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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.

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Keywords: peer effects • major choice • gender composition

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's 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 16 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% 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% 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.

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 (Lavy and Schlosser 2011, Oosterbeek and Van Ewijk 2014, Hill 2015, Brenøe and Zölitz 2020, Hill 2017, Goulas et al. 2018, Park 2018, Anelli and Peri 2019, 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 with 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.

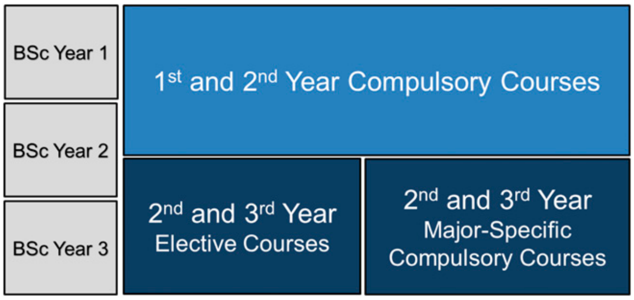
We make three contributions to the literature. First, we add to the peer effects literature by estimating the effect of peer gender on major choice in a business school—an important environment previously not studied. Second, we provide evidence on the longer-run labor market consequences of university 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% 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 16 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.

Figure 1. (Color online) 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.

Students are free to choose any major, and there are no grade requirements for any majors.

Each course comprises multiple sections of up to 16 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 2010–2011 academic year, the business school additionally stratified section assignments by student nationality to encourage a mixing of Dutch (25% of estimation sample) and German students (58%).[2] After the initial assignment, schedulers manually switch students between sections to resolve any scheduling conflicts, which occur for about 5% of students.[3] In our analysis, we address potential nonrandom 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 Online Appendix A.1 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 2009–2010 and 2014–2015. 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).

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 peer 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.

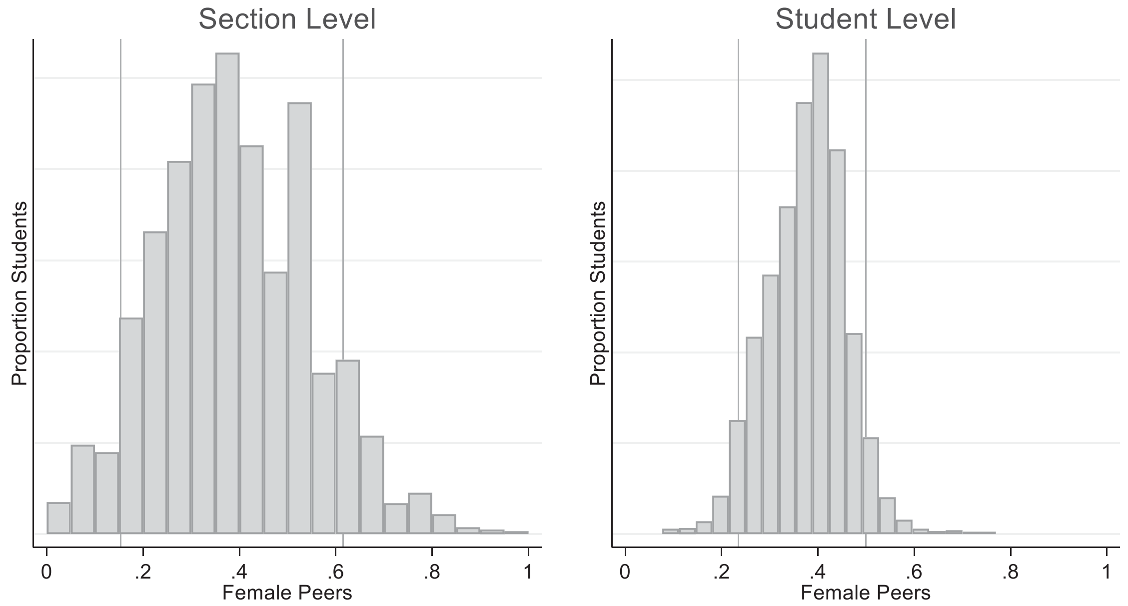
The key identifying assumption for estimating causal effects of peer gender is that students within compulsory

Table 1. Descriptive Statistics

Panel A	(1)	(2)	(3)	(4)	(5)
Student level characteristics	*N*	Mean	SD	Min	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	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Section level characteristics	*N*	Mean	SD	Min	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

Notes. This table is based on our estimation sample. SD refers to the standard deviation of the respective variable. Min, minimum; Max, maximum.

Figure 2. Proportion of Women in Sections



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

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]

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% in finance to 60% 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

Table 2. Test for Random Assignment

	(1)	(2)	(3)	(4)
Dependent variable	Proportion female peers	Proportion female peers	Proportion female peers	Proportion female peers
Female	−0.0026	−0.0027		
	(0.003)	(0.003)		
Standardized GPA			0.0004	0.0004
			(0.001)	(0.001)
Observations	29,211	29,211	29,211	29,211
R^2	0.152	0.161	0.151	0.160
Course-Year FE	Yes	Yes	Yes	Yes
Parallel-Course-Year FE	No	Yes	No	Yes

Notes. The dependent variable in all columns is the proportion of female section peers. Following the Guryan et al. (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. FE, fixed effects.

Table 3. Gender-Based Sorting into Majors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				First-year GPA		Mean annual earnings in thousand €	
Major	Percent female	Major classification	Percent compulsory mathematical courses in major	(Female)	(Male)	(Female)	(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 management	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

Notes. We define finance and IT management as male-dominated and organization and marketing as female-dominated majors. Data on annual earnings are taken from the 2016 graduate survey. $N = 1{,}713$.

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 ($\rho = -0.80$) 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.

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:

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

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] $\boldsymbol{X}_{\boldsymbol{ict}}$ 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 nonrandom assignment due to scheduling conflicts throughout. We control for students' own gender, and $\boldsymbol{X}_{\boldsymbol{ict}}$ 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 management by 0.8 percentage points (8%) and increase her probability of majoring in marketing or organization by 1 percentage point (2%). 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

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

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Male-dominated major	Female-dominated major	Proportion women in major	Any mathematical elective	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^2	0.125	0.235	0.167	0.216	0.248
Mean dependent variable	0.1999	0.3336	0.3975	0.5977	0.2271
Mean dependent variable women	0.0977	0.4797	0.4415	0.4963	0.1885
Mean dependent variable men	0.2687	0.2352	0.3679	0.6633	0.2521
p-values of test for gender equality of proportion female peers	0.0008	0.0001	<0.0001	0.0006	0.0450

Notes. 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, Standardized GPA, Dutch, and German. Robust standard errors using two-way clustering at the student and section levels are in parentheses.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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 A.3 in the online 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 A.4 in the online 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 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 A.5 in the online 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.

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%). We see no effect on men's choice of mathematical courses.

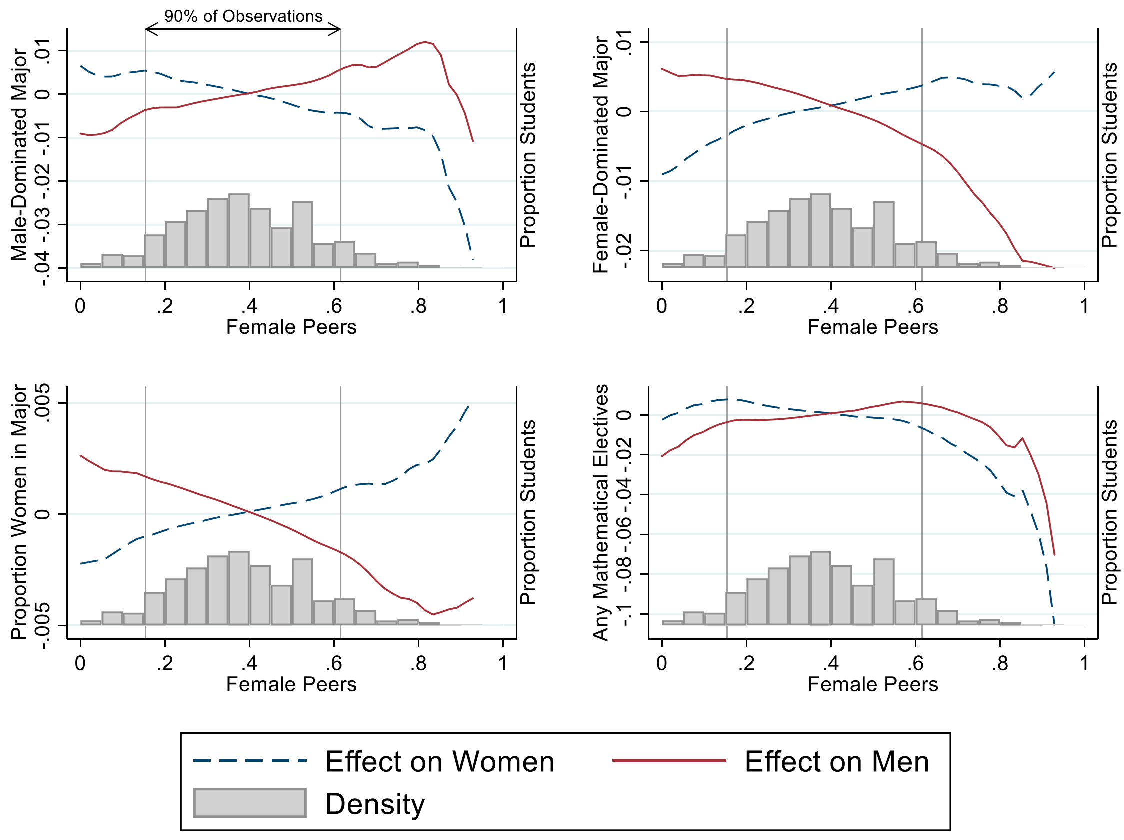
Taken together, our results show that an increase in the proportion of female peers leads to an increase in gender segregation in specialization choices. Having more female peers causes women and men to choose courses and majors that are more popular with their own gender. Our results are largely consistent with a study by Hill (2017), who finds suggestive evidence that women in U.S. 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 (2020) 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% 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.

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% and 62% female peers. These sections make up 90% of our observations. Outside of this range, the results are too imprecisely estimated to draw any

Figure 3. (Color online) Functional Form of the Effect of Peer Gender on Student Choices



Notes. 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).

conclusions about the functional form. Figure A.2 in the online appendix shows the relationship between the average proportion of female peers a student 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.

5. Mechanisms

5.1 Peer Effects on Early and Late Courses

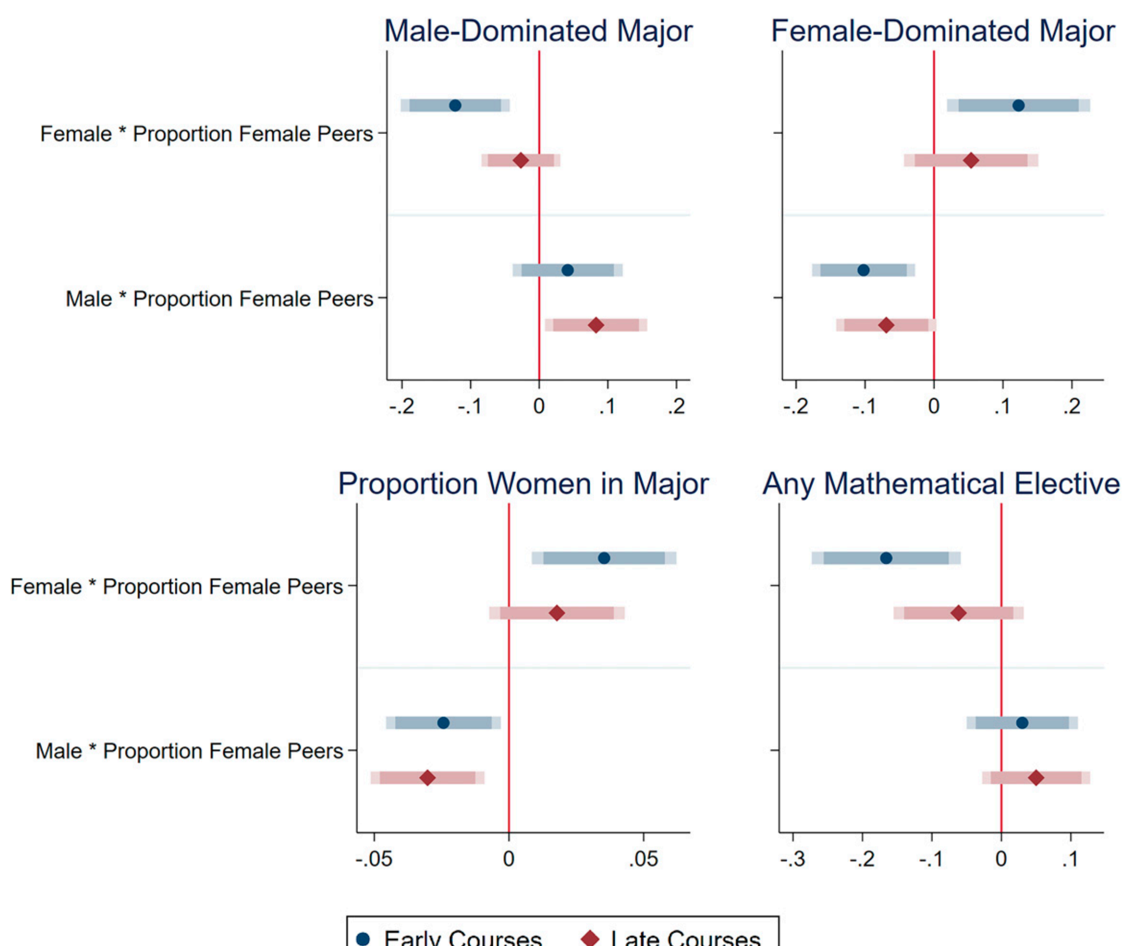
Our results might be driven by the effect of the peer composition on students' friendships at the beginning their studies. These social networks might affect students' choices through interactions outside the classroom, for example, in private study groups, in fraternities, or at parties. Peer groups formed early in students' studies have been shown to be important for students' dropout decisions, confidence, academic performance, and major choices (Fischer 2017, Thiemann 2018). 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 4 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.

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

Figure 4. (Color online) Main Results for Early versus Late Courses



Notes. This figure shows our main results estimated in separate samples for first-year courses (early courses) and second-year courses (late courses). Table A.6 in the online appendix shows the underlying regressions that have the same control as our main results regressions shown in Table 4. Horizontal bars show 90% and 95% confidence intervals that are based on standard errors clustered at the student and section levels.

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 Online Appendix A.3 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:

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

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, $\tilde{\boldsymbol{X}}_{\boldsymbol{c}}$ 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 5 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.

5.3 Peer Effects on Grades and Course Evaluations

Exposure to female peers can positively affect students' performance and the classroom atmosphere (e.g., Hoxby 2000; Whitmore 2005; Figlio 2007; Lavy and Schlosser 2011; Oosterbeek and Van Ewijk 2014; Hill 2015, 2017). 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 nonmathematical 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 A.7 in the online 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. Although 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,

Table 5. The Impact of Gender Composition on Diversity in Major Choice

	(1)	(2)	(3)
Dependent variable	Normalized Blau diversity index, all students	Normalized Blau diversity index, women	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^2	0.550	0.157	0.441
Mean dependent variable	0.921	0.930	0.906

Notes. 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.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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 6 show how the proportion of female peers affects students' grades. Although 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 nonmathematical courses, whereas the opposite holds for men. An increase in female peers by 10 percentage points increases women's grades in nonmathematical courses by 1.2% 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% of a standard deviation in mathematical courses but does not affect their grades in nonmathematical courses.

To estimate the effect of peer gender on course evaluations, we use data on students' satisfaction with the course and their section peer group.[11] 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 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 A.7 in the online appendix shows the summary statistics for the course evaluations.

Columns (3) to (6) of Table 6 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 nonmathematical courses: having 10 percentage points more female peers *reduces* women's evaluation of mathematical courses by 2.5% of a standard deviation and *increases* their evaluation of nonmathematical courses by 2.4% 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 nonmathematical courses.[12]

To explore how much of our effects can be explained by these mechanisms, we perform a mediation analysis broadly following Gelbach (2016), which consists 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 these variables with a dummy for mathematical courses to allow their effects to differ by course type.

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 evaluation of the group functioning is unrelated to the evaluation of the course overall. Despite these limitations, however, we believe that this mediation analysis is helpful for gauging the importance of grades and course evaluations for explaining the effects on educational choices.

Figure 5 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%. 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.

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 nonmathematical compared with 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

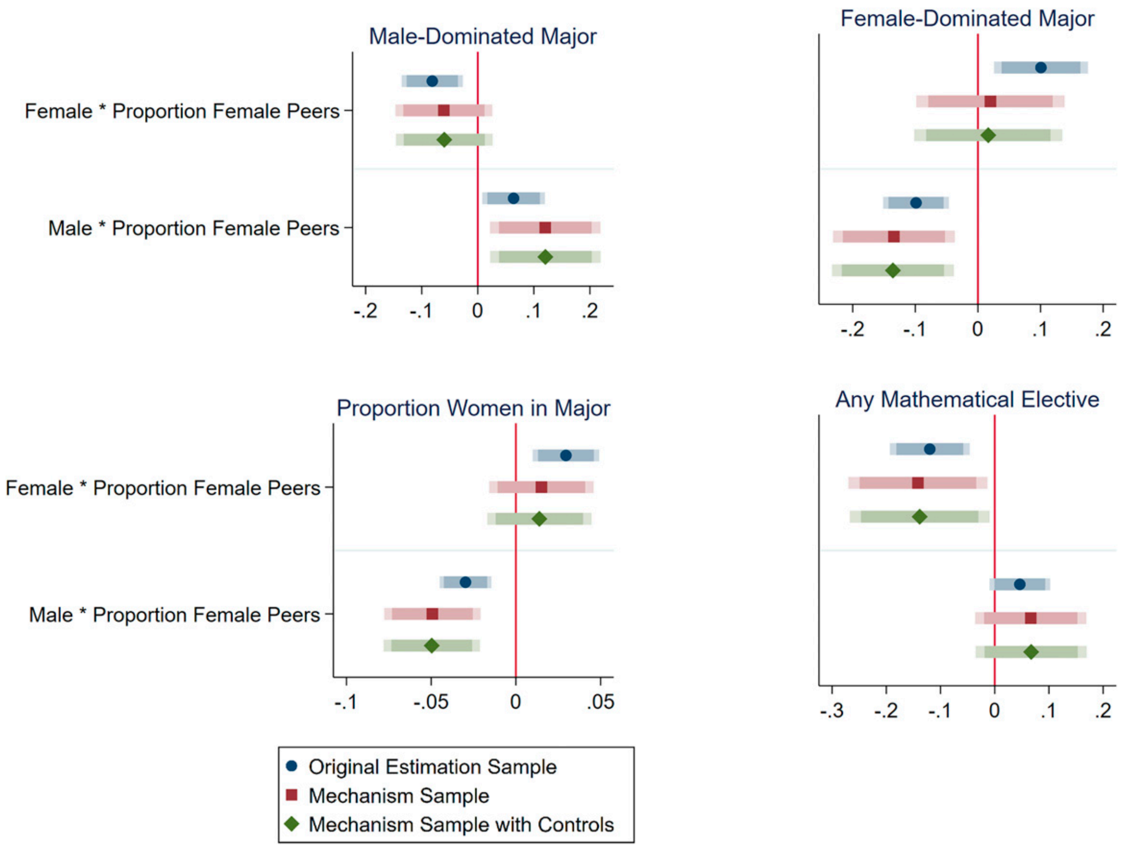
Table 6. The Effect of Gender Composition on Grades, Overall Evaluation, and Group Functioning

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Std. Grade	Std. Grade	Std. Overall Evaluation	Std. Overall Evaluation	Std. Group Functioning	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^2	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	0.0657	0.0657	−0.0327	−0.0327	−0.0003	−0.0003
Mean dependent variable men	−0.0432	−0.0432	0.0263	0.0263	0.0003	0.0003
p-values: test of gender equality for						
Proportion female peers	0.4508	0.0265	0.7929	0.5466	0.0793	0.0338
Proportion Female Peers × Math Course		<0.0001		<0.0001		0.0335

Notes. The dependent variable in columns (1) and (2) is standardized (Std.) 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.

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

Figure 5. (Color online) Main Results after Controlling for Grades and Course Evaluations



Notes. This figure shows our main estimates (see Table 4), our main estimates with a sample for which we observe all candidate mechanisms (see Table A.8), as well as estimates with this mechanism sample that additionally control for all candidate mechanisms (see Table A.8). All three specifications include course fixed effects, parallel course fixed effects, student gender, student nationality, and GPA. Horizontal bars show 90% and 95% confidence intervals, which are based on standard errors clustered at the student and section levels.

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.[13]

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.

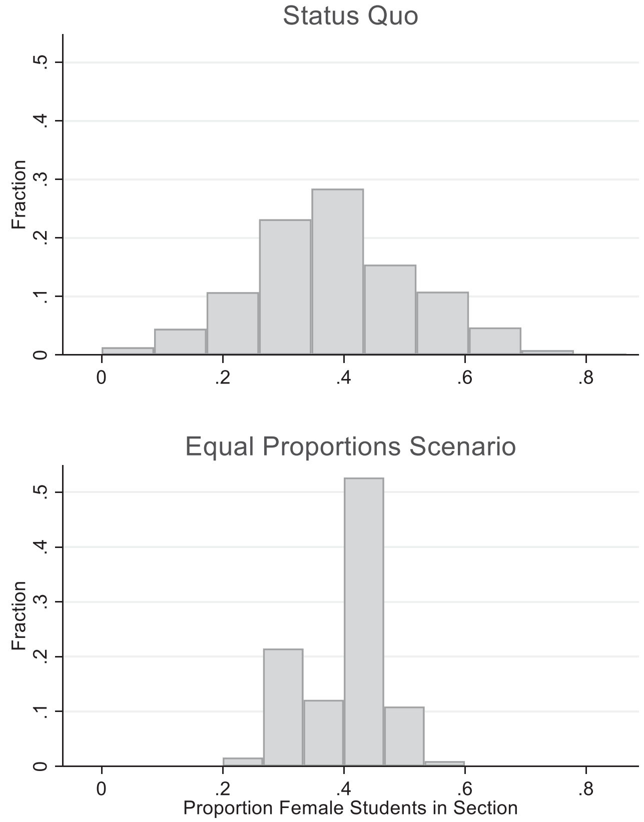
The two most extreme assignment polices would be single-sex sections and sections with equal proportions of women. Assuming that our effects are linear for all values of female peers, single-sex sections would lead to the lowest number of women and men choosing male-dominated majors. Under this assignment policy, women would be with 100% female peers; under this scenario, they would be least likely to choose a male-dominated major. Men would be with 0% female peers; under this scenario, they too would be least likely to 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 with 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 Online Appendix A.2 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. Although it is not possible to always equalize the proportion of female students, this assignment greatly reduces variation in female peers per section (see Figure 6). 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.

Figure 6. Gender Composition of Sections in Status Quo and 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 proportion 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% and 100%.

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.

Table 7 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% and the proportion of men choosing these majors by 12%. Because the effects for women and men go in the same direction, this policy would be less successful in increasing the proportion of women in male-dominated majors. In the status quo, women make up 19% of students in male-dominated majors. In the equal proportion scenario, this share increases to 21%. At the same time, the equal proportion assignment would reduce the number of women and men choosing female-dominated majors by 8% and 21% and increase the proportion of women in these majors from 56% to 60%.

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. Although 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. Although 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 coworkers are less satisfied with their jobs.

7. 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.[14] This survey includes several questions that allow us to obtain a detailed picture of graduates' occupational situation one to five years after graduation.[15]

Table 8 shows the estimated effect of peer gender on several key labor market outcomes.[16] University peers do not significantly affect men's labor market outcomes. For women, however, we see some significant and interesting effects. Although 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). This pattern holds in our sample as well. Women earn 4% less than men in their first job after graduation and 12% less than men in their current job.

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. Although 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. In particular, we estimate the effects of peer gender on earnings and earnings growth in specifications that

Table 7. Gender Composition in the Status Quo and the Equal Proportions Scenario

	(1)	(2)	(3)	(4)
	Status quo	Equal proportions scenario	Difference between equal proportions scenario and status quo	% 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%

Notes. 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.

Table 8. The Impact of Gender Composition on Labor Market Outcomes

	(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 satisfaction	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^2	0.104	0.104	0.038	0.071	0.165	0.127	0.046	0.043	0.596
Mean dependent variable	10.360	10.499	0.017	2.705	48.417	0.051	1.556	8.141	0.709
Mean dependent variable women	10.287	10.318	0.012	2.573	45.742	0.055	1.660	8.065	1.017
Mean dependent variable men	10.406	10.614	0.0204	2.788	50.144	0.0482	1.489	8.190	0.509
p-value of test for gender equality of proportion female peers	0.9668	0.1470	0.0039	0.2276	0.0673	0.3978	0.1950	0.4155	0.0825

Notes. 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, standardized 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.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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.

Figure 7 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% and becomes insignificant. The estimated effect of peer gender on women's earnings growth reduces by 6% and remains statistically significant at the 1% level. Women's major and job choices thus appear to only play a minor role in explaining the effect of peer gender on earnings.

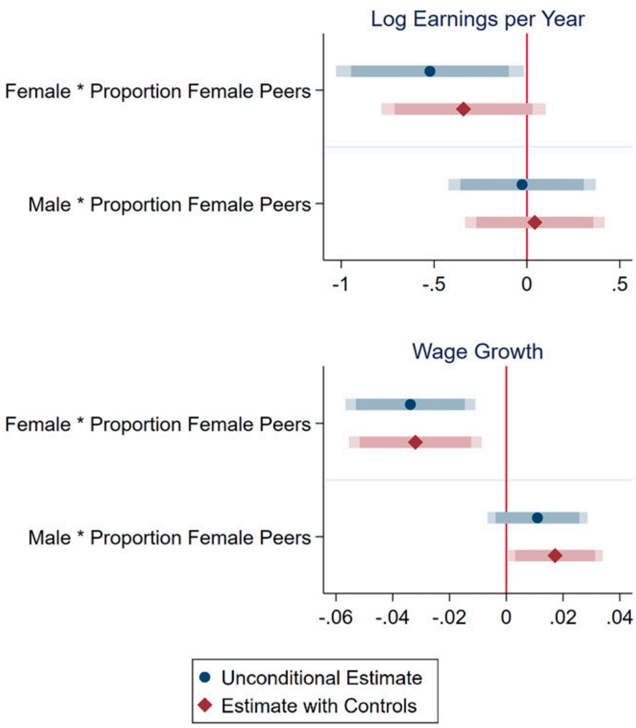
An alternative explanation is that having more female peers affects earnings through ways that are not captured by our included controls. For example, women who had more female peers might have children earlier. Such effects would be consistent with findings of Brenøe and Zölitz (2020), who show that 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.

8. 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.

Figure 7. (Color online) Effects on Earnings Controlling for Potential Mechanisms



Notes. 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 8. 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 A.12 in the online appendix shows the underlying regressions. Horizontal bars show 90% and 95% confidence intervals that are based on standard errors clustered at the student and section levels.

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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Endnotes

[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."

[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 2012–2013 academic year, about 10% 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 2013–2014 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 nonavailability 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 3% of all sessions are scheduled for this time slot. We have excluded evening sessions from our estimation sample.

[4] For an alternative and more flexible randomization check, see Table A.1 and Figure A.1 in the online appendix. In this randomization check, we regress pretreatment 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% of the courses as "mathematical."

[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 nonrandom. When peer group assignment is random, as is the case in our setting, classical measurement error will attenuate peer effects estimates, that is, 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.

[8] Table A.2 in the online 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.

[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.

[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.

[11] Evaluation survey response is unrelated to the proportion of female peers (see Table A.5 in the online appendix).

[12] We also explore whether the effect of having female peers on students' specialization choices differs between mathematical and nonmathematical courses. In Figure A.3 in the online 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 nonmathematical courses.

[13] 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.

[14] We designed and conducted the survey in cooperation with the business school's alumni office, which provided us with contact details for 75% 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% responded to either the email or phone survey, which means that we have labor market outcome information for 1,618 students, about 30% of our estimation sample. Table A.5 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).

[15] Table A.9 in the online appendix provides summary statistics for the labor market variables. Table A.10 in the online appendix shows the original survey questions, the survey answer options, and the definition of our dependent variables.

[16] Table A.11 in the online appendix shows estimations from specifications that use observations at the student level. These specifications lead to qualitatively similar results.

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