimated for all students in the sample. For the estimation of attrition, the regressions for the two "entry" points to the computing pipeline, which are taking any computing course and taking second semester programming, were still estimated using all students in the sample, the regression for declaring a major was estimated for all students who took any course in computing, and the regression for finishing a major was estimated for all students who ever declared a major in computing.

Table A.11 reports the log change in Y_{it} when the interaction term changes from 0 to 1.[27] β_2 roughly corresponds to the decrease in the probability of reaching a particular

[25]The regression is robust to the exclusion of the demographic controls and the cohort fixed effects; see appendix for full tables.

[26]This misses any effects from partial exposure, which is part of the reasoning for creating the structural model later.

[27]These are the marginal effects of the logit regressions. Following Puhani (2012), the marginal effect of

stage in the pipeline due to the dot-com crash. β_3 represents the additional change in the probability of reaching each stage in the pipeline for women after the dot-com crash. Panel A shows overall changes at every stage and Panel B shows attrition. While we can interpret these effects as indicating the direction of effects, they may not reliably show differences in magnitude.

Overall, at each stage of the computing pipeline, the effect of the dot-com crash got larger for women relative to men. Columns 1 and 2 of estimate the effect of the dot-com crash on entry to computing majors. Column 3 reports the effect of the dot-com crash on declaring any computing major, and column 4 reports the effect of the dot-com crash on completing any computing major. The dot-com crash reduced also reduced the probability that women would take second semester programming, declare a computing major, and finish a computing degree by more for women than men, with highly significant effects. Based on these estimates, while the dot-com crash had large effects on men at all stages of the computing degree, it had larger effects on women at all stages after the first computing course, and there is suggestive evidence that the dot-com crash had larger effects on women's entry as well.

Attrition largely occurred between the first two computing courses and between the first computing course and declaring a major.[28] The first two columns of Panel B are the same as Panel A. Columns 3 and 4 report the effect of the dot-com crash on persistence in computing majors at two stages: moving from taking a course to declaring a major, and moving from declaring a major to graduating college with a computing degree. Based on these estimates, the dot-com crash decreased persistence in the computing major at the declaration stage by more for women than for men, with a highly significant effect. There is also suggestive evidence that the dot-com crash decreased women's persistence at the late stage of the degree, but the crash seems to have had no effect on men.

A.7 Adding ability measures into the value function

One potential issue with the main specification is that there are few available baseline measures of ability. [29] I add indicators for each earned AP credits into the value function for

the interaction term is "average treatment effect on the treated" of the dot-com crash on women. Therefore, the Ai and Norton (2003) caution about marginal effects of interaction terms does not apply for this reason.

[28]Relative timing of the second computing course and the major declaration varied over the sample period.

[29]The nature of student administrative data at The University is that only data from transcripts is available for students who entered as freshmen between 1996 and 1999; in 2000, admissions data was added in with the transcript data, though admissions data is not fully complete for the 1999 entrants. Any student who re-entered the admissions process for a 2000 or later entry also has admissions data, but those are the students who came back for graduate school and therefore are a confusing sample.

period 1, but I do not add them in periods 2 and 3, both in order to simplify computation and because it is not necessarily clear that earned AP credits should influence students' utility at late stages of the degree.

In this section I describe two robustness checks where I have ability measures in the value function in every period. In the first, and perhaps more important, check, I estimate the model using only students who entered The University between 2000 and 2005. In this check, I add students' SAT Math and SAT Verbal scores into the value function for each major in every period. In the second check, I add indicators for earned AP credits back into the value function in every period.

A.7.1 Adding SAT scores into the value function

A.7.1.1 Students' value of majors when including SAT scores

I account for the effects of ability on the value of majors as follows. In period 1, students choose a track to maximize their expected lifetime utility, conditional on their demographic variables, SAT scores, and the AP credits they earned while in high school. The student's problem in period 1 is

$$\max_{c \in \mathcal{C}} \{\alpha_{10c} + \alpha_{11c} AP_i + \alpha_{12c} X_i + \alpha_{43c} SAT_i + \varepsilon_{1ic} + \beta \mathbb{E}\left[V_2(s_{i2}) | s_{i1}, c\right]\}$$

s_{it} is a vector of state variables in period t, including a student's AP credits AP_i, demographic information X_i, and SAT Math and Verbal scores SAT_i. $Post_i$, an indicator variable that is equal to 1 if the student entered The University in 2001 or later, is not included in this specification. ε_{1i} is distributed i.i.d extreme value type 1, making this a multinomial logit model.

At the end of sophomore year, the middle college period begins. During this period, students observe their previous academic performance, update their beliefs about the labor market and their future academic performance, declare their first major or drop out, and then take further coursework toward graduation if they did not drop out. Students choose their first major to maximize their expected lifetime utility, conditional on their choices and performance in period 1. The student's problem is

$$V_2(s_{i2}) = \max_{j \in \mathcal{M}} \{V_{2j}(s_{i2}, c^*) + \beta \mathbb{E}\left[V_3(s_{i3}) | s_{i2}, j\right]\}$$

where

$$V_{2j}(s_{i2}, c^*) = \begin{cases} \alpha_{20j} + \alpha_{21j,c^*} T_{i1,c^*} + \alpha_{22j,c^*} G_{i1,c^*} + \xi_{2j,c^*} + \alpha_{23j} X_{i2} + \alpha_{25j} SAT_i + \varepsilon_{2ij} & j \neq D \\ \log Y_{D,t_0} + \varepsilon_{2iD} & j = D \end{cases}$$

s_{i2} is the vector of state variables in period 2, which includes the full set of state variables from period 1 s_{i1}, the student's period 1 choice c^*, and realized performance from period 1. ξ_{2j,c^*} is a major-specific cost of choosing j conditional on having chosen c^*. AP credits no longer enter utility because they no longer directly affect the costs of choosing a particular major, but SAT scores continue to enter the value function. Grades – the period 1 overall GPA G_{ij1} and in-track GPA T_{ij1} – now also measure students' general and major-specific ability. How much the overall GPA matters to the payoff of a major depends on whether the student is choosing a major unrelated to their period 1 track, as a students' overall GPA from an unrelated track provides less information about their future performance than their overall GPA from a related track. Students who choose to drop out will enter the labor market and must stay there permanently.

The late college period begins at the end of junior year, when students are finishing up coursework and deciding whether to make last-minute major changes. During this period, students observe their performance in the second period, update their beliefs about the labor market, and decide whether to keep their first major and graduate, change their major and graduate, or drop out. Students have the same choice set as they did in the previous period.

Students choose their final major to maximize expected lifetime utility, conditional on their previous choices and performance in period 2. The student's problem is

$$V_3(s_{i3}) = \max_{j \in \mathcal{M}} \left\{ V_{3j}(s_{i3}, c^*, j_2^*) + \beta \mathbb{E}\left[V^{LM}(j, T) | s_{i3} \right] \right\}$$

where

$$V_{3j}(s_{i3}, c^*, j_2^*) = \begin{cases} \alpha_{30j} + \alpha_{31j} M_{ij2} + \alpha_{32}^N G_{i2} + \alpha_{33j} X_{i3} + \alpha_{35j} SAT_i + \xi_{3jc^*} + \varepsilon_{3ij} & j = j_2^*, j \neq D \\ \alpha_{30j} + \alpha_{32j}^S G_{i2} + \alpha_{33j} X_{i3} + \alpha_{35j} SAT_i + \xi_{3jc^*} + C_j + \varepsilon_{3ij} & j \neq j_2^*, j \neq D \\ \log Y_{D,t_0} + \varepsilon_{3iD} & j = D \end{cases}$$

s_{i3} is the vector of state variables in period 3, which includes the full set of state variables from period 2 s_{i2}, the period 1 choice c^*, the period 2 choice j_2^*, period 2 cumulative GPA G_{i2}, and period 2 in-major GPA M_{ij2}. ξ_{3jc^*} is a major-specific cost of choosing final major j conditional on having chosen track c, capturing the cumulative cost of multiple switches or the benefit of switching back to an original choice. M_{ij3} is only realized if the student chose major j in period 2, and therefore only enters the utility function for majors that would not involve a switch. C_j is a major-specific cost of switching into major j. Students who drop out at this stage will get one additional year of labor market experience, and students who dropped out in period 2 must choose $j = D$ in period 3.

A.7.1.2 Results of the specification including SAT scores

Including SAT scores in the estimated value functions for majors changes the magnitude and direction of coefficients on AP credits. Generally, though, the coefficients on grades stay the same direction and often get larger than they were before.

Table A.12 reports the coefficients on AP credits and SAT scores in value function for period 1. Overall, conditional on a particular SAT Math and Verbal score, the coefficients on AP credits in the period 1 value function are relatively different from the coefficients in the main specification. In the main specification, a strange result was that having AP credit for Calculus 1 negatively predicted choosing either STEM track for both men and women; now, it is positive. This is likely becuase math and verbal ability were loading onto the AP variables, and even some of the STEM AP credits were picking up, for instance, verbal ability. Notably, however, the coefficients on SAT scores are somewhat small, though significant.[30] My results suggest that SAT Math scores are positively correlated with both the probability of choosing both STEM tracks for women and choosing pre-Science for men, and that there is no correlation in the probability that men choose the Pre-Engineering/CS track and their SAT Math scores.[31] SAT Verbal scores are negatively correlated with the probability of choosing both STEM tracks relative to the non-STEM track.

Table A.13 reports the coefficients on grades and SAT scores in the value functions for periods 2 and 3. While having SAT scores in the value function does change the magnitudes of some coefficients, most have the same sign as they did before, and there is no systematic pattern of changes. Notably, the coefficients on GPA in period 2 for the value of a computer science major, conditional on students' having taken the Pre-Engineering/CS track, get larger in magnitude, as do the coefficients on in-major GPA in period 3 for the value of a computer science major. Women still tend to care more about their grades than men. The coefficients on SAT scores are still small but statistically significant. Perhaps strangely, the coefficient on SAT Math scores is largest for the business major for both men and women,

[30]The SAT Math and SAT Verbal scores were scaled down by 100. They are about an order of magnitude smaller than the coefficients on SAT scores in Arcidiacono (2004).

[31]It is important to note that these coefficients are conditional on college of entry, so it might be that women with relatively lower math skills who enter the College of Engineering are more likely to leave the College of Engineering before completing all of their prerequisites.

but this could potentially be because the business major also includes economics. For men, there is a negative coefficient on SAT Math scores for engineering and science.

A.7.2 Adding SAT scores into the value function

A.7.2.1 Students' value of majors when including AP credits in all periods

I account for the effects of ability on the value of majors as follows. The period 1 value function is the same as the main specification. In periods 2 and 3, AP scores enter the value function.

At the end of sophomore year, the middle college period begins. During this period, students observe their previous academic performance, update their beliefs about the labor market and their future academic performance, declare their first major or drop out, and then take further coursework toward graduation if they did not drop out. Students choose their first major to maximize their expected lifetime utility, conditional on their choices and performance in period 1. The student's problem is

$$V_2(s_{i2}, c^*) = \max_{j \in \mathcal{M}} \{V_{2j}(s_{i2}) + \beta \mathbb{E}\left[V_3(s_{i3})|s_{i2}, j\right]\}$$

where

$$V_{2j}(s_{i2}) = \begin{cases} \alpha_{20j} + \alpha_{21j,c^*}T_{i1,c^*} + \alpha_{22j,c^*}G_{i1,c^*} + \xi_{2j,c^*} + \alpha_{23j}X_{i2} + \alpha_{25j}AP_i + \varepsilon_{2ij} & j \neq D \\ \log Y_{D,t_0} + \varepsilon_{2iD} & j = D \end{cases}$$

s_{i2} is the vector of state variables in period 2, which includes the full set of state variables from period 1 s_{i1}, the student's period 1 choice c^*, and realized performance from period 1. ξ_{2j,c^*} is a major-specific cost of choosing j conditional on having chosen c^*. AP credits continue to enter the value function. Grades – the period 1 overall GPA G_{ij1} and in-track GPA T_{ij1} – now also measure students' general and major-specific ability. How much the overall GPA matters to the payoff of a major depends on whether the student is choosing a major unrelated to their period 1 track, as a students' overall GPA from an unrelated track provides less information about their future performance than their overall GPA from a related track. Students who choose to drop out will enter the labor market and must stay there permanently.

The late college period begins at the end of junior year, when students are finishing up coursework and deciding whether to make last-minute major changes. During this period, students observe their performance in the second period, update their beliefs about the labor market, and decide whether to keep their first major and graduate, change their major and graduate, or drop out. Students have the same choice set as they did in the previous period.

Students choose their final major to maximize expected lifetime utility, conditional on their previous choices and performance in period 2. The student's problem is

$$V_3(s_{i3}, c^*, j_2^*) = \max_{j \in \mathcal{M}} \left\{ V_{3j}(s_{i3}, c^*, j_2^*) + \beta \mathbb{E}\left[V^{LM}(j, T) | s_{i3}\right] \right\}$$

where

$$V_{3j}(s_{i3}, c^*, j_2^*) = \begin{cases} \alpha_{30j} + \alpha_{31j} M_{ij2} + \alpha_{32}^N G_{i2} + \alpha_{33j} X_{i3} + \alpha_{35j} AP_i + \xi_{3jc^*} + \varepsilon_{3ij} & j = j_2^*, j \neq D \\ \alpha_{30j} + \alpha_{32j}^S G_{i2} + \alpha_{33j} X_{i3} + \alpha_{35j} AP_i + \xi_{3jc^*} + C_j + \varepsilon_{3ij} & j \neq j_2^*, j \neq D \\ \log Y_{D,t_0} + \varepsilon_{3iD} & j = D \end{cases}$$

s_{i3} is the vector of state variables in period 3, which includes the full set of state variables from period 2 s_{i2}, the period 1 choice c^*, the period 2 choice j_2^*, period 2 cumulative GPA G_{i2}, and period 2 in-major GPA M_{ij2}. ξ_{3jc^*} is a major-specific cost of choosing final major j conditional on having chosen track c, capturing the cumulative cost of multiple switches or the benefit of switching back to an original choice. M_{ij3} is only realized if the student chose major j in period 2, and therefore only enters the utility function for majors that would not involve a switch. C_j is a major-specific cost of switching into major j. Students who drop out at this stage will get one additional year of labor market experience, and students who dropped out in period 2 must choose $j = D$ in period 3.

A.7.2.2 Results of the specification including AP credits in all periods

Table A.14 reports the coefficients on grades when AP credits are in the value function in all periods. Keeping AP credits in the value function does not have a particular systematic effect on the coefficients on grades, and most changes are relatively small.

When including AP credits in every period, the coefficients on grades for women choosing computer science tend to be slightly lower in magnitude than in the main specification. There are mixed effects for engineering and business. Grade coefficients in science are mostly larger than the main specification. There is little effect on grade coefficients in humanities and social sciences.

When including AP credits in every period, the coefficients on grades for women choosing computer science tend to be slightly higher in magnitude than in the main specification, though some stay the same or decrease slightly. There are mixed effects for engineering, science and business. There is little effect on grade coefficients in humanities and social sciences.

A.8 Alternative specifications of the labor market

A.8.1 Treating labor market shocks as transitory

In this section, I will discuss a version of my model where students treat shocks to unemployment and log salary as transitory rather than permanent. Recall that $\theta^Y_{ij\tau}$ is a student's stochastic draw of log starting salary, which incorporates labor market shocks into the salary portion of the labor market value of a major. I let $\theta^Y_{ij\tau}$ and the unemployment rate $P(U_{ij\tau} = 1)$ follow an AR(1) process, so that

$$\mathbb{E}\left[\theta^Y_{ij\tau}\right] = c^Y_j + r_Y \mathbb{E}\left[\theta^Y_{ij,\tau-1}\right] + e^Y_{ij\tau} \tag{A.7}$$

$$P(U_{ij\tau} = 1) = c^U_j + r_U P(U_{ij,\tau-1} = 1) + e^U_{ij\tau} \tag{A.8}$$

The results of these AR(1) regressions are reported in Table A.15. Using Equations A.7 and A.8, students' expectations of their future expected log salary and unemployment rate in year τ, conditional on graduating in year t_0, are

$$\mathbb{E}\left[\theta^Y_{ij\tau}\right] = c^Y_j r_Y \frac{1 - r_Y^{\tau - t_0}}{1 - r_Y} + r_Y \mathbb{E}\left[\theta^Y_{ij,\tau-1}\right] \tag{A.9}$$

$$P(U_{ij\tau} = 1) = c^U_j r_U \frac{1 - r_U^{\tau - t_0}}{1 - r_U} + r_U P(U_{ijt_0} = 1) \tag{A.10}$$

The rest of the model is the same as in Section 2.4.

The coefficients on earned AP credits in period 1 are reported in Table A.16. There is no particular pattern in the differences between these coefficients and the coefficients in the main specification.

The coefficients on GPA in periods 2 and 3 are reported in Table A.17. For the most part, coefficients on grades in period 2 are smaller in magnitude when labor market shocks follow an AR(1) process. In period 3, coefficients on both in-major and overall GPA tend to be smaller for women if the student is not switching majors, except for in computer science, where the magnitudes of coefficients are larger or the same as the main specification. For men, there is no systematic pattern in the differences between the AR(1) specification and the main specification.

During my sample period, an AR(1) specification for the labor market value of a major generally means that the labor market value of the major is higher than in the main specification. This is especially true for computer science and engineering. This all suggests that when the labor market is bad, students think that getting better grades might insulate them against labor market shocks. The fact that this is not true for women in computer science might be especially important.

A.8.2 Estimating the value of unemployment

Typically, we think that students, especially women, do not pay much attention to salary when choosing a major Zafar (2013). This means it is odd that the reaction to the dot-com crash was so large, and it raises concerns that the possibility of being unemployed after college is loading onto grades. One possibility, though, is that students do not care about salary but they have a high disutility of being unemployed. In this section, I estimate the value of unemployment $u(b_i)$ in my model rather than setting it to 0.

Table A.18 reports the coefficients on AP credits in period 1. There are few differences between the coefficients here and those in the main specification, and for the most part the differences that exist are not statistically significant.

Table A.19 reports the coefficients on grades in periods 2 and 3. There are few differences between the coefficients here and those in the main specification, and the differences that exist are again not statistically significant.

A.9 Sensitivity tests

A.9.1 Discount rate

In the main body of the paper, I calibrate the discount rate $\beta = 0.95$. In this section I will discuss how grades affect the value of a major when β is instead set to 0.8, 0.9, 0.98, and 0.99.

Table A.20 reports the coefficients on grades in the value function for computer science for each value of β. Higher values of β mean that students are more patient, which raises the relative value of the labor market when students choose majors. As a general rule, when β is higher, coefficients on grades in the computer science value function are larger in magnitude, especially for women. For men, the story is slightly different – men's coefficients on period 1 in-track GPA, conditional on taking the non-STEM track, on overall period 1 GPA, conditional on taking the pre-Engineering/CS track, and on period 2 overall GPA, conditional on having chosen computer science in period 2, fall as β rises.

The most likely reason for why grade coefficients tend to rise when β rises is that raising β inherently raises the relative value of the labor market. Coefficients on grades must therefore rise so that the same perturbation in GPA will produce the same change in probability of choosing a major.

The explanation for grade coefficients that fall when β rises is trickier. It seems likely that in that case, students think that having higher grades will actually lead to a higher payoff in the labor market. Suppose, for instance, that

$$\mathbb{E}\left[\log Y_{it}\right] = \tilde{\gamma}_{1j} exp_{it} + \tilde{\gamma}_{2j} exp_{it}^2 + \mathbb{E}\left[\theta_{ij,t_0}^{Y,g}\right] + \tilde{\gamma}_{3j} M_{ijt} + \tilde{\gamma}_{4j} G_{ijt}$$

where $\tilde{\gamma}_{4j} > 0$.[32] Then the contribution of overall grades to the full labor market value of a major is

$$\tilde{\gamma}_{4j} G_{it} \sum_{\tau=t}^{T} \beta^{\tau} P(U_{ij\tau} = 0) \tag{A.11}$$

A higher value of β would raise the magnitude of this value (i.e. make this value more negative). If unemployment rates do not fluctuate too much, then this value enters nearly linearly into the value of a major in period 3, and the coefficient on grades falls to account for the missing grade component in the labor market value of majors. When β rises, making the value of the labor market more important, the grade coefficients in the value function now need to do more work to account for how grades affect the labor market value of a major. The opposite explanation may also hold for the coefficients that rise when β rises.

A.9.2 Time to retirement

In the main body of the paper, I calibrate the lifespan $T = 12$. In this section I will discuss how grades affect the value of a major when T is instead set to 5, 10, 15, and 20.

Table A.21 reports the coefficients on grades in the value function for computer science for each value of T. Higher values of T mean that students expect to work longer, which raises the relative value of the labor market when students choose majors.[33] Similar to the effect of changes in β, as a general rule, when T is higher, coefficients on grades in the computer science value function are larger in magnitude, especially for women. For men, once again there are a few coefficients that fall when T rises. The explanations why coefficients might rise and fall with changes in T are similar to the explanations for changes in β.

[32] This could occur, for instance, if the students with the highest grades get PhDs, which tends to lower salaries.

[33] It is also important to note that higher values of T will magnify any effects of women's differential selection out of the labor market by major, because higher values of T mean that the model is more likely to include years where women are most likely to be out of the labor market due to childbearing.

A.9.3 Tables

Table A.1: Comparing Actual and Predicted Shares of Students Choosing Each Major

	Data							Model						
	Women			Men				Women			Men			
	Before	After	% Change	Before	After	% Change	Diff-in-Diff	Before	After	% Change	Before	After	% Change	Diff-in-Diff
							Period 1							
Non-STEM	0.625	0.658	5.1	0.482	0.494	2.5	2.6	0.625	0.658	5.1	0.482	0.494	2.5	2.6
Pre-Eng./CS	0.149	0.120	-23.5	0.343	0.321	-6.7	-16.8	0.149	0.120	-23.5	0.344	0.322	-6.7	-16.8
Pre-Science	0.227	0.222	-2.3	0.176	0.185	5.1	-7.3	0.227	0.222	-2.3	0.174	0.183	5.1	-7.3
							Period 2							
Drop-out	0.020	0.010	-50.2	0.033	0.020	-39.6	-10.6	0.020	0.011	-47.7	0.033	0.020	-38.5	-9.2
CS	0.024	0.011	-52.5	0.132	0.096	-27.3	-25.3	0.031	0.019	-37.2	0.118	0.105	-11.2	-26.1
Eng.	0.104	0.096	-8.2	0.201	0.217	8.3	-16.6	0.102	0.092	-9.9	0.201	0.210	4.5	-14.4
Science	0.101	0.144	41.5	0.093	0.134	44.6	-3.1	0.091	0.125	37.1	0.088	0.118	33.3	3.8
Bus.	0.106	0.087	-17.7	0.186	0.163	-12.7	-4.990	0.090	0.087	-3.0	0.171	0.173	1.2	-4.2
Hum./SS	0.645	0.652	1.2	0.355	0.370	4.2	-3.0	0.666	0.666	0	0.387	0.373	-3.7	3.7
							Period 3							
Drop-out	0.028	0.024	-14.2	0.046	0.034	-25.0	10.8	0.043	0.036	-16.2	0.093	0.064	-31.0	14.8
CS	0.024	0.010	-57.7	0.131	0.092	-29.4	-28.3	0.021	0.010	-54.8	0.070	0.056	-20.1	-34.7
Eng.	0.098	0.091	-7.3	0.188	0.209	11.5	-18.7	0.086	0.085	-1.3	0.180	0.223	24.0	-25.3
Science	0.095	0.144	52.0	0.089	0.132	48.4	3.623	0.044	0.061	38.8	0.065	0.076	17.0	21.8
Bus.	0.108	0.093	-14.0	0.192	0.173	-9.9	-4.2	0.032	0.052	59.9	0.128	0.189	47.4	12.5
Hum./SS	0.647	0.638	-1.4	0.354	0.358	1.2	-2.6	0.773	0.756	-2.2	0.464	0.392	-15.6	13.4

Notes: Table reports shares of students in data and model prediction that choose each major, before and after the crash. “Before” refers to entering The University between 1996 and 2000; “after” refers to entering The University between 2001 and 2005.

Table A.2: Effect of having less technical intro programming on the female share of computing degrees

	School year of exposure			
	Freshman	Sophomore	Junior	Senior
No CS 112	0.0164*	0.00886	0.00452	0.00574
	(0.00874)	(0.00886)	(0.00896)	(0.00875)
Observations	2053	2053	2053	2053
Inst. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Data from Integrated Postsecondary Education Data System on degrees awarded by institution, major, and gender. Sample used was computer and information science, computer engineering, and electrical engineering degrees from institutions with computer science programs ranked in the top 25 in the United States by *U.S. News and World Report* in 2019. All regressions include institution by gender fixed effects, year by gender fixed effects, and field by gender fixed effects.

Table A.3: Effect of diversification of upper level curriculum on the female share of computing degrees

	School year of exposure			
	Freshman	Sophomore	Junior	Senior
No OS	0.000319	-0.00288	-0.00672	-0.0112**
	(0.00573)	(0.00568)	(0.00565)	(0.00556)
Observations	1047	1108	1170	1232
Inst. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Data from Integrated Postsecondary Education Data System on degrees awarded by institution, major, and gender. Sample used was computer and information science degrees from institutions with computer science programs ranked in the top 25 in the United States by *U.S. News and World Report* in 2019. All regressions include institution by gender fixed effects, year by gender fixed effects, and field by gender fixed effects.

Table A.4: Average grade differences in previous classes

	(1)		
Course	Men	Women	Difference
Intro programming	-.092	-.067	-.024***
Programming 2	-.109	-.076	-.033***
Observations	137648		

Notes: Average grade difference (AGD) is calculated using $GP_{iks} - GPAO_{iks}$ and then averaged over all classes taken before or concurrently with the two programming classes. A negative AGD means that students earn lower grades than they might have expected based on their GPA elsewhere, and therefore suggests that a course is "graded harder" than average.

Table A.5: Student's self-reported rank in different majors

Student's Major	**Econ./Bus.**	**Eng./CS**	**Hum./Other SS**	**Nat. Science**	**No Degree**
Business/Economics	74.32	52.93	63.28	63.68	60.91
($n = 149$)	(24.90)	(28.52)	(27.26)	(26.32)	(43.15)
Engineering/CS	55.55	65.5	67.45	73.5	54.95
($n = 22$)	(29.00)	(29.86)	(27.72)	(25.11)	(41.59)
Humanities/Other	54.21	40.45	78.09	51.25	59.28
($n = 233$)	(26.60)	(28.18)	(24.66)	(27.62)	(41.87)
Natural Sciences	64.92	64.51	72.92	81.13	69.20
($n = 84$)	(28.77)	(26.18)	(22.12)	(21.87)	(41.44)
Overall Average	62.25	49.53	72.20	61.19	61.29
($N = 488$)	(27.95)	(29.56)	(25.96)	(28.41)	(42.22)

Notes: Source is Wiswall and Zafar (2015*a*) survey data from NYU. Rows indicate student major, while columns indicate the rank a student expects they would achieve, ability-wise, in a particular major. Standard deviations in parentheses.

Table A.6: Student's self-reported expected log earnings in different majors

Student's Major	**Econ./Bus.**	**Eng./CS**	**Hum./Other SS**	**Nat. Science**	**No Degree**
			Panel A: Age 30		
Business/Economics	2.45	2.16	1.77	2.01	1.21
($n = 149$)	(0.72)	(0.56)	(0.51)	(0.57)	0.70)
Engineering/CS	2.16	2.02	1.76	1.89	0.95
($n = 22$)	(0.38)	(0.54)	(0.38)	(0.41)	(0.64)
Humanities/Other SS	2.17	2.10	1.80	1.92	1.01
($n = 233$)	(0.56)	(0.48)	(0.47)	(0.55)	(0.52)
Natural Sciences	2.32	2.18	1.77	2.32	1.09
($n = 84$)	(0.66)	(0.51)	(0.43)	(0.66)	(0.62)
Overall Average	2.28	2.13	1.78	2.02	1.08
($N = 488$)	(0.64)	(0.52)	(0.47)	(0.58)	(0.61)
			Panel B: Age 45		
Business/Economics	2.75	2.45	2.14	2.30	1.77
($n = 149$)	(0.84)	(0.66)	(0.73)	(0.71)	(0.92)
Engineering/CS	2.20	2.21	1.90	1.99	1.19
($n = 22$)	(0.63)	(0.62)	(0.58)	(0.60)	(0.67)
Humanities/Other SS	2.35	2.21	2.05	2.12	1.41
($n = 233$)	(0.62)	(0.56)	(0.54)	(0.58)	(0.59)
Natural Sciences	2.51	2.30	1.99	2.43	1.49
($n = 84$)	(0.61)	(0.55)	(0.42)	(0.68)	(0.60)
Overall Average	2.49	2.30	2.06	2.22	1.52
($N = 488$)	(0.72)	(0.60)	(0.59)	(0.65)	(0.73)

Notes: Source is Wiswall and Zafar (2015*a*) survey data from NYU. Rows indicate student major, while columns indicate a student's expected earnings in a particular major.

Table A.7: Student's self-reported expected probability of nonwork in different majors

Student's Major	**Econ./Bus.**	**Eng./CS**	**Hum./Other SS**	**Nat. Science**	**No Degree**
			Panel A: Age 30		
Business/Economics	0.042	0.069	0.071	0.062	0.104
($n = 149$)	(0.063)	(0.144)	(0.121)	(0.103)	(0.155)
Engineering/CS	0.058	0.054	0.074	0.054	0.156
($n = 22$)	(0.077)	(0.080)	(0.085)	(0.075)	(0.230)
Humanities/Other SS	0.072	0.076	0.072	0.081	0.146
($n = 233$)	(0.105)	(0.124)	(0.093)	(0.132)	(0.188)
Natural Sciences	0.049	0.051	0.084	0.046	0.142
($n = 84$)	(0.062)	(0.064)	(0.100)	(0.060)	(0.177)
Overall Average	0.058	0.069	0.074	0.068	0.133
($N = 488$)	(0.087)	(0.121)	(0.103)	(0.112)	(0.179)
			Panel B: Age 45		
Business/Economics	0.054	0.060	0.058	0.056	0.070
($n = 149$)	(0.096)	(0.120)	(0.096)	(0.098)	(0.114)
Engineering/CS	0.061	0.054	0.074	0.054	0.135
($n = 22$)	(0.063)	(0.055)	(0.067)	(0.053)	(0.236)
Humanities/Other SS	0.068	0.066	0.069	0.062	0.087
($n = 233$)	(0.102)	(0.097)	(0.100)	(0.082)	(0.136)
Natural Sciences	0.047	0.047	0.061	0.050	0.088
($n = 84$)	(0.080)	(0.080)	(0.098)	(0.083)	(0.127)
Overall Average	0.060	0.060	0.065	0.058	0.084
($N = 488$)	(0.095)	(0.100)	(0.097)	(0.087)	(0.135)

Notes: Source is Wiswall and Zafar (2015*a*) survey data from NYU. Rows indicate student major, while columns indicate the rank a student expects they would, ability-wise, in a particular major.

Table A.8: Determinants of expected earnings by major

VARIABLES	(1) Nat. Sci.	(2) Hum./Other SS	(3) Eng./CS	(4) Bus./Econ.	(5) No Degree
		Panel A: Earnings expectations at 30			
Major-specific ability	0.00265**	0.00106	0.00112	0.00499***	0.00217***
	(0.00104)	(0.000933)	(0.000915)	(0.00111)	(0.000614)
Observations	488	488	488	488	488
R-squared	0.027	0.007	0.017	0.068	0.044
		Panel B: Earnings expectations at 45			
Major-specific ability	0.00395***	0.00127	0.00132	0.00572***	0.00200**
	(0.00110)	(0.00107)	(0.00101)	(0.00132)	(0.000828)
Observations	488	488	488	488	488
R-squared	0.038	0.025	0.016	0.059	0.038

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression of students' subjective earnings expectations at ages 30 and 45 in four majors (natural sciences, humanities/other social sciences, engineering/computer science, business/economics) and non-graduation on ability indicators. Source is Wiswall and Zafar (2015*a*) survey data. Controls include indicators for race and gender. Major-specific ability is a student's self-reported belief about their ability rank, with 100 the highest, among graduates of a particular major if they were to graduate with that major.

Table A.9: Determinants of expected nonwork probability by major

VARIABLES	(1) Nat. Sci.	(2) Hum./Other SS	(3) Eng./CS	(4) Bus./Econ.	(5) No Degree
Panel A: Nonwork expectations at 30					
Major-specific ability	-0.00179	-0.00391**	0.00199	-0.00120	-0.000192
	(0.00170)	(0.00171)	(0.00174)	(0.00150)	(0.00130)
Observations	488	488	488	488	488
R-squared	0.029	0.027	0.022	0.031	0.009
Panel B: Nonwork expectations at 45					
Major-specific ability	-0.00240	-0.00157	-0.000113	-0.000249	0.00126
	(0.00151)	(0.00167)	(0.00157)	(0.00156)	(0.00119)
Observations	488	488	488	488	488
R-squared	0.023	0.011	0.007	0.014	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression of students' subjective expected nonwork probability (probit coefficients) at ages 30 and 45 in four majors (natural sciences, humanities/other social sciences, engineering/computer science, business/economics) and non-graduation on ability indicators. Source is Wiswall and Zafar (2015*a*) survey data. Controls include indicators for race and gender. Major-specific ability is a student's self-reported belief about their ability rank, with 100 the highest, among graduates of a particular major if they were to graduate with that major.

Table A.10: Average bias in estimated earnings due to ability differences

	Econ./Bus.	**Eng./CS**	**Hum./Other SS**	**Nat. Science**
Age 30	0.061	0.017	0.006	0.054
	(0.017)	(0.016)	(0.006)	(0.023)
Age 45	0.069	0.021	0.008	0.080
	(0.020)	(0.019)	(0.007)	(0.025)

Notes: Bootstrap standard errors in parentheses. Source is Wiswall and Zafar (2015*a*) survey data from NYU. Table contains the average bias in earnings equations estimated using process described in section 1.4, which is $\gamma^{Y}(\mathbb{E}\left[A_{iMt}|M\right] - A_{iMt})$ Rows indicate age at which earnings are estimated, and columns indicate which major the bias is for.

Table A.11: Logit difference-in-difference marginal effects for the computing pipeline

	(1) Computing course	(2) Programming 2	(3) Declare	(4) Finish
Panel A: Overall changes at each stage				
Female	-0.893***	-1.652***	-1.689***	-1.688***
	(0.0227)	(0.0561)	(0.0641)	(0.0678)
Post	-0.266***	-0.483***	-0.533***	-0.543***
	(0.0363)	(0.0756)	(0.0855)	(0.0912)
Post $\times$ Female	-0.0592*	-0.266***	-0.377***	-0.456***
	(0.0321)	(0.0911)	(0.106)	(0.114)
Observations	44728	44728	44728	44728
Demographics	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Sample	All	All	All	All
Panel B: Attrition				
Female	-0.893***	-1.652***	-0.842***	0.000684
	(0.0227)	(0.0561)	(0.0568)	(0.0225)
Post	-0.266***	-0.483***	-0.327***	-0.00884
	(0.0363)	(0.0756)	(0.0768)	(0.0263)
Post $\times$ Female	-0.0592*	-0.266***	-0.231**	-0.0634*
	(0.0321)	(0.0911)	(0.0924)	(0.0336)
Observations	44728	44728	5983	3093
Demographics	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Sample	All	All	Took any course	Declared Major

Robust standard errors in parentheses. Logit difference-in-difference marginal effects for the computing pipeline. $*p < 0.1, **p < 0.05, ***p < 0.01$

Table A.12: Coefficients for Stage 1 when including SAT scores

	Women		Men	
	Pre-Eng./CS	Pre-Science	Pre-Eng./CS	Pre-Science
AP scores				
Calculus 1	0.57	0	0.33	-0.12
	(0.0017)	(0.00079)	(0.00092)	(8e-04)
Calculus 2	0.37	1.18	0.71	1.64
	(0.0025)	(0.0011)	(0.0012)	(0.00098)
English	0.26	-0.27	-0.16	-0.22
	(0.0017)	(0.00072)	(0.00096)	(0.00078)
Economics	-0.52	-0.48	0.03	-0.44
	(0.0032)	(0.0015)	(0.0014)	(0.0012)
Biology	0.37	0.97	0.03	0.95
	(0.0018)	(0.00073)	(0.0011)	(0.00077)
History	-0.82	-0.14	-0.28	-0.18
	(0.002)	(0.00085)	(0.001)	(8e-04)
Chemistry	0.58	0.95	0.41	0.31
	(0.0022)	(0.001)	(0.0011)	(0.00093)
Foreign Language	0.64	0.07	0.13	0.64
	(0.0055)	(0.0022)	(0.0035)	(0.0024)
Physics	1	0.26	0.84	0.2
	(0.0041)	(0.0018)	(0.0016)	(0.0013)
SAT Math / 100	0.43	0.37	-0.02	0.32
	(0.0012)	(0.00056)	(0.00069)	(0.00057)
SAT Verbal / 100	-0.8	-0.24	-0.62	-0.32
	(0.0011)	(0.00049)	(0.00059)	(0.00051)

Notes: Standard errors in parentheses. SAT scores for students who had only ACT scores had SAT scores were imputed according to Dorans (1999). Standard errors are estimated using the inverse of the Fisher information matrix and are not necessarily consistent; future versions of the paper will include bootstrapped standard errors. Estimated multinomial logit coefficients for stage 1 of structural model. Results are estimated separately for men and women, relative to Non-STEM. Estimation also includes controls for race, log average income in ZIP code of residence, in-state residency, international status, entering The University via the College of Liberal Arts, and estimated continuation value. Fields with multiple exams (e.g. foreign language, economics) represent having at least one credit in any exam in that group. Where an IB exam exists, credit gained from that exam is combined with the AP exam into a single indicator. Credit for AP Computer Science includes the placement exam for computer science.

Table A.13: Women's and Men's responses to grades and SAT scores

	Women					Men				
	C.S.	Eng.	Sci.	Bus.	Hum./SS	C.S.	Eng.	Sci.	Bus.	Hum./SS
						Panel A: Period 2 (first majors)				
In-Track GPA										
× Pre-Science	4.07	5.49	-0.4	0.42	-0.81	3.52	2.73	0.62	1.71	-0.23
	(0.024)	(0.0076)	(0.0043)	(0.005)	(0.0042)	(0.0062)	(0.006)	(0.0036)	(0.0039)	(0.0034)
× Pre-Eng./CS	-4.2	1.11	-0.86	-1.31	-2.4	0.65	1.54	0.41	-0.05	-1
	(0.0056)	(0.0053)	(0.006)	(0.0064)	(0.0055)	(0.0025)	(0.0023)	(0.0029)	(0.0032)	(0.0024)
× Non-STEM	18.41	10.62	7.95	-6.54	1.84	1.54	0.63	5	-4.49	0
	(0.011)	(0.01)	(0.0069)	(0.0074)	(0.0065)	(0.0056)	(0.0057)	(0.005)	(0.005)	(0.0045)
Overall GPA										
× Pre-Science	-0.35	-8.29	-0.04	-0.07	0.39	-4.12	-2.97	-0.7	-1.91	-0.07
	(0.037)	(0.0088)	(0.0057)	(0.0069)	(0.0056)	(0.0068)	(0.007)	(0.0046)	(0.0051)	(0.0045)
× Pre-Eng./CS	8.23	1.37	4.17	1.11	4.7	1.94	1.11	1.61	2.46	2.56
	(0.0085)	(0.0082)	(0.0092)	(0.01)	(0.0087)	(0.0035)	(0.0034)	(0.0042)	(0.0046)	(0.0038)
× Non-STEM	-12.41	-1.72	-7.43	5.65	-1.86	-1.79	-0.55	-4.55	4.46	-0.32
	(0.011)	(0.0088)	(0.0066)	(0.0073)	(0.0063)	(0.0055)	(0.0056)	(0.0049)	(0.0051)	(0.0046)
SAT Math / 100	0.67	0.72	0.48	0.36	0.06	0.29	0.35	0.16	-0.18	-0.32
	(0.0019)	(0.0015)	(0.0013)	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.001)	(0.00098)	(0.00094)
SAT Verbal / 100	-0.02	0.05	0.07	0.03	0.23	-0.21	-0.23	-0.26	-0.01	0.01
	(0.0017)	(0.0015)	(0.0013)	(0.0013)	(0.0012)	(0.001)	(0.00099)	(0.00095)	(0.00094)	(9e-04)
						Panel B: Period 3 (final majors)				
In-Major GPA	9.39	5.91	2.35	4.08	-2.29	5.28	3.77	2.02	3.11	-1.45
× No Switch	(0.015)	(0.0052)	(0.0026)	(0.0048)	(0.003)	(0.0047)	(0.0032)	(0.0035)	(0.0039)	(0.0033)
Overall GPA	-4.33	-1.33	1.69	1.12	6.37	-0.66	0.85	1.6	0.76	5.02
× No Switch	(0.018)	(0.0063)	(0.0039)	(0.0064)	(0.0033)	(0.0058)	(0.004)	(0.0043)	(0.0051)	(0.0035)
Overall GPA	5.73	3.5	4.45	5.16	4	5.37	3.73	4	4.34	3.3
× Switch	(0.009)	(0.0055)	(0.0023)	(0.0029)	(0.0024)	(0.004)	(0.0034)	(0.0023)	(0.0021)	(0.002)
SAT Math / 100	0.32	0.16	0.07	0.51	-0.17	0.2	-0.13	-0.04	0.23	-0.31
	(0.0035)	(0.0019)	(0.0012)	(0.0014)	(0.00092)	(0.0017)	(0.0013)	(0.0011)	(0.0012)	(0.00086)
SAT Verbal / 100	-1.7	-0.79	-0.82	-1.05	-0.78	-0.38	-0.57	-0.31	-0.89	-0.28
	(0.0033)	(0.0018)	(0.0012)	(0.0014)	(0.00094)	(0.0014)	(0.0012)	(0.0011)	(0.0011)	(0.00083)

Notes: Multinomial logit coefficients describing men's and women's responses to grades when choosing majors in periods 2 and 3 when SAT scores are included in the estimation. Only students who entered The University between 2000 and 2005 and who have either SAT or ACT scores were includes. SAT scores for students who had only ACT scores had SAT scores were imputed according to Dorans (1999). Standard errors are in parentheses. Standard errors were calculated using the inverse of the Fisher information matrix and are not necessarily consistent; future drafts will include bootstrapped standard errors. The outside option in periods 2 and 3 is permanently dropping out of college. Additional controls included are the log of the average income in student's ZIP code of residence, race/ethnicity, and indicators for being an international student, in-state residency, and entering The University via the College of Liberal Arts.

Table A.14: Women's and Men's responses to grades when including AP scores in every period

	Women					Men				
	C.S.	Eng.	Sci.	Bus.	Hum./SS	C.S.	Eng.	Sci.	Bus.	Hum./SS
					Panel A: Period 2 (first majors)					
In-Track GPA										
× Pre-Science	6.49	3.44	-0.9	0.36	-1.33	2.01	1.16	0.01	1.18	-0.82
	(0.012)	(0.0041)	(0.0025)	(0.0029)	(0.0024)	(0.0032)	(0.003)	(0.002)	(0.0022)	(0.0019)
× Pre-Eng./CS	-3.2	2.1	-0.61	-0.25	-1.49	0.88	1.58	0.53	0.23	-0.91
	(0.0029)	(0.0027)	(0.0031)	(0.0034)	(0.0028)	(0.0013)	(0.0013)	(0.0017)	(0.0018)	(0.0013)
× Non-STEM	16.68	10.15	8.25	-6.18	1.67	1.55	1.3	5.09	-3.45	0.37
	(0.0056)	(0.0057)	(0.0038)	(0.0041)	(0.0034)	(0.0032)	(0.0033)	(0.003)	(0.0028)	(0.0026)
Overall GPA										
× Pre-Science	-1.31	-5.31	1.19	0.39	1.02	-2.57	-1.6	-0.12	-1.7	0.19
	(0.016)	(0.0049)	(0.0032)	(0.0038)	(0.0032)	(0.0038)	(0.0037)	(0.0026)	(0.0027)	(0.0025)
× Pre-Eng./CS	7.68	0.25	3.83	0.46	3.18	0.85	-0.02	0.58	0.8	1.2
	(0.0045)	(0.0043)	(0.0048)	(0.0053)	(0.0045)	(0.0018)	(0.0017)	(0.0023)	(0.0024)	(0.0019)
× Non-STEM	-10.7	-2.13	-7.08	5.53	-1.9	-2.09	-1.64	-4.67	3.15	-1.12
	(0.0055)	(0.0048)	(0.0036)	(0.004)	(0.0034)	(0.0031)	(0.0031)	(0.0029)	(0.0029)	(0.0026)
					Panel B: Period 3 (final majors)					
In-Major GPA	8.36	5.17	3.22	3.05	-1.79	4.01	3.02	2.71	2.65	-0.76
× No Switch	(0.0081)	(0.0027)	(0.0018)	(0.0028)	(0.002)	(0.0023)	(0.0016)	(0.0023)	(0.0022)	(0.002)
Overall GPA	-5.51	-0.92	0.09	1.89	5.7	0.37	1.46	0.75	1.12	4.41
× No Switch	(0.01)	(0.0033)	(0.0027)	(0.0037)	(0.0021)	(0.003)	(0.002)	(0.0028)	(0.0028)	(0.0021)
Overall GPA	4.61	3.96	4.42	4.67	3.38	4.65	3.41	4.06	3.94	3.13
× Switch	(0.0042)	(0.0031)	(0.0015)	(0.0017)	(0.0014)	(0.0018)	(0.0019)	(0.0014)	(0.0012)	(0.0011)

Notes: Multinomial logit coefficients describing men's and women's responses to grades when AP credits are included in every period. Standard errors are in parentheses. Standard errors were calculated using the inverse of the Fisher information matrix and are not necessarily consistent; future drafts will include bootstrapped standard errors. The outside option in periods 2 and 3 is permanently dropping out of college. Additional controls included are the log of the average income in student's ZIP code of residence, race/ethnicity, and indicators for being an international student, in-state residency, and entering The University via the College of Liberal Arts.

Table A.15: AR(1) regression coefficients for log salary and unemployment

	(1) Log salary	(2) Unemployment
r	0.745	0.817
	(0.058)	(0.089)
Major FE		
Computer science	0.452	-0.001
	(0.099)	(0.003)
Engineering	0.436	-0.001
	(0.096)	(0.003)
Science	0.351	-0.005
	(0.079)	(0.003)
Business	0.385	-0.002
	(0.083)	(0.003)
Hum./SS/Other	0.306	-0.001
	(0.068)	(0.003)
Constant	2.353	0.008
	(0.534)	(0.004)
Observations	93	93

Notes: Standard errors in parentheses.

Table A.16: Coefficients for Stage 1 when labor market shocks are transitory

	Women		Men	
	Pre-Eng./CS	Pre-Science	Pre-Eng./CS	Pre-Science
Calculus 1	0.34	0.21	0.03	-0.11
	(0.00058)	(0.00031)	(0.00036)	(0.00033)
Calculus 2	0.44	1.06	0.15	1.42
	(0.001)	(0.00053)	(0.00057)	(0.00047)
English	-0.32	-0.07	-0.3	-0.27
	(0.00055)	(0.00027)	(0.00038)	(0.00032)
Economics	-0.68	-0.22	-0.05	-0.24
	(0.0014)	(0.00075)	(0.00067)	(6e-04)
Biology	-0.13	1.06	0.11	0.68
	(0.00069)	(3e-04)	(0.00046)	(0.00034)
History	0.12	-0.12	-0.39	-0.23
	(8e-04)	(0.00037)	(0.00044)	(0.00036)
Chemistry	0.01	1.09	0.2	0.3
	(0.00085)	(0.00048)	(0.00049)	(0.00043)
Foreign Language	0.22	0.1	0.18	0.47
	(0.0024)	(0.00099)	(0.0016)	(0.0011)
Physics	-0.04	0.21	1.04	0.23
	(0.0016)	(0.00082)	(7e-04)	(0.00059)

Notes: Standard errors in parentheses. Standard errors are estimated using the inverse of the Fisher information matrix and are not necessarily consistent; future versions of the paper will include bootstrapped standard errors. Estimated multinomial logit coefficients for stage 1 of structural model when employment and salary follow an AR(1) process. Results are estimated separately for men and women, relative to Non-STEM. Estimation also includes controls for race, log average income in ZIP code of residence, in-state residency, international status, entering The University via the College of Liberal Arts, and estimated continuation value. Fields with multiple exams (e.g. foreign language, economics) represent having at least one credit in any exam in that group. Where an IB exam exists, credit gained from that exam is combined with the AP exam into a single indicator. Credit for AP Computer Science includes the placement exam for computer science.

Table A.17: Women's and Men's responses to grades when labor market shocks are transitory

	Women					Men				
	Computing	Engineering	Science	Business	Other	Computing	Engineering	Science	Business	Other
						Panel A: Period 2 (first majors)				
In-Track GPA										
× Pre-Science	6.49	3.44	-0.9	0.36	-1.33	2.01	1.16	0.01	1.18	-0.82
	(0.012)	(0.0041)	(0.0025)	(0.0029)	(0.0024)	(0.0032)	(0.003)	(0.002)	(0.0022)	(0.0019)
× Pre-Eng./CS	-3.2	2.1	-0.61	-0.25	-1.49	0.88	1.58	0.53	0.23	-0.91
	(0.0029)	(0.0027)	(0.0031)	(0.0034)	(0.0028)	(0.0013)	(0.0013)	(0.0017)	(0.0018)	(0.0013)
× Non-STEM	16.68	10.15	8.25	-6.18	1.67	1.55	1.3	5.09	-3.45	0.37
	(0.0056)	(0.0057)	(0.0038)	(0.0041)	(0.0034)	(0.0032)	(0.0033)	(0.003)	(0.0028)	(0.0026)
Overall GPA										
× Pre-Science	-1.31	-5.31	1.19	0.39	1.02	-2.57	-1.6	-0.12	-1.7	0.19
	(0.016)	(0.0049)	(0.0032)	(0.0038)	(0.0032)	(0.0038)	(0.0037)	(0.0026)	(0.0027)	(0.0025)
× Pre-Eng./CS	7.68	0.25	3.83	0.46	3.18	0.85	-0.02	0.58	0.8	1.2
	(0.0045)	(0.0043)	(0.0048)	(0.0053)	(0.0045)	(0.0018)	(0.0017)	(0.0023)	(0.0024)	(0.0019)
× Non-STEM	-10.7	-2.13	-7.08	5.53	-1.9	-2.09	-1.64	-4.67	3.15	-1.12
	(0.0055)	(0.0048)	(0.0036)	(0.004)	(0.0034)	(0.0031)	(0.0031)	(0.0029)	(0.0029)	(0.0026)
						Panel B: Period 3 (final majors)				
In-Major GPA	8.36	5.17	3.22	3.05	-1.79	4.01	3.02	2.71	2.65	-0.76
× No Switch	(0.0081)	(0.0027)	(0.0018)	(0.0028)	(0.002)	(0.0023)	(0.0016)	(0.0023)	(0.0022)	(0.002)
Overall GPA	-5.51	-0.92	0.09	1.89	5.7	0.37	1.46	0.75	1.12	4.41
× No Switch	(0.01)	(0.0033)	(0.0027)	(0.0037)	(0.0021)	(0.003)	(0.002)	(0.0028)	(0.0028)	(0.0021)
Overall GPA	4.61	3.96	4.42	4.67	3.38	4.65	3.41	4.06	3.94	3.13
× Switch	(0.0042)	(0.0031)	(0.0015)	(0.0017)	(0.0014)	(0.0018)	(0.0019)	(0.0014)	(0.0012)	(0.0011)

Notes: Multinomial logit coefficients describing men's and women's responses to grades when choosing majors in periods 2 and 3, where salary and employment follow an AR(1) process. Standard errors are in parentheses. Standard errors were calculated using the inverse of the Fisher information matrix and are not necessarily consistent; future drafts will include bootstrapped standard errors. The outside option in periods 2 and 3 is permanently dropping out of college. Additional controls included are the log of the average income in student's ZIP code of residence, race/ethnicity, and indicators for being an international student, in-state residency, and entering The University via the College of Liberal Arts.

Table A.18: Coefficients for Stage 1 when estimating the value of unemployment

	Women		Men	
	Pre-Eng./CS	Pre-Science	Pre-Eng./CS	Pre-Science
Calculus 1	0.34	0.21	0.03	-0.11
	(0.00058)	(0.00031)	(0.00036)	(0.00033)
Calculus 2	0.43	1.06	0.15	1.42
	(0.001)	(0.00053)	(0.00057)	(0.00047)
English	-0.32	-0.07	-0.3	-0.27
	(0.00055)	(0.00027)	(0.00038)	(0.00032)
Economics	-0.68	-0.22	-0.05	-0.24
	(0.0014)	(0.00075)	(0.00067)	(6e-04)
Biology	-0.13	1.06	0.11	0.68
	(0.00069)	(3e-04)	(0.00046)	(0.00034)
History	0.11	-0.12	-0.39	-0.23
	(8e-04)	(0.00037)	(0.00044)	(0.00036)
Chemistry	0.01	1.1	0.21	0.3
	(0.00086)	(0.00048)	(0.00049)	(0.00043)
Foreign Language	0.21	0.11	0.18	0.47
	(0.0024)	(0.00099)	(0.0016)	(0.0011)
Physics	-0.03	0.21	1.04	0.23
	(0.0016)	(0.00082)	(7e-04)	(0.00059)

Notes: Standard errors in parentheses. Standard errors are estimated using the inverse of the Fisher information matrix and are not necessarily consistent; future versions of the paper will include bootstrapped standard errors. Estimated multinomial logit coefficients for stage 1 of structural model when the value of unemployment $u(b_i)$ is estimated rather than set to 0. Results are estimated separately for men and women, relative to Non-STEM. Estimation also includes controls for race, log average income in ZIP code of residence, in-state residency, international status, entering The University via the College of Liberal Arts, and estimated continuation value. Fields with multiple exams (e.g. foreign language, economics) represent having at least one credit in any exam in that group. Where an IB exam exists, credit gained from that exam is combined with the AP exam into a single indicator. Credit for AP Computer Science includes the placement exam for computer science.

Table A.19: Women's and Men's responses to grades when estimating the value of unemployment

	Women					Men				
	Computing	Engineering	Science	Business	Other	Computing	Engineering	Science	Business	Other
Panel A: Period 2 (first majors)										
In-Track GPA										
× Pre-Science	6.83	3.36	-0.77	0.4	-1.31	2.02	1.18	0.07	1.14	-0.82
	(0.012)	(0.0041)	(0.0025)	(0.0029)	(0.0024)	(0.0032)	(0.003)	(0.002)	(0.0021)	(0.0019)
× Pre-Eng./CS	-3.04	2	-0.47	-0.25	-1.48	0.88	1.53	0.59	0.21	-0.9
	(0.0028)	(0.0027)	(0.003)	(0.0033)	(0.0027)	(0.0013)	(0.0013)	(0.0017)	(0.0017)	(0.0013)
× Non-STEM	16.07	9.73	8.15	-6.32	1.65	1.55	1.29	5.03	-3.44	0.38
	(0.0056)	(0.0056)	(0.0038)	(0.0041)	(0.0034)	(0.0032)	(0.0033)	(0.003)	(0.0028)	(0.0026)
Overall GPA										
× Pre-Science	-2.09	-5.04	0.97	0.31	0.98	-2.56	-1.55	-0.2	-1.71	0.18
	(0.015)	(0.0049)	(0.0032)	(0.0038)	(0.0032)	(0.0038)	(0.0036)	(0.0025)	(0.0027)	(0.0025)
× Pre-Eng./CS	7.38	0.4	3.59	0.39	3.15	0.78	0.03	0.57	0.81	1.21
	(0.0044)	(0.0043)	(0.0048)	(0.0052)	(0.0045)	(0.0018)	(0.0017)	(0.0023)	(0.0024)	(0.0019)
× Non-STEM	-10.29	-2.05	-6.97	5.73	-1.86	-2.06	-1.51	-4.58	3.14	-1.11
	(0.0055)	(0.0048)	(0.0036)	(0.004)	(0.0034)	(0.0031)	(0.0031)	(0.0029)	(0.0029)	(0.0026)
Panel B: Period 3 (final majors)										
In-Major GPA	7.96	5.15	3.01	3.2	-1.77	3.93	2.94	2.45	2.66	-0.73
× No Switch	(0.0014)	(0.0079)	(0.0028)	(0.0018)	(0.0029)	(0.0011)	(0.0023)	(0.0016)	(0.0022)	(0.0022)
Overall GPA	-4.99	-1.01	0.43	1.71	5.68	0.43	1.44	1.06	1.13	4.37
× No Switch	(0.002)	(0.01)	(0.0034)	(0.0026)	(0.0038)	(0.002)	(0.0029)	(0.002)	(0.0027)	(0.0028)
Overall GPA	4.65	3.92	4.43	4.64	3.42	4.62	3.42	4.07	3.89	3.13
× Switch	(0.0041)	(0.0042)	(0.0031)	(0.0015)	(0.0017)	(0.0035)	(0.0018)	(0.0019)	(0.0014)	(0.0012)

Notes: Multinomial logit coefficients describing men's and women's responses to grades when choosing majors in periods 2 and 3, when the value of unemployment $u(b_i)$ is estimated rather than set to 0. Standard errors are in parentheses. Standard errors were calculated using the inverse of the Fisher information matrix and are not necessarily consistent; future drafts will include bootstrapped standard errors. The outside option in periods 2 and 3 is permanently dropping out of college. Additional controls included are the log of the average income in student's ZIP code of residence, race/ethnicity, and indicators for being an international student, in-state residency, and entering The University via the College of Liberal Arts.

Table A.20: Women's and Men's grade coefficients in computer science under different discount rates

	$\beta = 0.8$		$\beta = 0.9$		$\beta = 0.98$		$\beta = 0.99$	
	Women	Men	Women	Men	Women	Men	Women	Men
Panel A: Period 2 (first majors)								
In-Track GPA								
× Pre-Science	6.55	2.17	6.92	2.17	7.38	2.22	7.46	2.23
	(0.012)	(0.0032)	(0.012)	(0.0032)	(0.013)	(0.0033)	(0.013)	(0.0033)
× Pre-Eng./CS	-2.44	1.02	-3.04	0.87	-3.67	0.73	-3.77	0.71
	(0.0028)	(0.0013)	(0.0029)	(0.0013)	(0.0029)	(0.0013)	(0.0029)	(0.0013)
× Non-STEM	14.38	1.37	15.77	1.38	17.27	1.34	17.53	1.33
	(0.0055)	(0.0032)	(0.0056)	(0.0032)	(0.0057)	(0.0032)	(0.0057)	(0.0032)
Overall GPA								
× Pre-Science	-2.03	-2.26	-2.08	-2.61	-2.02	-3.01	-1.99	-3.07
	(0.015)	(0.0038)	(0.015)	(0.0038)	(0.015)	(0.0038)	(0.016)	(0.0038)
× Pre-Eng./CS	6.93	1.09	7.45	0.93	8.08	0.82	8.19	0.81
	(0.0044)	(0.0018)	(0.0045)	(0.0018)	(0.0045)	(0.0018)	(0.0046)	(0.0018)
× Non-STEM	-9.18	-1.45	-10.18	-1.81	-11.21	-2.11	-11.38	-2.14
	(0.0054)	(0.0031)	(0.0055)	(0.0031)	(0.0056)	(0.0031)	(0.0056)	(0.0031)
Panel B: Period 3 (final majors)								
In-Major GPA	8	3.96	8.17	4.04	8.56	4.23	8.64	4.26
× No Switch	(0.0079)	(0.0023)	(0.0079)	(0.0024)	(0.0081)	(0.0024)	(0.0081)	(0.0024)
Overall GPA	-4.98	0.46	-5.11	0.44	-5.46	0.38	-5.54	0.37
× No Switch	(0.01)	(0.0029)	(0.01)	(0.0029)	(0.01)	(0.003)	(0.01)	(0.003)
Overall GPA	4.69	4.61	4.71	4.63	4.76	4.69	4.77	4.71
× Switch	(0.0042)	(0.0018)	(0.0042)	(0.0018)	(0.0042)	(0.0019)	(0.0042)	(0.0019)

Notes: Estimated coefficients on grades in computer science under varying discount rates. Standard errors in parentheses calculated using inverse of Fisher information matrix and may not be consistent; future versions will bootstrap these coefficients.

Table A.21: Women's and Men's grade coefficients in computer science under different lifespans

	$T = 5$		$T = 10$		$T = 15$		$T = 20$	
	Women	Men	Women	Men	Women	Men	Women	Men
Panel A: Period 2 (first majors)								
In-Track GPA								
× Pre-Science	6.98	2.11	7.13	2.17	7.26	2.22	7.42	2.27
	(0.012)	(0.0032)	(0.012)	(0.0033)	(0.012)	(0.0033)	(0.013)	(0.0033)
× Pre-Eng./CS	-3.2	0.82	-3.35	0.79	-3.5	0.77	-3.63	0.76
	(0.0029)	(0.0013)	(0.0029)	(0.0013)	(0.0029)	(0.0013)	(0.0029)	(0.0013)
× Non-STEM	16.18	1.45	16.5	1.39	16.86	1.33	17.21	1.29
	(0.0056)	(0.0032)	(0.0057)	(0.0032)	(0.0057)	(0.0032)	(0.0057)	(0.0032)
Overall GPA								
× Pre-Science	-2.12	-2.69	-2.08	-2.8	-2.01	-2.9	-1.99	-3
	(0.015)	(0.0038)	(0.015)	(0.0038)	(0.015)	(0.0038)	(0.015)	(0.0038)
× Pre-Eng./CS	7.54	0.83	7.73	0.85	7.92	0.87	8.11	0.88
	(0.0045)	(0.0018)	(0.0045)	(0.0018)	(0.0045)	(0.0018)	(0.0046)	(0.0018)
× Non-STEM	-10.44	-2.01	-10.68	-2	-10.93	-1.99	-11.15	-2
	(0.0055)	(0.0031)	(0.0055)	(0.0031)	(0.0056)	(0.0031)	(0.0056)	(0.0031)
Panel B: Period 3 (final majors)								
In-Major GPA	8.03	3.97	8.27	4.09	8.52	4.21	8.77	4.32
× No Switch	(0.0079)	(0.0023)	(0.008)	(0.0024)	(0.0081)	(0.0024)	(0.0081)	(0.0024)
Overall GPA	-5.01	0.46	-5.2	0.43	-5.43	0.39	-5.66	0.35
× No Switch	(0.01)	(0.0029)	(0.01)	(0.003)	(0.01)	(0.003)	(0.011)	(0.003)
Overall GPA	4.69	4.61	4.73	4.65	4.76	4.69	4.8	4.73
× Switch	(0.0042)	(0.0018)	(0.0042)	(0.0019)	(0.0042)	(0.0019)	(0.0043)	(0.0019)

Notes: Estimated coefficients on grades in computer science under different. Standard errors in parentheses calculated using inverse of Fisher information matrix and may not be consistent; future versions will bootstrap these coefficients.

Table A.22: Experience coefficients in WZ

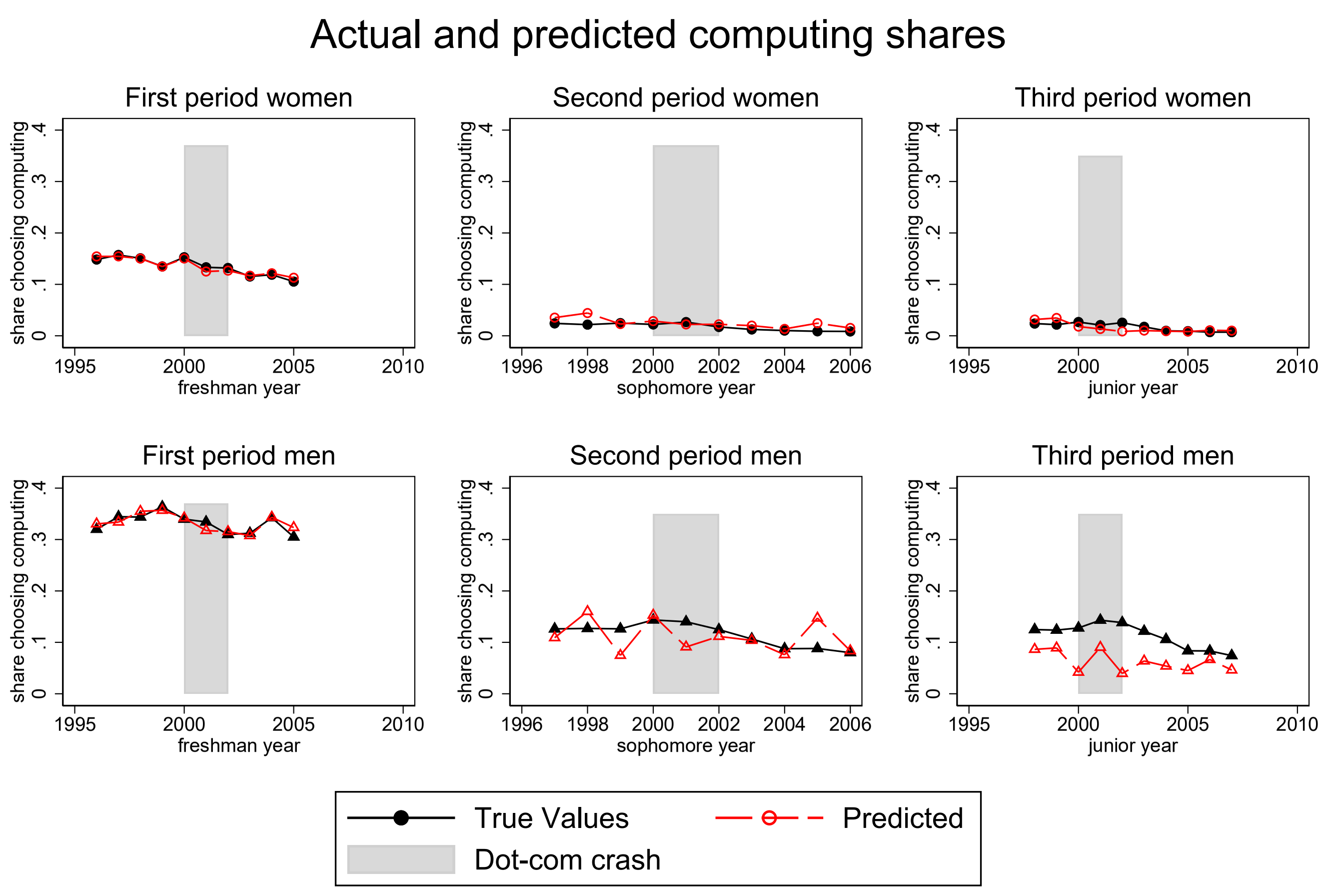
	(1) Engineering/CS	(2) Science	(3) Business/Economics	(4) Other	(5) Dropout
Experience	0.077***	0.084***	0.107***	0.075***	0.029***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
Experience^2	-0.002***	-0.002***	-0.003***	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1464	1464	1464	1464	1464

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Robust standard errors in parentheses clustered at the individual level. Regression includes individual fixed effects.

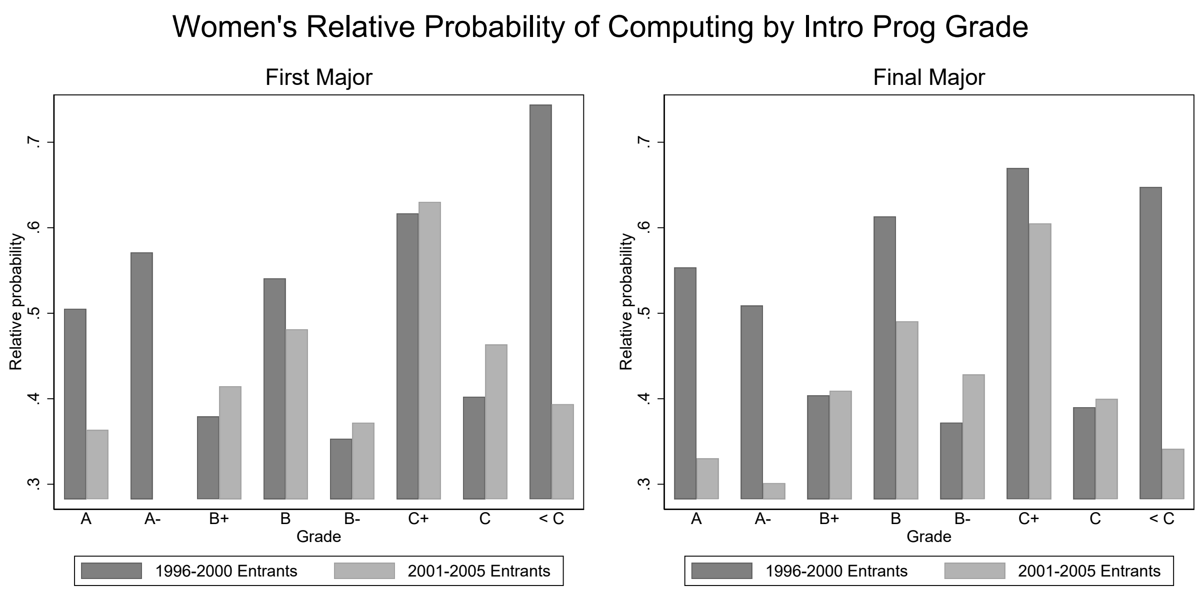
A.9.4 Figures

Figure A.1: Structural model fit



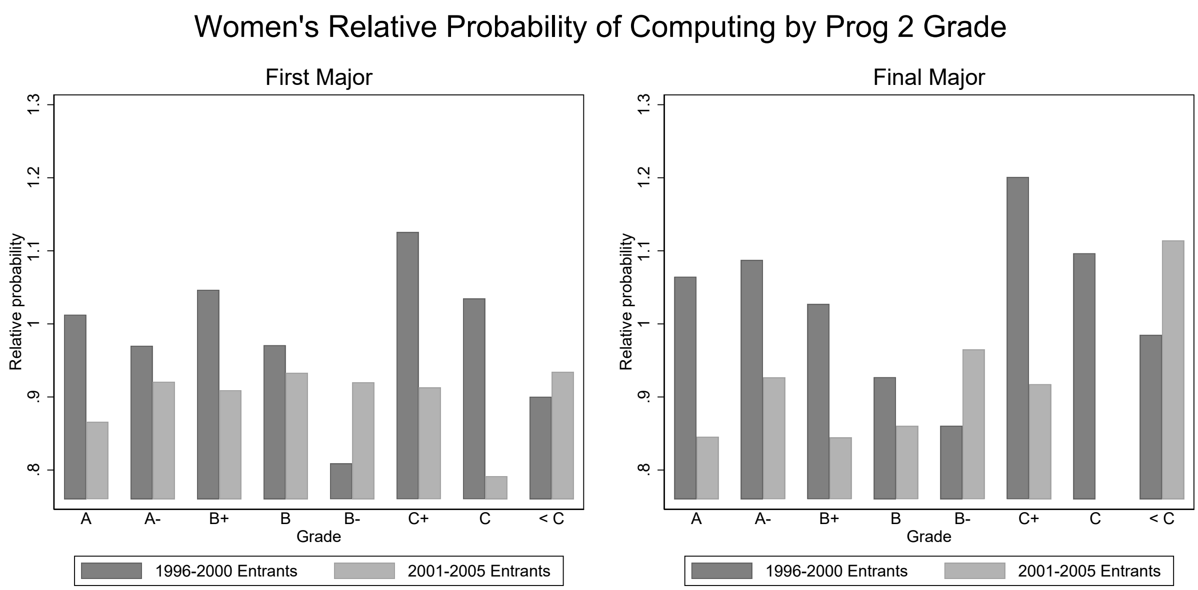
Notes: Source is administrative data on students at The University who entered between 1996 and 2005. True values are shares of students picking pre-engineering/CS in period 1 and computing in periods 2 and 3. The log number of computing students is calculated using $\log(predictedshare * cohortsize)$

Figure A.2: Relative probability that women choose computing majors by grade in introductory programming



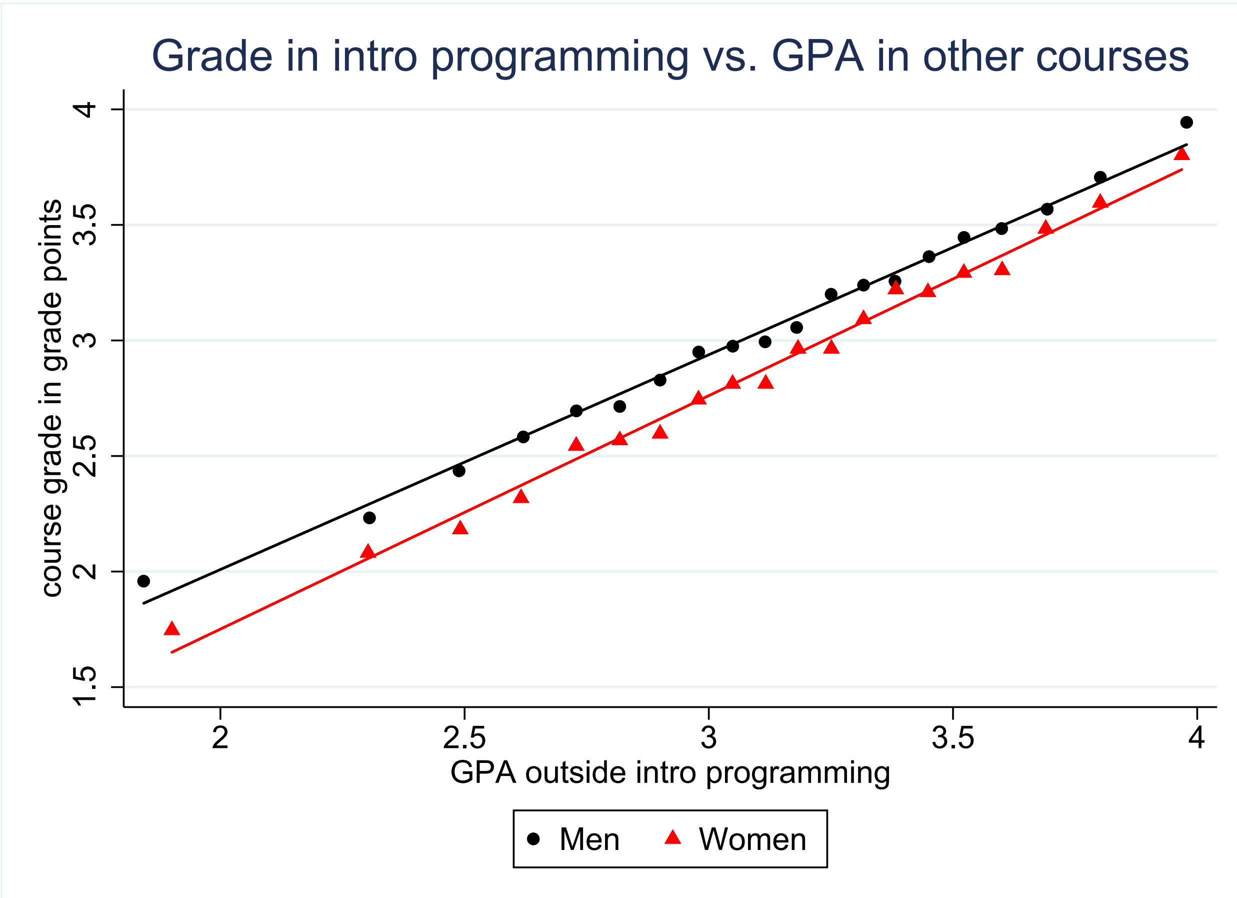
Notes: "Relative probability" refers to the probability that women who earn a particular letter grade in introductory programming choose computing as their first or final major divided by the same probability for men. Probabilities are unadjusted for student characteristics.

Figure A.3: Relative probability that women choose computing majors by grade in Programming 2



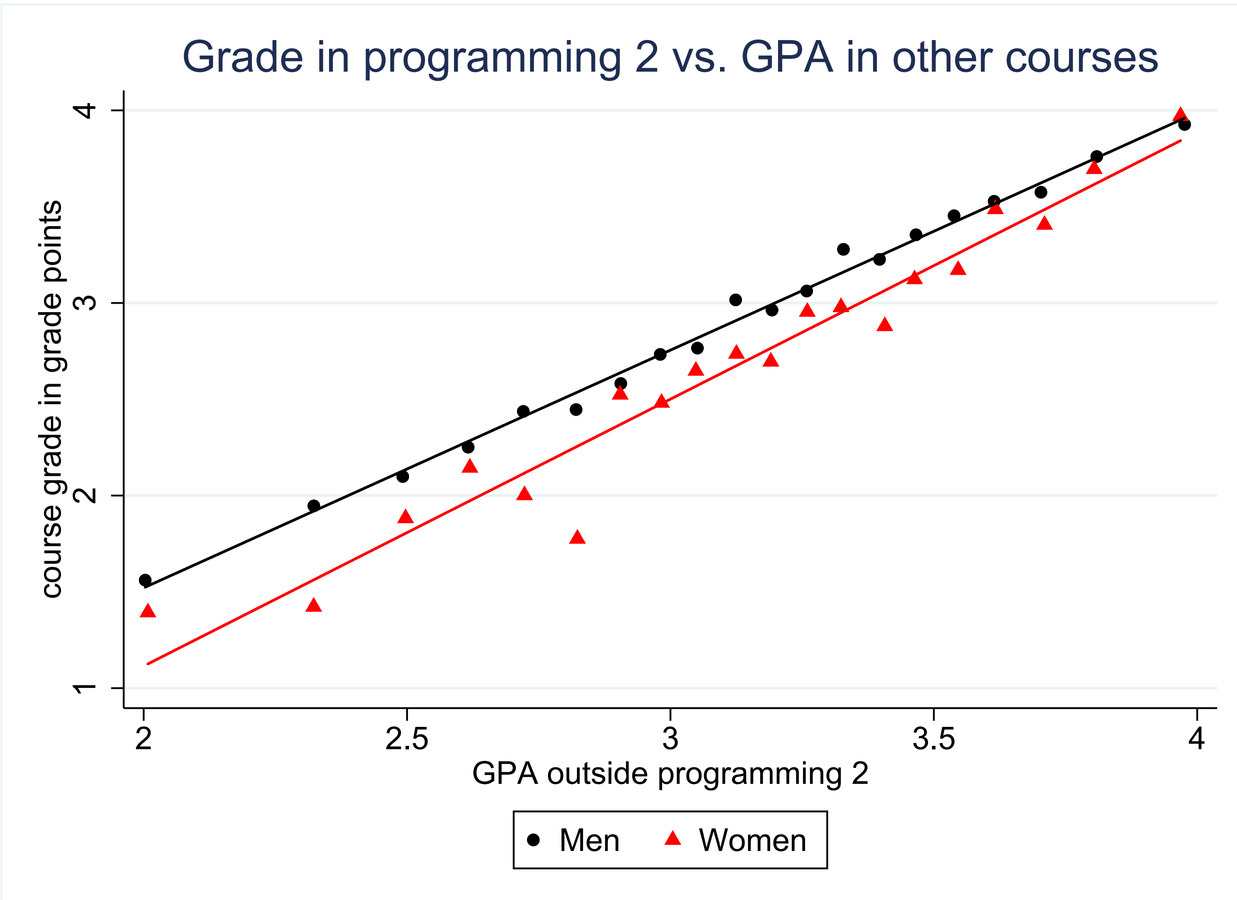
Notes: "Relative probability" refers to the probability that women who earn a particular letter grade in introductory programming choose computing as their first or final major divided by the same probability for men. Probabilities are unadjusted for student characteristics.

Figure A.4: Gendered performance differences in Intro Programming



Notes: "Gendered performance difference" refers to gender differences in underperformance in courses relative to GPA in other courses, following Koester, Grom and McKay (2016) and Matz et al. (2017). As discussed in Appendix A.2, introductory programming is a combination of three programming courses during my sample period. Binned scatterplot is residualized on term-by-course fixed effects, AP credits, an indicator for college of entry, and demographic variables. GPA in other courses is in courses before and during the same term as introductory programming was taken.

Figure A.5: Gendered performance differences in Programming 2



Notes: "Gendered performance difference" refers to gender differences in underperformance in courses relative to GPA in other courses, following Koester, Grom and McKay (2016) and Matz et al. (2017). Binned scatterplot is residualized on term fixed effects, AP credits, an indicator for college of entry, and demographic variables. GPA in other courses is in courses before and during the same term as programming 2 was taken.

APPENDIX B

Chapter II Supporting Material

B.1 A formal model of the effect of coeducation on women's STEM majoring

We use a simple Roy model of college and major choice to illustrate the possible effects of transition to co-education on subsequent women's outcomes. We assume there are 3 collegiate institutions in the market: h, j and k. There are two time periods: 0 and 1, which are separated by a substantial number of years. At $t = 0$, institutions h and j are women-only while k is co-educational. Between $t = 0$ and $t = 1$, institution h transitions to co-education. All institutions in each time period offer two majors: STEM (S) and non-STEM (NS).

Each time period consists of two stages. In the first stage, women make enrollment decisions η under uncertainty about the values of attending each college. In the second stage, women who have chosen to enroll in a college choose a major μ in which to graduate, with full information about major-specific payoffs. We assume that every woman enrolls in college, and every woman who starts college completes a degree at her starting institution. That is, there is no transferring between colleges. We also assume that women can choose any major they wish upon entering any institution.[1]

Consider a hypothetical high school senior w making decisions in period t. A given enrollment choice η_{wt} returns the expected payoff $V_{wt}(\eta_{wt})$. She chooses the enrollment choice η^*_{wt} that maximizes this function:

$$V_{wt}(\eta^*_{wt}) = \max\left\{V_{wt}(h), V_{wt}(j), V_{wt}(k)\right\}. \tag{B.1}$$

[1] Supply-side channels such as capacity constraints could theoretically also affect the major choices women make upon the transition to coeducation. While we do not include these in our theoretical framework, in Section 2.9 we find that capacity constraints cannot explain all of our results.

After making her enrollment choice, woman w realizes her major-specific payoffs and chooses her major μ_{wt}. We represent her payoff from choosing major μ at institution η as $v_{wt}(\mu_{wt}; \eta)$. Her major choice μ^*_{wt} thus satisfies:

$$v_{wt}(\mu^*_{wt}; \eta) = \max\left\{v_{wt}(S; \eta), v_{wt}(NS; \eta)\right\},\ \eta \in \{h, j, k\}. \tag{B.2}$$

Woman w's expected payoff from enrolling at institution η is simply equal to the expected payoff from choosing her most-preferred major at η:

$$V_{wt}(\eta) = E\left[v_{wt}(\mu^*_{wt}; \eta)\right] \tag{B.3}$$

Assume there are many women w in the market with varying preferences for colleges and majors. Consider the students who chose to enroll at women's institution h in period t. Denote each enrolled woman as belonging to the set A_{ht}. The share of this student body graduating from h with a STEM degree is given by $s_{STEM,ht}$:

$$s_{STEM,ht} = \frac{\sum_{w \in A_{ht}} \mathbf{1}\left\{S = \text{argmax}\left\{v_{wt}(S; h), v_{wt}(NS; h)\right\}\right\}}{\sum_w \mathbf{1}\left\{h = \text{argmax}\left\{V_{wt}(h), V_{wt}(j), V_{wt}(k)\right\}\right\}} \tag{B.4}$$

Suppose that, aside from institution h transitioning to co-education, nothing else changes between periods 0 and 1. Then, the object

$$\Delta = s_{STEM,h1} - s_{STEM,h0}$$

describes the treatment effect of co-education on the production of women STEM majors at institution h.

Two channels determine Δ. First, suppose that the set of women enrolling at institution h, A_h, does not change between time periods 0 and 1. Then, Δ simply depends on how the transition to co-education alters the payoffs to majoring in STEM ($v_w(S; h)$), relative to majoring in non-STEM ($v_w(N; h)$), for this population of women. There are several reasons to expect a reduction in these relative payoffs. As discussed above, evidence from the lab suggests that women tend to avoid competition with men, even holding relative ability fixed, in objectively-measured performance environments. In addition, an influx of men peers might create marriage market considerations that induce women to choose more traditionally-female subjects, to the extent that major choice is used by prospective partners to infer information about desirability (Bursztyn, Fujiwara and Pallais, 2017).[2]

[2]There is also the possibility that the switch to coeducation was accompanied by an increase in male representation among faculty and the administration, which in turn may weaken role-model effects that draw

Second, the transition to co-education might induce a change in the enrolled set of students A_h. To see why this might be the case, plug (3) into (1) and re-express the optimal enrollment decision as follows:

$$\eta_{wt} = \text{argmax}\left\{E\left[v_{wt}(\mu^*_{wt}; h)\right], E\left[v_{wt}(\mu^*_{wt}; j)\right], E\left[v_{wt}(\mu^*_{wt}; k)\right]\right\} \tag{B.5}$$

Thus, women forecast their (major-specific) payoffs from attending each institution, and use those expectations to guide their enrollment decisions. When institution h transitions to co-education, the women that strongly desire a single-gender environment may experience a reduction in $E\left[v_{wt}(\mu^*_{wt}; h)\right]$ and may substitute from h to women's college j. Additionally, the women that strongly desire a co-educational environment may experience an improvement in $E\left[v_{wt}(\mu^*_{wt}; h)\right]$, and may substitute from co-educational college k to h. If the women who most desire a single-gender environment also have the highest expected payoffs from majoring in STEM (say, because they are the most prepared for STEM coursework), then h's transition to co-education causes its subsequent population of women to become more negatively selected on expected STEM payoffs: plausibly leading to a reduction in STEM majoring. We call this channel the "composition effect."[3,4]

In the empirical analyses in Section 2.6 and 2.7, we estimate the overall treatment effect Δ.

B.2 Major codes

B.2.1 Coding scheme and crosswalks

This paper uses consistent 4-digit, 2-digit, and grouped 2-digit versions of major codes. The consistent coding scheme is based on the 1990 version of the Classification of Instructional Programs (CIP) from the National Center from Education Statistics (NCES).

Codes to describe college majors have been revised several times over our sample pe-

women into particular fields (recall the discussion in Section 2). We find no evidence of such a mechanism in our empirical analysis in section 2.7.

[3]The sign of the composition effect is theoretically ambiguous. However, because women's colleges produce more STEM majors per-capita than do co-educational institutions, it seems likelier than not that the composition effect, if nonzero, is negative.

[4]It is worth noting that the composition effect depends on whether woman high school seniors' expected payoffs are meaningfully affected by h's transition to co-education. The literature documents that students do not fully anticipate their own abilities or the effects of the collegiate environment on their abilities when forming enrollment and majoring decisions (Stange, 2012; **?**). The related work of Kuziemko et al. (2018) shows that college graduate women systematically under-anticipate the effects that motherhood will have on their careers. These findings suggest that women may make enrollment decisions without full or accurate knowledge about the effects of exposure to men on their subsequent choices.

riod. There were two sets of major codes in the HEGIS data, with a revision in 1970, and coding switched to the CIP in the early 1980s.[5] Revisions of the CIP occurred in 1985, 1990, 2000, and 2010.[6] Crosswalks between the 1970s HEGIS codes and the CIP, and between different versions of the CIP, are available from NCES, but they are not complete.

Similar to occupation codes, the CIP has 2-, 4-, and 6-digit versions of codes, while the HEGIS codes have only 2- and 4-digit versions. Revisions of the CIP only rarely move major categories across 2-digit codes,[7] though the 1990, 2000, 2010 revisions did move, split, and combine some two-digit codes.[8]

For this paper, all 6-digit codes were crosswalked to the 4-digit 1990 CIP. Where crosswalks provided by the NCES were incomplete, they were supplemented by lists and descriptions of CIP codes created by the NCES. When majors were not included in the NCES crosswalks, they were matched to the major of the most similar title and description in the 1990 CIP. If two 4-digit codes were combined in any version of major codings after 1970, they were combined in the consistent coding scheme. The same is true for the 2-digit codes. Six-digit majors that were created or deleted at any point were assigned to the same 4-digit code in the "other" category, and 4-digit codes that were ever created or deleted were assigned the the 4-digit code for "other" within the same 2-digit code.[9] Four-digit majors with fewer than 950 school-by-year observations were combined with majors that cover similar material[10] or with the "other" category within their two-digit code. Smaller 2-digit codes, such as Law, Library Science, and Military Science, were treated as a single 4-digit code.

For the main result, majors were combined into groups of 2-digit codes, with the most important of those groups being STEM. STEM in this case includes the 2-digit codes for Life Sciences, Physical Sciences, Engineering, Computer Science, and Mathematics. Alternative specifications also included Health Professions.

[5]The first version of the CIP was constructed in 1980, but HEGIS seems not to have adopted it until 1983.

[6]There seems to have been late adoption of the new coding schemes in the IPEDS data – the switches seem to have occurred in 1987, 1992, 2002, and 2012, and may not have occurred uniformly across schools. Revisions of the CIP vary in how many changes were made, with the 1985 revision being much smaller than subsequent revisions.

[7]Exceptions include clinical versions of the life sciences, materials science, and educational psychology, all of which could be considered to be part of multiple two-digit codes.

[8]For instance, the 1990 revision of the CIP combined category 17, Allied Health, with category 18, Health Sciences, into category 51, Health Professions and Related Sciences. Most of the 4-digit categories were preserved but re-numbered in the revision.

[9]For instance, African Languages were not included in the 1990 CIP and were therefore assigned to the 4-digit code for Other Foreign Languages.

[10]For instance, Architectural Engineering and Civil Engineering, Business Administration and Enterprise Management, and the health categories such as medicine, dentistry, and others which require a professional degree.

B.2.2 Categories of majors

The following list is the two-digit categories of majors in each group of 2-digit codes. Groups are in bold and the two-digit categories are listed afterward. Where the two-digit sets of codes are not informative, four-digit codes are included in parentheses. Some groups contain only one two-digit code. The "othe" group includes majors that generally cannot be found at small liberal arts colleges or that are generally very small.

Architecture Architecture and related services

Art Visual and performing arts

Business Business, marketing

Education Education other than math education

Health Professions Health professions and clinical services

Home Economics Home economics/family and consumer sciences

Humanities Area and group studies (e.g. gender studies, Hispanic Studies), English, foreign languages and linguistics, philosophy and religious studies

Psychology Psychology

Social Sciences Social sciences (general social science, anthropology, criminology, demography, economics, geography, history, international relations, political science, social science, urban studies), communications

STEM Life sciences, physical sciences, mathematics and statistics, computer and information science, engineering, engineering technology, science technology, math education

Other Agriculture, forestry, law, trades/vocational, military science, library science, multi- or inter-disciplinary, theology and religious vocations, protective services, public administration and social services

B.2.3 Major codes for students prepared to teach

The instructions for reporting students who are prepared to teach change over the years, especially with regards to students who are prepared to teach specific subjects.

Changes occur in the early 1970s with the introduction of additional major codes for students prepared to teach academic subjects and with clarifications to the standards of reporting in the mid 1980s.

In the 1960s, there are no specific major codes for math, science, or reading education, though there are codes for specialized subjects such as art education, physical education, and music education. Separate reporting for math, science and reading education begin in 1971.

From 1971 through the early 1980s, the instructions for the survey read, “Majors of students prepared to teach: The general rule is to classify degrees according to the major area of specialiazation. This means, in general, that degrees of students who are qualified to teach an academic subject, such as English, biology, or foreign languages, should be reported respectively in Letters, Biological Sciences, and Foreign Languages and NOT in Education. On the other hand, the degrees of students who have prepared to teach such special subjects as agriculture, art, music, etc. should be reported in agricultural education, art education, and music education.” Beginning in 1984, these instructions change to “Majors of students prepared to teach: The general rule is to classify degrees according to the major area of specialization. This means, in general, that degrees of students who are qualified to teach an academic subject, such as English, biology, or foreign languages, but did not go through a program solely for that purpose, should be reported respectively in Letters, Biological Sciences, and Foreign Languages and NOT in Education. On the other hand, the degrees of students who have gone through a program that is specifically preparing them to teach special subjects such as agriculture, art, music, etc. should be reported in agricultural education, art education, and music education, under Education.” It is not clear that the change in instructions in the 1980s reflects a material change in the standards of reporting rather than a clarification meant to reflect what the majority of colleges were already doing.

Our main specification does not include math education as part of STEM. As shown in Figure B.9, this does not affect our results on the effect of the switch to coeducation on math majoring. It also does not materially affect our results on the effect of the switch to coeducation on STEM majoring, as shown in Figure B.10.

B.3 School Codes

NCES uses two different coding schemes for individual schools at different points in the data. HEGIS identifies schools using FICE codes, which is a six-digit identification code assigned to schools doing business with the Office of Education in the 1960s. IPEDS uses the UnitID, which is also a six-digit code. Our data uses the FICE as a consistent identifier throughout the survey, with some modifications as detailed below.

Not every institution has a FICE code. Institutions that do not have a FICE code are those that entered the IPEDS data after the Institutional Characteristics file stopped listing FICE codes (which was during the 1990s). We drop those institutions from our sample, as according to the ICPSR files for IPEDS financial characteristics between 1988 and 1990, institutions that entered the sample after the beginning of the IPEDS have a much lower response rate than institutions in the HEGIS sample. However, the data set itself has the UnitID entered in place of the FICE code for those institutions.

Some institutions have multiple FICE codes. In most of these cases, a public institution originally reported all branches under one observation, and then switched to reporting each branch separately. The vast majority of cases where all degrees awarded are reported under the main campus occur in 1966, with a few additional cases between 1967 and 1969. We do not link such cases together. In other cases, an institution switched FICE codes in the middle of the sample. We are generally not sure why this occurs. We do link these cases together so that we have a single FICE code for all years the institution was in the data. Finally, there are a few institutions (notably Cornell and Columbia) with several different administrative units that separately report degrees awarded to IPEDS and HEGIS. We treat these institutions as a single observation and collapse them to a single FICE code.

Some FICE codes apply to multiple institutions. In these cases, all institutions are part of the same system, and the majority of these cases occur among institutions who enter the data in 1987 and later, especially among for-profit institutions with multiple campuses nationwide (e.g. the University of Phoenix). There are some cases where a public college with several branches (e.g. the University of Pittsburgh) reported degrees separately from each branch but reported the same FICE from each school. Where we could, we assigned these institutions to separate codes for each branch, but the rest of them are collapsed to the FICE level. We have also dropped schools that are ever classified as for-profit schools from our sample, which removes many of these cases from our analysis.

B.4 Years of the switch to coeducation

B.4.1 Data collection

We define the first year of coeducation as the first year that men were admitted to traditional four-year undergraduate programs with coeducational courses. Schools where men were admitted to these programs only as commuter students are counted as coeducational, but schools where men could only participate in evening or adult education classes or graduate programs are not. We exclude all coordinate institutions, that is, institutions such as Columbia and Barnard where a men's college and a women's college share a campus and allow cross-registration in classes. We also exclude cases where a women's college merged with a men's college.

We sourced the years that single-sex institutions switched to coeducation in three different ways. The first source of information was a comprehensive check of the top 120 liberal arts colleges and the top 80 universities in the 2018 *U.S. News and World Report* for the gender of the student body in 1966 and a date of switch to coeducation. The second source of information was a list of current and former women's colleges from the Women's College Coalition, including a date of switch to coeducation. Finally, we generated a list of institutions that awarded more than 90% of their degrees to women in the first year they appeared in the data and used a research assistant to track down which of those institutions are current or former women's colleges. The RA also found the date of the switch to coeducation for former women's colleges. The three lists were then compared. Institutions that appeared on multiple lists with matching switch dates were considered confirmed. Institutions with conflicts between the switch dates or that appeared on only one list were independently verified.

Our classification of the "gender" of an institution is based on the gender of the student body in 1966. Institutions that did not appear on any of the lists noted above were assigned a gender based on the HEGIS or IPEDS "sex code" variable in the first year they appeared in the data.

In total, we found 136 former women's colleges that switched to coeducation ("switchers"). Of these, 118 were never coordinate, entered the data before 1987, did not merge with a men's college, and were never for-profit.

B.4.2 Problems in the data

Sixty-four of our "switchers" had at least one man graduate before the official date of the full switch to coeducation. In the vast majority of cases, this seems to have been either occasional one-off male students or the introduction of a small coeducational adult education program. In other cases, schools either opened a men-only college on campus or had male commuter students before completely switching to coeducation. We denote problematic cases with the following flags:

1. A small number of men (≤ 10 per year) graduate from the institution before the switch to coeducation, or > 10 men graduate from the institution before the switch

and we can verify the existence of a coeducational adult education program that most likely did not interact with traditional undergraduates ($n = 46$)

2. A large number of men (> 10 per year) graduate from the institution before the switch to coeducation, and we cannot verify the existence of a coeducational adult education program that did not interact with traditional undergraduates. ($n = 10$)

3. Men were allowed as commuter students long before the official date of coeducation. We were sometimes, but not always, able to identify the true date that men were allowed to register in traditional undergraduate coursework. ($n = 8$)

4. Rather than becoming fully coeducational, the school opened a men's college (or men-only program) on campus – basically becoming coordinate rather than coeducational. ($n = 2$)

We exclude flags 2 through 4 from the main specification. We also exclude institutions that awarded zero bachelor's degrees in STEM fields to women in 1966 and institutions that closed shortly after a switch to coeducation. These cuts leaves us with 73 switchers in the final sample.

B.4.3 Defining our sample

Our sample includes institutions that:

- Were woman-only or coeducational in 1966 and entered the data in 1987 or earlier[11] ($N = 1,876$; $N_{switch} = 135$)[12]

- If switched to coeducation, did not close 9 years after the switch to coeducation (but not omitting schools that switched to coeducation in 2007 or later); if untreated, was in data for at least 15 years ($N = 1,571$; $N_{switch} = 123$)

- Had at least one woman complete a STEM (life or physical science, math, engineering, computer science) degree in 1966 ($N = 1,065$; $N_{switch} = 102$)

[11]ICPSR has concerns about the accuracy of imputation for nonresponses beginning with the switch to the IPEDS data in 1987. The IPEDS data dramatically expanded the sample to include schools that had not been classified as "institutions of higher learning" under Title IX and the response rate of those new institutions was much lower than the response rate of institutions included in HEGIS. See the ICPSR documentation of the 1986-1987 academic year finance data for further details.

[12]Note that the sample sizes here are meant to note how each subsequent restriction decreases the size of the sample, and different restrictions can overlap.

- Were never classified as a coordinate institution (a women's college sharing a campus with a men's college)/were not part of a merger with a men's college after 1966 ($N = 1,047$; $N_{switch} = 93$)

- Were never a for-profit institution ($N = 1,040$; $N_{switch} = 93$)

- Had fewer than 10 male students per year graduate before coeducation started or had coeducational adult education program that we could verify dates of existence for – that is, did not have a flag of 2, 3, or 4 ($N = 1,013$; $N_{switch} = 79$)

B.5 Tables and Figures

Table B.1: List of switchers and list of women's colleges with notes

FICE	Institution Name	Switch	Merger	Flag	Notes
2341	College of St. Benedict	1961	0	0	
2521	Webster College	1962	0	0	
3035	Ohio Dominican University	1964	0	0	
2185	Framingham State College	1964	0	0	up to 340 men in every year! Male students enroll for the first time in 1964.
2976	U North Carolina Greensboro	1964	0	3	
1939	Newman University	1965	0	0	
3167	Oklahoma College of Liberal Arts	1965	0	0	
1846	Briar Cliff College	1966	0	0	
3721	Madison College	1966	0	0	
2713	Dominican College of Blauvelt	1967	0	0	
2778	Mount St. Mary College	1967	0	0	
2023	Our Lady of the Holy Cross College	1967	0	0	
2228	Wheelock College	1967	0	0	
1602	Woman's College of Georgia	1967	0	0	
2896	Villa Maria College	1968	0	0	
3467	Presentation College	1968	0	0	
2482	Maryville College of the Sacred Heart	1968	0	0	
2777	Medaille College	1968	0	0	
2813	Sarah Lawrence College	1968	0	0	
1717	MacMurray College	1969	0	0	
2456	Columbia College	1969	0	0	

Table B.1: Switchers and problematic women's colleges list (continued)

1276	San Francisco College for Women	1972	0	0	
2449	Avila College	1969	0	0	
3682	Bennington College	1969	0	1	2 male art graduates in 1966.
3427	Coker College	1969	0	1	less than 5 men per year starting 1966
1179	College of Notre Dame	1969	0	3	10 men in 1969. Beginning 1967 it looks like male students could be commuters.
2705	College of St. Rose	1969	0	0	
2343	College of St. Scholastica	1969	0	0	
1379	Connecticut College	1969	0	0	
2718	Elmira College	1969	0	1	up to 20 men/year until 1969. Men were allowed in evening courses by the 1920s.
3850	Holy Family College	1969	0	0	
2480	Lindenwood College for Women	1969	0	4	1 male graduate 1968, 69. Also just added a College for men, didn't make classes coed.
1876	Marycrest College	1969	0	1	1 male graduate each in 1966, 69. planned merger with Newcrest in 1970s never went through.
2772	Mercy College	1969	0	0	1 man 1969.
3297	Mercyhurst College	1969	0	0	
3465	Mount Mary College	1969	0	1	one man 1968
1880	Mount Mercy College	1969	0	0	
3598	Our Lady of the Lake College	1969	0	1	3 men each 1966, 67
2316	Siena Heights College	1969	0	0	
2825	St. Joseph's College for Women	1969	0	0	
1768	St. Xavier College	1969	0	0	
2895	Vassar College	1969	0	0	
3241	Cabrini College	1970	0	0	
3837	Cardinal Stritch College	1970	0	0	
3848	Edgewood College of the Sacred Heart	1970	0	0	
3578	Incarnate Word College	1970	0	1	up to 10 men starting 1966.
3987	La Roche College	1970	0	0	
1356	Loretto Heights	1970	0	2	Up to 60 men until 1987. Closed and assets were given to Regis University. Had adult education program by 1959.

Table B.1: Switchers and problematic women's colleges list (continued)

3861	Marian College of Fond du Lac	1970	0	1	1 man 1967
2992	Mary College	1970	0	1	up to 10 men beginning 1966.
1172	Pitzer College	1970	0	0	
1750	Rosary College	1970	0	0	
2051	St. Joseph's College	1970	0	0	
3746	University of Mary Washington College	1970	0	0	
3911	Viterbo College	1970	0	0	
1505	Lynn University	1971	0	0	
3233	Alvernia College	1971	0	0	
1183	College of the Holy Names	1971	0	1	1-2 men between 1967 and 1972.
3685	College of St. Joseph the Provider	1971	0	0	
1664	College of St. Francis	1971	0	0	
2712	D'Youville College	1971	0	0	1 man each 1971, 72
1196	Dominican College of San Rafael	1971	0	0	
2464	Fontbonne College	1971	0	0	
3275	Holy Family College	1971	0	0	
12313	Holy Family College	1971	0	0	
2760	Manhattanville College of the Sacred Heart	1971	0	1	up to 5 men beginning 1966.
3588	Mary Hardin Baylor College	1971	0	3	Beginning 1922, a few men lived on campus every year before transferring to Baylor for senior year; seem to do work considered not suitable for women.
3074	Mary Manse College	1971	0	1	Up to 3 male grads beginning 1967.
2284	Marygrove College	1971	0	0	
2769	Marymount Manhattan College	1971	0	0	
2298	Nazareth College	1971	0	0	
2808	Rosary Hill College	1971	0	1	1 man 1968.
2814	Skidmore College	1971	0	0	1 man 1971.
1540	Webber College	1971	0	0	
1375	Annhurst College	1972	0	0	
1635	Barat College of the Sacred Heart	1972	0	0	
1556	Brenau College	1972	0	1	under 5 men, 1971-3; men were allowed in evening courses starting late 1960s.
2282	Madonna College	1972	0	0	

Table B.1: Switchers and problematic women's colleges list (continued)

3732	Radford College	1972	0	1	1 man 1966, 67
3937	Sacred Heart University	1972	0	3	Up to 300 men in some years! Starting 1974.
3646	Texas Woman's University	1972	0	0	
1324	U San Diego College for Women	1972	1	0	
3752	Virginia Intermont College	1972	0	0	
2117	Anna Maria College for Women	1973	0	0	
3235	Beaver College	1973	0	0	
1960	Catherine Spalding College	1973	0	1	up to 11 men/year until 1974.
3270	Gwynedd-Mercy College	1973	0	0	
1978	Nazareth College of Kentucky	1973	0	5	this merged with Catherine Spalding and went away. It actually was part of Catherine Spalding in the 50s too. Kind of weird to think of it as a separate College or one that went coed. But we only see one or two men.
2497	Notre Dame College	1973	0	1	1 male graduate 1973
3411	Salve Regina College	1973	0	1	small number of men in 1971, 72, all from "other programs" (no women graduate from that category)
2056	Westbrook College	1973	0	0	
2703	College of Mount St. Vincent	1974	0	0	1 man 1974 (year 0)
3199	Maryhurst College	1974	0	0	
2779	Nazareth College of Rochester	1974	0	1	up to 8 men beginning 1972.
2195	Newton College of the Sacred Heart	1974	0	0	
2001	Thomas More College	1974	0	0	
3456	Winthrop College	1974	0	1	Up to 10 men starting 1971. "1972 - the S.C. General Assembly passed limited admission of males." - College website
1466	Barry College	1975	0	0	
3247	College Misericordia	1975	0	1	3 men 1974
3069	Lourdes College	1975	0	0	

Table B.1: Switchers and problematic women's colleges list (continued)

3719	Longwood College	1976	0	3	Up to 10 men beginning 1966. "In 1964, the issue of coeducation arose but the Board of Visitors rejected the notion. the tide swung four years later, when Longwood began to admit male summer school transfers, and then junior and senior transfers in 1971. Men were admitted as day students in 1973, by order of the Virginia Department of Education until Longwood went fully coeducational in 1976."
2747	Ladycliff College	1978	0	1	up to 10 men beginning 1973.
1852	Clarke College	1979	0	0	
3988	Our Lady of Angels College	1980	0	1	Up to 21 men starting 1976.
2775	Molloy College	1982	0	1	up to 11 men beginning 1977. 1974 - Evening Division established (coeducational)
2422	Miss. State College for Women	1982	0	0	
1374	Albertus Magnus College	1985	0	1	small number of men ($<$ 5) 1979, 1982-4. 1982-4 are all from art programs.
2598	Caldwell College for Women	1985	0	1	1-2 men starting 1982. "In 1979, Caldwell College became one of the few institutions in the state to offer a unique external degree program." -College website
2744	Keuka College	1985	0	1	1-2 men, various years between 1976 and 1984 but not every year.
2584	Notre Dame College	1985	0	3	Beginning 1972, under 15 men. "Beginning in the 1970s, Notre Dame adopted a policy of partial coeducation by admitting men into its master's degree programs, its evening and weekend undergraduate programs, and as non-resident undergraduate day students."
1595	Tift College	1986	1	2	Merged to become Mercer.

Table B.1: Switchers and problematic women's colleges list (continued)

3724	Marymount University	1986	0	3	Up to 10 men starting 1975. "1972-Men are firSt. admitted to the Nursing program." - College website
3033	College of Mount St. Joseph in Ohio	1986	0	1	up to 30 men - 1 in 1966, then beginning 1971. Coed adult education program began in 1970s.
2610	Felician College	1986	0	1	1-2 men, 1975, 1978 and 1982. There were certificate programs at the time and men may have been allowed as night students.
2073	Goucher College	1986	0	0	
3066	Lake Erie College	1986	1	2	Merger with Garfield Senior College
2957	Queens College	1987	0	0	
2599	Centenary College for Women	1988	0	1	up to 12 men starting 1980. seems to have started offering coed evening classes in 1976.
1943	St. Mary College	1988	0	3	up to 30 men until 1989. "In 1932, the College became a four-year institute and started accepting a few men in certain areas of study." -Wikipedia. Looks like men had to commute.
2227	Wheaton College	1988	0		
3296	Marywood College	1989	0	4	Seem to have opened a College for men on campus rather than fully transitioned to coeducation.
2572	Colby Sawyer College	1990	0	1	I'm seeing 1-2 male graduates in 1975-1977 and 1979, mostly from art programs.
2586	Rivier College	1991	0	2	Up to 40 men beginning 1974
2148	Endicott College	1994	0	1	2 male business graduates in 1993.
2525	William Woods College	1996	0	1	under 10 male graduates starting 1994, 2 in 1979
2158	Lasell University	1997	0	0	

Table B.1: Switchers and problematic women's colleges list (continued)

2140	College of Our Lady of the Elms	1998	0	1	seeing some male graduates in 1966, 1986, 1989-1997. Always ten or fewer. Weekend College started in the late 1980s - may have been open to men.
2147	Emmanuel College	2001	0	1	At leaSt. one male graduate every year starting 1977. 40-60 male graduates each year after 1995. I think there muSt. have been phased in coeducation. There is a continuing education program here too.
3085	Notre Dame College	2001	0	0	
3362	Seton Hill College	2002	0	1	Seeing male graduates every year starting 1989. School of Fine Arts and the continuing education programs opened to men in 1986.
3245	Chestnut Hill College	2003	0	1	There's at least one male graduate every year since 1977. On their website: "In 1972, a Continuing Education department extended opportunities for undergraduate study to mature women and men."
2076	Hood College	2003	0	3	Men allowed as commuter students beginning 1971.
2901	Wells College	2004	0	0	
2398	Blue Mountain College	2005	0	1	Up to 25 men, every year until 2006. Seems to have had a program to train men for church occupations beginning in 1960.
3276	Immaculata College	2005		1	Up to 70 men beginning 1973. "It has also increased its academic offerings, adding evening classes, a continuing education office, and a graduate program in collaboration with nearby Marywood College from 1960 to 1980." - College website.

Table B.1: Switchers and problematic women's colleges list (continued)

2160	Lesley College	2005	0	2	1974-2006 - up to 100 men/year. May have been the case that the main College was the only one that was all-female?
3734	Randolph Macon Women's College	2007	0	1	1-2 men in a few years 1972-1981
2206	Regis College	2007	0	1	small number of men almoSt. every year beginning 1989. Can't find an explanation.
3360	Rosemont College	2009	0	2	Up to 40 men beginning 1996.
2953	William Peace University	2012	0	1	2 men in 2011.
2608	Georgian Court College	2013	0	1	up to 25 men, starting late 70s, probably from the evening program
3396	Wilson College	2013	0	1	Up to 12 men starting 1974.
2201	Pine Manor College	2014	0		
3244	Chatham College	2015	0	1	Up to 10 men 1987, 2009 on.
2600	College of St. Elizabeth	2015	0	1	up to 30 men - 1974, 1980 to coed. "1976 - the Weekend College program began allowing working men and women to attend classes while maintaining their current jobs." - College website
1835	St. Mary of the Woods College	2015	0	1	under 10 men each year beginning 2009. They opened an online program in 2005.
2704	College of New Rochelle	2016	0	1	Up to 120 men starting 1973. "In 1972, an innovative baccalaureate liberal arts program designed to address the needs of adult learners living in a complex urban world was introduced through the School of New Resources." - archived College website.
1975	Midway College	2016	0	1	up to 60 men, beginning 95. Seems like there was a night program based on Wikipedia, College website.

Table B.1: Switchers and problematic women's colleges list (continued)

3723	Mary Baldwin College	2017	0	3	Up to 25 men starting 1975. "Continuing its legacy of evolution and change, in 2017, the institution welcomed its firSt. residential men to campus (joining day students and graduate students, which had been co-educational since the mid-1970s)." - College website
1409	St. Joseph College	2018	0	2	Up to 6 men each year. Distributed across programs.
3832	Alverno College	-	0	1	1 man 1976
4767	Beth Jacob Hebrew Teachers College	-	0	2	10-24 men in a few years.
3403	Catholic Teachers College	-	0	1	1 man 1967, 69
3243	Cedar CreSt. College	-	0	1	Up to 21 men/year starting 1980. There's a College of adult education which seems to be coed.
2342	College of St. Catherine	-	0	1	33 men in 1995. up to 10 in various years, 2002-2016. They do have a College for adults.
2540	College of St. Mary	-	0	2	up to 25 men in various years.
7962	College of St. Rose	-	0	1	3 men in 1969
2344	College of St. Teresa	-	0	1	up to 10 men in various years before 1989 closure
2727	College of White Plains	-	0	2	up to 116 men 1973-96. It's really hard to find info on this College.
1351	Colorado Woman's College	-	1	0	Merged with U Denver
3430	Columbia College	-	0	1	Up to 10 men until 2014, then more. I think this is just night classes.
3431	Converse College	-	0	1	up to 10 men in various years. 13 in 1998. I think this is adult ed/grad programs
3605	Dominican College	-	0	1	up to 4 men in a few years. Closed 1974.
2721	Finch College	-	0	1	1 man 1975
4364	Heritage University	-	0	3	Up to 300 men in some years! Starting 1974.

Table B.1: Switchers and problematic women's colleges list (continued)

1213	Immaculate Heart College	-	0	2	Up to 45 men until 1980. Closed 1981. Can't find other info but in the 1960s it reorganized and became lay.
1023	Judson University	-	0	1	Up to 3 men, starting 1996
4795	Kirkland College	-	0	4	Coordinate institution with Hamilton
3436	Limestone College	-	0	3	Up to 260 men every year! Has been admitting men as commuters since early 1900s.
1235	Loyola Marymount	-	1	0	
2766	Mary Rogers College	-	0	1	3-4 men in 71-73. school muSt. have closed.
2768	Marymount College (NY)	-	0	1	merged with Fordham
1932	Marymount College (KS)	-	0	2	Up to 50 men, up to 1988.
2286	Marcy College	-	0	1	merged with U Detroit to become University of Detroit Mercy
2945	Meredith College	-	0	1	4 men in 1966
1238	Mills College	-	0	1	less than 10 men in a few years
3869	Mount Mary College	-	0	1	15 men 1983. up to 5 in 2007-2011.
3303	Mount Mercy College	-	0	3	Men first admitted 1945, but first men's dorm was built in the 70s.
2085	Mount St. Agnes College	-	0	1	1 man in each of two years
1935	Mount St. Scholastica College	-	1	0	merged with St. Benedict College
1452	Mount Vernon College	-	1	0	merged with GWU
1731	Mundelein College	-	1	0	
2789	Notre Dame Staten Island	-	1	0	merged with St. John's
3111	Our Lady of Cincinnati College	-	1	0	merged with Xavier
2156	Radcliffe College	-	1	0	
2810	Russell Sage College	-	0	4	Up to 95 men in every year. Second men's College on a separate campus. the Sage Colleges might be complicated for other reasons.
2959	Sacred Heart College	-	0	2	up to 15 men 1972, 1975-86. closed 87.
2960	Salem College	-	0	1	up to 10 men in several years
3516	Siena College	-	0	1	1 man 1971

Table B.1: Switchers and problematic women's colleges list (continued)

1831	St. Benedict	-	0	1	1-2 men in the late 60s. Closed 1970.
3120	St. John College of Cleveland	-	0	1	up to 3 men in three different years
2094	St. Joseph College	-	1	0	merged with Mount St. Mary's
2028	St. Mary's Dominican College	-	0	2	up to 20 men per year, 1973-84
3695	Trinity College	-	0	2	up to 46 men. 1975-2005. Closed 2000.
1460	Trinity Washington University	-	0	3	some undergraduate Colleges
3134	Ursuline College	-	0	3	up to 30 men starting 1975. I'm pretty sure this isn't actually all women but it is 90% women. I can't find a switch date.
2000	Ursuline College	-	1	0	merged with Bellarmine College
3387	Villa Maria College	-	1	0	merged with Gannon University
1600	Wesleyan College	-	0	1	1 man 1982
6250	WeSt. Suburban College of Nursing	-	1	0	
3136	Western College for Women	-	1	0	merged with Miami University

Table B.2: F-statistics for pre-trends in major-specific regressions

Major	**F statistic**	**p-value**
Biological Sciences	0.126	0.973
Physical Science	0.393	0.814
Physics	0.257	0.905
Chemistry	0.674	0.610
Engineering	0.534	0.710
Math	1.263	0.283
Math + Math Education	1.330	0.257
Economics	0.936	0.442

Notes: Results of F-test of joint significance of β_{-5}, β_{-4}, β_{-3}, and β_{-2} from estimates of Equation 2.2 with share of women choosing each major as dependent variable.

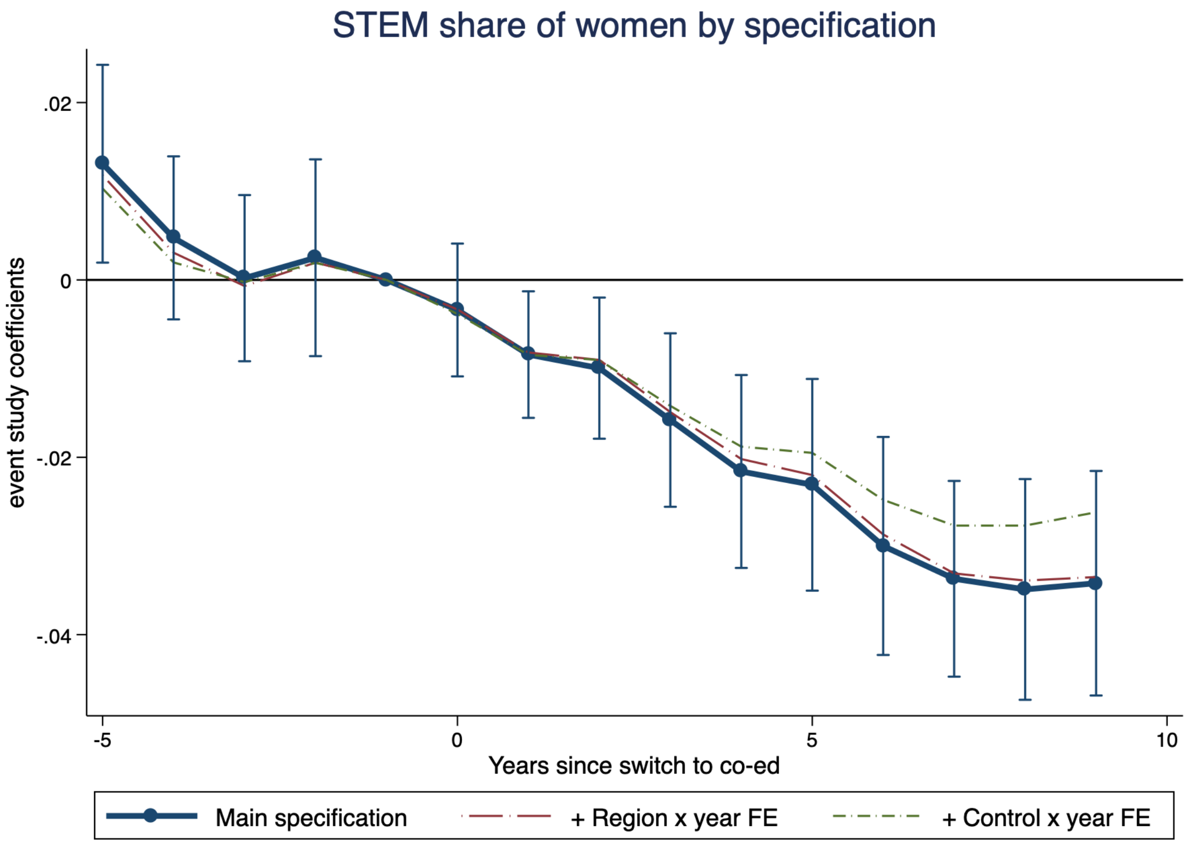
Table B.3: Determinants of the transition to coeducation

	(1) Switched	(2) Switched	(3) Switched before 1972	(4) Switched before 1972
Region = Midwest	-0.0264	0.0594	-0.569***	-0.496***
	(0.140)	(0.138)	(0.171)	(0.184)
Region = South	0.185*	0.200**	-0.425***	-0.371***
	(0.103)	(0.0928)	(0.127)	(0.126)
Region = West	-0.201	-0.254*	-0.279	-0.382**
	(0.157)	(0.150)	(0.190)	(0.187)
Ever Catholic	0.234**	0.114	-0.258*	-0.420***
	(0.111)	(0.127)	(0.131)	(0.126)
Log enrollment	0.00241	0.0127	-0.166*	-0.163*
	(0.0968)	(0.0884)	(0.0944)	(0.0878)
Selective		-0.257**		-0.264
		(0.122)		(0.159)
Observations	99	97	74	72
R-squared	0.193	0.235	0.194	0.235

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

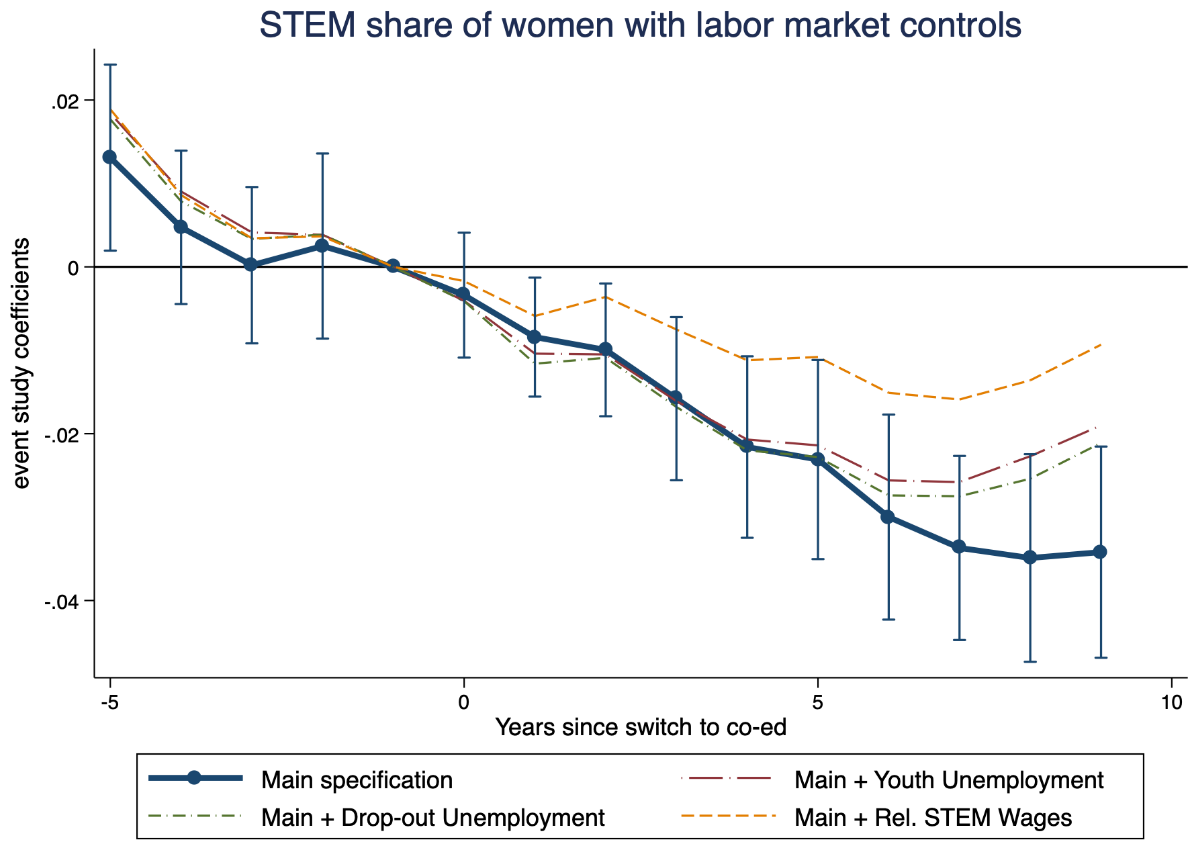
Notes: Table reports results of regression with a 0/1 variable for transitioning to coeducation and transitioning to coeducation before 1972 as the dependent variable. Robust standard errors in parentheses. Region refers to U.S. Census regions. Omitted category of region is the Northeast. “Selective” refers to a Barron’s rating of 1, 2, or 3 in 1972.

Figure B.1: The effect of becoming coeducational on the STEM share of degrees, under different specifications



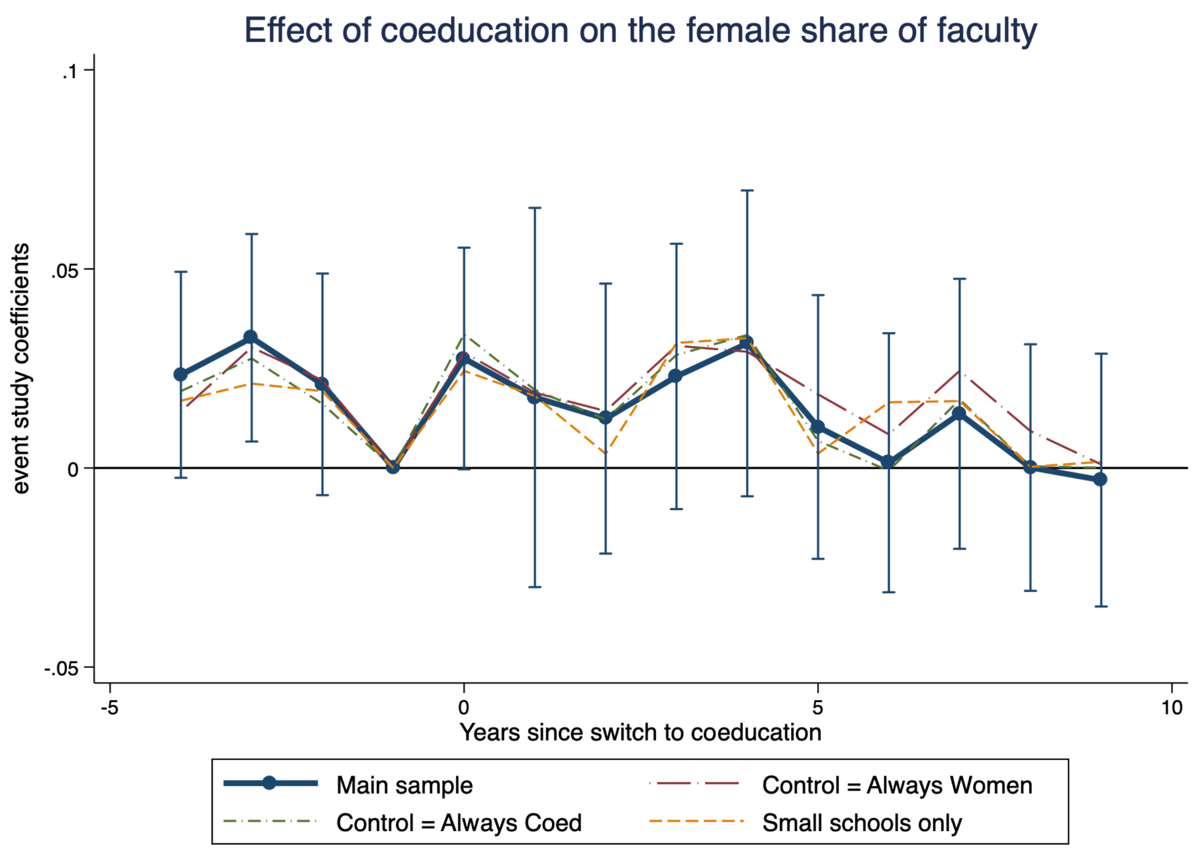
Notes: STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 when including various combinations of fixed effects. Standard errors are clustered at the institution level.

Figure B.2: The effect of becoming coeducational on the STEM share of degrees, including local labor market controls



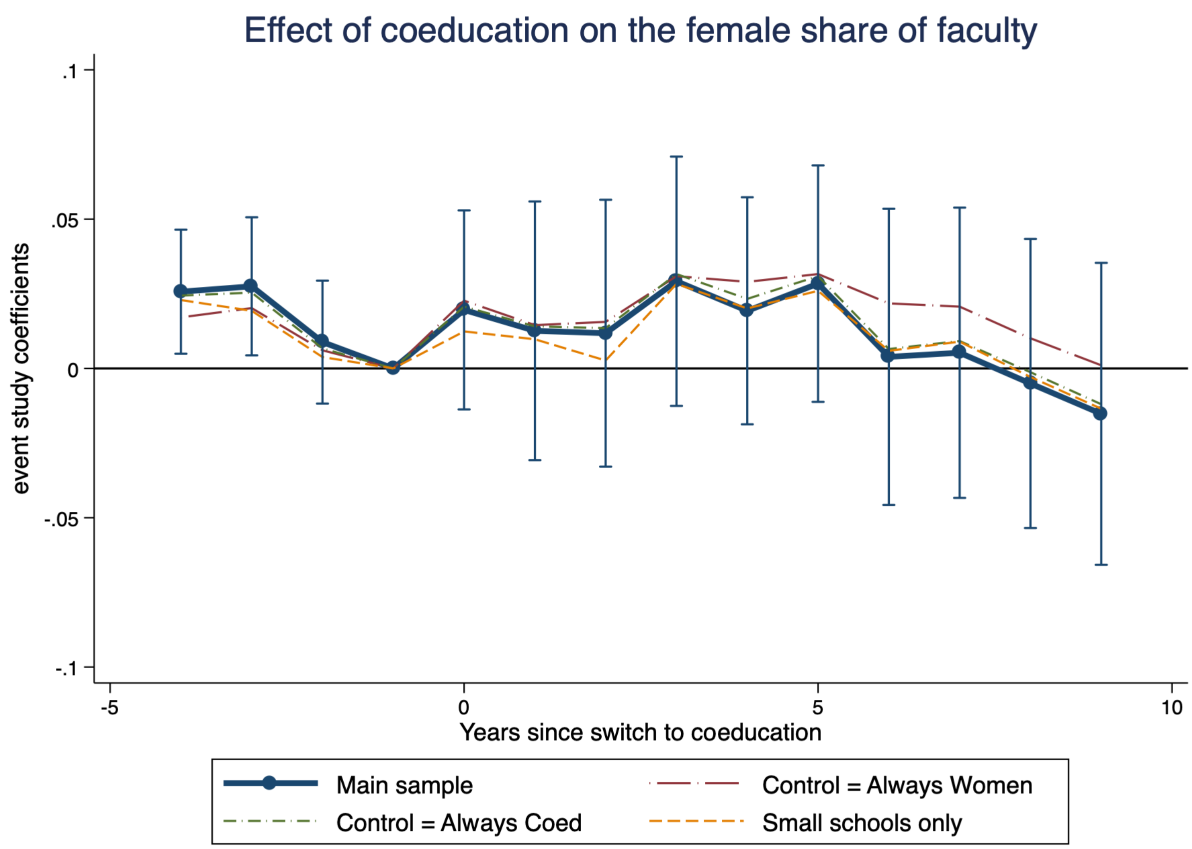
Notes: STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 when including different controls for local labor market conditions. Standard errors are clustered at the institution level.

Figure B.3: The effect of becoming coeducational on female share of faculty – all switchers



Notes: Data is drawn from records of the number of male and female faculty from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 when using all schools that transitioned to coeducation. Standard errors are clustered at the institution level.

Figure B.4: The effect of becoming coeducational on female share of faculty – post 1980 switchers



Notes: Data is drawn from records of the number of male and female faculty from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 when using all schools that transitioned to coeducation. Standard errors are clustered at the institution level.

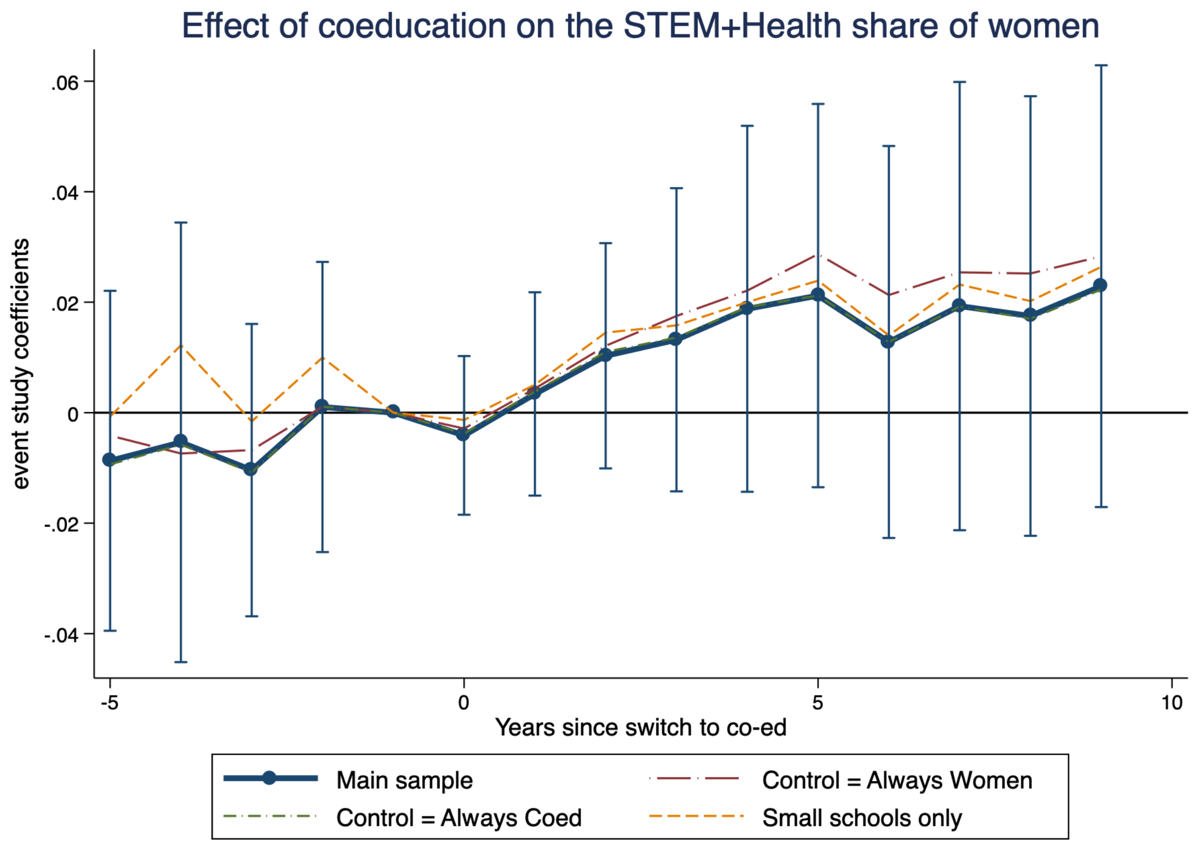


Figure B.5: Effect of coeducation on STEM + Health majoring

Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 with the share of women majoring in STEM or Health as the dependent variable. Standard errors are clustered at the institution level.

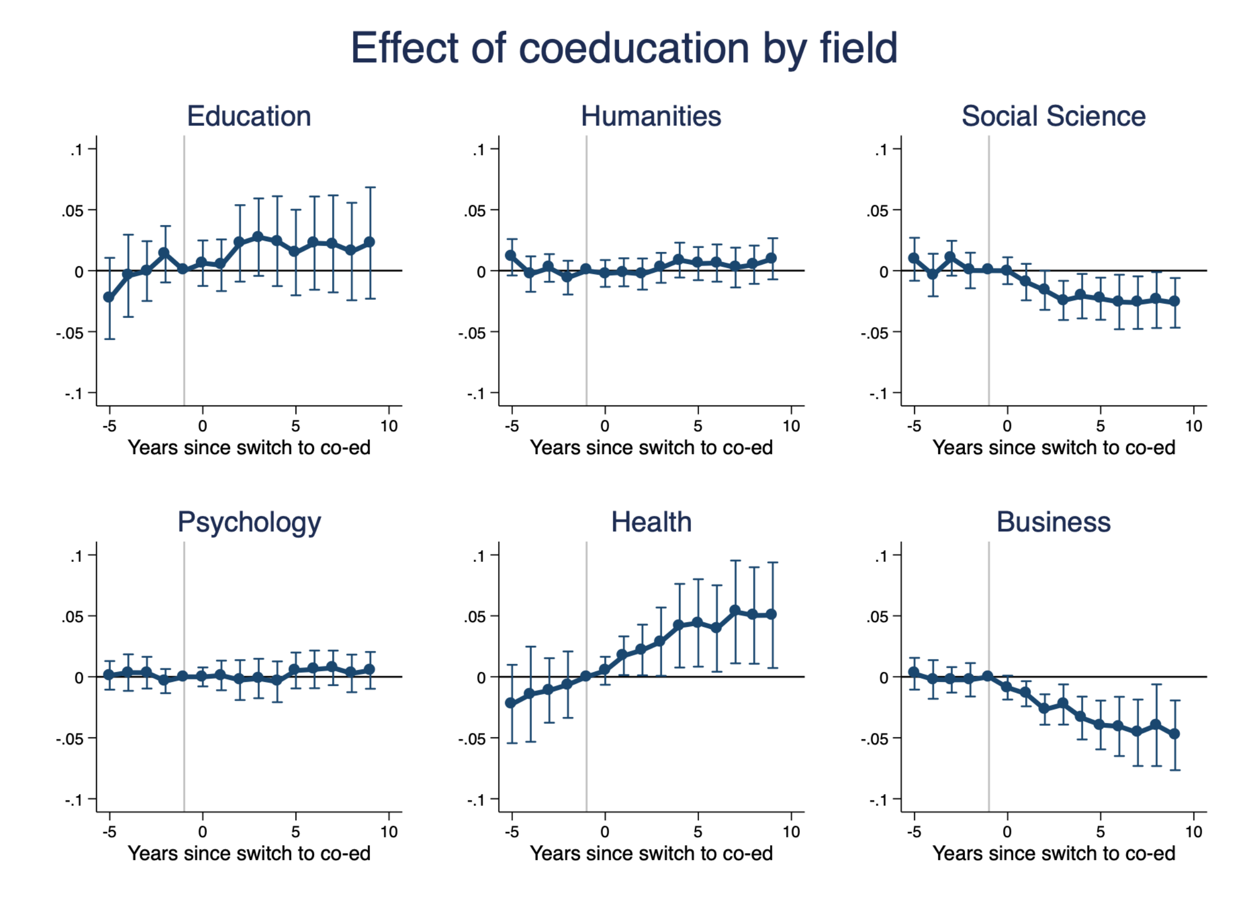


Figure B.6: Effect of coeducation on by field

Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 with the share of women majoring in each major as the dependent variable. Standard errors are clustered at the institution level.

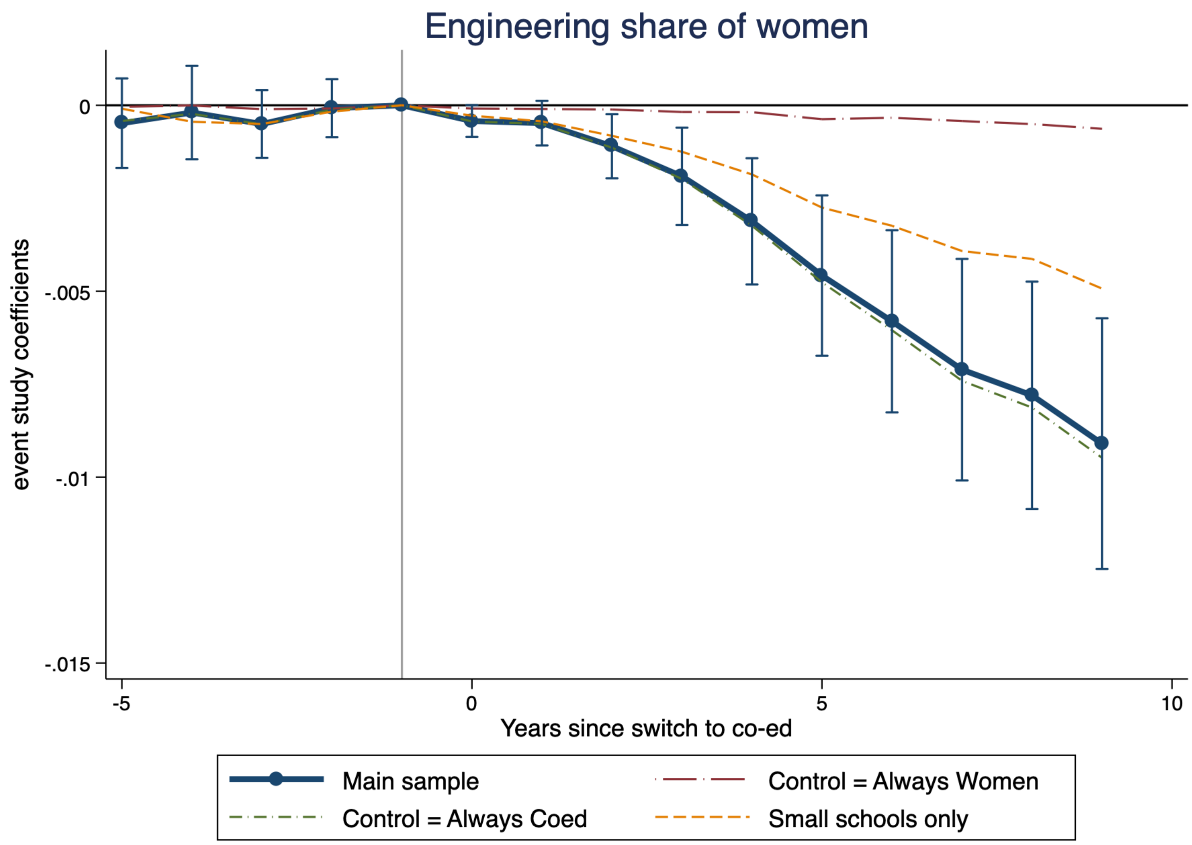
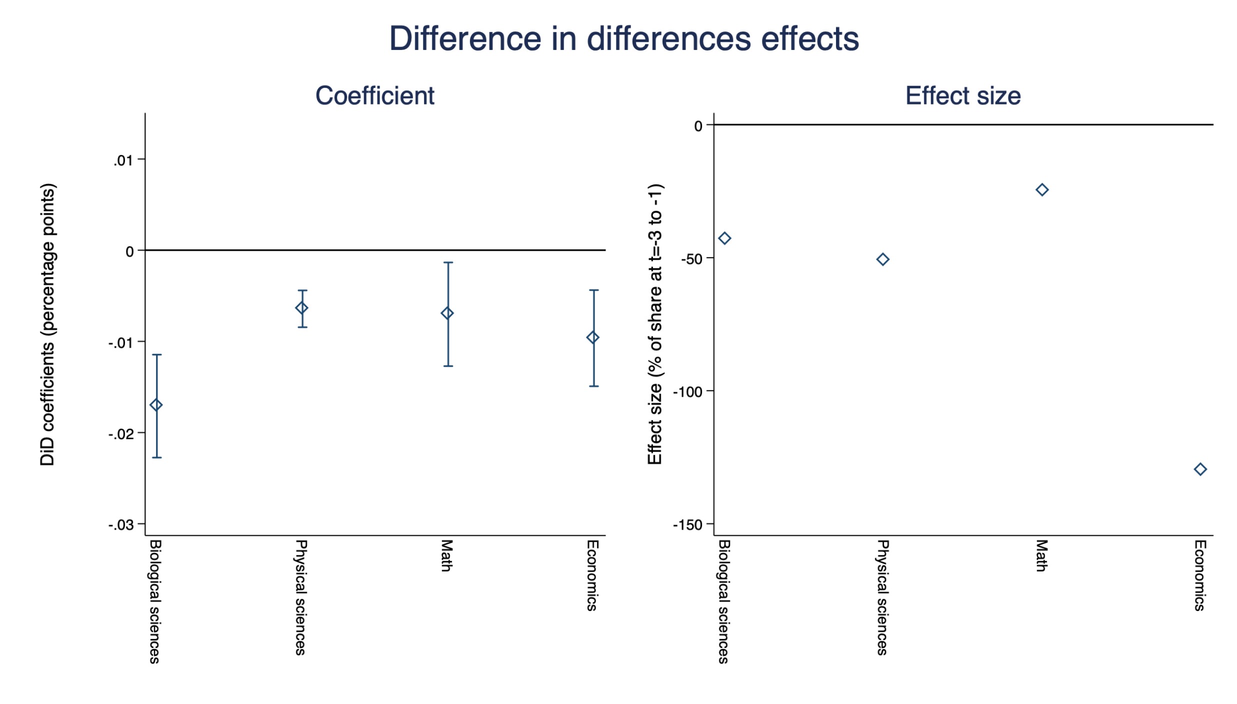


Figure B.7: Effect of coeducation on engineering majoring

Notes: Results of estimating 2.2 with the share of women majoring in Engineering as the dependent variable.

Figure B.8: The effect of becoming coeducational on the STEM share of degrees awarded to women, by field (difference in differences)



Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2. Standard errors are clustered at the institution level.

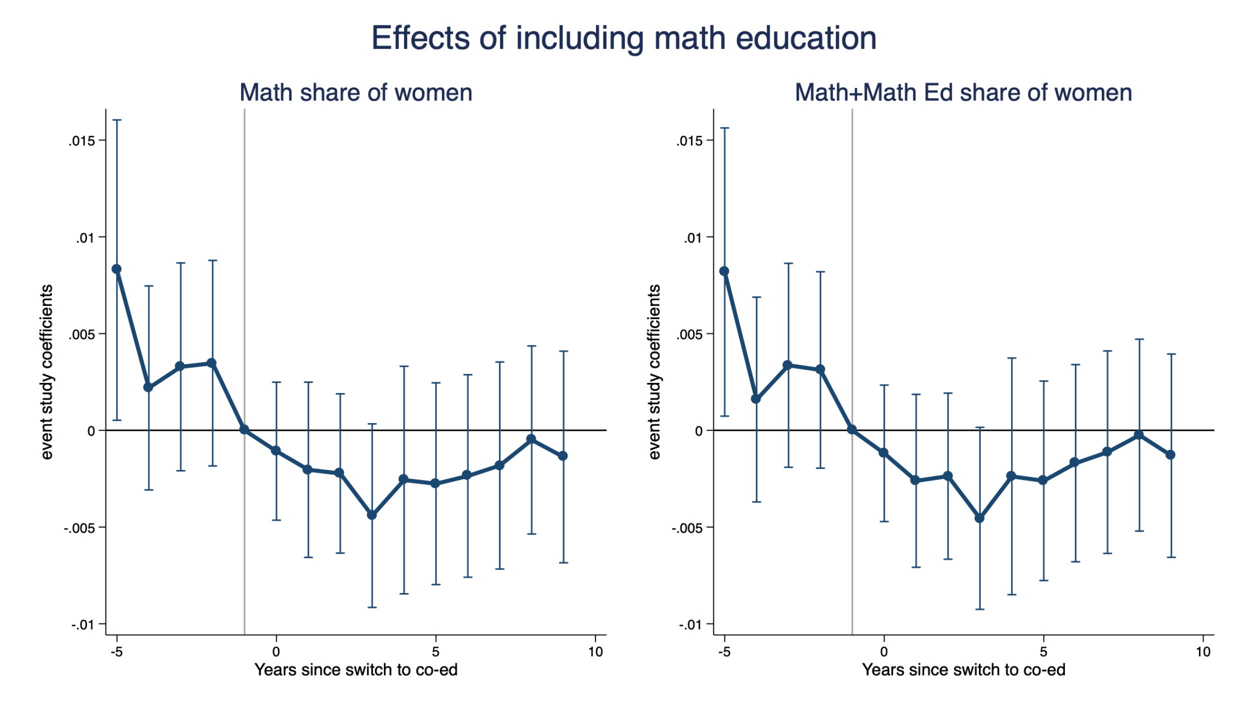


Figure B.9: Effect of coeducation on math majoring by definition

Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 with the share of women majoring in Math or Math and Math Education as the dependent variable. Standard errors are clustered at the institution level.

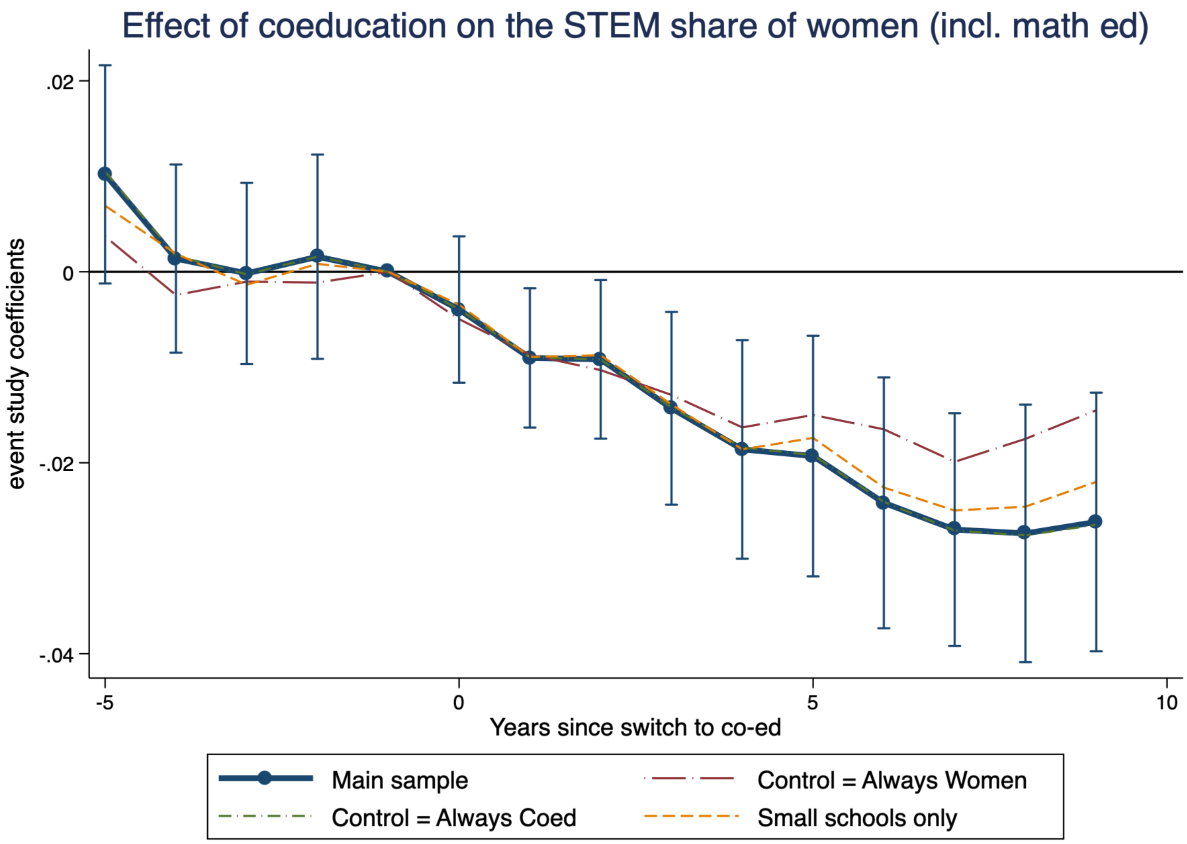


Figure B.10: Effect of coeducation on STEM majoring including math education

Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 with the share of women majoring in STEM, including math education, as the dependent variable. Standard errors are clustered at the institution level.

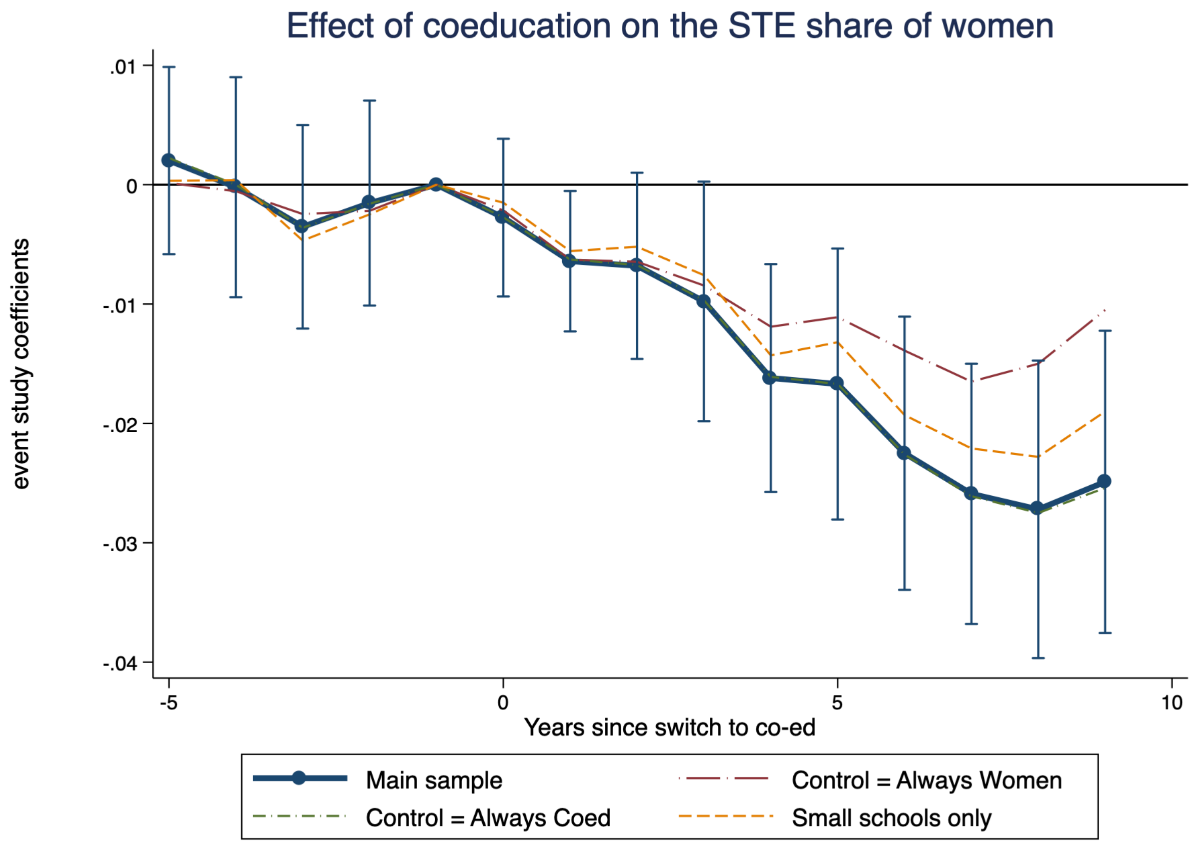
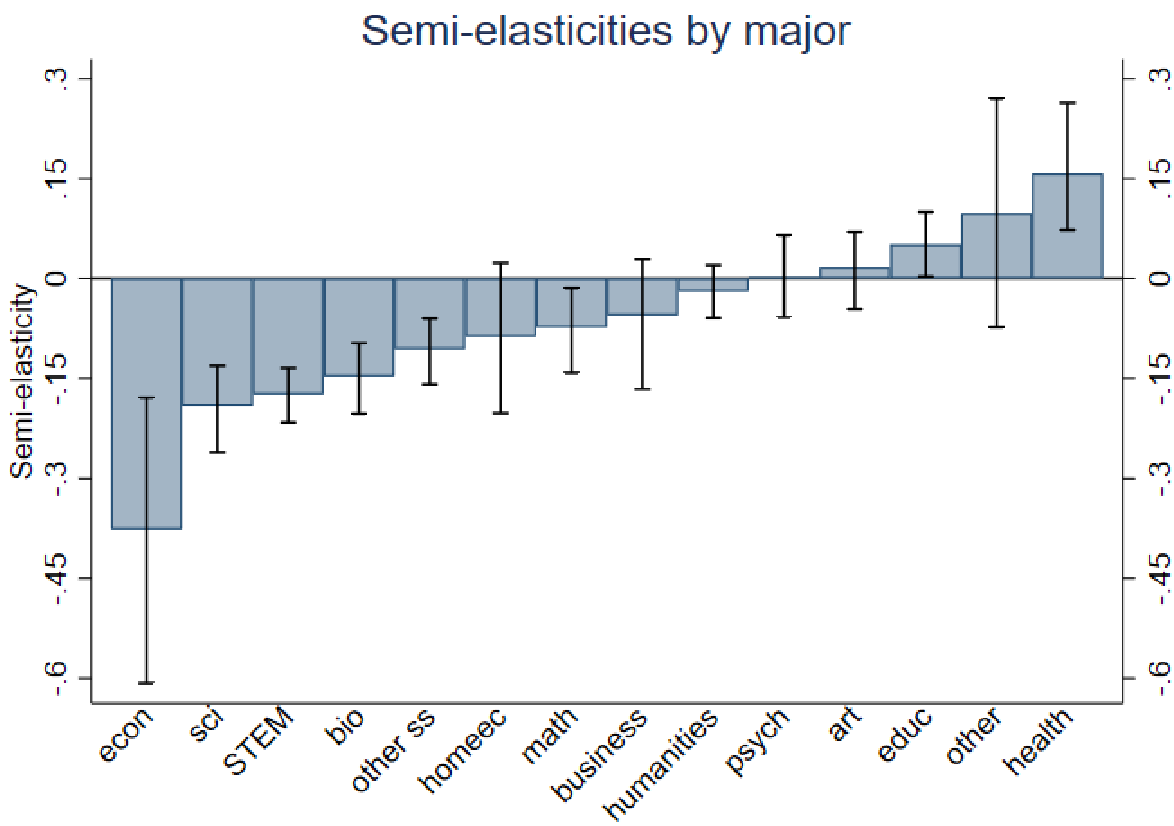


Figure B.11: Effect of coeducation on STE majoring

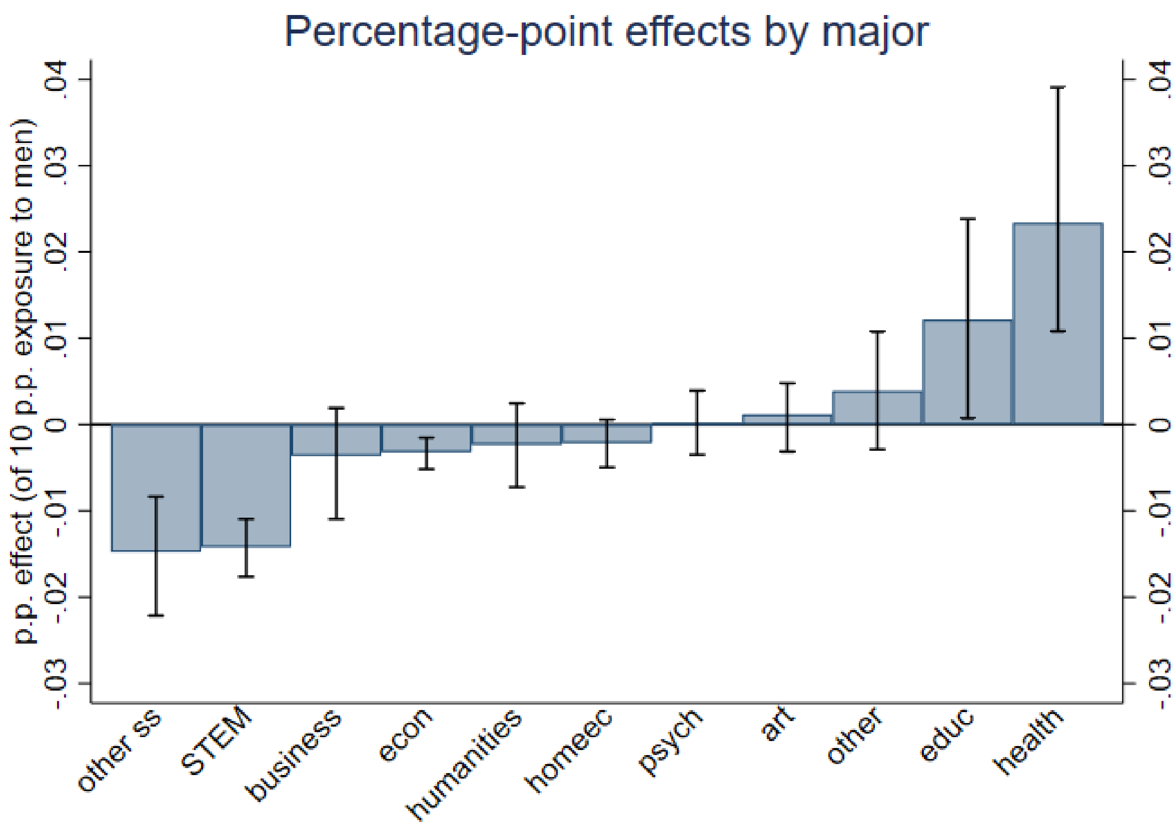
Notes: Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS). Figure shows estimate of β_s from equation 2.2 with the share of women majoring in science, technology, and engineering fields as the dependent variable. Standard errors are clustered at the institution level.

Figure B.12: The rescaled effect of general exposure to men on every major, including individual components of STEM



Notes: Plot shows the estimated effect of a cohort's share male on female students' propensity to graduate with eacj major, with the college's conversion from all-female to co-education used as an instrument for the share male. Estimates are constructed by regressing the share of women majoring in each major on the difference-in-difference version of equation 2.2, and scaling those estimates by the difference-in-difference estimate obtained from running the same regression with the share male as the outcome variable. Estimates are then divided by the share of women choosing each major at time -1 to construct a semi-elasticity and then multiplied by 10 to calculate the effect of a 10 percentage point increase in the male share of the graduating class. Ninety-five percent confidence intervals are obtained using a block bootstrap with 500 replications, clustering at the institution level. STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS).

Figure B.13: The rescaled effect of general exposure to men on every major, in percentage points



Notes: Plot shows the estimated effect of a cohort's share male on female students' propensity to graduate with eacj major, with the college's conversion from all-female to co-education used as an instrument for the share male. Estimates are constructed by regressing the share of women majoring in each major on the difference-in-difference version of equation 2.2, and scaling those estimates by the difference-in-difference estimate obtained from running the same regression with the share male as the outcome variable. Estimates are then multiplied by 10 to calculate the effect of a 10 percentage point increase in the male share of the graduating class. Ninety-five percent confidence intervals are obtained using a block bootstrap with 500 replications, clustering at the institution level. STEM degrees are defined as degrees in engineering, computer science, life and physical sciences, and mathematics. Data is drawn from records of the number of degrees awarded by year, institution, and gender from 1966-1969 and 1971-2016 in the Integrated Postsecondary Education Data System (IPEDS) and its predecessor, the Higher Education General Information Survey (HEGIS).

APPENDIX C

Chapter III Supporting Material

This appendix provides three supporting tables for Chapter III.

Table C.1 presents the tipping point, break size, and standard errors for programs in size quintiles 2, 3, and 4 when tipping occurs over a one year period.

Table C.2 presents the tipping point, break size, and standard errors for programs in size quintiles 2, 3, and 4 when tipping occurs over a five year period.

Table C.3 presents the tipping point, break size, and standard errors for programs in size quintiles 2, 3, and 4 when tipping occurs over a ten year period.

Table C.1: Tipping by quintile of program size for omitted quintiles, $\Delta t = 1$ years

	Quintile 2			Quintile 3			Quintile 4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0	0	0	0	0	0	0	0	0
1972	0	0	0	0	0	0	0	0	0
1973	0	0	0	0	0	0	0	0	0
1974	0	0	0	0	0	0	0	0	0
1975	0	0	0	0	0	0	0	0	0
1976	0	0	0	0	0	0	0	0	0
1977	0	0	0	0	0	0	0	0	0
1978	0	0	0	0	0	0	0	0	0
1979	0	0	0	0	0	0	0	0	0
1980	0	0	0	0	0	0	0	0	0
1981	0	0	0	0	0	0	0	0	0
1982	0	0	0	0	0	0	0	0	0
1983	0	0	0	0.979	-0.006	0.0257	0.017	-0.007	0.025
1984	0	0	0	0	0	0	0	0	0
1985	0	0	0	0	0	0	0.912	0.001	0.009
1986	0	0	0	0	0	0	0.997	0	0
1987	0	0	0	0	0	0	0	0	0
1988	0	0	0	0	0	0	0	0	0
1989	0	0	0	0	0	0	0.978	-0.003	0.009
1990	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0.005	0	0
1993	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0
1996	0	0	0	0	0	0	0	0	0
1997	0.970	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0
2000	0.978	0	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0.237	-0.006	0.006
2004	0	0	0	0	0	0	0	0	0
2005	0	0	0	0.0134	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0
2008	0	0	0	0	0	0	0	0	0
2009	0	0	0	0	0	0	0	0	0
2010	0	0	0	0	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth-order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

Table C.2: Tipping by quintile of program size for omitted quintiles, $\Delta t = 5$ years

	Quintile 2			Quintile 3			Quintile 4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0.047	0	0	0.019	0	0	0.003	0	0
1972	0.026	0	0	0.008	0	0	0	0	0
1973	0.033	0	0	0.009	0	0	0	0	0
1974	0	0	0	0	0	0	0	0	0
1975	0	0	0	0.008	0	0	0.002	0	0
1976	0.029	0	0	0.010	0	0	0	0	0
1977	0.030	0	0	0.011	0	0	0	0	0
1978	0	0	0	0.009	0	0	0	0	0
1979	0	0	0	0.994	0	0	0	0	0
1980	0.037	0	0	0.011	0	0	0	0	0
1981	0.034	0	0	0	0	0	0	0	0
1982	0.039	0	0	0	0	0	0.004	0	0
1983	0	0	0	0.018	0	0	0	0	0
1984	0.036	0	0	0.021	-0.011	0.123	0.009	0	0
1985	0.041	0.022	0.169	0.011	0	0	0.005	0	0
1986	0.124	-0.001	0.038	0.004	0	0	0	0	0
1987	0.035	0	0	0	0	0	0	0	0
1988	0.036	0	0	0.019	0	0	0	0	0
1989	0	0	0	0.015	0	0	0	0	0
1990	0	0	0	0	0	0	0	0	0
1991	0.035	0	0	0.014	0	0	0.668	0.012	0.011
1992	0.029	0	0	0.006	0	0	0	0	0
1993	0.040	0	0	0	0	0	0.002	0	0
1994	0	0	0	0	0	0	0	0	0
1995	0.138	-0.043	0.036	0	0	0	0	0	0
1996	0	0	0	0.360	0.012	0.014	0	0	0
1997	0.031	0	0	0	0	0	0.824	-0.014	0.012
1998	0	0	0	0	0	0	0	0	0
1999	0.018	0	0	0	0	0	0	0	0
2000	0.034	0	0	0	0	0	0	0	0
2001	0	0	0	0.015	0	0	0.112	0.031	0.020
2002	0	0	0	0.010	0	0	0.002	0	0
2003	0.036	0	0	0.017	0	0	0.010	0	0
2004	0.041	0	0	0.015	0	0	0.004	0	0
2005	0.043	-0.033	0.114	0.019	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0
2007	0.039	0	0	0	0	0	0.242	-0.007	0.011
2008	0.014	0	0	0.011	0	0	0	0	0
2009	0.035	0	0	0.009	0	0	0	0	0
2010	0.028	0	0	0	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth-order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

Table C.3: Tipping by quintile of program size for omitted quintiles, $\Delta t = 10$ years

	Quintile 2			Quintile 3			Quintile 4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.	Tipping Point	Break	s.e.
1971	0	0	0	0	0	0	0	0	0
1972	0	0	0	0	0	0	0	0	0
1973	0	0	0	0	0	0	0	0	0
1974	0	0	0	0	0	0	0	0	0
1975	0	0	0	0	0	0	0	0	0
1976	0	0	0	0	0	0	0	0	0
1977	0	0	0	0	0	0	0	0	0
1978	0	0	0	0	0	0	0	0	0
1979	0	0	0	0	0	0	0	0	0
1980	0	0	0	0	0	0	0	0	0
1981	0	0	0	0	0	0	0	0	0
1982	0	0	0	0	0	0	0	0	0
1983	0	0	0	0.979	-0.006	0.0257	0.017	-0.007	0.025
1984	0	0	0	0	0	0	0	0	0
1985	0	0	0	0	0	0	0.912	0.001	0.009
1986	0	0	0	0	0	0	0.997	0	0
1987	0	0	0	0	0	0	0	0	0
1988	0	0	0	0	0	0	0	0	0
1989	0	0	0	0	0	0	0.978	-0.003	0.009
1990	0	0	0	0	0	0	0	0	0
1991	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0.005	0	0
1993	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0
1996	0	0	0	0	0	0	0	0	0
1997	0.970	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0
2000	0.978	0	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0.237	-0.006	0.006
2004	0	0	0	0	0	0	0	0	0
2005	0	0	0	0.013	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0
2008	0	0	0	0	0	0	0	0	0
2009	0	0	0	0	0	0	0	0	0
2010	0	0	0	0	0	0	0	0	0

Notes: Analysis based on a three-year moving average of completions of men and women at the major×institution level. Results based on the raw data and five-year moving average are qualitatively similar. Observations with $f < 0.01$ or $f > 0.99$ are excluded; results are qualitatively similar from trimming up to $f < 0.05$ or $f > 0.95$. All regressions include a fourth-order polynomial in the distance between the female share and the tipping point, controls for characteristics of the major×school characteristics, and an institution fixed effect. Tipping points and the break size were calculated for the entire U.S. within quintiles of major size. $\frac{2}{3}$ of the sample was used to calculate tipping points and the remaining $\frac{1}{3}$ to calculate break size.

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