The Effect of Peer Gender on Major Choice in Business School*

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Abstract

Business degrees are popular and lead to high earnings. Female business graduates, however, earn less than their male counterparts. These gender differences can be traced back to university, where women shy away from majors like finance that lead to high earnings. In this paper, we investigate how the gender composition of peers in business school affects women's and men's major choices and labor market outcomes. We find that women who are randomly assigned to teaching sections with more female peers become less likely to choose male-dominated majors like finance and more likely to choose female-dominated majors like marketing. After graduation, these women end up in jobs where their earnings grow more slowly. Men, on the other hand, become more likely to choose male-dominated majors and less likely to choose female-dominated majors when they had more female peers in business school. However, men's labor market outcomes are not significantly affected. Taken together, our results show that studying with more female peers in business school increases gender segregation in educational choice and affects labor market outcomes.

Keywords: peer effects, major choice, gender composition
JEL classification: I21, I24, J24

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1. Introduction

Business degrees are popular and lead to high earnings (OECD 2018). Female business graduates, however, earn less than their male counterparts. In the United States, for example, the median earnings of female business graduates trail those of male graduates by $16,000 per year (Carnevale et al. 2014). Gender differences are already visible in university: although women outperform men academically, they shy away from majors like finance that lead to high earnings (Carnevale et al. 2014; OECD 2018). To understand why women who decided to study business end up in lower paying jobs, we need to understand what drives women's and men' major choices.

Women's and men's major choices may be influenced by their university peers. This influence can work through multiple mechanisms. Peers may influence major choices by affecting how well students perform academically and how much they enjoy their courses. They may also influence major choices through interactions outside the classroom. For example, students may want to choose the same major as their friends they met early in their academic career.

In this paper, we investigate how the peer gender composition in business school affects women's and men's major choices and labor market outcomes. We answer this question using data from a Dutch business school. At this institution, students first take a set of compulsory courses for which they are randomly assigned to teaching sections of up to sixteen students. After completing their compulsory courses, they choose one of eight majors that differ widely in their associated earnings and in how popular they are with women and men. Despite outperforming men academically, women are less likely to choose majors that are associated with high earnings. The most popular major among women is marketing. Marketing graduates earn, on average, €38,000 and work 46 hours per week. In contrast, the most popular major for men is finance; finance graduates earn €57,000 on average and work 53 hours per week.

Our short-run results show that the peer gender composition in business school affects students' major choices. Women exposed to a higher proportion of female peers become less likely to major in the male-dominated majors of finance and IT management and become more likely to major in the female-dominated majors of marketing and organization.[1] These effects are economically significant. Having 10 percentage points more female peers in a given section reduces women's probability of choosing a male-dominated major by 0.8 percentage points, reflecting an 8 percent decrease from the baseline. Men are affected in the opposite way. They become more likely to choose male-dominated majors and less likely to choose female-dominated majors after exposure to more female peers. These heterogeneous peer effects could be exploited to increase the number of women in male-dominated majors. We show in a policy simulation that assigning all students to sections with equal proportions of female peers can increase the number of women choosing a male-dominated major by 27 percent relative to the status quo.

When exploring which mechanisms drive our results, we find that peers in early courses especially matter for women's major choices. Women are also more likely to choose the same major as their female section peers if they are assigned to a section with a higher proportion of female peers. These results are consistent with women forming friendships with their female peers in early courses and then coordinating their major choices. This coordination can either be explicit or women may find majors more attractive if more of their female friends choose them. The proportion of female peers also affects women's and men's grades and women's course evaluations. These effects, however, only explain a small proportion of our results.

[1] We describe our results throughout this paper as the effects of increasing the proportion of female peers. However, this way of describing our results does not mean that the effects we observe are driven by the behavior of the female peers as opposed to male peers. Indeed, we could have also written the above sentence as: "Women exposed to a *higher proportion of male peers* become more likely to major in male-dominated majors, such as finance and IT management, and less likely to major in female-dominated majors such as marketing and organization."

Our longer-run results show that having more female peers affects women's but not men's labor market outcomes. Women who had more female peers end up in jobs in which their earnings grow more slowly. We also find suggestive evidence that these women work fewer hours, are more likely to work part-time, need less time to find their first job, and are more satisfied with their jobs. The welfare effect for women of having more female peers is therefore not obvious.

Although several papers study how peer gender affects specialization decisions, there is no consensus on the size or direction of these effects. (Anelli and Peri 2019; Brenoe and Zölitz 2017; Goulas et al. 2018; Hill, 2017; Hill 2015; Lavy and Schlosser 2011; Oosterbeek and Ewijk 2014; Schøne et al. 2019). These mixed results suggest it is important to pay attention to the specific context in which peer effects are studied. It is, for example, not obvious that the effects of gender are the same in primary school, high school, and university—particularly when the specialization decisions students face are substantially different. In this paper we focus on a context that has not yet been studied: business schools. Compared to high school peers, students enrolled in business school are more like each other in terms of their ability and subject interest. Despite these similarities, they often choose majors that put them on different career trajectories.

The two studies that are most related to our paper investigate the effect of peer gender on educational choices in university. Booth et al. (2013) show that women perform better when randomly assigned to a single-sex class in an introductory economics course. They find no statistically significant effect of single-sex classes on subsequent choices of technical courses, which may be due to the relatively small sample size of 400 observations and the resulting lack of statistical power. Hill (2017) uses data from 525 public four-year colleges in the United States to estimate the effect of peer gender. He finds that men's graduation rates increase when

they have had more female peers. In an additional analysis, he finds suggestive evidence that having more female peers makes women less likely to graduate with STEM majors.

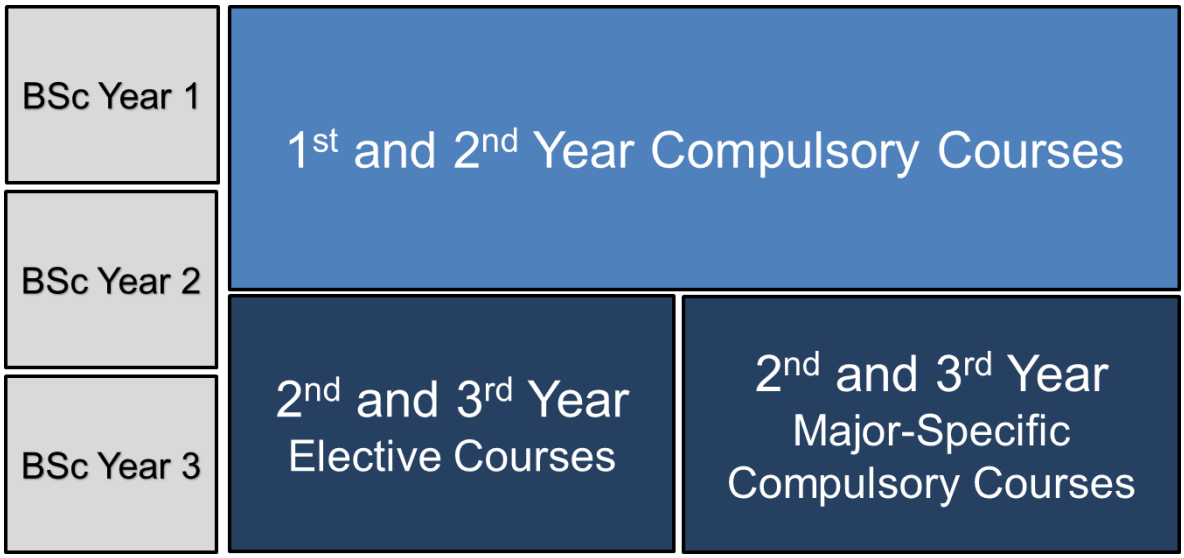
We make three contributions to the literature. First, we add to the peer effects literature by estimating the effect of peer gender on major choice in a business school—an important environment previously not studied. Second, we provide evidence on the longer-run labor market consequences of university peers. Because we can link administrative university data to survey data on graduates' labor market outcomes, we can test whether peers have longer-run effects that last beyond university. Third, and more broadly, our paper contributes to a better understanding of how the social environment shapes gender differences in educational choices and labor market outcomes.

2. Institutional Environment and Summary Statistics

2.1 Institutional Environment

The business school we study has about 4,300 students enrolled in bachelor's, master's, and PhD programs. Despite being in the Netherlands, the language of instruction at this institution is English. We focus our analysis on the institution's bachelor's study programs in business and business economics, in which students can choose between different majors. These two programs account for 86 percent of all enrolled bachelor's students. Figure 1 provides an overview of the program structure of these two programs. In the business program, students take sixteen program-specific compulsory courses (over the course of two years). In the business economics program, students take eight program-specific compulsory courses (over the course of one year). After the compulsory course phase, students can choose elective courses and a major, which consists of four major-specific compulsory courses. Students are free to choose any major, and there are no grade requirements for any majors.

Figure 1: Bachelor Program Structure



NOTE.—The figure shows the timing of compulsory courses, elective courses, and major-specific compulsory courses of the business and business economics programs.

Each course comprises multiple sections of up to sixteen students, which are the peer groups upon which we focus in this paper. For each course, students encounter a different group of section peers. Within each section, students typically meet peers for two weekly two-hour tutorial sessions. Students spend about two-thirds of their contact hours in these tutorials in which they intensively interact with their fellow students. In these tutorials, students solve problems and discuss the course material. These discussions typically follow a discussion-based approach, which involves students generating questions about a topic at the end of a session, trying to answer these questions in self-study, and then discussing their findings with their peers in the next session. Attendance in tutorials is mandatory and switching between sections is not allowed. Besides tutorials, a typical course has two-hour lectures each week or every other week, which all students in the course attend.

Students are randomly assigned to sections and thus to section peers. This assignment is done by the business school's scheduling department using scheduling software. Since the 2010–11 academic year, the business school additionally stratified section assignments by student nationality to encourage a mixing of Dutch (25 percent of estimation sample) and

German students (58 percent).[2] After the initial assignment, schedulers manually switch students between sections to resolve any scheduling conflicts, which occur for about 5 percent of students.[3] In our analysis, we address potential non-random assignment due to scheduling conflicts by including fixed effects for the other courses that the students take at the same time. Schedulers do not consider the student composition when assigning instructors to sections, which makes the peer composition unrelated to instructor characteristics. We have excluded the few cases in which course coordinators or other staff influenced the section assignment (see Appendix A1 for more detailed description of the sample restrictions). For our estimation sample, neither instructors, students, nor course coordinators influenced the section assignment.

2.2 Descriptive Statistics and Randomization Check

We use data for six academic years between 2009–10 and 2014–15. To observe students' compulsory course peers and their major choices, we restrict our estimation sample to students who we observe in their first and last year of their bachelor's program. This implies we can follow four complete bachelor's student cohorts. Table 1 shows some descriptive statistics of our estimation sample at the student level (Panel A) and section level (Panel B).

[2] The stratification is implemented as follows: the scheduler first selects all German students (who are not ordered by any observable characteristic) and then uses the option "Allocate Students set SPREAD," which assigns an equal number of German students to all sections. Subsequently, the scheduler repeats this process with the Dutch students and finally distributes the students of all other nationalities to the remaining spots. Until the 2012–13 academic year, about ten percent of the slots in each section were initially left empty and were filled with students who registered late. This procedure balanced the number of late registrants over the sections. The business school abolished the late registration system starting with the 2013–14 academic year.

[3] Compulsory courses are generally scheduled on different days to prevent scheduling conflicts. There are four reasons for students' scheduling conflicts: (1) the student is scheduled to take an elective course at the same time, (2) the student is also working as a student instructor and needs to be in class at the same time, (3) the student takes a language course at the same time, or (4) the student indicated non-availability for evening education. By default, all students are recorded as available for evening sessions. Students can opt out of evening classes in an online form. Evening sessions are scheduled from 6 p.m. to 8 p.m., and about three percent of all sessions are scheduled for this time slot. We have excluded evening sessions from our estimation sample.

Table 1: Descriptive Statistics

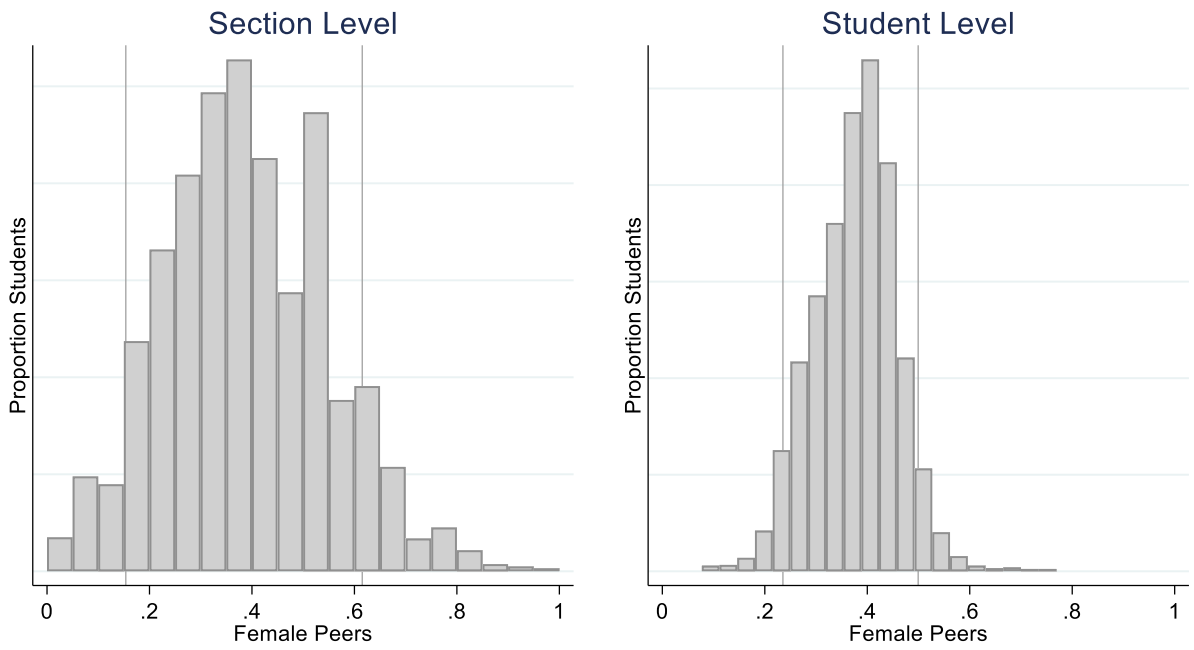
Panel A: Student Level Characteristics	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
Female	3,563	0.389	0.488	0	1
Dutch	3,563	0.251	0.434	0	1
German	3,563	0.583	0.493	0	1
Age	3,563	19.68	1.642	16.33	31.21
GPA	3,563	7.001	1.184	1	10
Bachelor student	3,563	1	0	1	1
BA Business	3,563	0.563	0.496	0	1
BA Business Economics	3,563	0.436	0.496	0	1
Courses taken	3,563	16.72	7.275	1	39

Panel B: Section Level Characteristics	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
Number of students in section	2,559	13.71	1.300	3	16
Proportion female peers	2,559	0.381	0.142	0	0.929

NOTE.—This table is based on our estimation sample. 'Sd' refers to the standard deviation of the respective variable.

Our explanatory variable of interest is the proportion of female section peers in compulsory courses. Thirty-nine percent of students, and thus peers, are female. Figure 2 shows the variation in the proportion of female peers we observe in the data. The histogram on the left shows the distribution of the proportion of female peers across all sections. The histogram on the right shows the distribution of the average proportion of female peers students had across all of their compulsory course sections. The relatively small section size and the random assignment leads to a relatively wide range of support that we can exploit to estimate the effect of peer gender.

Figure 2: Proportion of Women in Sections



NOTE.—The figure is based on our estimation sample. A one standard deviation in the proportion of female section peers is 14.2 percent. A one standard deviation in the proportion of female peers across all compulsory courses is 8.0 percent. The vertical lines show the 5th and 95th percentile of female peers.

The key identifying assumption for estimating causal effects of peer gender is that students within compulsory courses are randomly assigned to teaching sections. To confirm that this is the case, we test how the proportion of female section peers relates to two important variables: students' own gender and students' GPA before the start of the course (see Table 2). In particular, we regress the proportion of female peers on students' gender as well as course fixed effects (column 1) or course fixed effects and other course fixed effects (column 2). In these two specifications, we account for the mechanical relationship between own gender and the proportion of female peers by additionally including controls for the course level leave-out means of student gender (see Guryan et al. 2009). We also regress the proportion of female peers on students' GPA with the same sets of course and parallel course fixed effects (columns 3 and 4). The results show that the proportion of female section peers is not systematically

related to students' own gender or GPA, which confirms that the section assignment is random.[4]

Table 2: Test for Random Assignment

Dependent Variable:	(1) Proportion Female Peers	(2) Proportion Female Peers	(3) Proportion Female Peers	(4) Proportion Female Peers
Female	-0.0026	-0.0027		
	(0.003)	(0.003)		
Std. GPA			0.0004	0.0004
			(0.001)	(0.001)
Observations	29,211	29,211	29,211	29,211
R-squared	0.152	0.161	0.151	0.160
Course-Year FE	YES	YES	YES	YES
Parallel-Course-Year FE	NO	YES	NO	YES

NOTE.—The dependent variable in all columns is the proportion of female section peers. Following the Guryan, Kroft and Notowidigdo (2009) correction method, we control for the course-level leave-out-mean. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

2.3 *Gender Differences in Major Choice*

Table 3 provides an overview of the eight different majors that students can choose, ordered by the proportion of women per major, which ranges from 22 percent in finance to 60 percent in marketing. Interestingly, differences in major choices by gender mimic the occupational segregation observed in the labor market in two important dimensions. First, in line with women's underrepresentation in STEM occupations, we see that majors that are more popular among women have a lower proportion of mathematical compulsory courses.[5] Second, majors more popular with women are associated with lower earnings as evidenced by the negative correlation of the proportion of women per major with the average earnings of women ($\rho =$

[4] For an alternative and more flexible randomization check, see Table A1 and Figure A1 in the appendix. In this randomization check, we regress pre-treatment student characteristics on section dummies and scheduling controls for each course separately. We then perform *F*-tests for joint significance of the section dummies and show that the *p*-values of these *F*-tests for all courses in our sample have the properties that we would expect under random assignment: they are uniformly distributed with a mean close to 0.5.

[5] We categorize courses as mathematical if at least one of the following words appeared in the course description: "math, mathematics, mathematical, statistics, statistical, theory focused." Using this definition, we categorized 33 percent of the courses as "mathematical."

-0.80) and men ($\rho = -0.49$). The proportion of women per major is also negatively correlated with women's average first-year GPA ($\rho = -0.55$) and men ($\rho = -0.49$) at the major level. Even though women have higher average GPAs, majors with more women attract academically weaker students.

For our empirical analysis, we classify the two majors with the lowest proportion of female students as male-dominated and the two majors with the highest proportion of female students as female-dominated. Specifically, we classify finance and IT management as male-dominated and organization and marketing as female-dominated.

Table 3: Gender-Based Sorting into Majors

Major	(1) Percent Female	(2) Major Classification	(3) Percent Compulsory Mathematical Courses in Major	(4) First-Year GPA (Female)	(5) First-Year GPA (Male)	(6) Mean Annual Earnings in Thousand € (Female)	(7) Mean Annual Earnings in Thousand € (Male)
Finance	21.50	Male-dominated	50	7.29	7.15	55.86	58.33
IT Management	30.43	Male-dominated	50	6.78	6.50	43.63	43.31
Strategy	35.64	Balanced	0	6.94	6.52	43.58	47.87
Economics	37.76	Balanced	50	7.10	6.96	40.31	43.20
Accounting	39.09	Balanced	0	7.29	7.20	39.04	46.98
Supply Chain Mgmt	48.78	Balanced	25	6.93	6.55	38.72	40.77
Organization	59.51	Female-dominated	0	6.86	6.52	34.24	46.72
Marketing	60.34	Female-dominated	0	6.81	6.61	40.14	45.72

NOTE.—We define finance and IT management as male-dominated and organization and marketing as female-dominated majors. Data on annual earnings is taken from the 2016 graduate survey. N=1,713.

3. Empirical Strategy

Our goal is to estimate the effect of peer gender in first- and second-year compulsory courses on students' subsequent major choices and labor market outcomes. Equation (1) shows our main empirical model:

$$Y_{i\tau} = \alpha_1 F_i \times FP_{isct} + \alpha_2 M_i \times FP_{isct} + X_{ict}\gamma' + u_{isc\tau}, \quad (1)$$

where $Y_{i\tau}$ is the outcome of interest (major choice, course choice, or labor market outcome such as earnings) of student i at time $\tau > t$, that is, after having taken the compulsory course. $F_i \times FP_{isct}$ is a female dummy variable interacted with the proportion of female peers in section s of compulsory course c at time t, and $M_i \times FP_{isct}$ is a male dummy interacted with the proportion of female section peers. The parameters of interest are α_1 and α_2, which show the causal effect of increasing the proportion of female peers on the outcome of interest for women and men respectively.[6] X_{ict} is a vector of control variables that includes course-year fixed effects and parallel course fixed effects, which are fixed effects for the other course the students take in the same period. We include parallel course fixed effects to account for any non-random assignment due to scheduling conflicts throughout. We control for students' own gender, and X_{ict} also includes indicators for the students' nationality as well as their GPA at the start of the course (our *pre-assignment* measure of student ability). We cluster standard errors using two-way clustering at the student and section levels.[7]

4. Results

4.1. *Peer Effects on Major Choice*

Table 4 shows estimates of how the peer gender composition affects students' choice of male-dominated and female-dominated majors. Women who are randomly assigned to sections with more female peers become more likely to choose female-dominated majors and less likely to choose male-dominated majors. Our point estimates suggest that a 10 percentage point increase in female peers would reduce the probability of a woman's choosing to major in finance or IT

[6] We have shown in Feld and Zölitz (2017) that classical measurement error in the peer variable of interest can lead to substantial overestimation of peer effects when peer group assignment is non-random. When peer group assignment is random, as is the case in our setting, classical measurement error will attenuate peer effects estimates, i.e. bias them toward zero. As peer gender is measured with very little error, attenuation bias in regression estimates of α_1 and α_2 is not a concern.

[7] For almost all regression coefficients, we obtain smaller or same-sized standard errors when clustering at the section level or at the student level.

management by 0.8 percentage points (8 percent) and increase her probability of majoring in marketing or organization by 1 percentage point (2 percent). These effects are economically significant. For comparison, the estimated effect of increasing students' GPA by one standard deviation on women's probability of choosing a male-dominated major is 4.8 percentage points (based on the GPA coefficient of the regression reported in column 1). Men respond in the opposite way and become less likely to choose a female-dominated major and more likely to choose a male-dominated major when they had more female peers.[8]

We test the robustness of these results in three ways. First, we test whether our results are sensitive to the definition of male- and female-dominated majors by estimating a model with the proportion of women in the chosen major as the dependent variable (column 3). The results in this specification are qualitatively similar.

Second, we estimate our results without controls for student nationality and past GPA. Because past GPA is missing in the first period of the first term, this specification leads to somewhat larger sample sizes. Table A3 in the appendix shows that our results are qualitatively similar in these specifications.

Third, we test whether our results are similar in specifications in which we estimate the effect of the average proportion of female peers across *all compulsory courses* on students' major choice. These estimates are qualitatively similar (see Table A4 in the appendix). These specifications allow us to have one observation per student, which may be easier to interpret. However, we prefer specifications with observations at the student-course level as these allow us to include course-year fixed effects, which account for the level at which randomization

[8] Table A2 in the appendix shows results from eight specifications, using each of the eight possible majors as dependent variables. This table suggests that the effect on male-dominated majors are driven by effects on choosing finance: having a higher proportion of female peers decreases women's probability and increases men's probability of choosing this major. We also see that having more female peers reduces women's chances of majoring in IT management and men's chances of majoring in supply chain management.

takes place. We are nevertheless pleased to see that our results look similar under both empirical approaches.

One might be worried that peer gender affects students' dropout rate, which would complicate our interpretation of the estimates on major choice. To address this concern, we test whether peer gender and other student characteristics are related to the probability of observing a student's major choice. Table A5 in the appendix shows that we are more likely to observe the major choices of high-GPA students. However, student gender, student nationality, and most importantly, peer gender do not significantly predict the probability of observing major choices.

Table 4: The Impact of Gender Composition on Course and Major Choices

Dependent Variable:	(1) Male-Dominated Major	(2) Female-Dominated Major	(3) Proportion Women in Major	(4) Any Mathematical Elective	(5) Fraction Mathematical Electives
Female * Proportion Female Peers	-0.0812***	0.1007***	0.0296***	-0.1197***	-0.0399**
	(0.028)	(0.038)	(0.010)	(0.038)	(0.018)
Male * Proportion Female Peers	0.0639**	-0.0988***	-0.0297***	0.0463	0.0113
	(0.029)	(0.027)	(0.008)	(0.028)	(0.015)
Female	-0.1337***	0.1298***	0.0458***	-0.0654***	-0.0330***
	(0.019)	(0.022)	(0.006)	(0.021)	(0.012)
Observations	29,211	29,211	29,211	30,590	30,590
R-squared	0.125	0.235	0.167	0.216	0.248
Mean Dependent Variable	.1999	.3336	.3975	.5977	.2271
Mean Dependent Variable Women	.0977	.4797	.4415	.4963	.1885
Mean Dependent Variable Men	.2687	.2352	.3679	.6633	.2521
p-values of Test for Gender Equality of Proportion Female Peers	.0008	.0001	<.0001	.0006	.045

NOTE.—The dependent variables in columns (1) and (2) are dummy variables that are equal to 1 if students choose a male-dominated major and female-dominated major, respectively. The dependent variable in column (3) is the proportion of women in the chosen major. The dependent variable in column (4) is a dummy variable that is equal to 1 if the student chose at least one mathematical course. The dependent variable in column (5) is the fraction of chosen courses that are mathematical. Overall, we observe the course choices for 3,025 students and the major choices for 3,563 students. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course-year fixed effects, female, Std. GPA, Dutch and German. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In addition to looking at student major choices, we can also test whether peers affect the choice of students' elective courses.[9] Table 4 shows estimates of the effect of peer gender on the choice of *any* mathematical course and on the *proportion* of mathematical courses chosen. On both margins, we observe that women become less likely to choose mathematical courses if they are randomly assigned to more female peers. Our point estimate suggests that increasing the proportion of female peers by 10 percentage points reduces the probability of choosing a mathematical course by about 1.2 percentage points (2.4 percent). We see no effect on men's choice of mathematical courses.

Taken together, our results show that an increase in the proportion of female peers leads to an increase in gender segregation in specialization choices. Having more female peers causes women and men to choose courses and majors that are more popular with their own gender. Our results are largely consistent with a study by Hill (2017), who finds suggestive evidence that women in US colleges are less likely to graduate from STEM majors when they are in a cohort with more female peers. However, these results only hold in specifications with time trends. Two other studies have explored the effect of high school peer gender on university major choice. In line with our findings, Brenøe and Zölitz (2017) show that female students with more female peers in Danish high school are less likely to complete a STEM degree and more likely to complete a health degree. Contrary to our results, Anelli and Peri (2019) show that male students in Italian high schools with less than 20 percent female peers become *more* likely to choose a male-dominated major. The differences between studies may be a result of the different study environment and definitions of peer groups (high school cohort, university cohort, university section) and therefore different mechanisms through which peer effects operate. We will return to the importance of different underlying mechanisms in Section 5.

[9] When estimating the effect on course choice, we limit our sample to courses that students could choose either as an elective or as major-specific compulsory course.

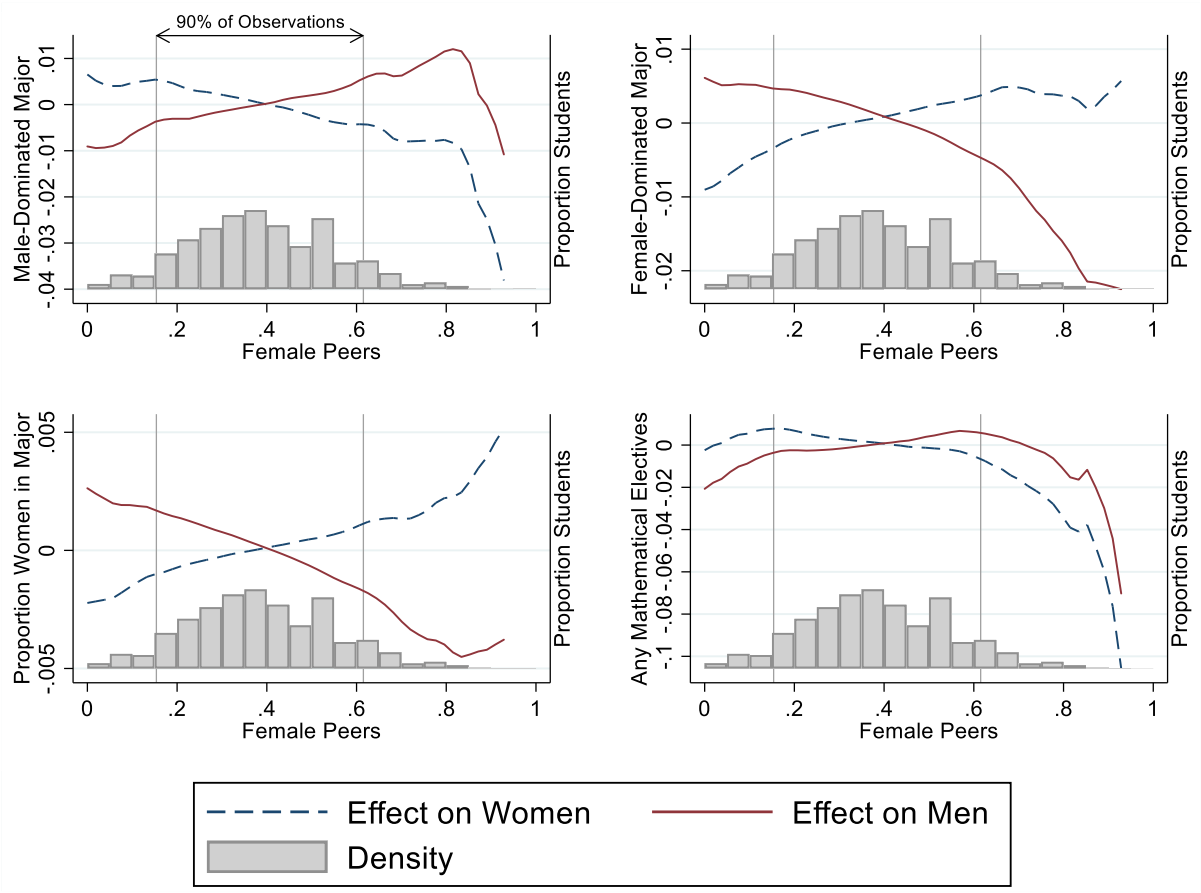
4.2. *Functional Form of Peer Effects*

We investigate the functional form of the relationship between peer gender composition and students' choices in two steps. First, we residualize our main outcomes by regressing students' educational choices on the set of control variables used in our main specification. Second, we relate these residualized student choices to the proportion of female section peers using smoothed local polynomial plots.[10] This method is similar to creating local averages of the unexplained part of educational choices over the proportion of female section peers.

Figure 3 shows that the effects of peer gender are fairly linear for all outcomes and both genders. Linearity is most apparent in sections that have between 15 percent and 62 percent female peers. These sections make up 90 percent of our observations. Outside of this range, the results are too imprecisely estimated to draw any conclusions about the functional form. Figure A2 in the appendix shows the relationship between the average proportion of female peers a students had in all compulsory courses and our main outcomes. This figure also confirms linearity for the range of data for which we have the most empirical support.

[10] We implement step 2 with Stata's lpoly command using the default smoothing degree. For more details, see https://www.stata.com/manuals/rlpoly.pdf

Figure 3: Functional Form of the Effect of Peer Gender on Student Choices



NOTE.— This figure shows local polynomial plots of the relationships between residualized outcomes measuring students' specialization choices (on the Y-axes) and the proportion of female section peers (on the X-axes). The grey histograms show the distribution of female peers to illustrate the underlying support in the data. The vertical lines show the 5th and 95th percentile of female peers. All outcomes are residualized using the same controls as in our main specification (see Table 4).

4.3. *Peer Effects on Labor Market Outcomes*

To test whether peer gender affects labor market outcomes, we use data from a 2016 graduate survey that we conducted among students who graduated between September 2010 and

September 2015.[11] This survey includes several questions that allow us to obtain a detailed picture of graduates' occupational situation one to five years after graduation.[12]

Table 5 shows the estimated effect of peer gender on several key labor market outcomes.[13] University peers do not significantly affect men's labor market outcomes. For women, however, we see some significant and interesting effects. While having more female peers has no significant effect on women's earnings in their first job after graduation, we see a negative effect on their current earnings. These findings suggest that having more female peers causes women to choose jobs that have lower earnings growth. This is indeed the case: women who are exposed to 10 percentage points more female peers end up in jobs in which their earnings have grown 0.3 percentage points less after graduation. Finding effects on earnings growth instead of earnings in first jobs is consistent with evidence showing that salary differences between MBA graduates are quite small one year after graduation, but increase substantially over time (Bertrand et al. 2010).

[11] We designed and conducted the survey in cooperation with the business school's alumni office, which provided us with contact details for 75 percent of bachelor's students in our estimation sample. We first contacted the graduates via email and provided them with a link to the online survey. We then hired a team of current students from the business school to call the graduates who did not respond to the online survey to conduct the survey over the phone. Out of the contacted graduates, 38 percent responded to either the email or phone survey, which means that we have labor market outcome information for 1,618 students, about 30 percent of our estimation sample. Table A5 shows that the proportion of female peers is unrelated to the probability of responding to the graduate survey (column 2) and the probability of responding to the survey and reporting to be working (column 3).

[12] Table A6 in the appendix provides summary statistics for the labor market variables. Table A7 in the appendix shows the original survey questions, the survey answer options, and the definition of our dependent variables.

[13] Table A8 in the appendix shows estimations from specifications that use observations at the student level. These specifications lead to qualitatively similar results.

Table 5: The Impact of Gender Composition on Labor Market Outcomes

Dependent Variable:	(1) Log First Earnings per Year	(2) Log Current Earnings per Year	(3) Earnings Growth	(4) Log Hourly Earnings	(5) Working Hours	(6) Working Part-Time	(7) Job Search Duration in Months	(8) Job Satis-faction	(9) Subjective Social Impact
Female * Proportion Female Peers	0.0704	-0.5224**	-0.0338***	-0.4280*	-3.2558*	0.0705*	-0.7358*	0.3504*	0.3378
	(0.131)	(0.266)	(0.012)	(0.244)	(1.706)	(0.042)	(0.413)	(0.211)	(0.242)
Male * Proportion Female Peers	0.0776	-0.0261	0.0110	-0.0369	1.0058	0.0272	-0.0116	0.0900	-0.2742
	(0.109)	(0.202)	(0.009)	(0.203)	(1.414)	(0.026)	(0.303)	(0.206)	(0.210)
Female	-0.1087	-0.1053	0.0081	-0.0711	-2.4958**	-0.0095	0.5038*	-0.2582	0.0175
	(0.087)	(0.130)	(0.008)	(0.127)	(1.046)	(0.020)	(0.287)	(0.157)	(0.177)
Observations	9,523	9,263	8,916	9,238	9,576	9,690	9,487	9,652	9,668
R-squared	0.104	0.104	0.038	0.071	0.165	0.127	0.046	0.043	0.596
Mean Dep. Var.	10.36	10.499	.0171	2.705	48.417	.0511	1.556	8.141	0.709
Mean Dep. Var. Women	10.287	10.318	.012	2.573	45.742	.0555	1.66	8.065	1.017
Mean Dep. Var. Men	10.406	10.614	.0204	2.788	50.144	.0482	1.489	8.19	0.509
p-value of Test for Gender Equality of Proportion Female Peers	.9668	0.1470	.0039	.2276	.0673	.3978	0.1950	.4155	.0825

NOTE.— The dependent variable in column (1) is equal to the log of self-reported yearly gross earnings in the first job after graduation including bonuses and holiday allowances. The dependent variable in column (2) is equal to the log of self-reported yearly gross earnings in the current job including bonuses and holiday allowances. The dependent variable in column (3) is earnings growth calculated as the difference between current and first earnings divided by first earnings. The dependent variable in column (4) is current log hourly earnings calculated based on information on current earnings and working hours. The dependent variables in column (5) is self-reported weekly working hours including overtime. The dependent variable in column (6) is equal to 1 if the survey respondent indicated that they work part-time and 0 if they did not. The dependent variable in column (7) shows job search duration in months. The dependent variable in column (8) is self-reported job satisfaction on a 1–10 scale. The dependent variable in column (9) is self-assessed social impact of the graduate's job measured on a scale ranging from −5 "Very negative social impact" over 0 "Neutral, no social impact" to +5 "Very positive social impact." All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, Dutch and German. All columns include a dummy for whether the survey data were collected by phone interviews (as opposed to email). Differences in the number of observations are due to students not answering specific questions. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

We further find suggestive evidence that women who had more female peers have lower hourly earnings, work fewer hours per week, are more likely to work part-time, and need less time for finding their first job after graduation. Women who had more female peers also report marginally significantly higher job satisfaction and a more positive social impact of their job, although the latter effect is not statistically significant. While all these point estimates fail to

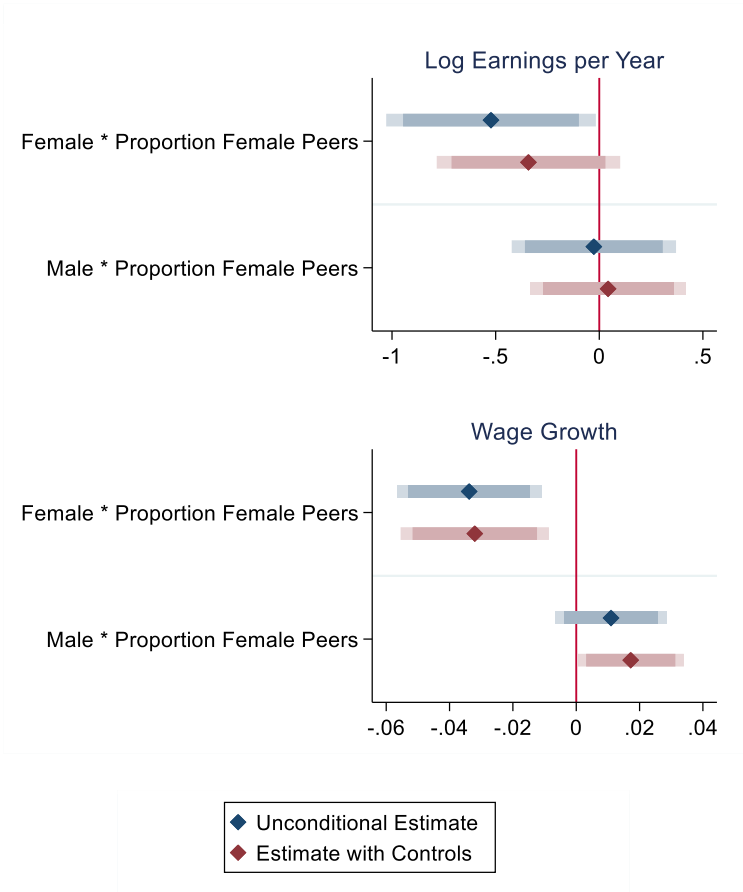
reach statistical significance at conventional levels, we interpret them as suggestive evidence that having more female peers affects which kinds of jobs women choose.

To explore how much of our effects on earnings and earnings growth can be explained by the effects of peer gender on the types of majors and jobs women choose, we perform a mediation analysis broadly following Gelbach (2016). In particular, we estimate the effects of peer gender on earnings and earnings growth in specifications that additionally control for major fixed effects, industry fixed effects, working part-time, working hours, and working hours squared. We then compare the point estimates from this regression and the original regression to see what proportion of the peer effect is explained by the mediators.

The results of this mediation analysis have to be interpreted with caution. Imai et al. (2010) show that interpreting this type of analysis in a causal way requires strong assumptions. One of these assumptions that was likely violated in our setting is the absence of cross impacts between different mediators. For example, it seems unlikely that the job industry is unrelated to number of weekly hours worked. Despite these limitations however, we believe that this mediation analysis is helpful for gauging the importance of major choices and job characteristics for explaining the effects on earnings.

Figure 4 shows that adding these controls only leads to small changes in the coefficients of interest. The estimated effect of having female peers on women's earnings reduces by 35 percent and becomes insignificant. The estimated effect of peer gender on women's earnings growth reduces by 6 percent and remains statistically significant at the 1 percent level. Women's major and job choices thus appear to only play a minor role in explaining the effect of peer gender on earnings.

Figure 4: Effects on Earnings Controlling for Potential Mechanisms



NOTE.— This figure shows estimated effects of peer gender on women's and men's Log current earnings and earnings growth. The "Unconditional Estimates" are taken from columns (2) and (3) from Table 6. The "Estimates with Controls" are from specifications that additionally include controls for major fixed effects, industry fixed effects, working part-time, working hours, and working hours squared. Table A9 in the appendix shows the underlying regressions. Horizontal bars show 90 and 95 percent confidence intervals that are based on standard errors clustered at the student and section levels.

An alternative explanation is that having more female peers affects earnings through ways that are not captured by our included controls. For example, women who had more female peers might have children earlier. Such effects would be consistent with findings of Brenøe and Zölitz (2019), who show that women exposed to more female peers in high school have their first child earlier. These women might choose jobs that are closer to home and have more flexible working hours but pay less. Unfortunately, we do not observe fertility outcomes in our survey.

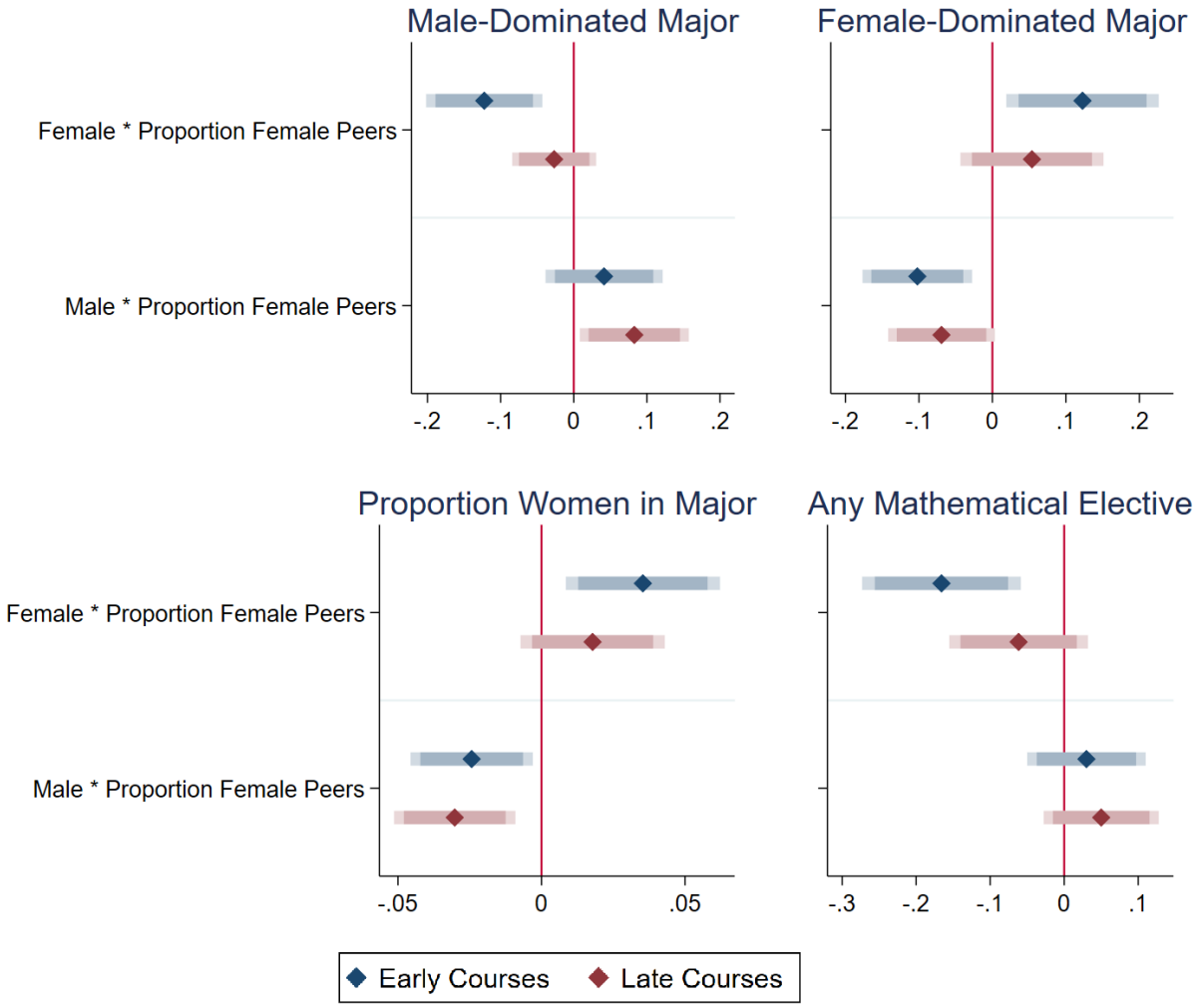
5. Mechanisms

5.1 *Peer Effects on Early and Late Courses*

Our results might be driven by the effect of the peer composition on students' friendships at the beginning their studies. These social networks might affect students' choices through interactions outside the classroom, for example, in private study groups, in fraternities or at parties. Peer groups formed early in students' studies have been shown to be important for students' dropout decisions, confidence, academic performance, and major choices (Thiemann 2018; Fischer 2017). We explore the importance of timing of peer exposure, by estimating our main results separately for courses taken in the first year (early courses) and courses taken in the second year (late courses).

Figure 5 shows the effects of having female peers in early and late courses. Women are more strongly affected in early courses. Having a higher proportion of female peers in these course decreases women's likelihood of choosing a male-dominated major and increases their likelihood of choosing a female-dominated major. Having more female peers in early courses also makes them choose majors with fewer women and reduces their likelihood of choosing any mathematical electives. In late courses, effects seems to go in the same direction but are smaller and fail to reach statistical significance. In contrast, men are similarly affected by the peer composition in early and late courses. For them, the timing of exposure to female peers matters less.

Figure 5: Main Results for Early vs. Late Courses



NOTE.— This figure shows our main results estimated in separate samples for first-year courses (early courses) and second-year courses (late courses). Table A10 in the appendix shows the underlying regressions that have the same control as our main results regressions shown in Table 5. Horizontal bars show 90 and 95 percent confidence intervals that are based on standard errors clustered at the student and section levels.

5.2 *Coordination of Major Choices*

Students may coordinate their major choices with their friends. Major choice coordination may drive our results if the section gender composition affects the number of friendships students form in a section. For example, a higher proportion of female section peers may cause women to choose more female-dominated majors, because these women want to choose the same majors as their same-gender peers. Women can either explicitly coordinate their major choices or find majors more attractive if more female peers plan to choose them.

To explore whether coordination of major choices drives our results, we test how the proportion of women in a section relates to the diversity of major choices among students in a given section. We measure major choice diversity using the normalized Blau index. This index is equal to 0 if all students in a given section choose the same major, it increases as heterogeneity in major choice grows, and is equal to 1 if all majors attract an equal proportion of students (see Appendix A3 for a more detailed description of the Blau index). There are many reasons students in the same section would be more likely to choose the same major (e.g. because they have the same instructor). Yet, observing that major choice diversity is related to the randomly assigned proportion of women in a section would provide evidence for coordination among same-gender or opposite-gender peers.

To estimate the effect of peer composition on diversity of major choice, we estimate the following model:

$$\tilde{B}_s = \delta_1 \bar{F}_s + \tilde{X}_c \tilde{\gamma}' + \varepsilon_s, \qquad (2)$$

where $\tilde{B}_s$ is the normalized Blau index for diversity of major choice in section s, $\bar{F}_s$ is the proportion of women in section s, $\tilde{X}_c$ is a vector of course-year fixed effects and ε_s is the error term. The parameter of interest is δ_1, which shows the causal effect of increasing the proportion of women in a section on the diversity of major choice of students in that section.

Table 6 shows the estimates of the effect of the proportion of women in a section on the diversity of major choices for all students (column 1), women (column 2) and men (column 3). We find a negative and statistically significant relationship between the proportion of women in a section and the Blau index based on all students' choices, indicating that major choices become more homogeneous when more women are in the same section. This effect is entirely driven by increased homogeneity in women's major choices. This increase in homogeneity is evidence that women coordinate their major choices with their female section peers. The diversity of men's major choices is not significantly affected.

Table 6: The Impact of Gender Composition on Diversity in Major Choice

Dependent Variable:	(1) Normalized Blau Diversity Index, all Students	(2) Normalized Blau Diversity Index, Women	(3) Normalized Blau Diversity Index, Men
Proportion Female Students in Section	-0.0227**	-0.1133***	0.0137
	(0.011)	(0.013)	(0.016)
Observations	2,004	2,004	2,004
R-squared	0.550	0.157	0.441
Mean Dependent Variable	0.921	0.930	0.906

NOTE.— The dependent variable in all columns is the normalized Blau diversity index, which is constructed based on the major choices in the given section. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects. In this table, we restrict the estimation to sections that contain at least two women and two men because we need at least two women (men) to calculate the Blau index for female (male) students. Robust standard errors clustered at the course level are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

5.3 *Peer Effects on Grades and Course Evaluations*

Exposure to female peers can positively affect students' performance and the classroom atmosphere (e.g. Hill 2015; 2017; Hoxby 2000; Lavy and Schlosser 2011; Whitmore 2005; Figlio 2007; Lavy and Schlosser 2011; Oosterbeek and van Ewijk 2014). We test whether such effects could drive our results by estimating how having female peers affects students' grades and course evaluations. We allow for separate effects in mathematical and non-mathematical

courses by also estimating models that include interaction terms of our peer variables of interest with a dummy variable for mathematical courses.

We start our analysis looking at student grades (see Table A11 in the appendix for grade summary statistics). Grades in compulsory courses are mainly determined by a student's final exam grade. In first-year courses, this final exam is the only graded component. In second-year courses, the final exam typically contributes most to the course grade, but there might be other graded components like presentations or participation. The material students discuss with their section peers covers most of the overall course material. While some content might only be covered in lectures, lectures make up only one-third of students' contact hours. Any curving of the exam grade typically happens at the course level, which affects grades of students in all sections equally. We are therefore not concerned that curving obscures any effects that section peers may have on grades.

Columns (1) and (2) of Table 7 show how the proportion of female peers affects students' grades. While women have higher grades when they have more female peers, men's grades are barely affected by the peer gender composition. However, these average effects hide important heterogeneity: women only benefit from female peers in non-mathematical courses, while the opposite holds for men. An increase in female peers by 10 percentage points increases women's grades in non-mathematical courses by 1.2 percent of a standard deviation, while not affecting their grades in mathematical courses. For men, a 10 percentage point increase in female peers increases their grades by 1.3 percent of a standard deviation in mathematical courses, but does not affect their grades in non-mathematical courses.

Table 7: The Effect of Gender Composition on Grades, Overall Evaluation, and Group Functioning

Dependent Variable:	(1) Std. Grade	(2) Std. Grade	(3) Std. Overall Evaluation	(4) Std. Overall Evaluation	(5) Std. Group Functioning	(6) Std. Group Functioning
Female * Proportion Female Peers	0.0804**	0.1214***	0.0711	0.2369*	0.1930	0.3595**
	(0.041)	(0.045)	(0.108)	(0.125)	(0.135)	(0.143)
Male * Proportion Female Peers	0.0386	-0.0047	0.1072	0.1519	-0.0840	0.0212
	(0.037)	(0.044)	(0.106)	(0.127)	(0.115)	(0.126)
Female * Proportion Female Peers * Math Course		-0.1305**		-0.4785***		-0.5424**
		(0.056)		(0.169)		(0.231)
Male * Proportion Female Peers * Math Course		0.1311**		-0.0782		-0.2938
		(0.054)		(0.163)		(0.197)
Female	0.0011	0.0053	-0.0220	-0.0112	-0.1130*	-0.1062
	(0.023)	(0.023)	(0.056)	(0.056)	(0.065)	(0.065)
Observations	36,549	36,549	11,077	11,077	10,220	10,220
R-squared	0.520	0.521	0.177	0.179	0.103	0.104
Mean Dependent Variable	0	0	0	0	0	0
Mean Dependent Variable Women	.0657	.0657	-.0327	-.0327	-.0003	-.0003
Mean Dependent Variable Men	-.0432	-.0432	.0263	.0263	.0003	.0003
p-values: Test of Gender Equality for						
Proportion Female Peers	.4508	.0265	.7929	.5466	.0793	.0338
Proportion Female Peers * Math course		<.0001		<.0001		.0335

NOTE.— The dependent variable in columns (1) and (2) is standardized course grade. The dependent variable in columns (3) and (4) is the standardized overall course evaluation. The dependent variable in columns (5) and (6) is standardized group functioning. "Group functioning" is measured using the standardized sum of standardized answers to the two questions: "My tutorial group has functioned well" and "Working in tutorial groups with my fellow students helped me to better understand the subject matters of this course." Overall course quality is measured with the question: "Please give an overall grade for the quality of this course." All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course fixed effects, female, Std. GPA, Dutch and German. Columns (2), (4), and (6) additionally control for the interaction between female and math course. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

To estimate the effect of peer gender on course evaluations, we use data on students' satisfaction with the course and their section peer group.[14] We measure course satisfaction with the answer to the question "*Please give an overall grade for the quality of this course.*" To facilitate the interpretation of the answers, we standardize the questionnaire responses to have a mean of zero and a standard deviation of one. To measure group functioning, we use the

[14] Evaluation survey response is unrelated to the proportion of female peers (see Table A5 in the appendix).

following two questions: (1) "*My tutorial group has functioned well*," and (2) "*Working in tutorial groups with my fellow students helped me to better understand the subject matter of this course*." We combine both questions to create a group functioning index by standardizing the answers to each question, calculating the average of the standardized values for each student, and then standardizing the resulting variable again to have a mean of zero and a standard deviation of one. Table A11 in the appendix shows the summary statistics for the course evaluations.

Columns (3) to (6) of Table 7 show estimates of how the gender composition affects students' evaluation of the course and their section peer group. On average, women's and men's overall course evaluations are not significantly affected by the peer gender composition. However, the effect of an increase in female peers for women significantly differs between mathematical and non-mathematical courses: having 10 percentage points more female peers *reduces* women's evaluation of mathematical courses by 2.5 percent of a standard deviation and *increases* their evaluation of non-mathematical courses by 2.4 percent of a standard deviation. These estimated effects closely resemble the estimates on group functioning. Having more female peers leads women to evaluate group functioning more negatively in mathematical courses and more positively in non-mathematical courses.[15]

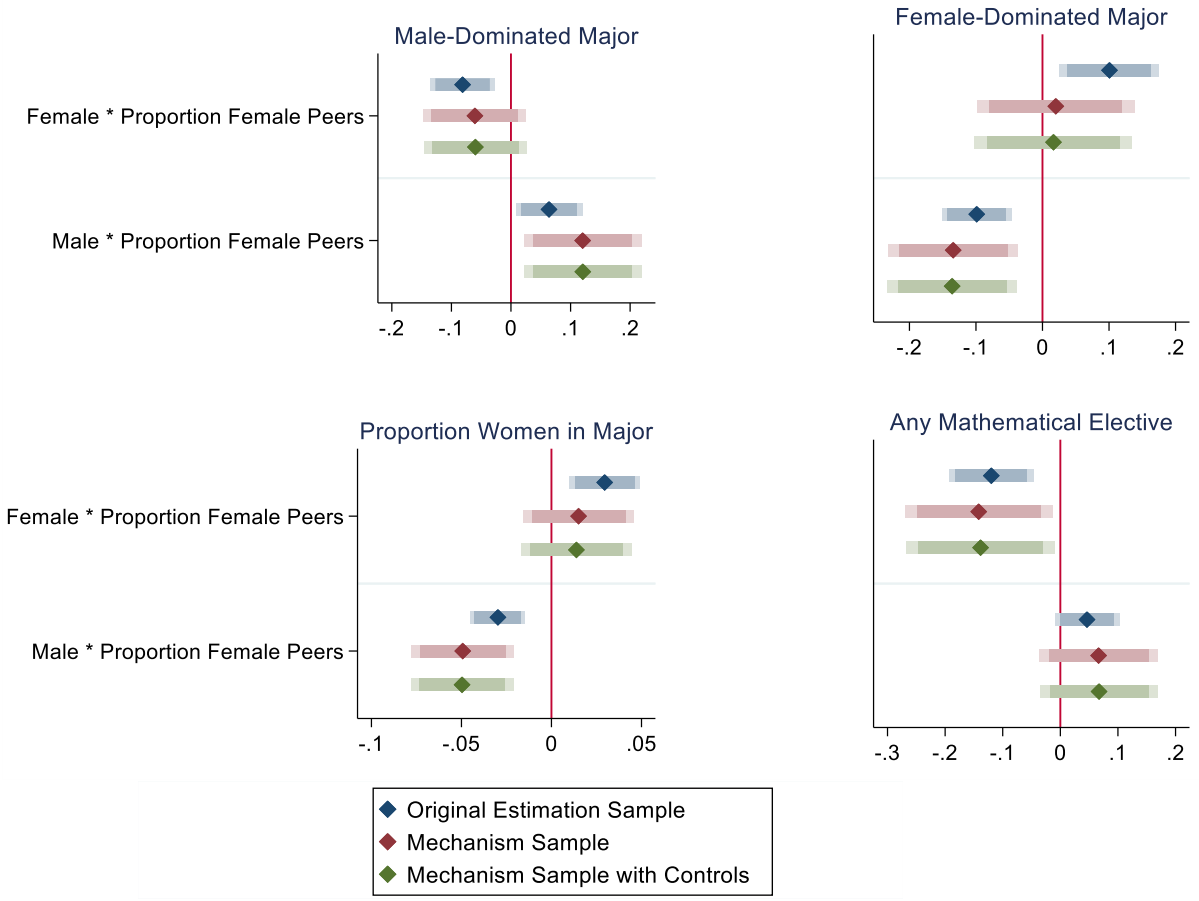
To explore how much of our effects can be explained by these mechanisms, we perform a mediation analysis consisting of two steps. First, we re-estimate our main analysis for the sample for which we observe all potential mechanisms. Second, we estimate our main results in specifications that additionally control for students' grades, their evaluation of the course overall, and their evaluation of group functioning. We also include interaction terms of each of

[15] We also explore whether the effect of having female peers on students' specialization choices differs between mathematical and non-mathematical courses. In Figure A3 in the appendix we show the estimated effects of peer gender on all our outcomes for these two types of courses. Our results show only meaningful differences for one out of eight coefficients of interest. The effect of peer gender on choosing a male-dominated major for men seems to be driven by the peer composition in non-mathematical courses.

these variables with a dummy for mathematical courses to allow their effects to differ by course type.

Figure 6 shows that our main results are less precisely estimated and qualitatively similar for the sample for which we observe all mechanisms. We further see that our estimates in this mechanism sample hardly change when we control for all candidate mechanisms. The reductions in point estimates for all outcome variables is smaller than 20 percent. Peers' influence on grades and course evaluation thus appear not to be quantitatively important mechanisms of the effect of peer gender on students' specialization choices.

Figure 6: Main Results after Controlling for Grades and Course Evaluations



NOTE.—This figure shows our main estimates (see Table 4), our main estimates with a sample for which we observe all candidate mechanisms (see Table A12), as well as estimates with this mechanism sample that additionally control for all candidate mechanisms (see Table A12). All three specifications include course fixed effects, parallel course fixed effects, student gender, student nationality, and GPA. Horizontal bars show 90 and 95 percent confidence intervals, which are based on standard errors clustered at the student and section levels.

5.4 *Mechanism – Discussion*

Our results show that women who have more female peers are more likely to coordinate their major choices and are more affected by their peers in early courses. These results might be driven by friendship networks among women who are assigned to the same sections at the beginning of their studies. Being around more female peers in the sensitive period at the start of university may affect with whom they form long-lasting friendships. Women's grades and course evaluations in compulsory courses suggest that having more female peers makes them fare better in non-mathematical compared to mathematical courses. Yet, these effects appear to explain only a small proportion of the observed effects on major choice.

For men, the picture on mechanisms is less clear. We see no evidence that formation of friendship networks in early courses explains our observed effects: men are similarly influenced by their peers in early and later courses, and having more female peers does not change who they coordinate their major choices with. They receive higher grades in mathematical course if they had more female peers. This experience may cause them to believe that they are better-suited for more-mathematical, male-dominated majors. Yet, our mediation analysis suggests that these effects only explain a small proportion of our observed effects.

Another prominent potential mechanism is a change in gender norms. For example, peers could affect what students consider to be the appropriate gender norms or which norms are more salient (Akerlof and Kranton 2000; 2002). A similar argument has been made to explain why girls are more likely to choose traditionally male subjects in single-sex schools: with no boys around, girls feel less compelled to "act like a girl" and they become more open to studying what they want to study (Solnick 1995; Thompson 2003).

The importance of gender norms could increase with the number of same-gender peers. For example, having more female peers in the classroom may provide women with more role models from which to learn or imitate gender norms. This mechanism is consistent with our

results that women choose more traditionally female majors when they have more female peers. However, the importance of gender norms could also *decrease* with the number of same-gender peers. For example, having more female peers in the classroom may make gender differences less salient and therefore reduce the importance of gender norms. Contrary to our findings, this mechanism would predict that women with more female peers choose less fewer traditionally female majors. Although we believe that gender norms are important in our context, it is unclear how these norms change when the proportion of female peers changes.[16]

6. Policy Simulation: Increasing the Number of Students in Male-Dominated Majors

Based on our results, we can assess the consequences of different student assignment policies. These policies can change the total number of students in different majors because the effect of peer gender differs for women and men. For example, increasing the proportion of female peers makes women less likely and men more likely to choose a male-dominated major. By exploiting these heterogenous effects, the business school could change the number of students in male-dominated majors through different section-assignment policies.

The two most extreme assignment polices would be single-sex sections and sections with equal proportions of women. Assuming that our effects are linear for all values of female peers, single-sex sections would lead to the lowest number of women and men choosing male-dominated majors. Under this assignment policy, women would be with 100 percent female peers; under this scenario, they would be least likely to choose a male-dominated major. Men would be with 0 percent female peers; under this scenario, they too would be least likely to

[16] A related mechanism that could explain our results has been suggested by Bursztyn et al. (2017). They propose that women may avoid career-enhancing actions because these signal traits, like ambition, that are undesirable in the marriage market. In line with this reasoning, a higher proportion of female peers may increase competition for men and thus may make women less likely to choose a competitive, male-dominated major that signals "undesirable" traits like ambition. By contrast, one could argue that increased competition for men may make women more likely to choose a male-dominated major because such a major would expose them to more potential mates.

choose a male-dominated major. At the other extreme, sections with equal proportions of women would lead to the highest number of women and men in male-dominated majors. Compared to all other section assignment policies, equal proportion sections would decrease the average proportion of female peers for women on and increase it for men (see Appendix A2 for an illustration). This change in peer composition would make both genders most likely to choose male-dominated majors.

These insights allow us to simulate the effects of a reassignment policy that aims to increase the number of women in male-dominated majors by assigning all students to sections with equal proportions of women. We abstain from simulating the single-sex assignment as this policy would be based on section compositions that we do not observe in the data. We perform the equal proportions simulation separately for male- and female-dominated majors in six steps.

First, we create a counterfactual section assignment in which we equalize the proportion of women per section in all compulsory courses. For this counterfactual assignment, we hold the total number of students and sections per course constant. While it is not possible to always equalize the proportion of female students, this assignment greatly reduces variation in female peers per section (see Figure 7). This assignment also decreases the proportion of female peers for the average woman by 4.5 percentage points and increases the proportion of female peers for the average man by 6.3 percentage points. Those changes in peer composition drive the changes in the number of women and men choosing different majors.

Second, for each student-course observation we calculate the change in female section peers that would result from moving from the status quo to equal proportions assignment.

Third, we multiply these changes in proportions of female peers with our point estimates of having female peers on choosing a male-dominated and a female-dominated major (see Table 4, columns (1) to (2)). The resulting products show us how much the predicted

probability of choosing male- or female-dominated majors changes by moving to the equal proportions assignment for each student-course observation.

Fourth, we calculate the predicted probability of choosing each major type for each student. We do this by adding the predicted probabilities of choosing a major in the status quo (taken from regressions shown in columns (1) and (2) of Table 4) to the changes in predicted probability (from step 3) and averaging the resulting sum at the student level.

Fifth, we round these predicted probabilities to be between 0 and 1 to ensure that each students' predicted probabilities of choosing a major are between 0 percent and 100 percent.

Sixth, we sum these changes for all women and men in all compulsory courses. The results of this last step show how many additional women and men would choose male- and female-dominated majors when moving from the status quo to an equal proportions assignment.

Figure 7: Gender Composition of Sections in Status Quo and Equal Proportions Assignment

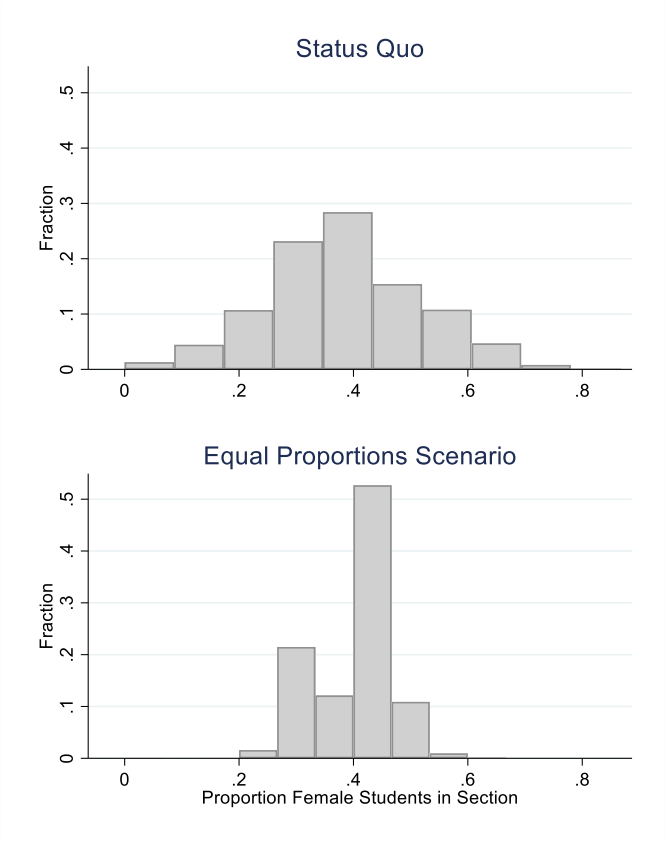


Table 8 shows the results of this simulation. Assigning all students to compulsory course sections with equal proportions of women would increase the number of women choosing male-dominated majors by 27 percent and the proportion of men choosing these majors by 12 percent. At the same time, the equal proportions assignment would reduce the number of women and men choosing female-dominated majors by 8 and 21 percent, respectively.

Table 8: Gender Composition in the Status Quo and the Equal Proportions Scenario

	(1) Status Quo	(2) Equal Proportions Scenario	(3) Difference between Equal Proportions Scenario and Status Quo	(4) % Difference
Women in Male-Dominated Majors	135	171	36	27%
Men in Male-Dominated Majors	585	655	70	12%
Women in Female-Dominated Majors	665	612	-53	-8%
Men in Female-Dominated Majors	512	404	-108	-21%

NOTE.— This table is based on the four cohorts we observe in the data. The total number of students in these cohorts is 3,563, of which 1,386 are female and 2,177 are male.

These results should be interpreted with caution for two reasons. First, reassignment policies can change the nature of peer interactions. Carrell et al. (2013) have shown that the nature of peer effects can change in unpredictable ways when peer assignment policies change. While the changes from random assignment to equal proportions assignment are rather modest, we cannot rule out that mandating equal proportions of women per section would affect the nature of the effects of peer gender. Second, the welfare implications of this reassignment policy are not clear. While encouraging women to choose fields that have been traditionally dominated by men is a prominent policy goal, it is not obvious if the marginal women would be better off choosing a male-dominated major. Choosing a male-dominated major likely has

positive and negative consequences. For example, our results imply that women who chose male-dominated majors because they had *fewer* female peers earn more but are less satisfied with their job. This latter result is in line with Lordan and Pischke (2016), who show that women who have more male co-workers are less satisfied with their jobs.

7. Conclusion

Although many women enroll in business studies, they are less likely than men to end up in high-paying positions. This gap is partly driven by women being less likely to specialize in majors, like finance, that are associated with high earnings.

In this paper we have identified one factor that influences this gender segregation in major choices: the gender composition of students' peers. Women who had more female peers at the start of their education become less likely to choose male-dominated majors like finance and more likely to choose female-dominated majors like marketing. In contrast, men who had more female peers become more likely to choose male-dominated majors and less likely to choose female-dominated majors. The peer gender composition also affects women's but not men's labor market outcomes. Women who had more female peers end up in jobs in which their earnings grow more slowly. We further find suggestive evidence that these women work fewer hours, are more likely to work part-time, and are more satisfied with their job. Taken together, our results show that studying with more female peers in business school increases gender segregation in educational choice and the labor market outcomes.

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APPENDIX A

A1 Data Restrictions

Our sample period includes the academic years 2009–10 through 2014–15. We derive our estimation sample in two steps. First, we exclude several observations from our estimation sample because they represent exceptions from the standard section assignment procedure. Second, we further limit our estimation sample to business and business economics bachelor's programs, which started in the academic years of 2009–10 through 2011–12 because we can follow these cohorts from their first until their last bachelor's year, and we can observe their major choices.

Below we list the observations we exclude due to exceptions to the scheduling procedure.

- We exclude eight courses in which the course coordinator or other education staff actively influenced the section composition. One course coordinator requested to balance student gender across sections. The business school's scheduling department informed us about these courses.
- We exclude 21 sections from the analysis that consisted mainly of students who registered late for the course. Before April 2014, the business school reserved one or two slots per section for students who registered late. In exceptional cases in which the number of late registration students substantially exceeded the number of empty spots, new sections were created that were mainly composed of late registering students. In April 2014, this late registration policy was abolished.
- We exclude 46 repeater sections from the analysis. One course coordinator explicitly requests to assign repeater students who failed his courses in the previous year to special repeater sections.

- We exclude 17 sections that consisted mainly of students from a special research-based program. For some courses, students in this program were assigned together to separate sections with a more-experienced instructor.
- We exclude 95 part-time MBA students because these students are typically scheduled for special evening classes with only part-time students.
- We exclude 4,274 student-year observations for students who were repeating courses. These students follow different attendance criteria and are graded under different standards.
- We exclude all observations of the first year and the first period students are observed. For these observations, we have no measure of students' past GPA at the business school, an essential covariate in our analyses.
- We exclude all observations from the first teaching period of 2009—the first period in our data set—for the same reasons outlined above.
- We exclude 1,229 student-year observations from sections that were held after 6:30 p.m. because before the fall of 2015, students could opt out of evening education, which makes the student assignment to these sections potentially non-random.

A2 Numerical Illustration of Proportion of Female Peers in Different Assignments

To see why equal proportions assignment would lead to the highest proportion of female peers for the men and the lowest proportion of female peers for women, consider the following numerical example: There are four men and four women who should be assigned to two sections (called A and B) of four students each. There are three different section assignments: (1) single-sex sections, (2) sections with unequal proportions of women, and (3) section with equal proportions of women.

Table A13 summarizes these three assignments. As we move from single-sex assignment to equal-proportions assignment, the average proportion of female peers increases for men and decreases for women. In the equal-proportions assignment, men have, on average, the highest proportion of female peers and women have, on average, the lowest proportion of female peers.

Note the difference between the equal proportions and unequal proportions assignments. If we move from equal proportions to unequal proportions, the change in female peers *per section* is constant (Section A: + 1 woman, Section B: –1 woman). However, now *one* man (in Section A) has more female peers, and *three* men (in Section B) have fewer female peers. The increase in female peers for the man in Section A is more than offset by the decrease in female peers for the men in Section B, leading to a decrease in the proportion of female peers for men on average. At the same time, now *one* woman (in Section A) has more female peers and *three* women (in Section B) have fewer female peers, leading to an increase in female peers on average. This illustration shows that moving toward more gender-balanced section assignments will provide women with fewer and men with more female peers.

Table A1: Alternative Randomization Check

Dependent Variable	Number Significant at the: 5%	1%	0.1%	Percent Significant at the: 5%	1%	0.1%	Total Number of Courses	Mean of *p*-value
Female	6	0	0	3%	0%	0%	172	0.5250
GPA	8	2	0	5%	1%	0%	153	0.4685
Age	8	4	0	5%	2%	0%	175	0.5044
ID Rank	6	0	0	3%	0%	0%	175	0.5133

NOTE.—This table is based on separate ordinary least squares regressions with gender, GPA, age, and ID rank as dependent variables. ID rank is the rank of student IDs which serves as a measure of student tenure at the business school. The explanatory variables are a set of section dummies and dummies for the other parallel course taken at the same time and the nationality indicators German and Dutch. Columns (2) and (3) show in how many regressions the *F*-test on joint significance of all included section dummies is statistically significant at the 5 percent and 1 percent level, respectively. Columns (5) and (6) show for what percentage of the regressions the *F*-test rejected the null hypothesis at the respective levels. Differences in the number of courses reported in column (1) are due to missing observations for some of the dependent variables. We do not include German and Dutch as dependent variables because these variables are mechanically balanced due to the stratification of assignment by nationality. For a more detailed explanation of this randomization check, see Feld and Zölitz (2017).

Table A2: Effects on Each Major Separately

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Finance	IT MGMT	Strategy	Economics	Accoun-ting	Supply Chain MGMT	Organi-zation	Marketing
Female * Proportion Female Peers	-0.0593**	-0.0230**	0.0555*	-0.0191	-0.0430*	0.0366	0.0476*	0.0259
	(0.026)	(0.010)	(0.030)	(0.020)	(0.023)	(0.032)	(0.028)	(0.029)
Male * Proportion Female Peers	0.0798***	-0.0155	0.0151	0.0102	0.0056	-0.0446**	-0.0256*	-0.0294*
	(0.028)	(0.009)	(0.024)	(0.019)	(0.018)	(0.020)	(0.015)	(0.018)
Female	-0.1276***	-0.0062	-0.0341**	0.0186	0.0090	0.0334**	0.0276**	0.0672***
	(0.018)	(0.007)	(0.016)	(0.017)	(0.014)	(0.016)	(0.012)	(0.016)
Proportion Female Students in Major	21.5	30.43	35.64	37.76	39.09	48.78	59.51	60.34
Observations	29,211	29,211	29,211	29,211	29,211	29,211	29,211	29,211
R-squared	0.127	0.016	0.085	0.620	0.047	0.089	0.072	0.079

NOTE.—The dependent variables in columns (1) to (8) are dummy variables that are equal to 1 if the student chooses the major indicated in the column title and 0 if any other major is chosen. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course fixed effects, and a female dummy. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Main Results Without Controls for GPA and Student Nationality

Dependent Variable:	(1) Male-Dominated Major	(2) Female-Dominated Major	(3) Proportion Women in Major	(4) Any Mathematical Elective	(5) Fraction Mathematical Electives
Female * Proportion Female Peers	-0.0812***	0.1243***	0.0349***	-0.1004***	-0.0670***
	(0.029)	(0.037)	(0.010)	(0.036)	(0.026)
Male * Proportion Female Peers	0.0823***	-0.1084***	-0.0344***	0.0352	0.0082
	(0.029)	(0.026)	(0.008)	(0.027)	(0.020)
Female	-0.1222***	0.1120***	0.0407***	-0.0729***	-0.0154
	(0.020)	(0.021)	(0.006)	(0.021)	(0.014)
Observations	34,503	34,503	34,503	36,650	17,463
R-squared	0.094	0.216	0.145	0.217	0.288
Mean Dependent Variable	.2024	.3336	.3971	.5978	.2506
Mean Dependent Variable Women	.099	.4803	.4414	.4955	.217
Mean Dependent Variable Men	.2718	.2352	.3673	.6641	.2706
p-values of Test for Gender Equality of Proportion Female Peers	.0002	<.0001	<.0001	.0041	.0257

NOTE.—The dependent variables in columns (1) and (2) are dummy variables that are equal to 1 if students choose a male-dominated major and female-dominated major, respectively. The dependent variable in column (3) is the proportion of women in the chosen major. The dependent variable in column (4) is a dummy variable that is equal to 1 if the student chose at least one mathematical course. The dependent variable in column (5) is the fraction of chosen courses that are mathematical. Overall, we observe the course choices for 3,025 students and the major choices for 3,563 students. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course fixed effects, and a female dummy. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Main Results With One Observation per Student

Dependent Variable:	(1) Male-Dominated Major	(2) Female-Dominated Major	(3) Proportion Women in Major	(4) Any Mathematical Elective	(5) Fraction Mathematical Electives
Female * Proportion Female Peers in all compulsory courses	-0.4377***	0.5368***	0.1675***	-0.6846***	-0.0035
	(0.133)	(0.163)	(0.044)	(0.180)	(0.090)
Male * Proportion Female Peers in all compulsory courses	0.0909	-0.3058***	-0.0711**	0.0732	0.2024**
	(0.124)	(0.111)	(0.033)	(0.141)	(0.080)
Female	0.0261	-0.1343**	-0.0272	0.1743**	0.0359
	(0.060)	(0.062)	(0.018)	(0.069)	(0.040)
Observations	3,563	3,563	3,563	3,025	3,025
R-squared	0.099	0.234	0.162	0.235	0.130
Mean Dependent Variable	.1948	.3	.3898	.6453	.6453
Mean Dependent Variable Female Students	.1003	.4372	.432	.5431	.5431
Mean Dependent Variable Male Students	.2549	.2127	.363	.7098	.7098
p-values for Test of Gender Equality of Proportion Female Peers	.0008	<.0001	<.0001	.0001	.0457

NOTE.—In this table, we test whether the results in Table 4 hold using specifications with one observation per student instead of one observation per student-course. The dependent variables are the same as in Table 4. All columns are estimated with ordinary least squares regressions that include dummy variables for female and Dutch and German, as well as study-program-by-year fixed effects. To compare the magnitude of the coefficients in this table with those reported in Table 4, note that we observe the average student in 8.2 compulsory courses in our estimation sample. For example, the first point estimate in column (1) suggests that being assigned to 10 percentage points more female peers *across all compulsory courses* decreases women's probability of choosing a male-dominated major by 4 percentage points. This point estimate implies that being assigned to 10 percentage points more female peers *in one course* decreases women's probability of choosing a male-dominated major by 0.5 percentage point (4 percentage points/8.2 courses). In comparison, the point estimate of the same effect is a 0.8 percentage points in the student-course level specification reported in Table 4. The difference between these two point estimates might be driven by the different control variables included. It may also be driven by different weighting of observations. In specifications reported in this table all students receive equal weight independent of how many compulsory courses we observe them in. In contrast, the specifications reported in Table 4 give more weight to students who we observe in more compulsory courses. Heteroskedasticity robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Testing for Attrition and Selective Survey Response

	(1)	(2)	(3)	(4)
Dependent Variable:	Observing Student Major Choice	Observing Graduate Survey Response	Observing Working	Teaching Evaluation Survey Response
Female * Proportion Female Peers	0.0009	-0.0254	-0.0261	-0.0472
	(0.021)	(0.031)	(0.031)	(0.030)
Male * Proportion Female Peers	-0.0032	-0.0083	0.0122	-0.0044
	(0.017)	(0.022)	(0.022)	(0.023)
Female	0.0013	0.0041	0.0150	0.0717***
	(0.014)	(0.021)	(0.021)	(0.018)
Dutch	0.0037	0.0487**	0.0626***	-0.0421***
	(0.013)	(0.019)	(0.019)	(0.013)
German	0.0089	-0.0014	-0.0004	0.0137
	(0.011)	(0.016)	(0.017)	(0.012)
GPA	0.0905***	0.0552***	0.0446***	0.0683***
	(0.004)	(0.004)	(0.004)	(0.003)
Observations	39,566	39,566	39,566	39,566
R-squared	0.534	0.148	0.144	0.142

NOTE.— For all columns, one observation is a student-course registration. The dependent variable in column (1) is equal to 1 if we observe a major choice for that observation and equal to zero if we do not. The dependent variable in column (2) is equal to 1 if we observe a response to the graduate survey and zero if we do not. The dependent variable in column (3) is equal to 1 if a response to the survey indicated that the respondent is working (full-time, part-time, or self-employed) and 0 if not. The dependent variable in column (4) is equal to 1 if we observe a response to the teaching evaluation survey. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects and parallel course fixed effects. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A6: Summary Statistics Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	All Students		Female Students		Male Students	
	Mean	Sd	Mean	Sd	Mean	Sd
First Earnings (in thousand € per Year)	41.78	38.81	38.73	36.56	43.56	39.99
Current Earnings (in thousand € per Year)	45.96	38.15	40.44	28.13	49.27	42.71
Working Hours	48.04	11.77	45.63	10.59	49.46	12.21
Working Part Time	0.04	0.20	0.05	0.22	0.04	0.19
Hourly Earnings	19.43	13.02	17.83	10.74	20.38	14.12
Job Satisfaction	8.11	1.44	8.03	1.45	8.15	1.43
Subjective Social Impact of Job	0.863	2.584	1.110	2.452	0.715	2.652

NOTE.— 'Sd' refers to the standard deviation of the respective variable.

Table A7: Labor Market Outcomes: Variables and Survey Questions

Variable	Graduate Survey Question	Answer Options
First Earnings per Year	Looking back at your first job after university, what was your entry salary? What was your yearly income before taxes? (including bonuses and holiday allowances)	0–1,000,000
Current Earnings per Year	What is your yearly income before taxes from your main job? (including bonuses and holiday allowances)	0–1,000,000
Working Hours	How many hours per week do you usually work in your main job? (including overtime)	0–120
Working Part Time	What describes your current situation best?	full-time employed; part-time employed; self-employed; studying; looking for a job; other (please specify)
Job Search Duration	After graduation, how long did it take you to find your first job?	“I already had a job lined up”, “1–2 months”, “3–4 months”, “4–6 months”, “6–12 months”, “more than 12 months”, “I have not (yet) started working after graduation.”
Hourly Earnings	*Calculated from current earnings and working hours*	
Job Satisfaction	How satisfied are you, all in all, with your current work?	10-point scale; 1 = "Totally unsatisfied" to 10 = "Totally satisfied"
Subjective Social Impact of Job	What do you think is the social impact of your current work?	11-point scale ranging from −5 = "Very negative social impact." over 0 = "Neutral, no social impact" to +5 = "Very positive social impact"

NOTE.— “Working Part Time” is an indicator variable that equals 1 if graduates answered “part time employed.” For job search duration we assigned the following values depending on respondents’ answers: “I already had a job lined up” (0 months), “1–2 months” (1.5 months), “3–4 months” (3.5 months), “4–6 months” (5 months), “6–12 months” (9 months), “more than 12 months” (12 months), “I have not (yet) started working after graduation” (missing).

Table A8: Labor Market Results with One Observation per Student

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Log First Earnings per Year	Log Current Earnings per Year	Earnings Growth	Log Hourly Earnings	Working Hours	Working Part-Time	Job Search Duration in Months	Job Satis-faction	Subjective Social Impact
Female * Proportion Female Peers	0.6029*	-1.0255*	-0.0968**	-0.9913*	-0.4534	0.1756*	-0.0723	0.4209	-0.4424
	(0.365)	(0.613)	(0.042)	(0.585)	(4.427)	(0.099)	(1.303)	(0.591)	(0.715)
Male * Proportion Female Peers	-0.0714	-0.5747	-0.0153	-0.6411	2.1249	0.0871	0.0153	0.2973	-1.8834***
	(0.270)	(0.433)	(0.032)	(0.423)	(4.380)	(0.065)	(0.887)	(0.546)	(0.609)
Female	-0.3871**	-0.1071	0.0250	-0.0478	-3.8603	-0.0266	0.2000	-0.2778	-0.3953
	(0.183)	(0.280)	(0.021)	(0.266)	(2.486)	(0.043)	(0.645)	(0.342)	(0.385)
Observations	862	835	808	832	867	883	858	877	878
R-squared	0.165	0.174	0.111	0.151	0.247	0.227	0.169	0.144	0.613
Mean Dependent Variable	10.4187	10.5374	.015	2.7259	49.0646	.0385	1.6684	8.122	.779
Mean Dep. Var. Women	10.3462	10.3583	.0103	2.6129	45.7938	.048	1.7174	8.0242	1.0813
Mean Dep. Var. Men	10.4612	10.6437	.0177	2.793	51.0258	.0327	1.639	8.1813	0.5952
p-value of Test for Gender Equality of Proportion Female Peers	.1078	0.5246	.1406	.6038	.6743	.4143	0.9539	0.8782	.1076

NOTE.— This table replicates Table 5 with observations at the student-level. Female * Proportion Female Peers shows a female dummy interacted with the average proportion of female peers a student had across all their compulsory courses. Similarly, Male * Proportion Female Peers shows a male dummy interacted with the average proportion of female peers a student had across all their compulsory courses. The dependent variables are the same as in Table 5. All columns are estimated with ordinary least squares regressions that include program-cohort fixed effects, female, Std. GPA at the end of the first year, Dutch and German, as well as a dummy for whether the survey data was collected by phone interviews (as opposed to email). Differences in the number of observations are due to students' not answering specific questions. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A9: Effects on Earnings: Main Results and Controlling for Potential Mechanisms

	(1)	(2)	(3)	(4)
Dependent Variable:	Current Log Earnings per Year	Current Log Earnings per Year	Earnings Growth	Earnings Growth
Female * Proportion Female Peers	-0.5224**	-0.3416	-0.0338***	-0.0320***
	(0.258)	(0.225)	(0.012)	(0.012)
Male * Proportion Female Peers	-0.0261	0.0425	0.0110	0.0172**
	(0.202)	(0.192)	(0.009)	(0.009)
Female	-0.1053	-0.0247	0.0081	0.0139*
	(0.128)	(0.122)	(0.008)	(0.008)
Observations	9,263	8,541	8,916	8,227
R-squared	0.104	0.201	0.038	0.061
Mean Dependent Variable	10.4993	10.5009	.0171	.0157
Mean Dep. Var. Women	10.3183	10.3126	.012	.0111
Mean Dep. Var. Men	10.6138	10.62	.0204	.0187
Endogenous Controls	No	Yes	No	Yes
p-value of Test for Gender Equality of Proportion Female Peers	.1369	.2185	.0038	.0026

NOTE.— The dependent variables in columns (1) and (2) are log current earnings. The dependent variables in columns (3) and (4) are earnings growth. Estimates in columns (1) and (3) are taken from columns (2) and (3) from Table 5. Estimates from columns (2) and (4) are from specifications that additionally control for major fixed effects, industry fixed effects, working part-time, working hours, and working hours squared. Industry fixed effects are dummies for the following industries based on the graduate survey: (1) Marketing or Advertising of Goods or Services, (2) Finance, Banking, Trading, or Insurance, (3) Accounting, (4) Supply Chain Management, Logistics and Transportation, (5) Telecommunications, Information Technology, Internet, (6) Human Resource Management, (7) Health or Pharma, (8) Management Consultancy, (9) Other. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A10: Heterogeneity by Early and Later Peer Exposure

Dependent Variable:	(1) Male-Dominated Major	(2) Female-Dominated Major	(3) Proportion Women in Major	(4) Any Mathematical Elective
Panel A: Early Courses (First Year)				
Female * Proportion Female Peers	-0.1224***	0.1227**	0.0353***	-0.1658***
	(0.041)	(0.053)	(0.014)	(0.053)
Male * Proportion Female Peers	0.0415	-0.1022***	-0.0243**	0.0301
	(0.041)	(0.038)	(0.011)	(0.041)
Female	-0.1182***	0.1008***	0.0404***	-0.0428
	(0.026)	(0.027)	(0.008)	(0.027)
Observations	15,654	15,654	15,654	15,533
R-squared	0.092	0.223	0.161	0.231
Mean Dependent Variable	.206	.299	.3866	0.6345
Mean Dependent Variable Female Students	.1046	.4376	.429	.5332
Mean Dependent Variable Male Students	.2713	.2099	.3593	0.6968
p-values for Test of Gender Equality of Proportion Female Peers	.0069	.001	.0014	.0041
Panel B: Late Courses (Second Year)				
Female * Proportion Female Peers	-0.0267	0.0538	0.0178	-0.0616
	(0.029)	(0.050)	(0.013)	(0.048)
Male * Proportion Female Peers	0.0828**	-0.0692*	-0.0302***	0.0500
	(0.038)	(0.037)	(0.011)	(0.039)
Female	-0.1585***	0.1860***	0.0572***	-0.0978***
	(0.023)	(0.030)	(0.008)	(0.029)
Observations	13,519	13,519	13,519	14,966
R-squared	0.167	0.241	0.164	0.197
Mean Dependent Variable	.1932	.3737	.4102	.5603
Mean Dependent Variable Female Students	.0904	.5259	.455	.4608
Mean Dependent Variable Male Students	.2662	.2657	.3783	.6278
p-values for Test of Gender Equality of Proportion Female Peers	.0255	.0496	.006	.0651

NOTE.— The dependent variables in columns (1) and (2) are dummy variables that are equal to 1 if students choose a male-dominated major and female-dominated major, respectively. The dependent variable in Column (3) is the proportion of women in the chosen major. The dependent variable in column (4) is a dummy variable is equal to 1 if the student chose at least one mathematical course. Overall, we observe the course choices for 3,025 students and the major choices for 3,563 students. All columns are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course fixed effects, female, Std. GPA, Dutch and German. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A11: Summary Statistics Student Course Evaluation Outcomes

		(1)	(2)	(3)	(4)	(5)	(6)
		All Students		Female Students		Male Students	
Outcome	Scale	Mean	Sd	Mean	Sd	Mean	Sd
Course grade	1 to 10 scale, 10 = highest grade	6.583	1.715	6.660	1.669	6.530	1.743
Please give an overall grade for the quality of this course.	1 to 10 scale, 10 = very good	7.070	1.843	7.011	1.764	7.118	1.903
Working in tutorial groups with my fellow students helped me to better understand the subject matter of this course.	1 to 5 scale, 5 = totally agree	3.966	0.941	3.985	0.965	3.951	0.921
My tutorial group has functioned well.	1 to 5 scale, 5 = totally agree	3.918	0.961	3.898	0.984	3.933	0.942

NOTE.— ”Sd” refers to the standard deviation of the respective variable.

Table A12: Main Results for Mechanism Sample With and Without Mechanism Controls

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Male-Dominated Major	Female-Dominated Major	Proportion Women in Major	Any Mathematical Elective	Fraction Mathematical Electives
Panel A: Main Results for Mechanisms Sample					
Female * Proportion Female Peers	-0.0605	0.0200	0.0151	-0.1416**	-0.0501*
	(0.044)	(0.060)	(0.016)	(0.065)	(0.030)
Male * Proportion Female Peers	0.1203**	-0.1342***	-0.0493***	0.0664	0.0220
	(0.050)	(0.050)	(0.014)	(0.052)	(0.030)
Female	-0.0868***	0.1456***	0.0391***	-0.0527	-0.0210
	(0.030)	(0.033)	(0.009)	(0.034)	(0.020)
Observations	9,146	9,146	9,146	8,344	8,344
R-squared	0.128	0.267	0.185	0.261	0.331
p-values of Test for Gender Equality of Proportion Female Peers	.0101	.0527	.0035	.0136	.102
Panel B: Main Results Controlling for Mechanisms					
Female * Proportion Female Peers	-0.0598	0.0165	0.0139	-0.1384**	-0.0495*
	(0.044)	(0.060)	(0.016)	(0.066)	(0.030)
Male * Proportion Female Peers	0.1206**	-0.1357***	-0.0497***	0.0672	0.0220
	(0.050)	(0.050)	(0.014)	(0.052)	(0.030)
Female	-0.0859***	0.1458***	0.0392***	-0.0519	-0.0210
	(0.030)	(0.033)	(0.009)	(0.034)	(0.020)
Observations	9,146	9,146	9,146	8,344	8,344
R-squared	0.129	0.269	0.187	0.262	0.332
p-values of Test for Gender Equality of Proportion Female Peers	.0102	.0554	.0039	.0149	.1042

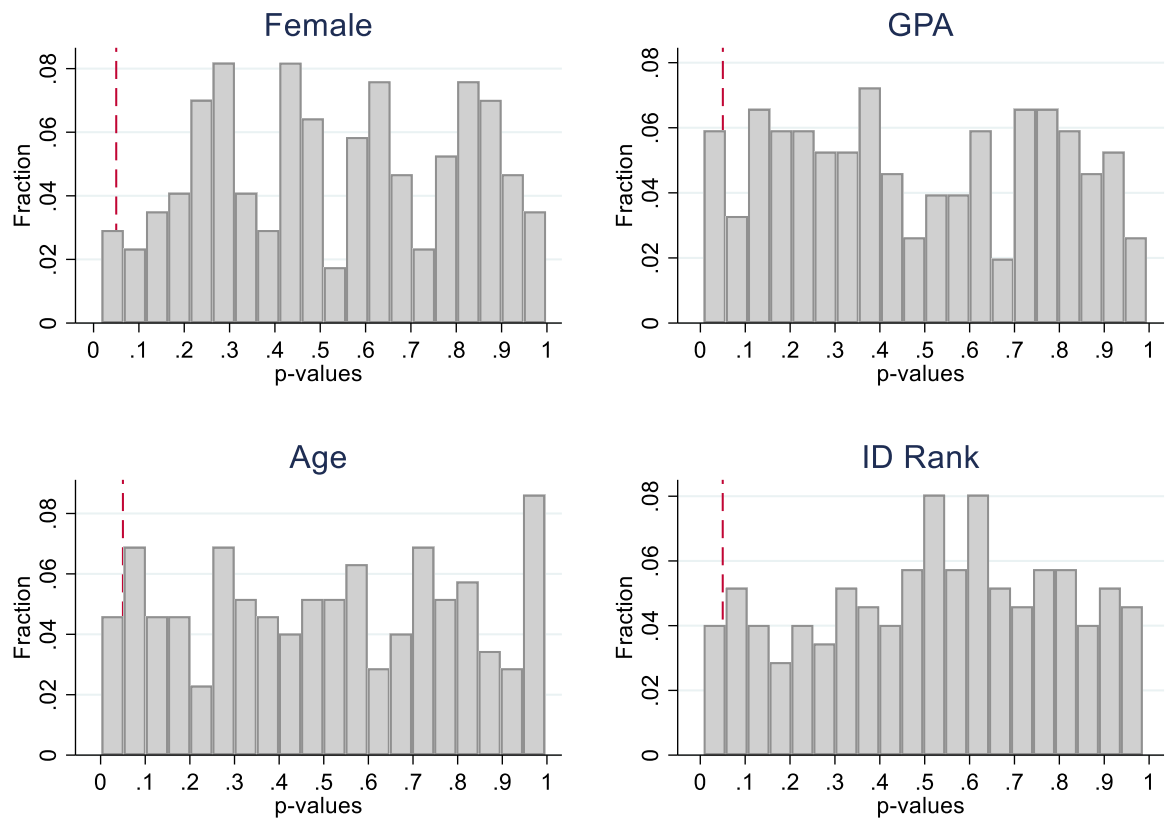
NOTE.— Panel A replicates the results in Table 4 for the sample of students for which we observe all mechanisms. Panel B uses the same sample as Panel B, but additionally includes the following controls: student grades, grades*math course, overall evaluation, overall evaluation*math course, group functioning, group functioning * math course. All specifications are estimated with ordinary least squares regressions that include course-times-year fixed effects, parallel course fixed effects, female, Std. GPA, Dutch and German. Robust standard errors using two-way clustering at the student and section levels are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A13: Proportion of Female Peers under Different Assignments

	(1) Single Sex	(2) Unequal Proportions	(3) Equal Proportions
Section A	4 men, 0 women	1 man, 3 women	2 men, 2 women
Section B	0 men, 4 women	3 men, 1 woman	2 men, 2 women
Average proportion of female peers for men	0%	50%	66%
Average proportion of female peers for women	100%	50%	33%

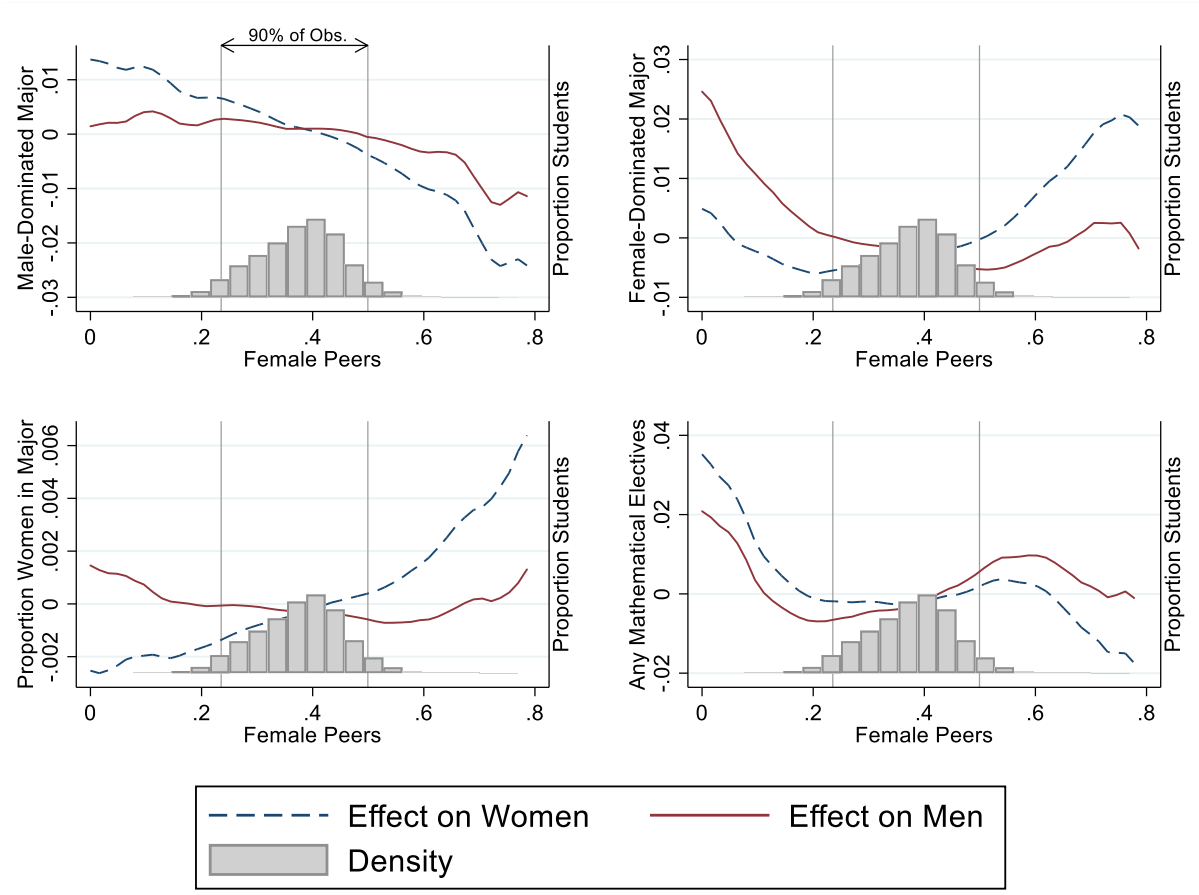
NOTE.— This table summarizes all possible assignment in our numerical example. Any other assignments than the ones shown in Table A13 would be equivalent of the unequal proportions assignment or single-sex section with relabelling of Sections A and B. For example, having four women in section A and four men in Section B would be equivalent to the single-sex assignment in Scenario 1.

Figure A1: Alternative Randomization Check – Distribution of *p*-values



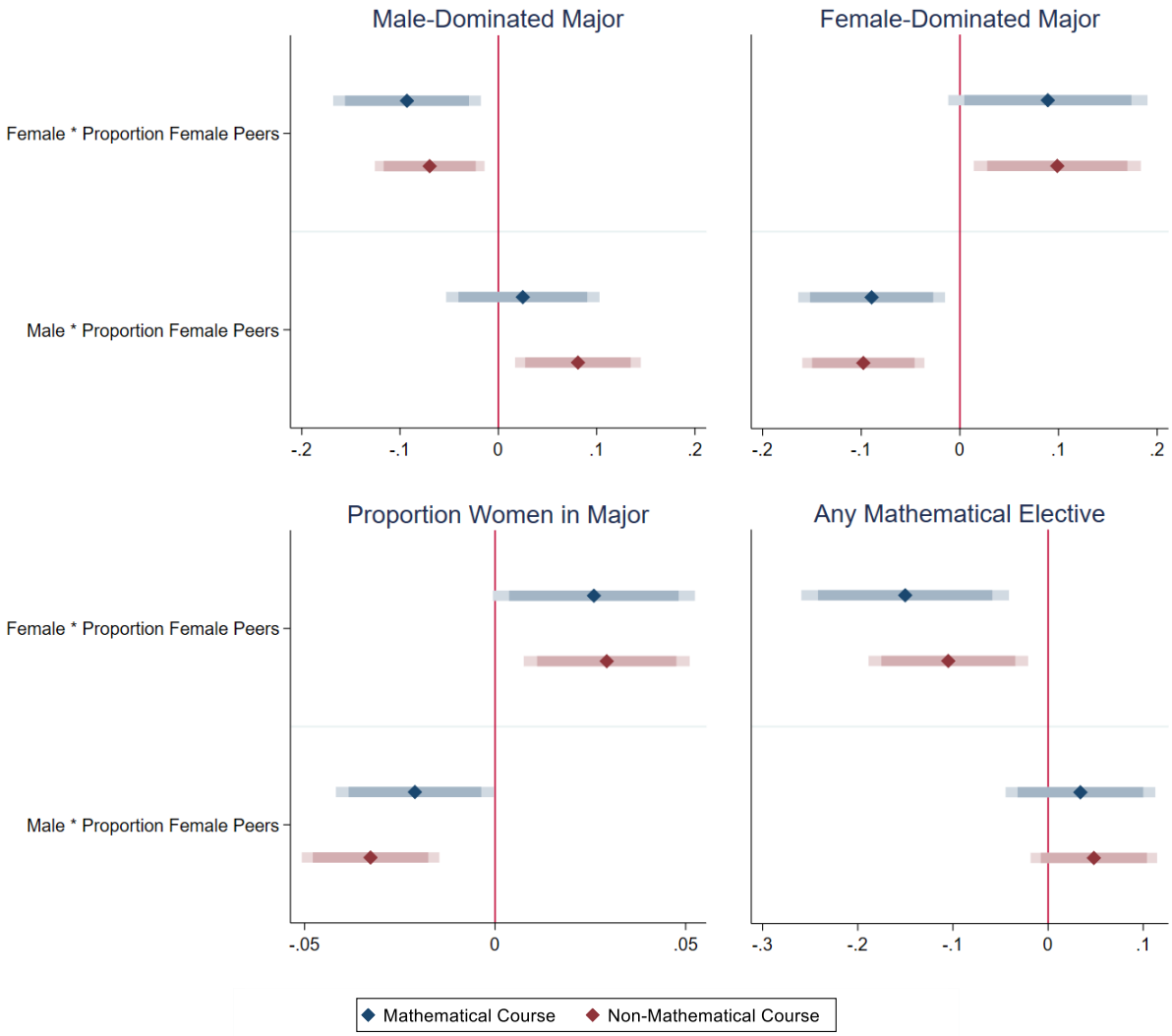
NOTE.—These are histograms with *p*-values from all the regressions reported in Table A13. The vertical line in each histogram shows the 5 percent significance level.

Figure A2: Functional Form of The Effect of Peer Gender on Student Choices (With Student-Level Observations)



NOTE.—This figure shows local polynomial plots of the relationships between residualized outcomes measuring students' specialization choices (on the Y-axes) and the average proportion of female section peers a student had in all their compulsory courses (on the X-axes). The grey histograms show the distribution of the average proportion of female peers to illustrate the underlying support in the data. The vertical lines show the 5th and 95th percentile of female peers. All outcomes are residualized from using students' GPA at the end of their first year, dummies for student nationality and gender, as well as cohort-program fixed effects.

Figure A3: Main Results for Mathematical vs. Non-Mathematical Courses



NOTE.—This figure shows our main results estimated separately for mathematical courses and non-mathematical compulsory courses. All specifications are estimated with ordinary least squares regressions, which include course fixed effects, parallel course fixed effects, student gender, student nationality, and GPA. Horizontal bars show 90 and 95 percent confidence intervals, which are based on standard errors clustered at the student and section levels.

A3 The Blau Diversity Index

We measure diversity in major choice among students in a section using the Blau diversity index (Blau 1977). [17] This index which can be written as follows:

$$B_s = (1 - \sum_{j=1}^{N} m_{js}^2), \tag{A1}$$

where m_{js} represents the proportion of students in section s that choose major j, and N is the total number of different majors chosen in that section. B_s is equal to 0 if all students in a given section choose the same major, then increases as heterogeneity in major choice grows, and is largest and closest to 1 when all majors attract an equal proportion of students. Intuitively, B_s can be interpreted as the probability that two students drawn at random (with replacement) from the same section choose the same major. The normalized Blau index shows the Blau index corrected for the number of choice alternatives and can therefore reach any number between 0 and 1.

[17] The Blau diversity index is equal to the inverse of the Herfindahl-Hirschman Index (Hirschman 1945; Herfindahl 1950).