The Effect of Higher-Achieving Peers on Major Choices and Labor Market Outcomes*

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This paper investigates how exposure to higher-achieving male and female peers in university affects students' major choices and labor market outcomes. For identification of causal effects, we exploit the random assignment of students to university sections in first-year compulsory courses. We present two main results. First, studying with higher-achieving peers has no statistically significant or economically meaningful effects on educational choices. Second, we find suggestive evidence that women who have been exposed to higher achieving male peers end up in jobs in which they are more satisfied.

Keywords: gender, major choice, peer effects
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1. Introduction

Women remain underrepresented in math-intensive subjects and majors (OECD, 2017). The desire to understand the origins of these gender differences has led to an interest in factors that influence women's and men's educational choices.

One factor that may influence students' educational choices is whether they study with higher-achieving peers. A large body of literature has shown that higher-achieving peers positively affect students' grades and the classroom atmosphere (Sacerdote, 2011). The effect of higher-achieving peers on educational choices, however, has received substantially less attention. Exposure to higher-achieving peers may lead to better grades, which may motivate students to choose more-challenging majors. Alternatively, students may be discouraged from entering challenging majors if they study with peers who seem to know everything. These effects may also be gender specific. For example, higher-achieving male peers may affect preferences for majors by creating a classroom atmosphere that men appreciate and women do not.

In this paper, we study how exposure to higher-achieving male and female peers in university affects students' course choices, major choices, and labor market outcomes. We use data from a Dutch business school in which students take several compulsory courses in their first year of study and then specialize through elective courses and majors. Within compulsory courses, students are randomly assigned up to 15 section peers with whom they spend a large share of their university contact hours. This setting allows us to test how random exposure to peers with higher achievement, as measured by their past GPAs, affects students' educational choices. We look at the effect of peers on mathematical majors, which attract higher-achieving students and are associated with higher earnings in the labor market. Additionally, we conduct a graduate survey that allows us to document the labor market consequences of high-achieving peers one to five years after graduation. Data from this survey provide a detailed picture of how peers affect different aspects of graduates' careers, including earnings and job satisfaction.

Our results show no significant effects of peer achievement on students' probability of choosing a mathematical elective course or major. The point estimates are small and precisely estimated. For example, we predict that being assigned to one course with male peers who have one standard deviation higher GPAs decreases women's probability of choosing a mathematical major by 0.82 percentage points. The corresponding 95-percent confidence interval allows us to rule out effects smaller than -2.0 and larger than +.04 percentage points. When looking at the effect on labor market outcomes, we find no significant effects on earnings, working hours, or the probability of being employed. These estimates, however, are less precisely estimated. We do, however, find suggestive evidence that women who were assigned to higher achieving male peers are more satisfied in their job.

Our paper complements four previous studies which have investigated the effect of higher-achieving peers on educational choices and labor market outcomes. Most related to our study, Fischer et al. (2020) investigate the effect of being randomly assigned to higher achieving peers at Copenhagen Business School. They find that studying with higher achieving peers reduces women's earnings by 4 percent. This effect is driven by being assigned to higher-achieving male peers and becomes stronger over time. Cools et al. (2019) show that higher-achieving male peers—as proxied by the education of their parents—reduce female students' math and science grades and their probability of completing a bachelor's degree. Similarly, Mouganie and Wang (2020) show that higher-achieving male peers reduce female students' likelihood of choosing a science, technology, engineering, or math (STEM) major. Fischer (2017) investigates how peer achievement affects educational choices without distinguishing peer achievement by gender. She exploits an as-good-as-random assignment of students to classes with an average of 330 students in an introductory chemistry course at the University of California, Santa Barbara. Her results show that women who are exposed to higher achieving peers are less likely to graduate with a STEM degree. Taken together, these studies suggest that higher achieving peers affect educational choices, with particularly negative impacts for women assigned to higher achieving male peers.

Our study contributes to the literature by suggesting that both of these conclusions are not universal: Peers do not always have measurable effects on educational choices, and, at least in our setting, women get some long-term benefits from being assigned to higher-achieving male peers. More generally, we contribute to the scientific discourse by answering the same research question with a credible identification strategy in a different context. This endeavor, together with a commitment to documenting null results, is a crucial part of the scientific discourse, allowing researchers and policymakers to assess the robustness and generalizability of effects.

This paper also relates to our previous work in which, using data from the same environment, we investigate how students' educational choices and labor market outcomes are affected by the proportion of female peers (Zölitz & Feld, forthcoming). In this previous study, we show that women who are randomly assigned to a higher proportion of female peers are more likely to choose female-dominated majors like marketing and less likely to choose a male-dominated major like finance. Men, on the other hand, become more likely to choose a male-dominated major after being assigned to a higher proportion of female peers. After graduation, we see no effect on men's labor market outcomes, but women who had a higher proportion of female peers see slower wage growth. While our previous paper shows that the quantity of female peers matters, the current paper tests whether the quality of male and female peers – as measured by their GPA – matters as well.

2. Institutional Environment and Summary Statistics

2.1 Institutional Environment

We study the effect of peer achievement on course choice, major choice, and labor market outcomes using data from a Dutch business school for the academic years 2009/10 through 2014/15. We limit our analysis to two bachelor programs: Business and Business Economics. Both programs take three years to complete. Each academic year consists of four eight-week teaching periods during which students typically take two courses simultaneously. In the first year of the bachelor programs we focus on, students take eight compulsory courses in a fixed sequence and then choose several elective courses and one major in their second and third years.

Table 1 shows the list of first year compulsory courses for each program. For our analysis, we distinguish between mathematical courses and non-mathematical courses. We define a course as mathematical if its description contains one of the following terms: math, mathematics, mathematical, statistics, statistical, or theory-focused. Following this definition, the students in the Business program take four mathematical compulsory courses (Quantitative Methods I and II, Economics and Business, and Finance) and students in the Business Economics program take four mathematical compulsory courses (Quantitative Methods I and II, Microeconomics, and Finance).

Each course consists of multiple sections that have an average of 14 and a maximum of 16 students. The section composition is different for each course students take. Sections are the peer group we focus on in this paper. Over an entire course, students typically meet their section peers for twelve two-hour tutorial sessions. Besides tutorials, a typical course consists of three to seven two-hour lectures that all students attend.

Table 1: Compulsory Courses in the First Year

Teaching period	Study Program: Business	Study Program: Business Economics
1	Management of Organisations and Marketing / *Quantitative Methods I*	Management of Organisations and Marketing / *Quantitative Methods I*
2	Accounting and Financial Reporting / *Economics and Business*	Accounting and Financial Reporting / *Microeconomics*
3	Strategy / *Quantitative Methods II*	Macroeconomics / *Quantitative Methods II*
4	*Finance* / Fundamentals of Supply Chain Management	*Finance* / International Economic Relations

NOTE — Courses in *italic* are mathematical courses based on the definition provided in the main text.

During tutorial sessions, students typically discuss the course material and solutions to exercises with their section peers. The teaching style of this business school emphasizes classroom discussion, and students typically prepare the course material and solve exercises before the tutorial sessions. The main role of the tutorial instructor is to guide the discussion. Within a course, all sections use the same course material and follow the same course plan. Business school guidelines require students to attend the tutorial sessions and forbid them from switching between tutorial sections.

Panel A of Table 2 shows descriptive statistics for the sample we study. We observe 2,903 students, about 38 percent of whom are female and whose average age is 19. 57 percent of students are German and 24 percent are Dutch. The business school's language of instruction is English.

A key feature of our environment is that the business school's scheduling department randomly assigns students to sections within each course. This assignment is done with a scheduling software. Beginning with the 2010/11 academic year, the scheduling department additionally stratified section assignment by student nationality. After the initial assignment, the schedulers manually switch students between sections to resolve any scheduling conflicts. For first year courses, scheduling conflicts are very rare because all students take the same set of compulsory courses. There are three main reasons for scheduling conflicts. First, a student takes another course at the same time. This may happen for students who are repeating their first-year courses or students who take voluntary elective courses. Second, a student takes a language course at the same time. Third, a student has opted out of evening classes. Evening sections are scheduled from 6 pm until 8 pm and students can opt out of these classes by filling in an online form. Unfortunately, we do not observe scheduling conflicts but only the final section assignment.

Table 2: Descriptive Statistics

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Panel A: Student Demographic Characteristics					
Female	2,903	0.375	0.484	0	1
Dutch	2,903	0.235	0.424	0	1
German	2,903	0.565	0.496	0	1
Age	2,788	19.21	1.462	16.19	30.95
Panel B: Explanatory and Outcome Variables					
Section Level Characteristics					
GPA of female peers	14,292	6.874	0.820	2.375	9.625
GPA of male peers	14,292	6.682	0.580	4.518	9.750
Number of students in section	14,292	13.92	0.947	8	16
Course and Major Choices:					
Any Quantitative Elective	14,292	0.480	0.500	0	1
Fraction Quantitative Electives	14,292	0.171	0.220	0	1
Quantitative Major	14,292	0.304	0.460	0	1
Labor Market Outcomes:					
Working	7,281	0.633	0.482	0	1
Hourly earnings	4,797	3.828	0.321	0.693	4.605
Yearly earnings	5,720	44.10	42.16	0.00100	650
Weekly working hours	4,797	47.93	12.17	2	100
Job satisfaction	4,856	8.102	1.459	1	10
Subjective social impact	4,867	0.639	2.701	-5	5

NOTE — This table is based on our estimation sample. All explanatory and outcome variables are reported at the student-course level.

We remove observations for which the business school deviated from their standard scheduling procedure. Appendix A.2 details these exceptions and our other sample restrictions. We test, in Section 2.3, if the section assignment is as good as random in our estimation sample.

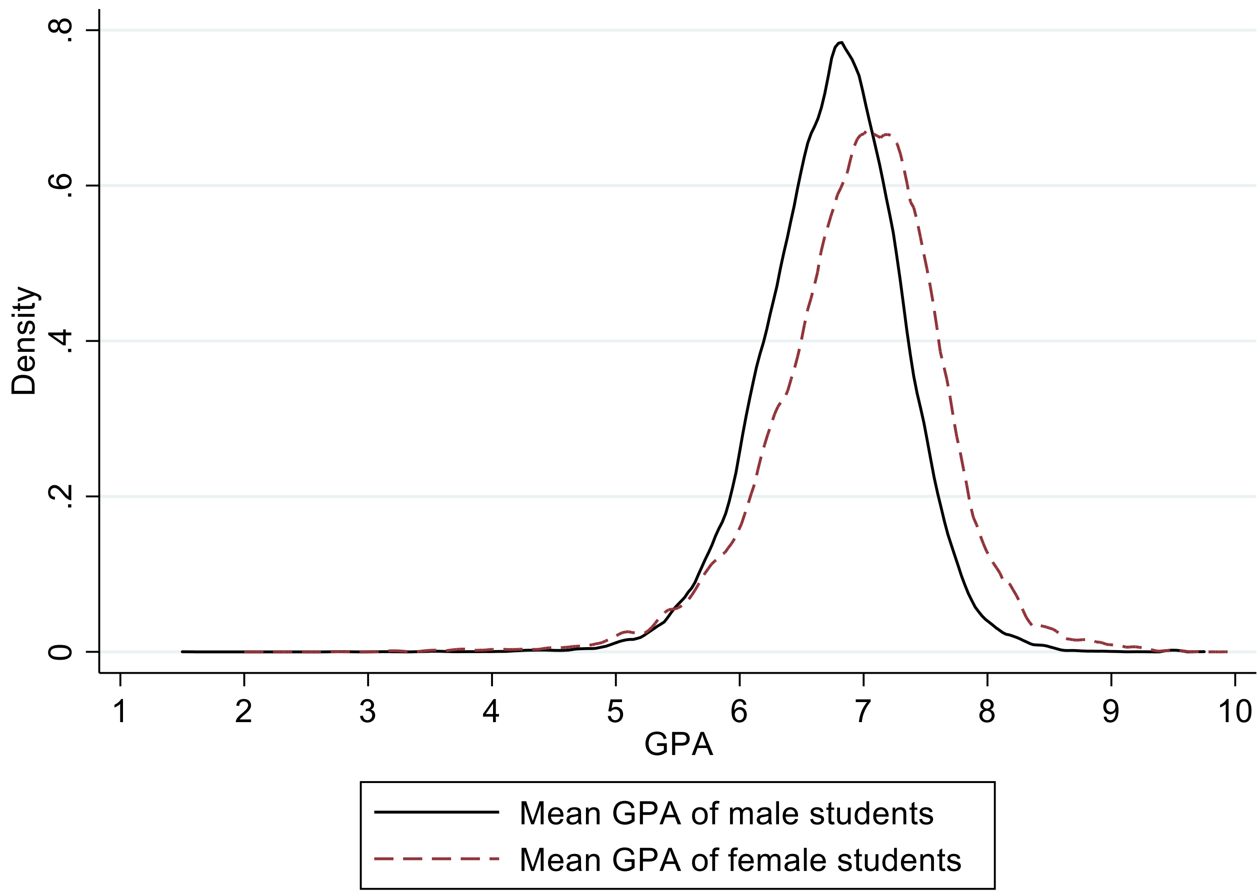
2.2 Explanatory Variables and Outcome Variables

Panel B of Table 2 shows the explanatory variables and outcome variables we use in this paper. We report the summary statistics for these variables at the student-course level instead of at the student-level. This presentation of the summary statistics gives more weight to students observed more often – as does our empirical analysis.

Explanatory Variables: Throughout the paper, the explanatory variables of interest are the GPAs of male and female section peers. To avoid the reflection problem (Manski, 1993), each student's GPA is constructed based on grades obtained before they are assigned to a section. Male peer GPA and female peer GPA are the leave-out means of the pre-assignment GPAs, that is, they are the average GPAs of all male or female students in a given section except for the student in question. Because we only use pre-assignment grades, we cannot construct peer GPAs for the courses which students take in the first teaching period. Our analysis therefore relies on the six compulsory courses students take in the second, third, and fourth teaching periods of their first year.

The average GPA of female peers is 6.9 on a 10-point scale, which is significantly higher than the 6.7 average GPA of male peers. This difference reflects that, at this business school, as in many other educational environments, women outperform men academically. Figure 1 shows the average section-level GPA of male and female students, which provides us with an idea of the underlying achievement variation in the peer composition.

Figure 1: Distribution of the Section-Level Mean GPA of Male and Female Students



Outcomes Variables – Course and Major Choices: Our main academic outcomes are students' choices of mathematical courses and majors. Seventeen percent of all elective course observations are mathematical courses, which include mathematical electives and major-specific mathematical compulsory courses.

Each major consists of four major-specific compulsory courses. We define a major as mathematical if at least half of its compulsory courses are mathematical. This approach leaves us with three mathematical majors (Finance, IT Management, and Economics) and five non-mathematical majors (Strategy, Accounting, Supply-Chain Management, Organization, and Marketing). Students are free to choose any major, as there are no GPA requirements. Table 3 shows additional information on all eight majors. It shows that women are less likely to choose mathematical majors and that mathematical majors are associated with higher earnings.

Table 3: The Major Choice Set

Major	(1) Major Classification	(2) Percent Compulsory Mathematical Courses in Major	(3) Percent Female	(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	Mathematical major	50	18.28	7.31	7.17	53.20	55.17
IT Management	Mathematical major	50	31.11	6.97	6.63	39.86	45.09
Economics	Mathematical major	50	32.82	7.30	7.16	38.20	45.62
Supply Chain Mgmt	-	25	52.09	6.97	6.56	36.25	42.86
Strategy	-	0	37.72	6.94	6.55	38.15	36.86
Accounting	-	0	40.66	7.34	7.20	40.96	45.16
Organization	-	0	59.74	6.84	6.71	32.39	50.93
Marketing	-	0	62.66	6.74	6.63	28.12	39.68

NOTE — This table is based on our estimation sample. Mean earnings by gender in Columns (6) and (7) are taken from the graduate survey described below.

Outcomes Variables – Labor Market Outcomes: In 2016, we gathered data on students' labor market outcomes by sending a survey to students who graduated between September 2010 and September 2015. From this survey, we use six outcomes: 1) A dummy variable indicating if a person is employed (full-time employed, part-time employed, or self-employed) 2) yearly earnings from main job in euro before taxes, 3) weekly working hours, 4) hourly earnings, 5) job satisfaction, and 6) the subjective social impact of the job. We measured job satisfaction using the question, "*How satisfied are you, all in all, with your current work?*" Responses are based on a 10-point scale, with 10 being "most satisfied." We measured subjective social impact using the question, "*What do you think is the social impact of your current work?"* Here, responses are based on an 11-point scale, ranging from –5 *"very negative"* to +5 *"very positive,"* with 0 being *"no impact*." Panel B of Table 2 shows average earnings in our sample are 44,100 euro per year and respondents work, on average, 48 hours per week. Average job satisfaction is 8.1 points, and the average social impact of the job is 0.6 points. The graduate survey response rate was 35 percent and the probability that we observe students in the labor market—they answered the survey and work—is unrelated to our peer variables of interest (see Table A2 in the Appendix).

2.3 Randomization Check

To confirm that the peer composition is random, we test whether students' "pretreatment" characteristics, i.e., previous GPA, age, and the rank of the student ID—a proxy for a student's tenure at the business school—systematically relate to the GPA of their male and female peers as well as the proportion of their section peers that are female.

We implement these tests by regressing each peer variable (GPA of female peers, GPA of male peers, proportion of female peers) separately on one pretreatment characteristic (students' own GPA, age, rank of ID) and a set of fixed effects (either course-year fixed effects or course-year fixed effects *and* parallel-course-year fixed effects). In specifications where we relate students' own GPA with the GPA of their same gender peers, we additionally control for the course-level leave-out mean of GPA. This approach was introduced by Guryan, Kroft, and Notowidigdo (2009) who show that it accounts for the mechanical relationship between own- and peer-level variables. As in our main analysis, we perform these randomization tests separately for women and men.

Table 4 confirms that all three pretreatment characteristics are unrelated to our peer variables of interest. All point estimates are small and none of the coefficients of interest are statistically significant.

Table 4: Test for Random Assignment — Regression of Peer GPA and Gender on Student Pretreatment Characteristics

Panel A: Women	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Std. GPA of Female Peers	Std. GPA of Male Peers	Std. GPA of Female Peers	Std. GPA of Male Peers	Proportion Female Peers
Std. GPA	0.0702	0.0048	0.0587	0.0052	0.0011
	(0.058)	(0.014)	(0.059)	(0.014)	(0.002)
Age	-0.0114	-0.0147	-0.0107	-0.0162	0.0003
	(0.012)	(0.010)	(0.012)	(0.010)	(0.002)
ID rank	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5,517	5,517	5,504	5,504	5,517
Course-year FE	YES	YES	YES	YES	YES
Parallel Course-year FE	NO	NO	YES	YES	YES

Panel B: Men					
Std. GPA	0.0124	-0.0208	0.0150	-0.0314	-0.0001
	(0.013)	(0.034)	(0.013)	(0.035)	(0.002)
Age	-0.0014	-0.0098	-0.0005	-0.0091	0.0016
	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)
ID rank	-0.0000	0.0000	-0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,775	8,775	8,732	8,732	8,775
Course-year FE	YES	YES	YES	YES	YES
Parallel Course-year FE	NO	NO	YES	YES	YES

NOTE — Each cell in this table is estimated with a separate ordinary least squares regression including course-year fixed effects. Regression estimates shown in columns (3), (4), and (5) additionally include parallel-course-year fixed effects. Following the Guryan, Kroft, and Notowidigdo (2009) correction method, we control for the leave-out mean of the peers' GPA at the course level when relating students' GPA to the GPA of their same gender peers (Panel A: specification reported in row 1, Columns (1) and (3); Panel B: specifications reported in row 1, Columns (2) and (4)). Robust standard errors clustered at the student level are in parentheses.

We additionally perform a more flexible randomization check by testing if section dummies predict the pretreatment characteristics GPA, age, gender and student ID rank. For each course in our sample, we first regress one pretreatment characteristic on section dummies and balancing indicators (dummies for student nationality and parallel-course-year fixed effects), and then run an F-test for joint significance of the section dummies. This means we run 48 regressions for each of the pretreatment characteristics. Under conditional random assignment, the *p*-values of the F-tests of these regressions should in expectations be uniformly distributed with a mean of 0.5 (Murdoch, Tsai, and Adcock 2008). Furthermore, if students are randomly assigned to sections within each course, the F-tests should reject the null hypothesis of no relation between section assignment and students' pretreatment characteristics at the 5 percent and 1 percent significance levels for 5 percent and 1 percent of the cases, respectively. Table A1 and Figure A1 in the appendix confirm these predictions. Consistent with random assignment, we see that the p-values of the F-tests are roughly uniformly distributed, with means close to 0.5 and rejection rates close to the expected levels for each pretreatment characteristic.

3. Empirical Strategy

To understand how peer achievement affects students' specialization choices and labor market outcomes, we estimate the following model:

$$y_{i\tau} = \alpha_1 \overline{Male\ GPA}_{ict-1} + \beta_1 \overline{Female\ GPA}_{ict-1} + X\gamma' + u_{ic\tau}, \tag{1}$$

where $y_{i\tau}$ is the course choice, major choice, or a labor market outcome of student *i* at time $\tau > t$, that is, after having taken the compulsory course *c* at time *t*, where she was exposed to a given group of section peers. We have two independent variables of interest. $\overline{Male\ GPA}_{ict-1}$ is the average GPAs of all male section peers based on all courses students took at time *t-1*, that is, before the start of the course. Analogously, $\overline{Female\ GPA}_{ict-1}$ is the average pre-assignment GPAs of all female section peers. Each student's pre-assignment GPA consists of all grades achieved before the start of the course, and therefore neither male nor female peer GPA contain any contemporaneous grades. X is a vector of control variables that includes course-year fixed effects and parallel-course-year fixed effects, which are fixed effects for the other courses the students take in the same teaching period. X also includes students' own pre-assignment GPA as well as indicators for their gender and nationality. $u_{ic\tau}$ is the error term.

The parameters of interest are α_1 and β_1. Parameter α_1 is the causal effect of a student's assignment to higher-GPA male peers and β_1 is the causal effect of assignment to higher-GPA female peers on the outcome of interest.

Throughout, we estimate Equation (1) separately for women and men. This approach allows the coefficients of interests as well as the control coefficients to vary by gender. We estimate Equation (1) at the student-by-course level, where one observation refers to one student in one first-year course. This level of analysis allows us to include course fixed effects, which are required to obtain unbiased estimates of the impact of peers. We observe only one major choice for each student even though each student appears multiple times in our dataset with different peer groups. We take this data structure into account by clustering standard errors at the student level. In robustness checks, we also estimate models with one observation per student for which we cannot include course fixed effects.

For all estimates that rely on survey outcomes, we account for systematic differences in survey responses based on observable characteristics following Wooldridge (2007)'s inverse probability weighting. Specifically, we first estimate the probability of observing students' labor market outcomes (see Table A2 in the Appendix). We then winsorize these predicted probabilities at the 1st and 99th percentile of all positive predicted values. Finally, we estimate the effect of peer achievement on survey outcomes by weighting each observation by the inverse of the winsorized predicted response probabilities. To simplify the interpretation of our results, we standardize male peer GPA and female peer GPA over the estimation sample to have means of zero and standard deviations of one.

4. Results

A. Effects on Choice of Mathematical Majors and Courses

Table 5 shows that having higher achieving male or female peers is not significantly related to students' probability of choosing a mathematical major. All four point estimates are small and none of them is statistically significant at the 5 percent level. For example, our point estimates suggest that being in one course with male peers who have one standard deviation higher GPAs reduces women's likelihood of choosing a mathematical major by 0.82 percentage points. The 95 percent confidence interval of this estimate allows us to rule out effects smaller than -2.0 and larger than +.0.4 percentage points (see Panel A). The equivalent coefficient for men is estimated with similar precision and suggests that having male peers with one standard deviation higher GPAs increases the likelihood of choosing a mathematical major by 0.26 percentage points (see Panel B).

The estimated effects of having higher achieving male or female peers on the probability of choosing a mathematical elective (Column 2) or the fraction of mathematical electives (Column 3) are also statistically insignificant and small. For women and men, all point estimates suggest that the effect of having male or female peers with one standard deviation higher GPAs on choosing any mathematical elective is smaller than 0.8 percentage points in absolute terms. The equivalent point estimates on the fraction of mathematical electives are all smaller than 0.5 percentage points in absolute terms. Taken together, we see little evidence that higher achieving female or male peers affect students' specialization choices.

Table 5: The Effect of Peer Achievement on Course and Major Choice

Panel A: Women	(1)	(2)	(3)
Dependent Variable:	Mathematical Major	Any Mathematical Elective	Fraction Mathematical Electives
Std. GPA of Male Peers	-0.0082	0.0000	-0.0006
	(0.0061)	(0.0070)	(0.0027)
	[-0.0201 - 0.0038]	[-0.0137 - 0.0138]	[-0.0058 - 0.0046]
Std. GPA of Female Peers	0.0015	0.0012	0.0014
	(0.0059)	(0.0068)	(0.0026)
	[-0.0102 - 0.0131]	[-0.0121 - 0.0146]	[-0.0037 - 0.0066]
Observations	5,504	5,504	5,504
R-squared	0.2221	0.2534	0.1168
Mean Dependent Variable Female Students	.1893	.3272	.1037
Panel B: Men			
Std. GPA of Male Peers	0.0026	0.0022	0.0010
	(0.0065)	(0.0067)	(0.0034)
	[-0.0101 - 0.0152]	[-0.0110 - 0.0153]	[-0.0056 - 0.0076]
Std. GPA of Female Peers	-0.0066	-0.0079	-0.0045*
	(0.0056)	(0.0052)	(0.0026)
	[-0.0176 - 0.0043]	[-0.0181 - 0.0023]	[-0.0096 - 0.0005]
Observations	8,768	8,768	8,768
R-squared	0.1493	0.1778	0.0545
Mean Dependent Variable Male Students	.3757	.5765	.2142

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, Std. GPA, and indicators for being Dutch or German. Robust standard errors clustered at the student level are in parentheses. Ninety-five percent confidence intervals are reported in square brackets. * p<0.1.

We conducted two robustness checks. First, we estimate specifications identical to those shown in Table 5, except that they additionally include a control variable for the proportion of section peers in a given course that are female. These specifications lead to almost identical results (see Table A3 in the Appendix). Second, we estimate models with observations at the student level (see Table A4 in the Appendix). In these specifications, our main independent variables are the average pre-assignment GPAs of all male or female peers which students had in teaching-periods 2-4 (there is no pre-assignment GPA for teaching period 1). In each specification, we then regress for each student one outcome variable (e.g. mathematical major) on two independent variables of interest (male/female GPA of all peers over periods 2-4). We also control for cohort-study-program fixed effects (e.g. Business-2012) and dummy variables for student nationality (Dutch and German). In these specifications, 2 out of 12 point estimates are statistically significant at the 5 percent level. These estimates suggest that men who had female peers with one standard deviation higher GPAs across all their first year courses are 4.9 percentage points less likely to choose a mathematical elective and choose 2.3 percentage point fewer mathematical electives. These point estimates go in the same direction as their counterparts in our main specification. However, we interpret these results as merely suggestive because students were randomly assigned to sections at the course level and these specifications do not allow us to include course-year fixed effects.

We further explore heterogeneous results in four ways. First, we estimate our main results using peer GPA based exclusively on students' grades in mathematical courses. This measure of peer ability might better capture the relevant aspect of ability that affects students' choices of mathematical specializations. Second, we estimate our main results by replacing our peer GPA measures with the *proportion of top decile female peers*, that is, the proportion of all female peers that are in the top decile of the GPA distribution of female students in a given course, and, equivalently defined, the *proportion of top decile male peers*. These measures allow us to explore if our results, using average peer GPA, hide effects of very high achieving peers on specialization choices. Third, we estimate our results separately for students whose GPA is above and below the median. Fourth, we estimate our result separately for mathematical and non-mathematical compulsory courses.

Out of 72 point-estimates of interest, only four are statistically significant at the 5 percent level. Table A5 in the appendix shows that women are significantly less likely to choose a mathematical major if they have been assigned male peers with a higher GPA *based on mathematical courses*. Table A6 shows no systematic effect of being assigned to peers with top decile GPAs. Table A7 shows that men *whose own GPA are above the median* are less likely to choose a mathematical major after being assigned to higher achieving female peers. Finally, Table A8 shows that men who have been assigned to higher achieving female peers *in non-mathematical compulsory courses* are less likely to choose at least one mathematical elective and choose a lower fraction of mathematical electives. Overall, we see little evidence for meaningful heterogeneity.

Two other concerns are that the absence of meaningful effects is driven by peers not mattering in our setting or educational choices not being sufficiently malleable. Four studies with data from the same environment allow us to rule out both of these concerns. In Feld and Zölitz (2017), we show that having higher achieving peers improves students' grades and course evaluations; Golsteyn et al. (2021) show that peer personality affects student achievement. In Zölitz and Feld (forthcoming), we show that the proportion of female peers increases women's likelihood of choosing a male-dominated major and decreases their likelihood of choosing a female-dominated major; effects for men go in the opposite direction. Elsner et al. (forthcoming) show that having a higher rank amongst one's tutorial peers increases the likelihood of choosing follow-up courses and majors in the same subject.

A final concern is that we fail to estimate significant effects because peer GPA measures peer ability with error. The direction of the bias caused by classical measurement error, as we have shown in Feld and Zölitz (2017), depends on the how peers are assigned to groups. If peer group assignment is nonrandom, classical measurement error in the peer variable of interest can lead to substantial overestimation of peer effects. If peer group assignment is random, classical measurement error will bias peer effects estimates toward zero. Since students in our setting are randomly assigned to sections, our estimates are likely attenuated. However, because our measure of peer ability – peer GPA – consists of many grades, we expect measurement error and the resulting attenuation bias to be small.

Our estimated effect of higher-achieving male peers on women's specialization choices are not consistent with those found in previous studies that estimate the effect of high school peers. Cools et al. (2019) show that female students with high-achieving male peers receive lower math and science grades, are less likely to complete a bachelor's degree, and are more likely have a child before they turn 18. Mouganie and Wang (2020) show that high-achieving male peers reduce female students' likelihood of choosing a science, technology, engineering, or math (STEM) major. Our results are also not consistent with Fischer (2017), who finds that female university students with higher-achieving peers in an introductory STEM course are less likely to major in a STEM field.

B. Effects on Labor Market Outcomes

Table 6 shows how peer achievement affects women's and men's labor market outcomes. For women, we see no significant effects on the probability of being employed, yearly earnings, or working hours. We do see a significant effect on hourly wage. Women who in one course had female peers with one standard deviation higher GPAs appear to be earning 6 percent more per hour. However, this estimate is large and imprecise which raises concerns that it might have been as result of chance. Indeed, the statistical significance vanishes (p = 0.54) once we adjust for the fact that we test 36 hypotheses[1] using the Westfall-Young stepdown procedure with 1,000

[1] We have considered 9 outcomes of interests (3 specialization choices and 6 labor market outcomes). For each of these outcomes, we test four hypotheses (two for women and two for men) which adds up to 36 hypotheses.

bootstrap replications (Westfall et al. 1993; Reif, 2017). For men, we see no significant peer effects on the probability of being employed, earnings, working hours or hourly wage, but our coefficients are imprecisely estimated. Overall, we lack sufficient statistical power to draw any conclusions on the effect of peer achievement on women's or men's employment status, earnings, or working hours.

The best evidence on the effect of peer achievement on earnings comes from Fischer et al. (2020), who observe earnings in Danish registry data for up to 25 years after enrolment. They find that higher achieving peers reduces women's earnings by 4 percent on average, is driven by exposure of higher achieving male peers, and becomes stronger as graduates get older. We cannot directly compare our point estimates with the estimates by Fischer et al. (2020) because standardized peer achievement is not comparable across settings. However, the direction of our point estimates also suggest that women earn less after being exposed to higher achieving male peers.

Table 6 further shows the estimates of having higher achieving peers on job satisfaction and subjective social impact of one's job. We have coded both measures as binary variables. *High Job Satisfaction* is equal to one if respondents rated their job satisfaction as 8 points or higher, and zero otherwise. *Positive Social Impact* is equal to one if respondents rate the social impact of their job as positive and zero if they rate it as neutral or negative. The results show no significant effects on women's or men's positive social impact and a precisely estimated effect of having higher achieving male peers on women's job satisfaction. Women who had one course with male peers who have one standard deviation higher GPAs are 4.2 percentage points more likely to report a high job satisfaction. This point estimate is statistically significant at the 1 percent level and remains significant (p =0.046) after applying the aforementioned multiple hypothesis testing correction.

Table 6: The Impact of Peer Achievement on Labor Market Outcomes

Panel A: Women	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Employed	Log Yearly Earnings	Log Working Hours	Log Hourly Wage	Job Satisfaction 8+	Positive Subjective Social Impact
Std. GPA of Male Peers	-0.0104	-0.0572	-0.0152	-0.0668	0.0418***	0.0105
	(0.0105)	(0.0474)	(0.0107)	(0.0528)	(0.0141)	(0.0106)
	[-0.0310 - 0.0102]	[-0.1504 - 0.0360]	[-0.0362 - 0.0058]	[-0.1708 - 0.0371]	[0.0142 - 0.0695]	[-0.0103 - 0.0313]
Std. GPA of Female Peers	-0.0080	0.0159	0.0005	0.0633**	0.0171	-0.0103
	(0.0091)	(0.0344)	(0.0061)	(0.0296)	(0.0113)	(0.0089)
	[-0.0259 - 0.0098]	[-0.0518 - 0.0836]	[-0.0115 - 0.0124]	[0.0051 - 0.1215]	[-0.0052 - 0.0393]	[-0.0278 - 0.0072]
Observations	2,840	2,175	1,820	1,726	1,872	1,872
R-squared	0.2878	0.1513	0.1780	0.0989	0.0614	0.5310
Mean Dependent Variable Female Students	0.6194	10.0955	45.2934	2.4988	.7025	0.5951
Panel B: Men						
Std. GPA of Male Peers	0.0117	0.0482	0.0039	0.0329	0.0131	0.0054
	(0.0087)	(0.0297)	(0.0093)	(0.0258)	(0.0099)	(0.0092)
	[-0.0055 - 0.0288]	[-0.0101 - 0.1065]	[-0.0143 - 0.0221]	[-0.0178 - 0.0835]	[-0.0064 - 0.0326]	[-0.0128 - 0.0235]
Std. GPA of Female Peers	-0.0104	-0.0260	-0.0050	0.0190	0.0114	-0.0026
	(0.0069)	(0.0268)	(0.0064)	(0.0213)	(0.0090)	(0.0076)
	[-0.0240 - 0.0032]	[-0.0786 - 0.0266]	[-0.0176 - 0.0076]	[-0.0228 - 0.0608]	[-0.0063 - 0.0290]	[-0.0175 - 0.0123]
Observations	4,434	3,562	2,970	2,824	3,000	3,000
R-squared	0.2626	0.0565	0.0898	0.0537	0.0440	0.4632
Mean Dependent Variable Male Students	0.6416	10.363	49.5552	2.725	.772	.5073

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, and indicators for being Dutch or German. Following Wooldridge (2007), for all specifications, we weight the observations by the inverse of the probability of observing the outcome. Robust standard errors using two-way clustering at the student level and section level are in parentheses. Ninety-five percent confidence intervals are reported in square brackets. * p<0.1, ** p<0.05, *** p<0.01.

One concern is that we lose valuable information with the binary coding of job satisfaction and social impact. Why not use both variables in their original scales? This is not trivial because job satisfaction and social impact are measured on ordinal scales. Any effect on the job satisfaction score is difficult to interpret because we do not know, for example, how an increase in job satisfaction from 4 to 5 points compares to an increase from 9 to 10 points. When comparing two groups, the group with the higher average job satisfaction score may actually be less satisfied on average. This problem is called a sign reversal and there is an open debate in the economics of happiness literature on how likely this is in practice. Bond and Lang (2019) conclude that "*it is essentially impossible to rank two groups on the basis of their mean happiness using the types of survey questions prevalent in the literature.*" In contrast, Kaiser and Vendrik (2020) argue that sign reversals are often implausible or impossible because, among other things, people typically interpret ordinal scales fairly linearly. When we use the ordinal, non-transformed, scale of job satisfaction and social impact as dependent variables, we see significant results for both outcomes. Appendix Table A9 suggests that women who had male peers with one standard deviation higher GPAs are 0.13 points (9 percent of a standard deviation) more satisfied and report that their job has a 0.13 points (5 percent of a standard deviation) more positive social impact. The effect on job satisfaction remains marginally significant after correcting for multiple hypothesis testing (p =0.07). Taken together with our estimates using binary dependent variables, we interpret these results as suggestive evidence that higher achieving male peers increases women's job satisfaction.

6. Conclusion

We have explored how having higher achieving peers affects men's and women's educational choices and labor market outcomes. In contrast to previous studies, we did not find any significant effects on educational choices. We have also shown suggestive evidence that women who have studied with higher achieving male peers are more satisfied with their jobs. These results complement previous findings which have found several negative effects of studying with higher achieving male peers on women's later-life outcomes. As with peer effects on achievement, peer effects on choices also seem to be complex and context dependent.

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APPENDIX

A.1 ADDITIONAL TABLES

Table A1: Alternative Randomization Check

Dependent Variable:	(1) Total Number of Courses	(2) Number significant: 5%	(3) 1%	(4) 0.1%	(5) Percent significant: 5%	(6) 1%	(7) 0.1%	(8) Mean of p-value
Female	48	3	0	0	0.063	0.000	0.000	0.5347
GPA	48	4	1	0	0.083	0.021	0.000	0.4894
Age	48	4	1	0	0.083	0.021	0.000	0.4942
ID rank	48	0	0	0	0.000	0.000	0.000	0.6079

NOTE — This table is based on separate OLS regressions with female, GPA, age, and ID rank as dependent variables. The explanatory variables are a set of section dummies, dummies for the other courses taken at the same time, and dummies for being of German or Dutch nationality.

Table A2: Testing for Attrition and Selective Survey Response

	(1)	(2)	(3)	(4)
Subsample:	Women		Men	
Dependent Variable:	Major Observed	Observed in Labor Market	Major Observed	Observed in Labor Market
Std. GPA of Male Peers	0.0022	0.0002	-0.0014	-0.0050
	(0.003)	(0.008)	(0.003)	(0.007)
Std. GPA of Female Peers	0.0035	-0.0049	0.0024	-0.0095*
	(0.003)	(0.007)	(0.003)	(0.005)
Dutch	0.0070	0.0148	0.0046	0.0790*
	(0.024)	(0.056)	(0.019)	(0.043)
German	0.0237	-0.0994**	0.0021	0.0075
	(0.020)	(0.049)	(0.016)	(0.037)
Pre-assignment GPA	0.0344***	0.0412***	0.0391***	0.0196*
	(0.008)	(0.014)	(0.006)	(0.011)
Observations	6,089	5,052	9,411	7,681
R-squared	0.601	0.077	0.518	0.083
Mean Dependent Variable Female Students	0.9762	.348	.	.
Mean Dependent Variable Male Students	.	.	.9738	.3661
p-value of Test for joint Significance of Peer Variables	.4385	0.8009	.5646	.1751

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, and indicators for being Dutch or German. The dependent variable in column (1) and (3) is equal to 1 if we observe a student's major and 0 otherwise. The dependent variable in column (2) and (4) is equal to 1 if we observe the student in the labor market, that is, if the student has answered the alumni survey and indicated that they are part-time, full-time, or self-employed, and 0 if they do not respond to the survey or they are not part-time, full-time, or self-employed – for example because they are still studying. . Robust standard errors clustered at the student level are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Robustness – Estimations Controlling for the Proportion Female Section Peers

Panel A: Women	(1)	(2)	(3)
Dependent Variable:	Mathematical Major	Any Mathematical Elective	Fraction Mathematical Electives
Std. GPA of Male Peers	-0.0080	0.0003	-0.0004
	(0.0061)	(0.0070)	(0.0026)
Std. GPA of Female Peers	0.0015	0.0012	0.0014
	(0.0059)	(0.0068)	(0.0026)
Observations	5,504	5,504	5,504
R-squared	0.2221	0.2535	0.1170
Mean Dependent Variable Female Students	.1893	.3272	.1037
Panel B: Men			
Std. GPA of Male Peers	0.0025	0.0021	0.0010
	(0.0064)	(0.0067)	(0.0034)
Std. GPA of Female Peers	-0.0065	-0.0078	-0.0045*
	(0.0056)	(0.0052)	(0.0026)
Observations	8,768	8,768	8,768
R-squared	0.1494	0.1781	0.0545
Mean Dependent Variable Male Students	.3757	.5765	.2142

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, and indicators for being Dutch or German. Robust standard errors clustered at the student level are in parentheses. * p<0.1.

Table A4: Robustness – Estimations with One Observation per Student

Panel A: Women	(1)	(2)	(3)
Dependent Variable:	Mathematical Major	Any Mathematical Elective	Fraction Mathematical Electives
Std. GPA of Male Peers	-0.0215	-0.0143	-0.0058
	(0.015)	(0.018)	(0.007)
Std. GPA of Female Peers	0.0034	-0.0161	-0.0021
	(0.016)	(0.019)	(0.007)
Observations	985	985	985
R-squared	0.192	0.239	0.084
Mean Dependent Variable Female Students	.1898	.331	.1057
Panel B: Men			
Std. GPA of Male Peers	-0.0133	-0.0033	-0.0011
	(0.016)	(0.016)	(0.008)
Std. GPA of Female Peers	-0.0201	-0.0362**	-0.0183**
	(0.017)	(0.015)	(0.008)
Observations	1,603	1,603	1,603
R-squared	0.082	0.168	0.028
Mean Dependent Variable Male Students	.3706	0.577	.2128

NOTE — All columns are estimated with ordinary least squares regressions that include cohort and study program fixed effects, and indicators for being Dutch or German. Heteroskedasticity robust standard errors are in parentheses. ** $p < 0.05$.

Table A5: Main Results using Peer Math GPA

Panel A: Women	(1)	(2)	(3)
Dependent Variable:	Mathematical Major	Any Mathematical Elective	Fraction Mathematical Electives
Std. Math GPA of Male Peers	-0.0137**	0.0003	-0.0021
	(0.0068)	(0.0081)	(0.0031)
Std. Math GPA of Female Peers	0.0066	0.0044	0.0029
	(0.0068)	(0.0077)	(0.0029)
Observations	5,504	5,504	5,504
R-squared	0.2227	0.2535	0.1171
Mean Dependent Variable Female Students	.1893	.3272	.1037
Panel B: Men			
Std. Math GPA of Male Peers	0.0057	0.0007	0.0004
	(0.0070)	(0.0073)	(0.0035)
Std. Math GPA of Female Peers	0.0007	-0.0072	-0.0036
	(0.0063)	(0.0058)	(0.0028)
Observations	8,768	8,768	8,768
R-squared	0.1492	0.1777	0.0543
Mean Dependent Variable Male Students	.3757	.5765	.2142

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, Std. Math GPA, and indicators for being Dutch or German. Peer and own GPA are constructed based on mathematical courses. Robust standard errors clustered at the student level are in parentheses. ** $p<0.05$.

Table A6: Effect of Female and Male Top GPA Decile Peers

Panel A: Women	(1)	(2)	(3)
Dependent Variable:	Mathematical Major	Any Mathematical Elective	Fraction Mathematical Electives
Proportion Top 10 Male Peers	-0.0081	0.0475	0.0192
	(0.104)	(0.120)	(0.046)
Proportion Top 10 Female Peers	0.0731	0.0922	0.0114
	(0.108)	(0.129)	(0.059)
Observations	5,504	5,504	5,504
R-squared	0.222	0.254	0.117
Mean Dependent Variable Female Students	.1893	.3272	.1037
Panel B: Men			
Proportion Top 10 Male Peers	0.0092	-0.0401	-0.0256
	(0.093)	(0.092)	(0.047)
Proportion Top 10 Female Peers	-0.2386*	-0.0776	-0.1035
	(0.122)	(0.128)	(0.065)
Observations	8,768	8,768	8,768
R-squared	0.150	0.178	0.054
Mean Dependent Variable Male Students	.3757	.5765	.2142

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, Std. GPA, and indicators for being Dutch or German. The proportion top 10 peers are based on course level GPA distributions. Robust standard errors clustered at the student level are in parentheses.

Table A7: Heterogeneous Effects by Student GPA

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Mathematical Major		Any Mathematical Elective		Fraction Mathematical Electives	
Panel A: Women	Below median GPA students	Above median GPA students	Below median GPA students	Above median GPA students	Below median GPA students	Above median GPA students
Std. GPA of Male Peers	-0.0011	-0.0135	0.0055	-0.0027	0.0012	-0.0016
	(0.007)	(0.009)	(0.009)	(0.010)	(0.003)	(0.004)
Std. GPA of Female Peers	-0.0043	0.0053	-0.0112	0.0077	-0.0048	0.0046
	(0.009)	(0.007)	(0.009)	(0.009)	(0.004)	(0.003)
Observations	2,124	3,374	2,124	3,374	2,124	3,374
R-squared	0.224	0.230	0.405	0.186	0.209	0.086
Mean Dependent Variable Female Students	.1224	.2318	.2764	.3592	.0786	.1195
p-values for Test of Gender Equality of GPA Male Peers	.8847	.1125	.5332	.7779	.6942	.6933
p-values for Test of Gender Equality of GPA Female Peers	.6191	.4835	.2351	.3905	.2108	.1802
Panel B: Men						
Std. GPA of Male Peers	0.0059	-0.0028	-0.0063	0.0088	-0.0020	0.0027
	(0.009)	(0.009)	(0.010)	(0.009)	(0.004)	(0.005)
Std. GPA of Female Peers	0.0043	-0.0156**	-0.0102	-0.0064	-0.0065*	-0.0035
	(0.008)	(0.008)	(0.008)	(0.007)	(0.004)	(0.004)
Observations	3,856	4,903	3,856	4,903	3,856	4,903
R-squared	0.079	0.128	0.236	0.122	0.042	0.047
Mean Dependent Variable Male Students	.2417	.4817	0.5005	.6368	.17	.2493
p-values for Test of Gender Equality of GPA Male Peers	.5058	.7581	.5178	.3386	0.6396	.5866
p-values for Test of Gender Equality of GPA Female Peers	.5898	.04	.1728	.3895	.0852	.3341

NOTE — This shows regressions that are separately estimated for students whose GPA was above the median and students whose GPA was below the median of the course-specific GPA distribution. Additional controls include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, and indicators for being Dutch or German. Robust standard errors clustered at the student level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A8: Heterogeneity by First Year Course Type (Math vs. Non-mathematical Courses)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Mathematical Major		Any Mathematical Elective		Fraction Mathematical Electives	
Panel A: Women	Math course	Non-Math Course	Math course	Non-Math Course	Math course	Non-Math Course
Std. GPA of Male Peers	-0.0100	-0.0060	0.0027	-0.0023	-0.0015	0.0003
	(0.0071)	(0.0081)	(0.0084)	(0.0090)	(0.0035)	(0.0035)
Std. GPA of Female Peers	0.0057	-0.0027	-0.0001	0.0025	0.0018	0.0011
	(0.0073)	(0.0072)	(0.0081)	(0.0083)	(0.0032)	(0.0032)
Observations	2,779	2,706	2,779	2,706	2,779	2,706
R-squared	0.2207	0.2221	0.2516	0.2508	0.1094	0.1198
Mean Dependent Variable	.1882	.1911	.3267	.3267	.3267	.3267
Panel B: Men						
Std. GPA of Male Peers	0.0094	-0.0041	0.0048	-0.0006	0.0033	-0.0015
	(0.0077)	(0.0079)	(0.0081)	(0.0081)	(0.0041)	(0.0041)
Std. GPA of Female Peers	-0.0034	-0.0104	-0.0041	-0.0134**	-0.0030	-0.0066**
	(0.0064)	(0.0071)	(0.0058)	(0.0067)	(0.0030)	(0.0033)
Observations	4,452	4,293	4,452	4,293	4,452	4,293
R-squared	0.1508	0.1495	0.1780	0.1768	0.0544	0.0512
Mean Dependent Variable	.3735	.3792	.5728	0.5809	0.5809	0.5809

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, Std. GPA, and indicators for being Dutch or German. Robust standard errors clustered at the student level are in parentheses. ** $p<0.05$.

Table A9: Non-transformed Job Satisfaction and Social Impact

Panel A: Women	(1)	(2)
Dependent Variable:	Job Satisfaction	Social Impact
Std. GPA of Male Peers	0.1260***	0.1277***
	(0.0438)	(0.0444)
Std. GPA of Female Peers	0.0036	-0.0257
	(0.0339)	(0.0404)
Observations	1,860	1,872
R-squared	0.0659	0.6375
Panel B: Men		
Std. GPA of Male Peers	0.0559	0.0308
	(0.0341)	(0.0444)
Std. GPA of Female Peers	0.0457	-0.0765**
	(0.0329)	(0.0356)
Observations	2,989	2,988
R-squared	0.0502	0.5989

NOTE — All columns are estimated with ordinary least squares regressions that include course-year fixed effects, parallel-course-year fixed effects, female, Std. GPA, and indicators for being Dutch or German. Following Wooldridge (2007), for all specifications, we weight the observations by the inverse of the probability of observing the outcome. Robust standard errors clustered at the student level are in parentheses. Ninety-five percent confidence intervals are reported in square brackets. * p<0.1, ** p<0.05, *** p<0.01.

A.2 SAMPLE RESTRICTIONS

Our sample period comprises the academic years 2009/2010 through 2014/2015. We derive our estimation sample in three steps. First, we exclude several observations from our estimation sample because they represent exceptions from the standard section assignment procedure. These exceptions are the same as those documented in Feld, Salamanca, and Zölitz (forthcoming) and Zölitz and Feld (2019), who use data from the same environment and sample period.

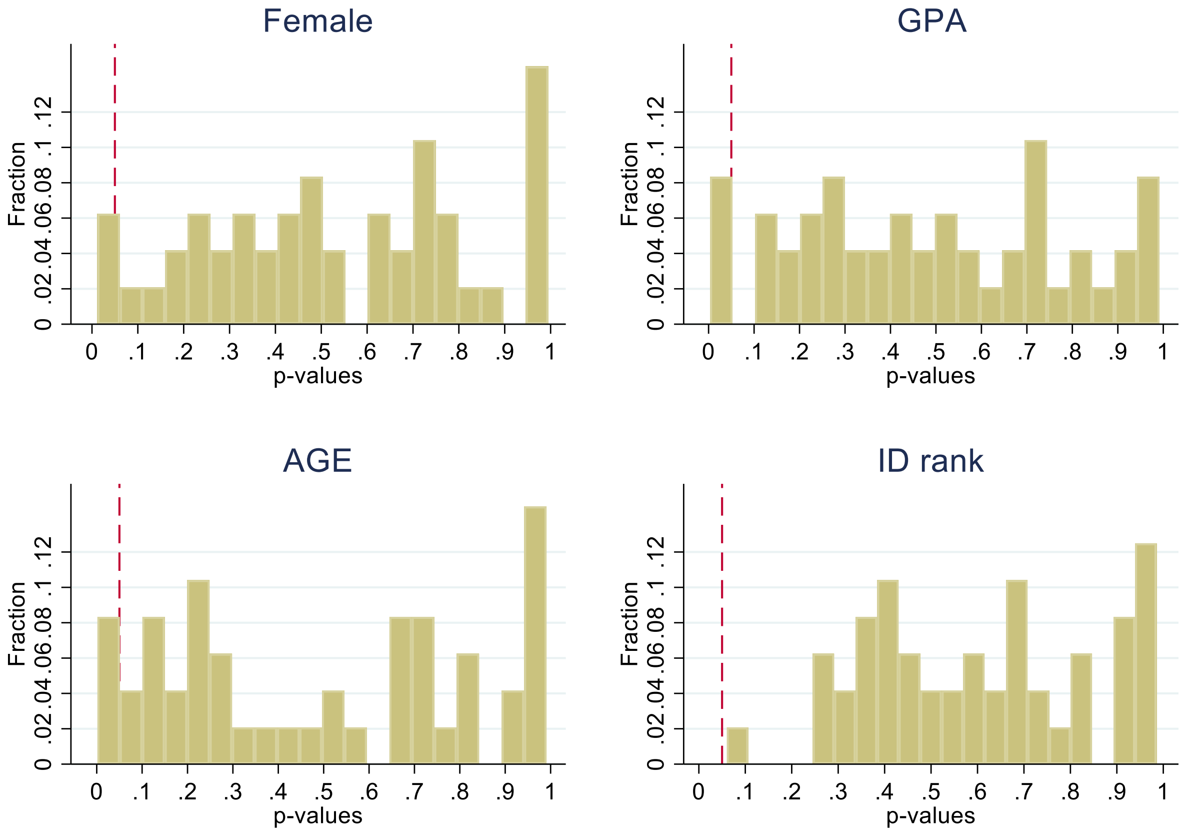
- We exclude eight courses in which the course coordinator or other education staff actively influenced the section composition. One course coordinator requested to balance student gender across sections. The business school's scheduling department informed us about these courses.
- We exclude 21 sections 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 comprised mainly of late-registering students were created. The business school abolished the late registration policy in April 2014.
- We exclude 46 repeater sections from the analysis. One course coordinator explicitly requests that students who failed his/her courses in the previous year be assigned to special repeater sections.
- We exclude 17 tutorial groups that consisted mainly of students from a special research-based program. For some courses, students in this program were assigned together to separate tutorial groups with a more experienced teacher.
- 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 a different attendance criterion and are graded under different standards.
- We exclude all observations from the first teaching periods in students' first years because for these observations, we have no measure of previous performance and therefore cannot calculate our measures of peer achievement.
- We exclude 1,229 student-year observations from sections that take place after 6:30 p.m. because prior to the Fall 2015 semester, students could opt out of evening education, which makes the student assignment to these sections potentially nonrandom.

Second, we further limit our estimation sample to the bachelor's programs Business and Business Economics offered at the business school from the academic years 2009/2010 through 2011/2012 because we can follow these cohorts from their first until their last bachelor's year and observe their major choices. For students in these programs, we only use peer GPA from the first-year compulsory courses from the teaching periods 2-4 (see Table 1). We exclude compulsory courses from the first teaching period because for these courses we have no measure of pre-assignment GPA. This sample restriction has two additional implications. First, we do not use peer GPA from any voluntary elective courses students may take on top of their compulsory courses. Second, we do not use peer GPA from compulsory courses from other bachelor's programs (e.g. bachelor's in econometrics) even if students in these programs later switched to a business or business economics bachelor's program.

Third, we exclude sections with fewer than two female or fewer than two male students. In these sections, one of our core independent variables, either the male peer GPA or the female peer GPA, is missing.

Figure A1: Alternative Randomization Check — Distributions of *p*-values



NOTE — These are histograms showing the distribution of *p*-values from all the regressions reported in Table A1. The vertical line in each histogram shows the 5 percent significance level.