Gender Differences in the Choice of Major: The Importance of Female Role Models*

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Abstract

Women have been traditionally underrepresented in several fields of study, notably those with the highest returns. While in the last two decades many disciplines, including mathematics and physical sciences, have made significant progress in attracting and retaining women, there has been little improvement in the field of economics, which remains heavily male-dominated. We report results from a field experiment aimed at increasing the percentage of women majoring in economics through exposure to carefully chosen female role models. We randomly selected a subset of Principles of Economics classes to be assigned to our role model treatment. Since the same classes were also offered and taught by the same instructors the previous year, we are able to employ a difference-in-differences estimation strategy to test whether the role model intervention increased the percentage of women planning to major in economics (survey-based) and enrolling in intermediate economics classes (administrative data) the semester and year following the intervention. Our results suggest that, while the role model intervention had no impact on male students, it significantly increased female students' likelihood of expressing interest in the economics major and enrolling in further economics classes.

Keywords: Education gender gap, role models, field experiment, economics.

JEL classification codes: A22, C93, I23, I24, J16.

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1 Introduction

Women's participation in higher education has increased dramatically in the last 60 years.[1] In the US, the percentage of bachelor degrees awarded to women has risen from about 25% in the 1950s to over 50% in the 2000s (National Center for Education Statistics and NSF, Science & Engineering Indicators, 2016). The gender distribution across undergraduate fields of studies has also changed over time. According to the latest data provided by the National Center for Education Statistics, many traditionally male-dominated fields of study – including physical sciences, mathematics, natural sciences and business studies – have seen a steady increase in the enrollment and graduation of women.[2] In contrast, other fields have made little progress over the years and remain heavily male-dominated. Economics is one of these, with only 30% of bachelor degrees awarded to women – the same percentage as in the mid 1990s.[3]

As recently discussed in Bayer and Rouse (2016), one reason why achieving higher gender diversity within majors is important and desirable is that it may enhance productivity and overall performance in team work, and it may contribute to the production of novel ideas (Ellison and Mullin, 2014; Hoogendoorn et al., 2013; Bear and Woolley, 2011). Moreover, recent studies (e.g. Arcidiacono (2004), and Kirkeboen et al. (2016)) show that the choice of major significantly affects one's earnings potential, and male-dominated fields tend to lead to higher paying jobs. Economics, for instance, is the highest earning major in the social sciences (Black et al., 2003; Carnevale and Cheah, 2015) and has been shown to generate higher earnings than a business degree (Black et al., 2003).[4] This suggests that closing the gender gap in male-dominated majors may significantly contribute to the reduction of gender differences in access to high paying jobs and/or leadership positions.[5] Greater gender diversity may also have important consequences on aggregate outcomes. Indeed, under the assumption of no gender differences in innate abilities, gender imbalances in self-selection into fields of study (and subsequent careers) may result in misallocation of talents – where individuals are not pursuing their comparative advantages – that could significantly affect aggregate outputs, as recently shown in Hsieh et al. (2013).

The existing literature has looked at a number of factors that may affect the under-representation of women in certain fields, including economics, e.g., gender differences in math aptitude (Emerson et al., 2012), sensitivity to grades (Rask and Tiefenthaler, 2008; Goldin, 2013; Kugler et al., 2017), taste for the subject matter (Dynan and Rouse, 1997; Wiswall and Zafar, 2014)[6] and preferences over different job attributes, which are linked to different majors (Wiswall and Zafar, 2016).[7] Moreover, in a recent study, Reuben et al. (2015) identify a robust link between gender differences in students' overconfidence and competitiveness and their expectations of future earnings, which in turn are likely to affect the choice of major.[8]

In this paper, we depart from the above studies and ask whether the gender imbalance observed in

[1] For a review of the evolution of female participation in tertiary education in the US, see Goldin et al. (2006).

[2] About 47% of business degrees, 46% of natural sciences degrees and 43% of math degrees and 39% of physical science degrees are currently awarded by women. See: https://nces.ed.gov/programs/digest/current_tables.asp

[3] Engineering and computer science are also lagging noticeably behind, with only 19% and 18% of degrees conferred to women in 2013 (NSF, Science & Engineering Indicators, 2016).

[4] Using recent census data, Carnevale and Cheah (2015) also report that the median salary of an experienced worker, aged 30 to 54 years of age, who majored in economics is the highest in the social sciences and the thirteen highest among all majors.

[5] Carroll et al. (2014), for instance, estimate that women with an economics major bachelor degree earn 20.1 percent more than women with other majors.

[6] For a review of the literature, see Allgood et al. (2015) and Bayer and Rouse (2016).

[7] The authors found that men prioritize earnings prospects while women tend to favor jobs that provide flexibility and job stability.

[8] For evidence on gender differences in competitiveness, see the seminal study by Niederle and Vesterlund (2007).

certain fields of study may be partly due to a lack of female role models. Specifically, we employ a field experiment to test whether exposure to carefully selected female role models may be an effective way to induce more women to major in a male-dominated field. We focus on economics, although our methodology could be easily applied to other fields of study.

Theoretically, the importance of mentoring, broadly defined as information-sharing, career advice and informal teaching, has been studied by Athey et al. (2000), which employs a model with different types of employees (e.g., male and female) within an organization under the assumption of type-based mentoring, whereby upper-level employees of one type – say women – would mentor lower-level employees of the same type. The model shows that increasing the number of upper-level employees of the minority type – e.g., women – may have long-run benefits due to advantageous mentoring of low-level employees of the same type. The empirical evidence of the effects of role models and/or mentorship programs on individual behaviors and outcomes is scarce. A recent study by Lyle and Smith (2014) exploits the random nature of junior officers' assignments to senior officer mentors within the US Army to provide evidence of the causal impact of high quality mentorship on career advancements. Using a similar identification strategy, Kofoed et al. (2017) find evidence of a significant impact of mentorship by a female rather than a male officer on the occupational preferences of female cadets at the United States Military Academy at West Point. In academia, Blau et al. (2010) assess the impact of a mentoring program in economics that randomly assigned applicants – all junior female faculty – to either a control group or a treatment group that received mentorship from a senior female faculty; the program was successful in increasing the number of publications of junior female faculty and the number of grants awarded to them.[9] [10]

Could female role models induce more women to major in a male-dominated field? A number of studies have attempted to address this question by examining the effect of female professors on female students' decision to major in a given field, showing mixed results (see for example Bettinger and Long (2005); Canes and Rosen (1995); Dynan and Rouse (1997); Hoffmann and Oreopoulos (2009); Rask and Bailey (2002)).[11] A limitation of these studies lies in the students' ability to self-select into classes and therefore choose their professors; this creates important challenges for the identification of the causal impact of the gender (or other characteristics) of the instructor on students' choice of major. Three recent studies overcome these challenges by examining contexts where students are randomly assigned to instructors. Lim and Meer (2017a) exploit the random assignment of students to classrooms in Korean middle schools and show that female students perform better in standardized test scores when they are matched with female instructors. In a follow-up paper, Lim and Meer (2017b) find that female students that are matched with female math teachers in 7th grade are more likely to take advanced math courses in high school, to attend a STEM-focused high school and to plan to major in STEM. Carrell et al. (2010) exploit the randomized assignment of instructors of mandatory standardized courses to students at the US Air Force Academy. They find that the proportion of introductory courses taught by female professors significantly increased the likelihood that top female students, as measured by their SAT math score, would complete a STEM major.[12]

[9] On the other hand, Gardecki and Neumark (1998) find no evidence of the gender of the Chair of the department and the number of female faculty on job outcomes of female PhD students in economics.

[10] Another important study providing evidence of the importance of female role models in a different setting, is Beaman et al. (2012), who examine the impact that an increase in the presence of women in government councils had on the educational attainment of girls in India. The results show that continuous exposure to female leaders significantly affected the aspirations of young women and eliminated the gender gap in educational attainment among adolescents.

[11] For a review, see Allgood et al. (2015) and Bayer and Rouse (2016).

[12] The authors then examine unobservable differences between male and female professors by estimating a professor-specific "value-added" for male and female students. While the value-added is correlated with professor gender, it does not predict long term outcomes, leaving open questions on what exactly is the main driver of the estimated impact of female professors

All existing studies, including Lim and Meer (2017a,b) and Carrell et al. (2010), implicitly assume that a professor could act and be perceived by a student as a role model based purely on gender matching. We adopt a different approach. We define *female role models* as women that could inspire female students to make their same education choices in order to have a similar career path. From this perspective, female professors would act as role models to female students only if they inspired them to imitate their career choices, i.e., if they induced them to become university professors. In other words, while gender matching is likely to be important, and possibly necessary, it may not be sufficient for the identification of a role model that could successfully induce women to choose a male-dominated major.[13] In this paper, we employ a novel methodology to identify female role models in the field of economics. We enlisted two female students currently majoring in economics and, with their help, we shortlisted economics alumnae on the basis of the students' interests in their current sectors of work. We then contacted the shortlisted alumnae and invited them to be interviewed via Skype. The students conducted scripted interviews with the finalists that agreed to be interviewed, and chose the best two on the basis of their assessment of the alumnae's jobs, communication skills and overall charisma.

We employed a field experiment to examine the impact that these carefully selected role models might have on young women's decisions to major in economics. In particular, we randomly selected principles of economics classes – which are typically large and gender balanced – to receive visits by each of the two role models in the 2016 Spring semester. Each visit consisted of a discussion about the role model's experience as an economics major, a description of their career paths and achievements, and an explanation of how their specific major (economics) contributed to their success on the job.

Since treatment and control classes existed and were taught by the same instructors also the year preceding the intervention (Spring 2015), we are able to employ a difference-in-differences estimation strategy to assess the impact of the role model visits on male and female students' interest in the economics major. We have two outcome variables: actual enrollment in an intermediate economics class either the semester or the year following the intervention, and self-stated intention to major in economics, as registered through a survey conducted at the end of the semester in both Spring 2016 and Spring 2015.

Our results show that the role model intervention had a significant and large impact on both outcomes for female students, while having no impact on male students. Being in a class that received the role model visits increased the likelihood that a female student would take an intermediate microeconomics class the following academic year by 12 percentage points, and the likelihood that she would express the intention to major in economics by 7.8 points. This corresponds to a 100 percent increase in both variables. Similarly to Carrell et al. (2010), the effect of the intervention is especially large for top female students, defined as those who have a cumulative GPA of 3.7 or higher; they see a 26 percentage point increase in the likelihood of enrolling in intermediate micro the following year and a 12 percentage point increase in expressing a desire to major in economics.

Our survey data also allows us to examine which fields of study the intervention is more likely to have attracted female students from. This is important, since, if we were pulling women away from other male-dominated fields also leading to high-paying jobs – e.g., STEM – our intervention would possibly be

on top female students' choices and behavior.

[13] A few studies in social psychology have also investigated the impact that role models may have on female students' attitudes toward male-dominated fields. For instance, Stout et al. (2011) conducted experiments where math or STEM majors are either exposed to confederates posing as math majors (study 1) or are asked to read biographies of female versus male engineers (study 2). The outcome variables are students' subsequent answers to Implicit Association Tests aimed at measuring implicit attitudes toward math or STEM, as well as direct elicitation of such attitudes.

counter-productive, as it would diminish gender diversity in other male-dominated fields and possibly also lower the earnings potential of our target population. Our data suggests that the role model intervention did not affect the intentions of women planning to major in male-dominated fields leading to high wages, including STEM, business and finance. Instead, the intervention significantly lowered the percentage of women planning to major in humanities or languages. This suggests that the economic impact of our role model intervention may be significant, as the future wages of our target population could be substantially larger as a result.

Overall, our study provides strong evidence of the impact of female role models on women's self-selection into fields of study in which men are traditionally overrepresented. What makes the study unique is the use of a controlled field experiment, which allows clear identification of the impact of the role models, and the novel methodology employed to identify such role models, which crucially relied on the opinions of current female students. Lastly, the simplicity of the design makes our intervention easily replicable (in economics as well as in other male-dominated fields) and suggests that the long-term goal of moving towards gender parity in the economics profession at all levels could be achieved at a relatively low cost by exposing students enrolled in principle classes to successful and inspiring alumnae.

The paper is organized as follows. In Section 2 we describe the field experiment and the university setting in which it was implemented. In Section 3, we describe our data and present our empirical strategy. Section 4 describes our results and Section 5 conducts robustness checks. Finally, Section 6 concludes.

2 Experimental Design

As part of the study, we conducted: 1) a survey of students enrolled in principles of economics classes in Spring 2015 and Spring 2016; 2) a field experiment consisting in randomly selecting 4 of the 10 principles of economics classes offered in Spring 2016 to receive visits by two carefully chosen role models. In order to estimate the impact of the role model visits on female students' interest in economics, we also collected administrative data on students' enrollment in intermediate economics classes the year following the intervention (or following the survey). In this section, we start by describing the university setting where the experiment took place (Section 2.1). We then provide details about our field experiment and study procedures (Section 2.2). We conclude by describing our estimation strategy (Section 2.3).

2.1 The University Setting

We conducted our study at Southern Methodist University (SMU). Although SMU is a small private university,[14] the number of students majoring in economics every year, averaging 166 between 2009 and 2015, is comparable to that of larger universities and is in line with the average number of economics majors across the top 100 US universities (Goldin, 2015).[15]

SMU operates over two semesters: a Fall semester, starting in August and ending in December, and a Spring semester, starting in January and ending in May. Our study involves students enrolled in principles

[14]SMU is located in Dallas, Texas. In the latest (2017) university ranking provided by the US News and World Report, SMU appears ranked 56th in the nation, same as the University of Texas-Austin and George Washington University. In 2015, SMU had a total of 11,739 students. For additional information about SMU, see: http://www.smu.edu/AboutSMU/Facts

[15]See: https://scholar.harvard.edu/files/goldin/files/planninggroup_data_notes_0.pdf

of economics classes in either Spring 2015 or Spring 2016.[16] Principles of economics classes are especially popular at SMU, with over 600 students enrolled and multiple classes – or sections – being offered every semester. Crucially, these classes are typically gender balanced, with women making up between 44 and 47 percent of the enrolled students in the past 6 academic years.[17] In contrast, intermediate economics classes – for which principles classes are a prerequisite – are gender imbalanced, with only about 26% of the enrolled students being women (2009-2015 average). The gender imbalance remains and even worsens by the time of graduation, with less than one fourth of economics degrees being awarded to women, the average being 21% in the last 6 years. This is below the national average of 30% (Bayer and Rouse, 2016). Using Goldin (2015)'s conversion ratio, which is the ratio of the percentage of men majoring in economics to the percentage of women majoring in economics in a given university, SMU has a score of 4.493 (2011-2013 average), meaning that there are more than 4 men for every woman majoring in economics. This is substantially higher than the average for the top 100 US universities computed for the same time period, which is equal to 3.

The above statistics make SMU the ideal setting for a study aimed at increasing the percentage of women majoring in economics. Below, we provide details on our experimental design and empirical strategy.

2.2 The Field Experiment

The study started in Spring 2015, when we surveyed all students taking principles of economics classes. There were 11 classes being offered and taught by seven instructors, four women and three men, at different days and times of the week.[18] Students could enroll in any of the available classes following a first come first serve rule. A total of 722 students took a principles class in Spring 2015. We conducted our survey in the last week of classes at the end of April 2015, involving a total of 549 students.[19] We collected demographic characteristics and, most importantly, we asked students to state their intended major. We conducted an identical survey the following year, at the end of April, with the 2016 Spring cohort.

The same classes, with two exceptions, where offered in Spring 2016. A total of 688 students were enrolled in a principles class that semester; we have survey data for 503 of them.[20] Out of the 10 available classes, taught by 8 instructors,[21] we randomly selected 4 to be our treatment classes. The randomization was stratified by class size, as there were 4 small classes (i.e., capped at 40 students) and 6 large classes (i.e., of 100 or more students) being offered. We randomly selected one small class and three large classes to receive the role model intervention. Our overall objective was to have a balanced number of students in the 2016 treatment and control classes. Note that our randomization also defined treatment and control classes in Spring 2015, even though the treatment classes were treated only in 2016. The fact that treatment

[16]SMU also has two 4-week long Summer terms, in June and July. Classes held during the summer are very different than standard classes, as they take place daily and they are typically very small (i.e., less than 20 students). The student population taking summer classes is also quite different, i.e., typically older and in need of credit hours, e.g., in order to graduate by an imminent date. Given these differences between summer classes and regular classes, we exclude summer classes from our analysis.

[17]One reason for the high number of students taking the principles classes is the presence of a Business School, which requires prospective students to take such classes.

[18]Three instructors taught two classes each.

[19]The survey was conducted during class time. Therefore, we have data only on the students that were present the day of the survey (76%).

[20]Again, participation in the survey was conditional on class attendance.

[21]Two instructors taught two classes each. One instructor who taught two classes in 2015 only taught one class in 2016, hence the number of classes being 10 rather than 11 in Spring 2016. One control class changed instructor and weekly schedule in 2016. In Section 5, we conduct robustness checks of our main findings by dropping the classes that changed between the two years.

and control classes existed the year prior the intervention allows us to employ a difference-in-differences estimation strategy, as discussed in Section 2.3.

The most crucial feature of our design is the identification of role models that could inspire female students enrolled in principle classes to keep studying economics and eventually graduate with an economics degree. We identified such role models during the Fall 2015 semester with the help of two undergraduate female students currently majoring in economics. We first obtained the list of economics alumni who graduated between 1985 and 2010 and then preceded to shortlist 18 role model candidates based purely on the students' interest in the alumni's sector of work and current job. We contacted the shortlisted candidates via email asking for their availability and willingness to be interviewed via Skype by our female students. The email did not mention the specific aim of the study; it only stated that the economics department had shortlisted 18 especially inspiring alumni[22] and we aimed to gather some additional information about their current position, as well as their previous jobs and their experience as an economics student at SMU.[23]

Seven alumni replied expressing their availability for and interest in the Skype interview. The Skype (scripted) interviews were conducted by our two female students, which then proceeded to select our final two role models based on their impressions on the candidates' jobs, their appreciation for the field of economics, and, crucially, their communication skills and overall charisma. One role model graduated in 2008 and started her career by working in management consulting for two years. She had then decided to completely change her career path by going to work for an international NGO in Nicaragua, and then as a director of operations at a toy company based in Honduras. She now works in Operations at a fast-growing candy retail company. The second role model graduated in 1991 and has had a stellar career in marketing, becoming the senior director of North American Marketing & Information Technology at a large international communications company. While the two role models work in very different sectors, what they have in common is that their jobs are not stereotypically associated with the economics major.

We formally invited each role model to visit SMU in Spring 2016. Both role models gladly accepted our invitation and independently visited four principles of economics classes – our treatment classes – between March and April 2016.[24] The purpose of the visit was to talk about their experiences as economics majors, their career choices and their current jobs. More importantly, we asked them to discuss how majoring in economics helped them succeed in their careers. We also emphasized that it was important to try and involve students in the discussion (e.g. welcoming their questions) as much as possible. We did not inform the role models about the objective of the research study and therefore they did not know that we intended to examine the impact that their visit would have on female students' decision to continue studying economics. As a result, the speeches to the classes were gender-neutral, i.e., no gender-specific issues were discussed. This allows us to examine whether the women were perceived as role models by female students more than by male students not due to the content of the discussion being "female-oriented" but rather the fact that their gender, their jobs and their personal experiences were, by design, more inspiring to females than males.

It is important to note that the two role models chosen happened to both be female, as these two were the most inspiring to the undergraduate female students that assisted us in the role model selection process.[25] Ideally, we would have liked to also include a treatment that exposed students to two "identical"

[22] We did not restrict the selection to females. Therefore, we initially shortlisted 9 women and 10 men.

[23] The specific content of the email is available upon request.

[24] The first role model visited each class on March 21st or 22nd, depending on the class schedule. The second role model visited each class on April 6th or April 7th.

[25] The initial shortlist did include males, and three men made it to the Skype interviews but were ultimately not chosen by

male role models in order to disentangle the role of gender matching from the role of information about the two specific career paths chosen by our female role models. However, even if we had a sample size large enough to include an additional set of treatment classes in our study (which we did not), it would have been impossible to find male "clones" of our female role models, i.e., two men with same career profiles, comparable levels of charisma and other individual characteristics to create the perfect comparison group.

2.3 Empirical Strategy

As outlined above, the treatment took place at the class level in 2016, yet the treatment and control classes also existed in 2015. Since class attendance was not mandatory the days of the role model visits, we estimate the intent-to-treat effects of the intervention using equation 1 below,

$$Y_i = \beta_0 + \beta_1 dt_i + \beta_2 dT_i + \beta_3 dt_i * dT_i + \delta \mathbf{X}_i + u_i \tag{1}$$

where Y_i is our proxy for student i's interest in the economics major; dt is a dummy equal to 1 if the student took the class in 2016 and 0 if he or she took a class in 2015; dT is a dummy equal to 1 if the student is in a treatment class and 0 if he or she is in a control class. The interaction between these two dummies is our coefficient of interest.

Naturally, given the small number of classes in the randomization (and that students can self-select into classes) achieving balance was unlikely. Hence we include X, a vector of demographic controls, to account for slight differences seen in our balance tests (see below for further discussion).

Our ideal outcome variable is a student's decision to major in economics. However, at SMU, students can declare their major at any time after having completed 30 credit hours (in any field). There is no deadline for declaring a major; thus, students can choose their major at any time, up to their final semester at SMU. This implies that having the decision to major in economics as our outcome variable would require waiting three more years to be able to estimate the impact of the intervention. Instead, we examine the effect of our treatment on three outcome variables that are meaningful proxies for a student's interest in the economics major. First, we look at whether the student enrolled in Intermediate Microeconomics (ECO 3301) the following Fall. Second, we examine whether the student enrolled in Intermediate Microeconomics the following academic year, either in Fall or Spring. Third, we employ a dummy equal to 1 if the student self-reported (in our survey) his or her intention to major in economics. In Section 3, we provide evidence that these variables are a good indication of a student's majoring decision. Given the dichotomous nature of our dependent variables, we estimate equation 1 using probit regressions.

As students in the same class face the same stimuli, i.e., they have the same instructor, same economics textbook, homework assignments and other course requirements, we cluster the standard errors at the class level.[26] Since there are fewer than 30 clusters (21 clusters), we follow Angrist and Pischke (2008) and Cameron and Miller (2015) and apply the correction for the small number of clusters by using wild score bootstrapping (Kline et al., 2012), which is appropriate for nonlinear models.[27]

the two female students that conducted the scripted interviews.

[26] In our robustness section, we also employ class-level fixed effects, while restricting the analysis to the 9 classes that did not change between 2015 and 2016.

[27] Note that linear probability model with Wild Bootstrapped standard errors give extremely similar results.

3 Results

3.1 A first look at the data

A total of 1410 students took a principle of economics class in either Spring 2015 (722) or Spring 2016 (688). Of them, 45% (632) were women. Of the Spring 2016 cohort, 49% (340) of the students were in a class which was treated, i.e. visited by the role models. While the gender compositions of the treatment and control classes in 2015 are not significantly different from each other, with 46% and 44% of students being women, respectively, in 2016 the treatment classes had significantly fewer women enrolled than the control classes (38% versus 51%, p-value of 0.001).

In Table 1, we report descriptive statistics and conduct balance tests using the administrative data. In particular, we have information about the students' in-state or out-of-state status, their year of study, e.g. whether they are freshmen, their cumulative GPA, whether they are American or international students, and the grades they obtained in their principles class. Additionally, we note whether they attended a principle class taught by a female professor. In the survey, we collected additional information on our students, i.e., whether they belong to a fraternity or a sorority, whether they are athletes and whether they took an economics class in high school. In the appendix we report additional balance tests for the subsample of our students for which we have survey data.[28]

Testing for significant differences in student characteristics between control and treatment classes in 2016, on both the male and female student samples, shows some significant differences, as might be expected given the small number of classes from which we were able to randomize our treatment and control sets of students. In particular, we see that there are significantly fewer American students in the female treatment group, as well as more freshmen and fewer students in a class with a female professor. Moreover, in both the male and female samples the cumulative GPA of students enrolled in treatment classes is slightly lower. Consequently, the grades obtained in the principles classes by the treated students are also significantly lower, both for male and female students.[29] We take these imbalances into account in our empirical analysis in Section 3, where we include student characteristics in our set of controls; we also conduct robustness checks by restricting the analysis to American students only. Finally, following Carrell et al. (2010), we also estimate treatment effects separately for the top performing female students.

3.2 Impact on Enrollment in Intermediate Microeconomics

Intermediate Microeconomics is a prerequisite for upper level economics classes. Therefore, if a student wants to major in economics, he or she needs to take this class, the sooner the better. In order to assess the validity of using enrollment in Intermediate Microeconomics as a proxy for interest in the economics major, we examined administrative data on students who took Principles of Economics in the Spring semesters of 2008 or 2009 and completed their degree by Fall 2014. About 80% of the 2008 and 2009 cohorts who

[28]We do not see any significant differences in the survey-based individual characteristics between treatment and control classes for the female sample. The same is true for the male sample with the exception of the percentage of students that took economics in high school, which is lower for the treatment group in 2015.

[29]Previous research (Goldin, 2013; Rask and Tiefenthaler, 2008) suggests that women may be especially sensitive to their grades, i.e., their decision to pursue a given major may be conditional on obtaining a high grade in introductory courses, and they may be especially responsive to female instructors. If this is true, the lower average grades and the lower proportion of female students being taught by female professors in the treatment classes would work against us finding a positive impact of the role model intervention on female students' decision to pursue further studies in economics. In other words, if we do find a positive impact of the intervention, it would be despite the fact that the treated female students were less likely to be taught by a female instructor and less likely to earn a high grade in the class.

majored in Economics took the Intermediate class the year following their Principles class, and 44% in the Fall semester following Principles. This compares to 21 and 15%, respectively, of students who were in the same principles classes and did not major in Economics (differences significant at the 1 percent level).[30] This confirms that enrollment in Intermediate Microeconomics is indicative of a student's intention to major in economics.

Figure 1 and the top panel of Table 2 show the percentages of male and female students who took an Intermediate Microeconomics class the semester immediately following their Principles class, i.e. Fall 2015 for the 2015 cohort and Fall 2016 for the 2016 cohort. Since about 7% of students failed the principles class, we exclude them from our sample, as they would not be eligible to take an intermediate economics class the following semester. This leaves us with 1310 students, of which 46% (601) are women. Table 2 also reports the p-values generated by Chi square tests aimed at identifying either differences between treatment and control in a given year, or gender differences within treatment and control classes in 2015 or 2016.

Around 12% of men enrolled in an Intermediate Microeconomics class in the Fall following the spring semester in which they took a principles class. This proportion is the same across the treatment and control classes and the two years. In 2015, the proportion of women who enrolled in Intermediate Microeconomics in the Fall is just below 7%, and is the same across treatment and control groups. In 2016, the proportion in the untreated classes fell to 4.7%, whereas over 11% of women in the treated classes had enrolled; this difference is significant at the 5 percent level ($p = 0.031$).

Naturally a higher number of students enroll in Intermediate Microeconomics within a year of taking the Principles class, as shown in Figure 2 and in the bottom panel of Table 2. For men, the proportion is approximately 25% with some variation across years and classes, albeit not statistically significant. For women, the average is significantly lower for all the untreated classes. In particular, while about 13% of female students enrolled in Intermediate Micro in 2015, with no statistically significant difference between treatment and control classes, the percentage of women in the 2016 treatment classes who took Intermediate Micro within a year is significantly higher. At 18.85% this is considerably higher than the percentage of women in the 2016 control classes (about 11%).

Next, we present results from the regression analysis, which allows us to examine the effects of the role model intervention on male and female students by conducting difference-in-differences estimation, as explained in Section 2.3. Table 3 shows the probit results when the dependent variable is a dummy equal to 1 if the student took the Intermediate class in the Fall semester directly following their Principles class, and 0 otherwise. We analyze men and women separately. In the first and third columns, we employ our most parsimonious specification, which only includes the 2016 year dummy, the treatment class dummy and the interaction between the two. In the second and fourth columns, we include the controls obtained form administrative data. For all specifications we report both the p-values obtained when clustering the standard error at the class level (in parentheses) and the p-values obtained when implementing the wild score bootstrapping (Kline et al., 2012) correction for the small number of clusters (in square brackets).

The estimates displayed in the first two columns of Table 3 show that the role model intervention had no effect on men's decisions to enroll in Intermediate Micro the following semester. In contrast, we find strong evidence that the intervention had a positive and significant effect women's enrollment rates,

[30] We also looked at the percentage of students who took Intermediate Micro the year following their principles class and decided to major in economics. The 2008 and 2009 cohort data show that 53% of the students that took Intermediate Microeconomics the year following their Spring Principles class ended up majoring in economics, as compared to 7% of those who did not (the difference is significant at the 1 percent level).

when controlling for student characteristics and gender of the instructor. Interpreting the interaction term in a probit model is not straightforward. Norton et al. (2004) show this is the case for all non-linear models. Importantly, they show that the marginal effect of the interaction term may not be the same as the coefficient (β_3 in our case), and further that the standard t-test is inaccurate. We therefore use the methodology introduced by Norton et al. (2004) to calculate the marginal effect of the interaction term. For the male students, we can confirm that there is no significant effect. For female students the interaction is significant ($z = 2.022$), and the mean is 0.093, which we interpret as a nine percentage point increase in enrollment rate caused by the role model intervention.[31] Another noticeable result is that having a female professor and getting a high grade in the class had both a positive significant impact on women's enrollment decisions, while having no significant impact on men's decisions, which confirms the findings of previous studies (Bettinger and Long, 2005; Carrell et al., 2010).[32]

Table 4 replicates the analysis by employing as the dependent variable the students' decisions to enroll in Intermediate Microeconomics the academic year, i.e., either in Fall or Spring, following the semester in which they took the Principles class. The estimates show a similar pattern to those in Table 3. Columns 1 and 2 show that while male students in the 2015 treatment classes have higher enrollment rates than students in control classes the same year, the role model intervention had no impact on enrollment decisions. In contrast, columns 3 and 4 show that the intervention has a significant impact on female students' decision to enroll in Intermediate Micro the year following their Principles class. The marginal effect of the intervention for females is 0.12 in column 4 (significant at the 5 percent level), which is even higher than the estimated impact on enrollment in the Fall following the Principles class. This is quite a considerable effect, considering that the average baseline enrollment rate is about 12%. In fact, our estimates suggest that the role model intervention doubled the percentage of female students taking Intermediate Micro the academic year following their enrollment in a Principles class.[33]

3.3 Impact on Intention to Major in Economics

The analysis of self stated intention to major in economics is restricted to the students that were present the day we conducted the in-class survey, i.e. 549 students (77%) in 2015 and 503 (73%) in 2016.[34] As part of our survey, we asked students enrolled in Principles classes to state their intended major. In the self-administered questionnaire, they could write down up to two desired majors. Here, our outcome variable is a dummy equal to 1 if the student listed economics as one of their intended majors, and 0 otherwise.

One concern may be that students may have over-reported their intention to major in economics, given that the survey was not anonymous and it was conducted during an economics class, under the supervision

[31] Note that when we compute marginal effects of interaction terms, we cannot apply the wild score bootstrapping. However, since wild score bootstrapping does not affect the point estimates and we have found little difference between the corrected and uncorrected p-values, we do not see this as a problem.

[32] Though note that Bettiger and Long (2005) did not find positive effects of female instructor for the field of economics; rather for Maths, Geology, Education and Psychology.

[33] Getting a high grade in the class still has a positive significant impact on women's enrollment decisions. The negative impact of cumulative GPA on both male and female students' likelihood to enroll in intermediate microeconomics may reflect the decision of top students to enroll in the SMU Business School after taking the principles classes. In fact, both taking the princpes classes and obtaining a GPA of 3.3 or higher are a requirement for acceptance into the SMU Business School.

[34] When testing for selection into the survey, we see no significant difference between the proportion of treated and untreated students entering the surveyed sub-sample. Females were however more likely to be present the day of the survey, and those surveyed were more likely to have a female instructor. Students who were present in class were (reassuringly for the instructors) more likely to get a high grade - defined as greater than a B – in the class. Since the survey was unannounced by the class instructor, we can assume that attendance the day of the survey is a good indication of average attendance during the semester. When restricting the sample to the surveyed subjects, we see no significant difference between treatment and control classes in their gender composition.

of their economics instructor. The bias may be even larger for the treatment classes, since, during their visits, the role models emphasized the importance of the economics major.[35]

One way to address these concerns is to examine the correlation between self-reported intention to major in economics and subsequent enrollment in further economics classes – a more objective measure of actual interest in the economics field. We find that intention to major in economics is a strong and significant predictor of male and female students' decision to enroll in Intermediate Microeconomics the following semester or the following academic year. In particular, probit regressions show that men and women that stated their intention to major in economics in the survey are, respectively, about 41 and 61 percentage points more likely to enroll in Intermediate Microeconomics the following semester.

Table 5 and Figure 3 show the percentages of male and female students enrolled in treatment and control classes in 2015 and 2016 who stated their intention to major in economics.

For the three untreated class groups the proportion of men planning to major in economics is significantly higher (about 17% on average) than that of women (around 7%). Moreover, there are no differences between treatment and control classes, both in 2015 and 2016, with respect to men students' plans to major in economics. The same applies to female students enrolled in the 2015 control and treatment classes. In contrast, the classes that received the role model intervention saw a higher proportion of women planning to major in economics (11.93%) as compared to the women in the control classes (6.98%). Although the difference is not statistically significant, the increase in the percentage of women interested in the economics major – caused by the role model intervention – seems to have annulled the gender gap observed in all the other class groups.

In Table 6 we employ the same specifications as in Tables 3 and 4. The dependent variable is now a dummy equal to 1 if the student listed economics as his or her intended major, and 0 otherwise. Mirroring the enrollment results, we find no significant effect of the role model intervention on male students. However, we do find a significant impact on female students, when controlling for student characteristics (column 4). When we compute the marginal effect of the treatment on women we find that the role model visits increased the percentage of female students wishing to major in economics by 7.8 percentage points.[36] This suggests that the impact of the intervention was, once again, large, given that the baseline percentage of women interested in economics is about 7%. We note also that, in accordance to the results shown in Table 3, and in line with the findings of other studies, having a female instructor seems to have a significant and positive correlation with majoring intention, as does getting a high grade in the Principles class.

3.4 Impact on top students

An important finding of Carrell et al. (2010) is that female instructors had a significant impact on the majoring decision only of top female students. In fact, Carrell et al. (2010) find that, for the highest ability women, having exclusively female introductory math and science professors increased the likelihood of majoring in STEM by 26 percentage points as compared to being assigned exclusively to male faculty. Following Carrell et al. (2010), in this section we investigate whether the role model intervention was especially impactful on female students that have a cumulative GPA $\geqslant 3.7$. About 30% of all female students belong to the top student category with no significant differences across years and treatment and

[35]We limited this possibility by making sure that the role model visits took place 3 to 5 weeks before the administration of the survey.

[36]We use the methodology introduced by Norton et al. (2004) to calculate the marginal effect of the interaction term, as above.

control classes.

In Table 7, we replicate the analyses conducted in Tables 4, 5 and 6 while restricting the sample to the top female students. The results are striking: the marginal effect of the role model intervention on the intent to major in economics is 12 percentage points ($z = 2.07$); it is 24 percentage points on enrollment in Intermediate Microeconomics the following Fall ($z = 2.22$), and 26 percentage points on enrollment in Intermediate Microeconomics the following academic year ($z = 2.36$). These percentage point increases resemble very closely those found by Carrell et al. (2010).

Figure A1 in the Appendix also shows the enrollment rates of top male students in control and treatment classes in both 2015 and 2016.[37] It appears that 2016 saw a significant decline in top male students enrolling in Intermediate Micro, in both treatment and control classes. We conclude that our intervention was not the cause, as the decline is not significantly different between control and treatment classes.

3.5 Where are we attracting female students from?

Overall, our empirical estimates show that the role model intervention had a positive, significant and sizeable impact on female students' interest in the field of economics. The impact was especially large for top female students. While we believe that achieving gender balance in a male dominated field like economics should be seen as a goal in itself, role model interventions like ours would be especially desirable if they could positively affect the earnings potential of female students that would otherwise major in a field conducive to lower incomes than their male counterpart. Conversely, having an intervention that attracted toward economics female students that would have otherwise majored in another male-dominated high-earnings field (e.g. finance or STEM), may be counter-productive in terms of its overall economic impact.

Here we use data from our survey to identify the fields of study that saw a reduction in female students' interest as a result of our intervention. Based on students' open-ended answers to our question on their desired majors – note that they could enter up to two – we generate a series of 0-1 dummies associated with their interest in majoring in different fields of study. We distinguish between high-earning majors, defined as STEM, finance, business and marketing, and low-earning majors, defined as other social sciences (e.g., psychology, anthropology and political science), arts, communication studies, and humanities and languages.

Figures 4 and 5 display the percentage of male and female students, in control and treatment classes in 2015 and 2016, stating each field of study, grouped in either the high-earning or the low-earning category, as one of their desired majors (or the only desired one). Figure 4 shows that the role model intervention did not cause a decline in women's (or men's) interest in any of the high-earning majors. Figure 5 suggests that the role model intervention reduced the percentage of women interested in humanities and languages majors.

This is confirmed by probit regressions, displayed in Table 8, where the dependent variable is a dummy equal to 1 if the student expressed the desire to major in humanities or languages and 0 otherwise. The estimates in columns 3 and 4 suggest that the role model visits significantly reduced the likelihood that female students expressed an interest in humanities or languages majors, while having no significant impact

[37] In both years and no matter the type of class (treatment or control), male students have a significantly lower cumulative GPA than female students. In order to make the sample of top male students comparable in size to that of top female students, we define top male students as those with a cumulative GPA of 3.52 or higher. This corresponds to 30 percent of the male student sample.

on men. The marginal effects are 11 and 12 percentage points respectively for the interaction terms in columns (3) and (4).

3.6 Female student performance in Intermediate Microeconomics

An important follow up question is whether the performance of the treated female students in the intermediate economics classes is in any way different than that of the untreated students. If we had attracted female economics students that are unlikely to do well in this field, we would see a decline in the average performance of female students that were in the treated principles classes as compared to those in the control classes. This would be less than optimal for two reasons. First, the intervention would have possibly contributed to a misallocation of talents, where individuals pursuing a given major are not those that have a comparative advantage in it, as discussed in Hsieh et al. (2013). Second, if the female students that enrolled in intermediate economics classes as a result of the intervention were to perform less well as others, they would be less likely to enroll in upper level economics classes and ultimately major in economics.[38] This implies that the role model intervention would have only a short term impact on female students' choices and behaviors.

The analysis of the average grades obtained in treatment versus control classes in both 2015 and 2016, displayed in Table 9, shows that treated women achieved higher grades on average than those that were enrolled in control principles classes, although the difference is not statistically significant. Besides reporting average grades obtained in Intermediate Micro, Table 9 also displays the average scores obtained in a Core Exam, which all the students enrolled in Intermediate Microeconomics need to take toward the end of the semester. This exam provides a more objective measure of student performance, as it is prepared and administered by the economics department rather than the students' instructors, and it is the same for all the students enrolled in an Intermediate Microeconomics class in a given semester.[39] Descriptives on students' performance in the Core Exam confirm that the treated female students performed equally, if not better, than the control female students.

4 Robustness Checks

4.1 Treatment Effects on the American students

As discussed in Section 3.1, there were some imbalances in the percentage of American versus foreign female students enrolled in control versus treatment classes in 2016. In particular, the treatment classes have a significantly lower percentage of American students. If foreign female students are more likely to pursue economics studies than domestic students, which is the case in our sample,[40] our treatment effects could

[38] This is especially true given the empirical evidence on women's sensitivity to course grades (Goldin, 2013; Rask and Tiefenthaler, 2008).

[39] In Fall 2015, there were 5 classes of ECO 3301 being offered, taught by 4 instructors. In Fall 2016, there were 4 classes being offered, taught by 3 professors. Of these 4 classes, 3 were the same as in Fall 2015. In Spring 2016 and Spring 2017, there were 4 classes offered, each taught by a different professor. Two classes were identical between the 2 years. Comparing the two academic years, in 2015-2016, 328 students were able to take Intermediate Micro, versus 304 in 2016-2017. Note that it is the department of Economics, not student demand, that decides the number of classes being offered every semester. The decision is made based on funding, instructor availability and classroom constraints. A t-test of class size between treated and control students showed no significant differences.

[40] In our overall sample, across the two years, 18% of foreign female students versus 7% of American female students stated the desire to major in economics in our survey ($p = 0.018$). The difference in the preferences of foreign and domestic students holds also for men, with 31% of foreign male students interested in the economics major versus 15% of American students ($p = 0.007$).

simply be a reflection of the different compositions of the female student body in control versus treatment classes. In this section, we check whether this is the case by first including an American dummy in our empirical specification, and then by estimating the treatment effects on American female students only (Table 10).

The estimates in the first column of Table 10 show that controlling for the American dummy does lower the statistical significance of our treatment effect on the self-stated intention to major in economics. The estimated impacts of the treatment on enrollment in intermediate micro in the following fall or year, however, remain statistically significant, and are very similar in magnitude to those observed in Tables 3 and 4. As an additional robustness check, in columns 4-6 , we test whether the American female students, in particular, were affected by our role model interventions. We found that they were. Our estimates suggest that the American female students that were in a treated principles class in 2016 are about 7 percentage points more likely to express an interest for the economics major, 9 percentage points more likely to enroll in intermediate micro the following fall and 10 percentage points more likely to enroll in intermediate micro within a year.

4.2 Excluding the two control classes that changed in 2016

As mentioned in Section 2.2, 11 principles classes were offered in Spring 2015 versus 10 in Spring 2016. Between the two years, two control classes changed. One class that was offered in 2015 was not offered in 2016, whereas another class changed instructor and time schedule. In this section, we check whether our main findings are robust to dropping these classes from the empirical analysis.

In Table 11, we replicate the analysis reported in Tables 3 to 5. The estimates show that our results are robust to restricting the sample to the 9 principles classes that did not change instructor or teaching schedule between 2015 and 2016. Not only is our coefficient of interest statistically significant in columns 2, 4 and 6, but the point estimates are also very close to those obtained in Tables 3 to 5. We repeat this check for the top female students in table A2 in the Annex, again the main results are robust to dropping the control classes that changed between the two years.

Finally, we include class fixed effects in a robustness check for the classes that did not change, reported in table 12. Even though the sample size is naturally smaller, the main results concerning student enrollment in intermediate micro the semester or the year following the intervention are robust to the inclusion of class fixed effects. The results concerning self-reported plans to major in economics are weaker, possibly due to the smaller sample size. The same robustness check for male students is shown in Annex table A3.[41]

4.3 Pre-Intervention Trends

An important assumption of the difference in differences estimation model is that, in the absence of the intervention under study, the difference between the treatment and control group would be constant over time. In order to check whether the assumption of parallel trends holds in our setting, we obtained data on enrollment in intermediate micro for the Spring 2014 cohort, i.e., the students that took Principles classes in Spring 2014. Naturally for this students we only have administrative data, since their enrollment in Principles classes preceded the start of our study. One complication is that a total of 4 classes changed

[41] Note that the sample is smaller in the male "took micro in fall" column, since there was no variation in one of the classes over time so it was dropped.

between Spring 2014 and Spring 2016. Therefore, our analysis is restricted to 7 classes – 3 treatment classes and 4 control classes – that remained unchanged between the three years.

Figure 6 displays the percentages of male and female students that took Principles classes in Spring 2014, Spring 2015 or Spring 2016 and enrolled in Intermediate Micro the following academic year. The figure shows that the pre-intervention enrollment trends are almost identical for the female students in the 2014 and 2015 cohorts, whereas the post-treatment trends diverge sharply, with the women in the treatment classes showing a significant increase in their enrollment rates and the women in the control classes following the downward trend observed in previous years. This confirms the validity of our estimated treatment effects.

5 Conclusions

Closing the gender gap in quantitative, high-paying subjects such as economics is an important goal, that has proven remarkably stubborn to achieve. Existing research has generated mixed evidence on what may lead women to stay away from certain majors and, consequently, certain career paths. In the field of economics, a number of studies have disproved the existence of a link between math aptitude and the existing gender gap in majoring choices, and have provided contradictory results with respect to the role that instructor gender may have on students' study decisions. Crucially, the existing empirical investigations raise questions about identification and causality, since shared information about instructor characteristics and teaching methods play a significant role in both students' self-selection into a given class and their decisions regarding future studies in a given field.

In this paper, we employed a field experiment to investigate the impact that female role models may play in young women's decisions to major in economics. Our underlying assumption is that the scarcity of female economics majors, which has remained quite constant for the last 60 years, has led to a very low likelihood that young women can come into direct contact with successful and accomplished women, working in interesting fields, having majored in economics. This, in turn, may be one of the leading factors contributing to the scarcity of young women thinking of economics as their potential field of study and subsequent work. We tested whether and to what extent female role models are important by conducting a randomized intervention that put female students enrolled in principles of economics classes in direct contact with two successful economics alumnae. A crucial feature of our study is that we chose the role models with the help of two current female economics majors on the basis of their interest in the role models' careers and their assessment of the role models' communication skills and charisma. As a result, the fields of work of the chosen role models – non-profit, sale management and marketing – are not stereotypically associated with the economics major.

We randomly selected principles of economics classes – which are typically large and gender balanced – being offered in Spring 2016 to receive a 15 minute visit by each role model. Since the same classes were offered the previous year, we employ difference-in-differences regressions to estimate the impact of the intervention on both enrollment in intermediate economics classes and self-stated (survey-based) intention to major in economics.

We found evidence of a strong and large effect of the role model visits on both outcomes for female students and on neither outcome for male students. In particular, the intervention doubled both female students' rate of enrollment in intermediate microeconomics the year following the intervention and the percentage of women stating an interest in the economics major. The treatment effect is especially large for top female students, i.e., those with a GPA higher than 3.7. Survey data also allowed us to investigate which fields of study female students would have likely majored in, absent the intervention. We found that the treatment did not take women from other high-earning subjects, such as STEM or finance. Rather, the role model visits caused a decline in the percentage of women interested in humanities and languages majors, providing suggestive evidence that the intervention attracted towards economics women that would have otherwise majored in fields leading to lower-earning jobs. One concern may be that the intervention may have led to a misallocation of talents by attracting women that are unlikely to succeed in the field of economics. Our analysis of students' performance in the intermediate economics classes show that this is not the case, as the treated female students performed equally, if not better, than the female students coming from the control principles classes.

Overall, the evidence presented shows that a simple, and low cost intervention can significantly increase the percentage of women majoring in Economics. This is an important finding for a number of reasons. First, achieving gender diversity in economics, as in any other field of study, is desirable per se, due to the potential effects of diversity on the contribution of ideas, as well as on team productivity and performance. Second, since the economics major leads to high-paying jobs, increasing the percentage of women in this field may contribute to the reduction of the gender gap in top-earning careers and leadership positions. Finally, attracting more women toward economics may also have important aggregate consequences in terms of sorting and efficiency – if women who are likely to be successful in economics (or any other subject) are not choosing it, then nudging them into the field will improve the overall allocation of talents within the economy.

One possible caveat of our study is that, by design, we are unable to identify precisely which characteristics of the role models were the most important in influencing young women to pursue economics: whether it was that the careers they both had pursued were more attractive to women, yet not usually perceived as linked to the economics major, or the information they provided on how their economics studies helped them on the job, or simply their charisma and personal experiences which were influential. Nevertheless, the crucial factor in our design was that the role models were chosen by female undergraduates – who perhaps implicitly knew best what would inspire their peers. Since we only had female role models, we are also unable to assess the role that the gender of the role models played in influencing our female students, although the fact that we found no effect on male students is indicative that gender matching is important. Further work could compare male and female role models and their differential effects on male and female students, as well as experiment with the careers of the role models. The analysis could also be easily extended to other male-dominated or female-dominated fields of study. Overall, we consider this paper a first step in a rich potential area of research on role model effects, not just in undergraduate Economics.

References

Allgood, S., W. B. Walstad, and J. J. Siegfried (2015). Research on teaching economics to undergraduates. *Journal of Economic Literature 53*(2), 285–325.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics 121*(1), 343–375.

Athey, S., C. Avery, and P. Zemsky (2000). Mentoring and diversity. *American Economic Review 90*(4), 765–786.

Bayer, A. and C. E. Rouse (2016). Diversity in the economics profession: A new attack on an old problem. *The Journal of Economic Perspectives 30*(4), 221–242.

Beaman, L., E. Duflo, R. Pande, and P. Topalova (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in india. *science 335*(6068), 582–586.

Bear, J. B. and A. W. Woolley (2011). The role of gender in team collaboration and performance. *Interdisciplinary science reviews 36*(2), 146–153.

Bettinger, E. P. and B. T. Long (2005). Do faculty serve as role models? the impact of instructor gender on female students. *The American Economic Review 95*(2), 152–157.

Black, D. A., S. Sanders, and L. Taylor (2003). The economic reward for studying economics. *Economic Inquiry 41*(3), 365–377.

Blau, F. D., J. M. Currie, R. T. Croson, and D. K. Ginther (2010). Can mentoring help female assistant professors? interim results from a randomized trial. *The American Economic Review 100*(2), 348–352.

Cameron, A. C. and D. L. Miller (2015). A practitioners guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Canes, B. J. and H. S. Rosen (1995). Following in her footsteps? women's choices of college majors and faculty gender composition. *Industrial and Labor Relations Review 48*(3), 486.

Carnevale, A. P. and B. Cheah (2015). From hard times to better times: College majors, unemployment, and earnings. *Georgetown University Center on Education and the Workforce*.

Carrell, S. E., M. E. Page, and J. E. West (2010). Sex and science: How professor gender perpetuates the gender gap. *The Quarterly Journal of Economics 125*(3), 1101–1144.

Carroll, T., D. Assane, and J. Busker (2014). Why it pays to major in economics. *The Journal of Economic Education 45*(3), 251–261.

Dynan, K. E. and C. E. Rouse (1997). The underrepresentation of women in economics: A study of undergraduate economics students. *The Journal of Economic Education 28*(4), 350–368.

Ellison, S. F. and W. P. Mullin (2014). Diversity, social goods provision, and performance in the firm. *Journal of Economics & Management Strategy 23*(2), 465–481.

Emerson, T. L., K. McGoldrick, and K. J. Mumford (2012). Women and the choice to study economics. *The Journal of Economic Education 43*(4), 349–362.

Gardecki, R. and D. Neumark (1998). Order from chaos? the effects of early labor market experiences on adult labor market outcomes. *ILR Review 51*(2), 299–322.

Goldin, C. (2013). Notes on women and the undergraduate economics major. *CSWEP Newsletter 2013*(15), 4–6.

Goldin, C., L. F. Katz, and I. Kuziemko (2006). The homecoming of american college women: The reversal of the college gender gap. *The Journal of Economic Perspectives 20*(4), 133–133.

Hoffmann, F. and P. Oreopoulos (2009). A professor like me the influence of instructor gender on college achievement. *Journal of Human Resources 44*(2), 479–494.

Hoogendoorn, S., H. Oosterbeek, and M. Van Praag (2013). The impact of gender diversity on the performance of business teams: Evidence from a field experiment. *Management Science 59*(7), 1514–1528.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2013). The allocation of talent and us economic growth. Technical report, National Bureau of Economic Research.

Kirkeboen, L. J., E. Leuven, and M. Mogstad (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics 131*(3), 1057–1111.

Kline, P., A. Santos, et al. (2012). A score based approach to wild bootstrap inference. *Journal of Econometric Methods 1*(1), 23–41.

Kofoed, M. S. et al. (2017). The effect of same-gender and same-race role models on occupation choice: Evidence from randomly assigned mentors at west point. *Journal of Human Resources*, 0416–7838r1.

Kugler, A. D., C. H. Tinsley, and O. Ukhaneva (2017). Choice of majors: Are women really different from men? Technical report, National Bureau of Economic Research.

Lim, J. and J. Meer (2017a). The impact of teacher-student gender matches: Random assignment evidence from south korea. *Journal of Human Resources*, 1215–7585R1.

Lim, J. and J. Meer (2017b). Persistent effects of teacher-student gender matches. *mimeo*.

Lyle, D. S. and J. Z. Smith (2014). The effect of high-performing mentors on junior officer promotion in the us army. *Journal of Labor Economics 32*(2), 229–258.

Niederle, M. and L. Vesterlund (2007). Do women shy away from competition? do men compete too much? *The Quarterly Journal of Economics 122*(3), 1067–1101.

Norton, E. C., H. Wang, C. Ai, et al. (2004). Computing interaction effects and standard errors in logit and probit models. *Stata Journal 4*, 154–167.

Rask, K. and J. Tiefenthaler (2008). The role of grade sensitivity in explaining the gender imbalance in undergraduate economics. *Economics of Education Review 27*(6), 676–687.

Rask, K. N. and E. M. Bailey (2002). Are faculty role models? evidence from major choice in an undergraduate institution. *The Journal of Economic Education 33*(2), 99–124.

Reuben, E., M. Wiswall, and B. Zafar (2015). Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender. *The Economic Journal*.

Roodman, D. et al. (2016). Boottest: Stata module to provide fast execution of the wild bootstrap with null imposed. *Statistical Software Components*.

Stout, J. G., N. Dasgupta, M. Hunsinger, and M. A. McManus (2011). STEMing the tide: using ingroup experts to inoculate women's self-concept in science, technology, engineering, and mathematics (STEM). *Journal of personality and social psychology 100*(2), 255.

Wiswall, M. and B. Zafar (2014). Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies 82*(2), 791–824.

Wiswall, M. and B. Zafar (2016). Preference for the workplace, human capital, and gender. Technical report, National Bureau of Economic Research.

Tables and Figures

Table 1: Balance Tests

	Control classes 2015 (untreated)	Treatment classes 2015 (untreated)	Control classes 2016 (untreated)	Treatment classes 2016 (treated)
Men	57%	54%	49%	62%**
American student	89.27%	88.14%	93.49%	88.57%
In-state student	25.37%	16.49%**	20.71%	20.00%
Freshman	82.93%	89.69%**	86.39%	90.48%
In a class with a female professor	49.76%	45.88%	57.40%	50.00%
Cumulative GPA	3.13	3.19	3.30	3.19**
Grade in Principles Class	2.77	2.92	3.02	2.62***
Women	43%	46%	51%	38%**
American student	92.95%	94.61%	92.18%	79.23%***
In-state student	22.44%	24.55%	21.23%	21.54%
Freshman	83.97%	84.43	82.68%	95.38%***
In a class with a female professor	50%	54.49%	62.57%	45.38%***
Cumulative GPA	3.44	3.40	3.48	3.39*
Grade in Principles Class	3.02	3.01	3.10	2.86**

Notes: Asterisks indicate a significant difference between treatment and control groups in the corresponding year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Enrollment in Intermediate Micro by treatment class, year and gender

	Control classes 2015 (untreated)	Treatment classes 2015 (untreated)	Control classes 2016 (untreated)	Treatment classes 2016 (treated)
Enrolled in ECO3301 the following semester				
Male	13.33%	13.48%	11.32%	10.44%
Female	7.24%	6.37%	4.71%	11.48%
H0: Male=Female (p-value)	0.072*	0.031*	0.026**	0.776
H0: Control=Treatment; male, 2015 (p-value)	0.967			
H0: Control=Treatment; female, 2015 (p-value)	0.762			
H0: Control=Treatment; male, 2016 (p-value)	0.794			
H0: Control=Treatment; female, 2016 (p-value)	0.031**			
Enrolled in ECO3301 within a year				
Male	22.78%	30.34%	22.01%	25.27%
Female	15.13%	11.46 %	11.18%	18.85%
H0: Male=Female (p-value)	0.078*	0.000***	0.008***	0.190
H0: Control=Treatment; male, 2015 (p-value)	0.105			
H0: Control=Treatment; female, 2015 (p-value)	0.342			
H0: Control=Treatment; male 2016 (p-value)	0.480			
H0: Control=Treatment; female, 2016 (p-value)	0.065*			

Note: The analysis is restricted to students that passed the principles class in Spring 2015 or Spring 2016.

Table 3: Treatment Effects on Enrollment in Intermediate Micro (following semester)

Dep. Variable: Dummy equal 1 if s/he took Microeconomics in Fall				
	Men	Men	Women	Women
Year 2016	-0.095	-0.114	-0.216*	-0.282
	(0.601)	(0.457)	(0.097)	(0.137)
	[0.617]	[0.529]	[0.173]	[0.163]
Treatment class (in 2015)	0.007	0.012	-0.066	-0.077
	(0.980)	(0.961)	(0.798)	(0.716)
	[0.982]	[0.966]	[0.814]	[0.727]
Treatment class x 2016	-0.054	0.021	0.539	0.701**
	(0.861)	(0.947)	(0.147)	(0.042)
	[0.868]	[0.947]	[0.193]	[0.060]
Female professor		0.298*		0.340**
		(0.096)		(0.041)
		[0.121]		[0.085]
In-state student		-0.219		0.051
		(0.238)		(0.690)
		[0.207]		[0.695]
Freshman		-0.337*		-0.343
		(0.092)		(0.171)
		[0.126]		[0.257]
Cumulative GPA		-0.294*		-0.139
		(0.083)		(0.657)
		[0.128]		[0.762]
Grade in Principles		0.117		0.258**
		(0.343)		(0.043)
		[0.340]		[0.058]
Constant	-1.111***	-0.337	-1.458***	-1.727*
	(0.000)	(0.340)	(0.000)	(0.078)
Observations	699	699	601	601

Notes: Probit regressions. Dependent variable is a dummy equal 1 if s/he took ECO3301 the following semester. Standard errors are clustered at the class level (21 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 4: Treatment Effects on Enrollment in Intermediate Micro (Year Following Treatment)

Dep. Variable: Dummy equal 1 if s/he took Microeconomics within a year				
	Men	Men	Women	Women
Year 2016	-0.026	-0.005	-0.186	-0.218
	(0.821)	(0.967)	(0.171)	(0.179)
	[0.835]	[0.969]	[0.203]	[0.198]
Treatment class (in 2015)	0.231**	0.250**	-0.171	-0.204*
	(0.027)	(0.021)	(0.171)	(0.058)
	[0.109]	[0.106]	[0.161]	[0.054]
Treatment class x 2016	-0.126	-0.138	0.505**	0.574**
	(0.478)	(0.486)	(0.029)	(0.017)
	[0.477]	[0.500]	[0.036]	[0.026]
Female professor		0.148		0.138
		(0.117)		(0.242)
		[0.133]		[0.268]
In-state student		-0.024		-0.075
		(0.901)		(0.525)
		[0.901]		[0509]
Freshman		-0.146		0.092
		(0.488)		(0.648)
		[0.521]		[0.682]
Cumulative GPA		-0.304**		-0.537**
		(0.028)		(0.029)
		[0.060]		[0.048]
Grade in Principles		0.002		0.280**
		(0.985)		(0.030)
		[0.985]		[0.038]
Constant	-0.746***	0.284	-1.031***	-0.178
	(0.000)	(0.462)	(0.000)	(0.801)
Observations	699	699	601	601

Notes: Probit regressions. Dependent variable is a dummy equal 1 if s/he took ECO3301 the following year. Standard errors are clustered at the class level (21 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 5: Interest in the field of Economics by treatment class, year and gender

	Control classes 2015 (untreated)	Treatment classes 2015 (untreated)	Control classes 2016 (untreated)	Treatment classes 2016 (treated)
Plans to major in Economics				
Male	19.55%	16.79%	15.04%	15.79%
Female	7.14%	6.99%	6.98%	11.93%
H0: Male=Female (p-value)	0.004***	0.011**	0.043**	0.390
H0: Control=Treatment; male, 2015 (p-value)	0.556			
H0: Control=Treatment; female, 2015 (p-value)	0.962			
H0: Control=Treatment; male, 2016 (p-value)	0.872			
H0: Control=Treatment; female, 2016 (p-value)	0.189			

Notes: Surveyed students only (N=1052).

Table 6: Treatment effects on the intention to major in economics

	Dummy equal 1 if s/he plans to major in economics			
	Men	Men	Women	Women
Year 2016	-0.18	-0.14	-0.01	-0.00
	(0.109)	(0.287)	(0.950)	(0.982)
	[0.152]	[0.311]	[0.949]	[0.981]
Treatment class (in 2015)	-0.10	-0.05	-0.01	0.02
	(0.532)	(0.703)	(0.951)	(0.910)
	[0.550]	[0.721]	[0.951]	[0.913]
Treatment class x 2016	0.14	0.10	0.31	0.47*
	(0.476)	(0.610)	(0.201)	(0.077)
	[0.484]	[0.613]	[0.236]	[0.105]
Female professor		0.26***		0.27*
		(0.006)		(0.083)
		[0.015]		[0.085]
In-state student		0.21		-0.10
		(0.127)		(0.533)
		[0.138]		[0.522]
Freshman		-0.34		-0.53*
		(0.114)		(0.054)
		[0.195]		[0.128]
Cumulative GPA		-0.33*		-0.28
		(0.053)		(0.418)
		[0.076]		[0.445]
Grade in Principles		0.10		0.34**
		(0.304)		(0.034)
		[0.321]		[0.055]
Constant	-0.86***	-0.06	-1.47***	-1.34*
	(0.000)	(0.891)	(0.000)	(0.087)
Observations	516	516	507	507

Probit regressions. Dep. Variable: Dummy equal to 1 if student plans to major in economics, 0 otherwise Standard errors are clustered at the class level for 21 clusters. P-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 7: Treatment Effects on Top Female Students

	Took Micro (Fall)		Took Micro (Year)		Econ Major	
Year 2016	-0.487*	-0.510**	-0.580***	-0.563***	0.038	-0.090
	(0.053)	(0.042)	(0.000)	(0.001)	(0.866)	(0.699)
	[0.091]	[0.067]	[0.006]	[0.014]	[0.870]	[0.707]
Treatment class (in 2015)	-0.496	-0.510	-0.442*	-0.426*	-0.217	-0.258
	(0.151)	(0.104)	(0.075)	(0.083)	(0.333)	(0.266)
	[0.127]	[0.102]	[0.075]	[0.089]	[0.349]	[0.253]
Treatment class x 2016	1.537***	1.506***	1.393***	1.292***	0.605*	0.690*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.058)	(0.065)
	[0.005]	[0.003]	[0.005]	[0.008]	[0.055]	[0.063]
Female professor		0.357		0.002		0.103
		(0.300)		(0.994)		(0.682)
		[0.261]		[0.994]		[0.677]
In-state student		-0.120		0.167		-0.154
		(0.589)		(0.425)		(0.529)
		[0.596]		[0.447]		[0.521]
Freshman		0.274		0.454		-0.832
		(0.637)		(0.409)		(0.115)
		[0.716]		[0.383]		[0.271]
Cumulative GPA		0.996		1.816		2.197
		[0.594]		[0.212]		(0.121)
		(0.514)		(0.189)		(0.129)
Grade in Principles		-0.143		-0.183		-0.190
		[0.843]		[0.669]		(0.390)
		(0.703)		(0.605)		(0.460)
Constant	-1.282***	-5.054	-0.994***	-7.788*	-1.348***	-8.384
	(0.000)	(0.310)	(0.000)	(0.087)	(0.000)	(0.112)
Observations	185	185	185	185	166	166

Notes: Probit regressions. Dep. Variable: Dummy equal 1 if the student plans to major in economic and/or took ECO3301 the fall/year following the principles class. Standard errors are clustered at the class level (21 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 8: Intention to major in Humanities or Languages

	Dummy=1 if s/he intends to major in Humanities or Languages			
	Men	Men	Women	Women
Year 2016	0.076	0.060	0.249	0.194
	(0.815)	(0.842)	(0.183)	(0.424)
	[0.881]	[0.883]	[0.226]	[0.542]
Treatment class	0.271**	0.271**	0.346	0.325
	(0.039)	(0.039)	(0.168)	(0.177)
	[0.101]	[0.114]	[0.389]	[0.396]
Treatment x 2016	-0.347	-0.347	-0.859**	-0.867***
	(0.356)	(0.356)	(0.017)	(0.010)
	[0.463]	[0.390]	[0.034]	[0.017]
Female Professor		0.004		0.254
		(0.983)		(0.129)
		[0.986]		[0.175]
In-state student		0.010		-0.168
		(0.960)		(0.305)
		[0.962]		[0.306]
Freshman		0.035		0.621**
		(0.915)		(0.026)
		[0.915]		[0.006]
Cumulative GPA		0.502***		0.030
		(0.010)		(0.933)
		[0.008]		[0.933]
Grade in Principles		-0.174		-0.098
		(0.123)		(0.502)
		[0.167]		[0.513]
Constant	-1.779***	-2.967***	-1.526***	-1.977**
	(0.000)	(0.000)	(0.000)	(0.027)
Observations	516	516	507	507

Notes: Probit regressions. Dep. Variable: Dummy equal 1 if s/he plans to major in humanities or languages. Standard errors are clustered at the class level (21 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016)

Table 9: Performance in Intermediate Microeconomics by treatment class, year and gender

	Control classes 2015 (untreated)	Treatment classes 2015 (treated)	Control classes 2016 (untreated)	Treatment classes 2016 (treated)
Average grade	3.33	3.39	3.02	3.26
H0: Control=Treatment; 2015 (p-value)	0.813			
H0: Control=Treatment; 2016 (p-value)	0.452			
Core Exam score	0.63	0.60	0.59	0.69
H0: Control=Treatment; 2015 (p-value)	0.499			
H0: Control=Treatment; 2016 (p-value)	0.212			

Note: The p-values in the upper panel are generated by two-sided tests of equality of means (ttests).

Table 10: Controlling for American students

Dummy equal 1 if she plans to major in economics and/or took Micro						
	Full Female Sample			Only American Female students		
	Took Micro (Fall)	Took Micro (Year)	Econ Major	Took Micro (Fall)	Took Micro (Year)	Econ Major
Year 2016	-0.291	-0.223	-0.032	-0.328	-0.236	-0.201
	(0.139)	(0.169)	(0.885)	(0.110)	(0.160)	(0.430)
	[0.154]	[0.183]	[0.889]	[0.132]	[0.176]	[0.439]
Treatment Class	-0.078	-0.208*	0.031	-0.145	-0.267**	-0.000
	(0.714)	(0.055)	(0.863)	(0.477)	(0.034)	(0.999)
	[0.714]	[0.060]	[0.864]	[0.477]	[0.033]	[0.999]
Treatment class x 2016	0.673**	0.505**	0.400	0.690**	0.522**	0.519*
	(0.048)	(0.040)	(0.134)	(0.037)	(0.048)	(0.082)
	[0.070]	[0.054]	[0.157]	[0.051]	[0.065]	[0.093]
Female professor	0.349**	0.157	0.315*	0.263*	0.097	0.211
	(0.047)	(0.224)	(0.059)	(0.092)	(0.439)	(0.229)
	[0.090]	[0.248]	[0.062]	[0.123]	[0.452]	[0.227]
In-state student	0.076	-0.020	-0.052	0.049	-0.028	-0.063
	(0.562)	(0.865)	(0.751)	(0.721)	(0.808)	(0.656)
	[0.581]	[0.871]	[0.759]	[0.731]	[0.812]	[0.653]
Freshmen	-0.344	0.085	-0.541*	-0.296	0.090	-0.493*
	(0.171)	(0.676)	(0.053)	(0.240)	(0.678)	(0.090)
	[0.257]	[0.684]	[0.136]	[0.346]	[0.687]	[0.193]
Cumulative GPA	-0.150	-0.547**	-0.296	-0.237	-0.500**	-0.375
	(0.632)	(0.030)	(0.395)	(0.435)	(0.050)	(0.308)
	[0.751]	[0.047]	[0.415]	[0.574]	[0.078]	[0.333]
Grade in Principles	0.267**	0.300**	0.357**	0.282**	0.324**	0.349**
	(0.040)	(0.023)	(0.029)	(0.028)	(0.020)	(0.019)
	[0.055]	[0.031]	[0.043]	[0.050]	[0.036]	[0.032]
American	-0.266	-0.536***	-0.582*			
	(0.332)	(0.000)	(0.064)			
	[0.442]	[0.019]	[0.159]			
Constant	-1.481	0.271	-0.809	-1.419	-0.442	-0.993
	(0.122)	(0.709)	(0.299)	(0.129)	(0.513)	(0.268)
Observations	601	601	507	547	547	468

Notes: Probit regressions. Dependent variable is a dummy equal 1 if she took ECO3301 the following semester. Standard errors are clustered at the class level (21 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 11: Robustness: Excluding classes that changed between 2015 and 2016

	Dummy equal 1 if she plans to major in economics and/or took Micro					
	Micro (Fall)		Micro (Year)		Econ Major	
Year 2016	-0.198	-0.269	-0.123	-0.171	-0.024	-0.017
	(0.199)	(0.219)	(0.416)	(0.339)	(0.921)	(0.948)
	[0.305]	[0.252]	[0.454]	[0.371]	[0.925]	[0.952]
Treatment class (in 2015)	-0.068	-0.115	-0.109	-0.165	0.015	0.012
	(0.801)	(0.590)	(0.357)	(0.134)	(0.945)	(0.952)
	[0.812]	[0.600]	[0.366]	[0.160]	[0.944]	[0.955]
Treatment class x 2016	0.521	0.685*	0.442*	0.522**	0.322	0.471
	(0.173)	(0.052)	(0.066)	(0.044)	(0.259)	(0.120)
	[0.217]	[0.075]	[0.087]	[0.063]	[0.324]	[0.164]
Female professor		0.370**		0.096		0.263*
		(0.029)		(0.449)		(0.098)
		[0.075]		[0.468]		[0.106]
In-state student		0.060		-0.076		0.014
		(0.660)		(0.551)		(0.923)
		[0.679]		[0.524]		[0.923]
Freshman		-0.227		0.119		-0.482
		(0.437)		(0.622)		(0.146)
		[0.544]		[0.640]		[0.250]
Cumulative GPA		-0.237		-0.552**		-0.269
		(0.455)		(0.043)		(0.468)
		[0.585]		[073]		[0.488]
Grade in Principles		0.303**		0.294**		0.340*
		(0.029)		(0.039)		(0.054)
		[0.037]		[0.045]		[0.066]
Constant	-1.457***	-1.617	-1.093***	-0.209	-1.491***	-1.421
	(0.000)	(0.114)	(0.000)	(0.789)	(0.000)	(0.106)
Observations	546	546	546	546	463	463

Notes: Probit regressions. Dependent variable is a dummy equal 1 if s/he took ECO3301 the following semester. Standard errors are clustered at the class level (18 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table 12: Robustness: Including Class Fixed Effects

	Dummy equal 1 if she plans to major in economic and/or took Micro					
	Micro (Fall)		Micro (Year)		Econ Major	
Year 2016	-0.153	-0.0790	-0.0396	-0.0468	0.0236	0.198
	(0.218)	(0.122)	(0.102)	(0.0942)	(0.181)	(0.205)
	[0.303]	[0.534]	[0.702]	[0.614]	[0.897]	[0.401]
Treatment class x 2016	0.613***	0.672***	0.416***	0.489***	0.319	0.319
	(0.000)	(0.142)	(0.114)	(0.111)	(0.201)	(0.212)
	[0.005]	[0.001]	[0.003)	[0.000]	[0.139]	[0.128]
In-state student		-0.00821		-0.116		-0.0116
		(0.142)		(0.129)		(0.148)
		[0.957]		[0.343]		[0.938]
Freshman		-0.507*		-0.0931		-0.658*
		(0.305)		(0.256)		(0.365)
		[0.200]		[0.757]		[0.182]
Cumulative GPA		-0.383		-0.651**		-0.354
		(0.378)		(0.286)		(0.393)
		[0.455]		[0.052]		[0.3900]
Grade Principles		0.400**		0.367**		0.429**
		(0.167)		(0.153)		(0.200)
		[0.256]		[0.259]		[0.041]
Constant	-2.117***	-1.644	-1.358***	-0.209	-1.696***	-1.245
	(0.000)	(1.178)	(0.0640)	(0.808)	(0.114)	(0.853)
Observations	546	546	546	546	463	463

Notes: Probit regressions with Class Fixed effects. Dependent variable is a dummy equal 1 if s/he took Micro the following semester, following year, or plans to major in economics respectively. Standard errors are clustered at the class level (18 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Figure 1: Enrollment in Intermediate Micro, following semester

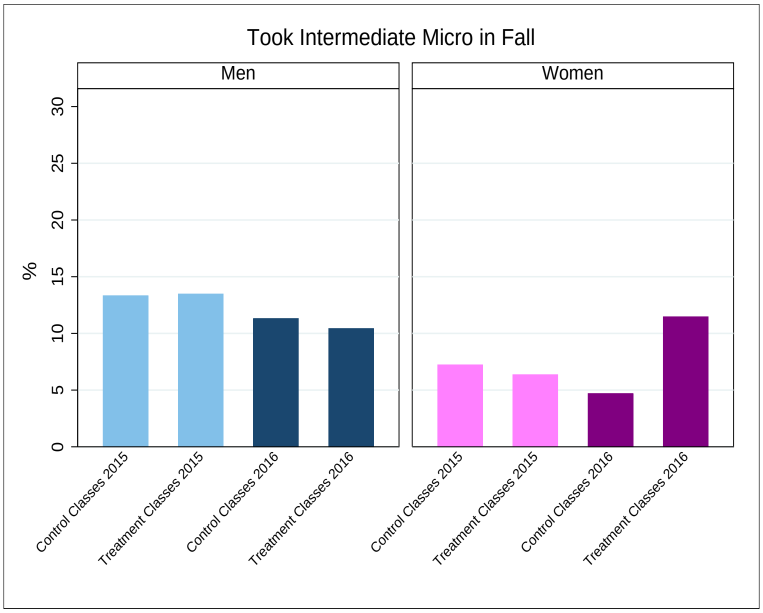


Figure 2: Enrollment in Intermediate Micro, following year

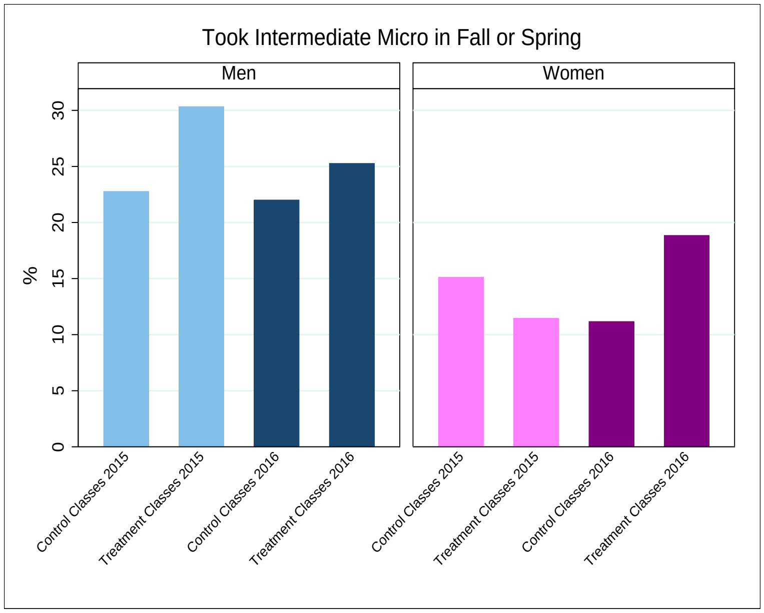


Figure 3: Intention to Major in Economics

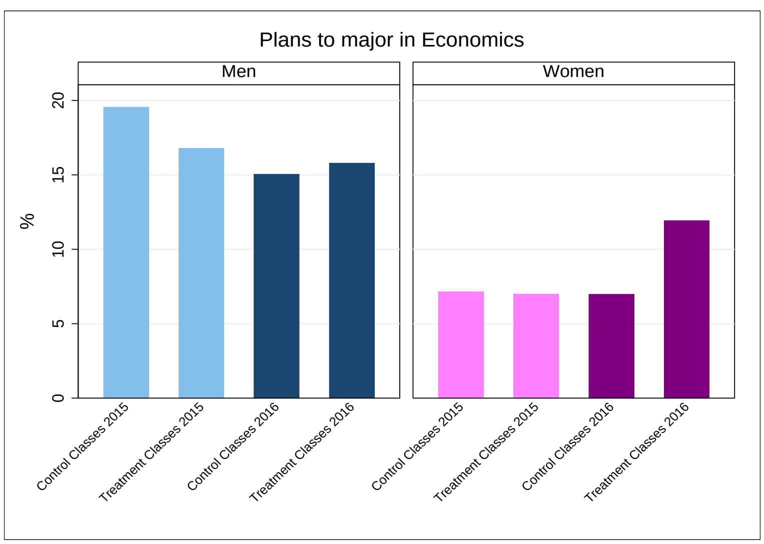


Figure 4: Intention to major in other high-earning fields

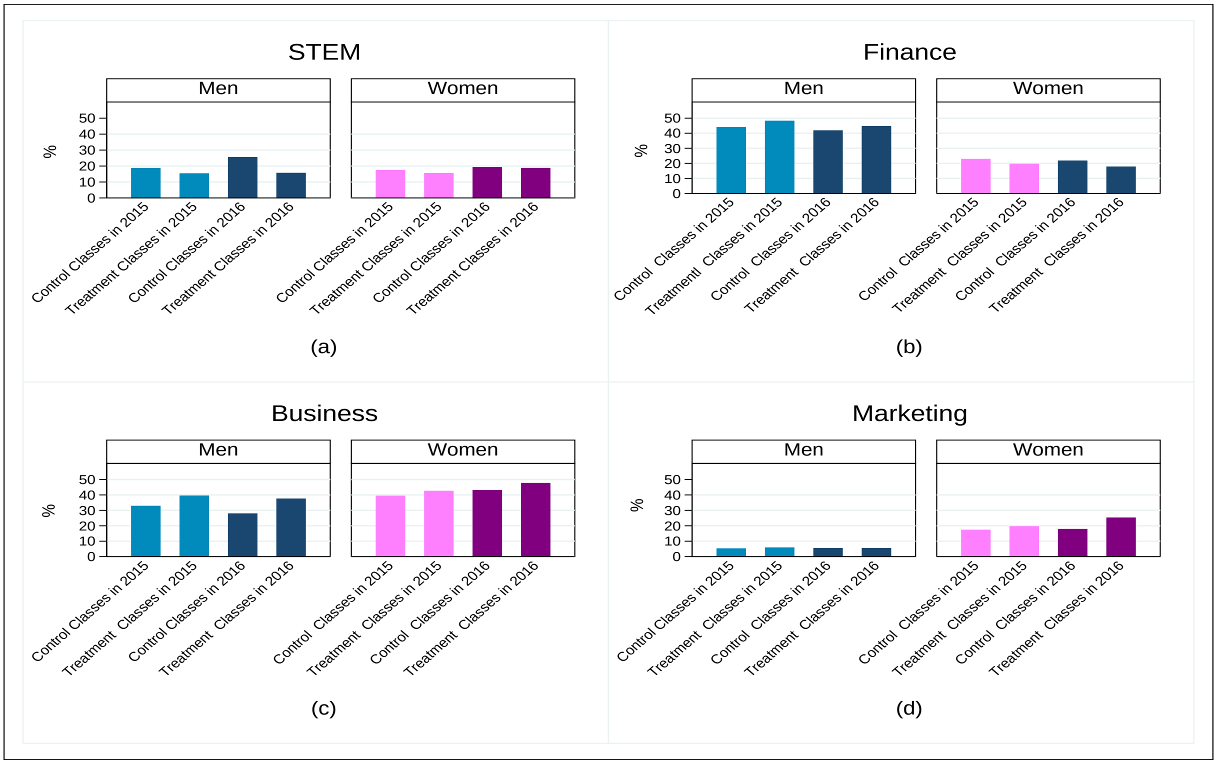


Figure 5: Intention to Major in lower-earning fields

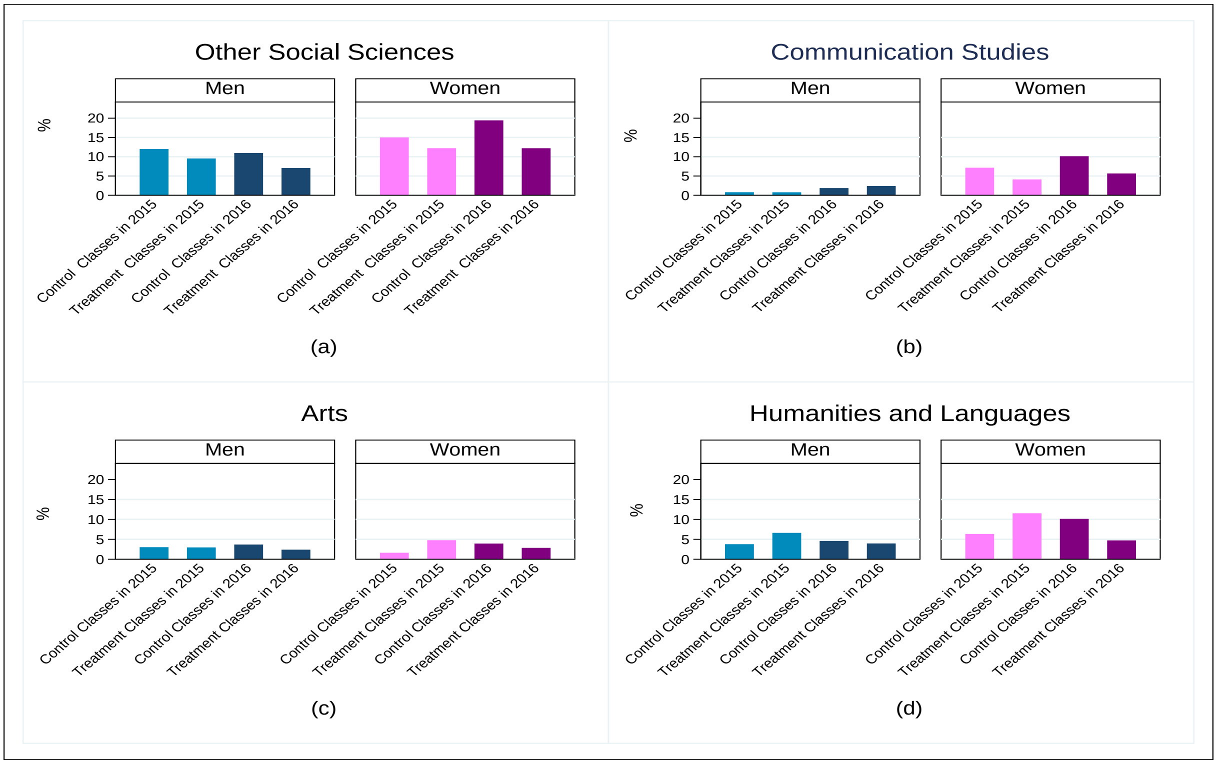
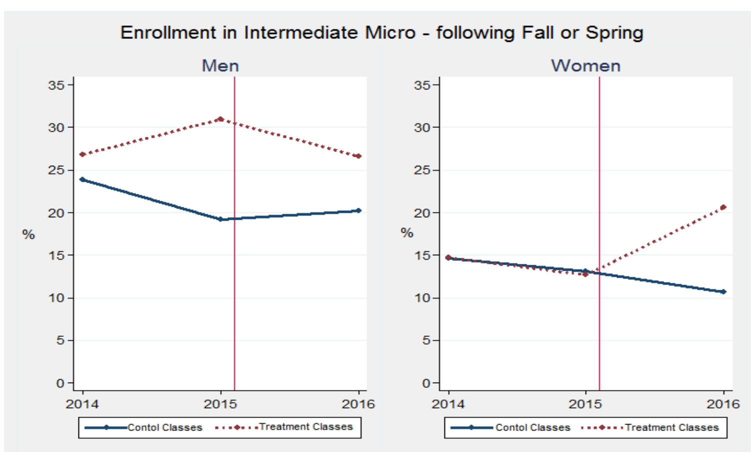


Figure 6: Common trend



Annex

Table A1: Balance Tests- Survey data

	Control classes 2015 (untreated)	Treatment classes 2015 (untreated)	Control classes 2016 (untreated)	Treatment classes 2016 (treated)
Men	135 (51%)	138 (48%)	117 (47%)	140 (56%)**
Belongs to fraternity or sorority	52.59%	51.45%	44.83%	44.29%
Took econ in high school	70.90%	56.93%**	63.38%	62.59%
Athlete	5.30%	4.38%	5.36%	6.77%
Women	128 (49%)	148 (42%)	134 (53%)	112 (54%)**
Belongs to fraternity or sorority	28.13%	29.73%	29.85%	25.00%
Took econ in high school	64.06%	63.51%	66.92%	58.04%
Athlete	7.14%	5.59%	7.09%	10.09%

Notes: Asterisks indicate a significant difference between treatment and control groups in the corresponding year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Treatment Effects on Top Female Students (Excluding classes that changed)

	Took Micro (Fall)		Took Micro (Year)		Econ Major	
Year 2016	-0.370	-0.404	-0.712***	-0.661***	0.194	0.161
	(0.159)	(0.151)	(0.000)	(0.002)	(0.409)	(0.508)
	[0.267]	[0.253]	[0.007]	[0.023]	[0.415]	[0.502]
Treatment class (in 2015)	-0.468	-0.503	-0.469*	-0.440*	-0.167	-0.181
	(0.205)	(0.155)	(0.063)	(0.089)	(0.505)	(0.483)
	[0.234]	[0.197]	[0.071]	[0.101]	[0.549]	[0.498]
Treatment class x 2016	1.420***	1.383***	1.526***	1.395***	0.450	0.415
	(0.003)	(0.002)	(0.000)	(0.001)	(0.166)	(0.289)
	[0.016]	[0.015]	[0.008]	[0.007]	[0.193]	[0.302]
Female professor		0.336		-0.035		0.083
		(0.325)		(0.890)		(0.748)
		[0.300]		[0.886]		[0.752]
In-state student		-0.070		0.103		-0.072
		(0.745)		(0.640)		(0.760)
		[0.747]		[0.654]		[0.077]
Freshman		0.231		0.370		-0.957*
		(0.707)		(0.518)		(0.092)
		[0.783]		[0.550]		[0.025]
Cumulative GPA		1.481		1.990		3.210**
		(0.390)		(0.195)		(0.027)
		[0.453]		[0.232]		[0.044]
Grade in Principles		-0.080		-0.158		-0.163
		(0.853)		(0.685)		(0.529)
		[0.936]		[0.728]		[0.611]
Constant	-1.309***	-7.118	-0.967***	-8.416*	-1.398***	-12.382**
	(0.000)	(0.191)	(0.000)	(0.089)	(0.000)	(0.019)
Observations	168	168	168	168	151	151

Notes: Probit regressions. Dep. Variable: Dummy equal 1 if the student plans to major in economic and/or took ECO3301 the fall/year following the principles class. Classes that changed between years are removed from the analysis. Standard errors are clustered at the class level (18 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Table A3: Robustness: Including Class Fixed Effects (Males)

	Dummy equal 1 if he plans to major in economic and/or took Micro					
	Without Class fixed effects			With Class Fixed Effects		
	Micro (Fall)	Micro (Year)	Econ Major	Micro (Fall)	Micro (Year)	Econ Major
Year 2016	-0.096	-0.015	-0.039	-0.007	0.0159	0.0747
	(0.664)	(0.919)	(0.795)	(0.947)	(0.0919)	(0.109)
	[0.681]	[0.922]	[0.810]	[0.951]	[0.865]	[0.512]
Treatment class (in 2015)	0.073	0.255**	0.028	-	-	-
	(0.789)	(0.041)	(0.845)			
	[0.803]	[0.119]	[0.850]			
Treatment class x 2016	-0.015	-0.126	-0.016	-0.049	-0.152	-0.107
	(0.965)	(0.564)	(0.940)	(0.823)	(0.126)	(0.176)
	[0.967]	[0.559]	[0.938]	[0.833]	[0.236]	[0.548]
Female professor	0.311	0.150	0.285***	-	-	-
	(0.101)	(0.135)	(0.006)			
	[0.130]	[0.148]	[0.021]			
In-state student	-0.153	0.033	0.258*	-0.140	0.0614	0.277*
	(0.430)	(0.872)	(0.079)	(0.472)	(0.206)	(0.149)
	[0.401]	[0.880]	[0.093]	[0.441]	[0.785]	[0.068]
Freshman	-0.377*	-0.208	-0.501**	-0.626***	-0.325	-0.577**
	(0.088)	(0.366)	(0.023)	(0.005)	(0.227)	(0.229)
	[0.129]	[0.432]	[0.085]	[0.015]	[0.245]	[0.064]
Cumulative GPA	-0.236	-0.305**	-0.365**	-0.313*	-0.309**	-0.439**
	(0.198)	(0.045)	(0.043)	(0.067)	(0.155)	(0.180)
	[0.235]	[0.082]	[0.067]	[0.127]	[0.081]	[0.365]
Grade in Principles	0.112	0.009	0.089	0.107	-0.0220	0.144
	(0.388)	(0.921)	(0.418)	(0.411)	(0.118)	(0.121)
	[0.381]	[0.920]	[0.442]	[0.434]	[0.852]	[0.256]
Constant	-0.554	0.305	0.152	-0.556	0.503	0.189
	(0.155)	(0.486)	(0.708)	(0.392)	(0.409)	(0.408)
Observations	651	651	471	628	651	471

Notes: Probit regressions. Dependent variable is a dummy equal 1 if he took ECO3301 the following semester. year or plans to major in economics. Standard errors are clustered at the class level (18 clusters). Robust p-values in parentheses. In square brackets we report score wild cluster bootstrap p-values (Kline et al., 2012) generated using boottest command in Stata 14 (Roodman et al., 2016).

Figure A1: Enrollment in Intermediate Micro