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Does exposure to more women in male-dominated fields render female students more career-oriented?

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Keywords: gender, economics, higher education, glass ceiling, labor market.

JEL Codes: J16, J24, I23.

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February 27, 2021

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1 Introduction

Despite women's recent progress in labor market outcomes, women remain underrepresented among top earners (Bertrand, 2018). Female participation in work and study environments provides role models that could indirectly modify perceptions and give women access to mentorship and specific knowledge, helping them find better career opportunities.[1] Therefore, the exposure to successful women may improve female labor market outcomes by prompting women to aspire to high-status job positions, reducing the so-called glass ceiling.[2]

This paper tests for gender composition effects in Economics, a historically male-dominated field of study.[3] We investigate the impact of female peers and professors on women economists' career decisions by exploiting an environment, the prestigious University of Sao Paulo (USP) in Brazil, which randomly assigns Economics students to first-semester course-sections. This setting generates an exogenous variation in classmates' and professors' gender, allowing us to address threats to internal validity, such as self-selection of students into courses and professors. By focusing on compulsory classes, we also deal with issues of gender-specific selection of students into subjects.

In addition to the low proportion of women, some studies show a hostile environment for women in Economics, reinforcing the importance of female representation in the field. Wu (2018) measures gender-biased language in an anonymous professional Economics forum using text-analysis techniques. She finds that while economists describe their male colleagues in professional terms, comments on women focus on their physical appearance. In Chilean universities, Paredes et al. (2020) find that not only sexist students self-select into Economics, but the training received throughout the Economics major boosts gender-biased perceptions. Importantly, they show that higher shares of female professors and peers lead to less gender-biased students' views.

Our paper estimates the long-term impacts of female peers and professors during Economics undergraduate studies on career outcomes. We combine detailed administrative data from USP admission and undergraduate records with two administrative datasets from the Brazilian federal government, a matched

[1] Mani and Riley (2019) review the literature on social networks and suggest that female role models and peers play a relevant role in the decision-making process, influencing women's beliefs and aspirations.

[2] Glass ceiling is a term to define difficulties in career advancement.

[3] Worldwide, Economics is a research field with low women representation. In the United States, female faculty share in tenure track positions is 20%, and in Brazil, this percentage is 25% (CSWEP, 2017; BWE, 2018). In our setting, we verify low proportions of female undergraduate students (23%) and professors (18%). Besides, the female shares have not increased over the period under analysis, 2000-2008 (Figures A.1 and A.2).

employer-employee formal labor market data (RAIS), and publicly available firm ownership data. Our database allows us to investigate impacts on female labor force participation rates, occupational choice, career progression, and wages up to five years after (expected) graduation.

Our results suggest that female students react to a broader women representation in Economics by becoming more career-driven. Higher shares of female classmates lead to increases in female labor force participation rates. A one standard deviation rise in female classmates' percentage results in a female labor force participation of 0.21 and 0.15 standard deviations higher two and five years after graduating. A one standard deviation higher percentage of high-performing female peers increases female labor force participation two and five years after graduating by 0.17 and 0.11 standard deviations. Overall, we find little impact on career choice (occupation and industry).

Notably, our findings suggest that female role-models affect career advancement. In particular, female professors' share increases the probability that a female student works as a top manager after graduation: a one standard deviation increase in this share raises by 0.16 standard deviations the likelihood that a female student works as a top manager. These impacts are robust once we correct for selection into the formal labor market using a Heckman Two-Step procedure.

We then investigate the potential channels underlying our results. We start by examining the impacts of female professors and peers on performance. In general, the previous literature found that female peers (Han and Li, 2009; Oosterbeek and Ewijk, 2014; Bostwick and Weinberg, 2018), and professors (Carrell et al., 2010; Griffith, 2014) have positive impacts on female students' performance. We do not find similar effects of female role models on women's educational outcomes. For the average female student, the share of female classmates or high-performing peers does not impact achievement. In first-semester courses, female students perform relatively better in sections taught by female vs. male instructors, having higher grades and pass rates than their male colleagues. However, these results arise because male students perform worse in course sections taught by female professors, as in Hoffman and Oreopoulos (2009). In the long run, female faculty shares do not influence female students' performance. Our analysis also shows that female professors and peers do not affect elective courses' choice, the propensity to choose a female advisor (Kato and Song, 2018; Gaule and Piacentini, 2018; Funk et al., 2019), or to pursue an academic career in Economics (Gaule and Piacentini, 2018; Porter and Serra, 2020).

Finally, we analyze if professors' and classmates' gender composition impacts female students' likelihood of working during undergraduate studies. The share of female professors does not differentially affect this job decision for women. However, if female classmates' share rises by one standard deviation, female students are 0.15 standard deviations more likely to work during their undergraduate studies. Given that most USP Economics undergraduates work or do internships in firms and banks, we can interpret this effect as an early career-oriented option. Female students exposed to more female peers seem to focus on their future careers by working while in undergraduate studies, leading to a higher degree of labor market attachment, even though this could potentially jeopardize their academic performance (see, e.g., Stinebrickner and Stinebrickner, 2003).

A valuable contribution of our paper is to look at the longer-term effects of exposure to both female peers and professors on labor market outcomes. Most studies analyzing the impact of female representation in math-intensive fields concentrate on educational outcomes, such as college performance, course-taking behavior, and major choice (Hoffman and Oreopoulos, 2009; Carrell et al., 2010; Oosterbeek and Ewijk, 2014).[4] The few papers examining gender composition effects on career outcomes focus on instructor effects. Mansour et al. (2020) estimate the impacts of female STEM professors on occupational choice and postgraduate studies for the United States Air Force Academy students. For high-achieving female students, an increase in female professors' share results in a higher likelihood of obtaining a STEM degree, working in a STEM occupation, and earning a master's degree in a STEM field. Kato and Song (2018) analyze same-gender advisor impacts at a liberal arts university on undergraduate studies' outcomes (GPA and degree completion) and career outcomes (employment and graduate studies). While having an own-gender advisor positively impacts performance (graduation rates and grades), there is no impact on labor market outcomes. For lower ability students, a same-gender advisor increases the probability of enrolling in a graduate school. Mouganie and Wang (2020) estimate the effects of high-achieving female peers at high school in China on the decision to pursue a STEM career. Female students exposed to higher percentages of high-performing female peers are more likely to choose a STEM course-track. Like our paper, Brodaty and Gurgand (2016) examine peer and instructor effects in an undergraduate program in Economics from a French university. However, their article estimates ability effects on educational outcomes, while ours focus on gender composition and look at long-term results.

We organize the remainder of the paper as follows. In Section 2, we present background information on the undergraduate program in Economics at the University of Sao Paulo. Section 3 describes our data and

[4] As Brazilian students choose their major in the university application process, the major choice is not directly affected by faculty or university peers.

the main variables used in our analysis. Section 4 discusses identifying assumptions and the econometric model. Section 5 reports our results, and Section 6 explores possible channels driving our effects. Section 7 concludes.

2 Institutional background

In Brazil, public (federal, state, or municipal) universities enroll approximately 25% of tertiary education students (INEP/MEC, 2008). Since they do not charge tuition fees and have a good reputation, their admission processes are typically competitive. The remaining students attend private institutions, which can be for-profit or non-profit, with varying degrees of reputation/quality.

In contrast to the U.S. higher education system, in Brazil, students choose the major when they apply for each college/university. At the end of high school, students take admission exams for each institution they are interested in attending (decentralized system).[5] Changing majors is costly in this educational context, as students typically have to take another admission exam.[6]

The University of Sao Paulo (USP) is a large research-intensive state university located in Sao Paulo, the country's wealthiest state. USP is a selective Brazilian university, one of the most prestigious universities in Latin America.[7]

All students interested in attending an undergraduate program at the University of Sao Paulo must take an admission exam called *vestibular*, held once a year, administered by *Fundação Universitária para o Vestibular* (FUVEST). The admission exam has two phases, held in November/December (Phase 1) and January (Phase 2). The Economics undergraduate program offers 180 places, 90 in the daytime stream and 90 in the evening stream, so the 180 best-ranked students, in terms of Phase 1 and 2 scores, are invited to enroll in the first admission list. USP publishes additional admission lists until there are no more remaining places. Students approved in the admission process will start to attend the university in February. Students may apply and enroll in more than one major at USP sequentially but not concurrently.

Although USP offers programs in many cities, our data is from the main campus located in Sao Paulo city, which offers the most prestigious Economics undergraduate degree. Since all Brazilian universities, in-

[5] Until 2010, most public (federal and state) universities administered their admission exam. More recently, federal and some state universities joined SISU, a centralized system (Machado and Szerman, 2016).

[6] In our sample, few students (38) transferred to other USP majors, and only two students transferred to other universities. In both cases, we cannot observe the new major or university. For students who dropped out, we have no information if they enrolled in different universities/fields.

[7] See, for example, Times Higher Education (2019).

cluding USP, also offer Business undergraduate degrees, the Economics degree at USP is highly specialized in economics courses, not including business-related disciplines as core courses. At the admission process, students selecting the Economics degree can opt for daytime or evening classes. The coursework is the same in both streams. Students have the same compulsory courses and need to earn the same amount of total credits to graduate. However, the expected duration is longer for the evening stream (four years for the daytime and five years for the evening) since they have fewer courses per semester.[8]

Different from most U.S. universities, the coursework structure is relatively rigid. About 57% of credits are in compulsory (core) courses, and introductory courses are pre-requisites for more advanced courses, implying that students typically follow courses with their admission cohorts. Although professors from the Department of Economics teach most of the compulsory courses (73%), subjects such as Calculus, Accounting, Law, etc., are lectured by professors from other USP departments. USP hires professors through civil service examinations, and they have tenure nearly from the beginning. The university rarely relies on temporary lecturers, implying that the faculty composition changes slowly.[9] To graduate, students also have to write a bachelor thesis under a professor's supervision.

As in other Brazilian universities, it is not uncommon for students to work during their undergraduate studies, either in internships or regular jobs. In our sample, we verify that 82% of students work at some point in their undergraduate education (60% do internships and 53% as regular workers at the formal labor market). Unlike the U.S., students typically work for firms or banks during their studies, in occupations closely related to their future careers. Since 2005, students can earn course credits for internships. Internships require a three-party contract, signed by the worker, firm, and educational institution, allowing students to work between 20 and 30 hours per week. When we analyze internship contracts from USP students between 2006 and 2016, we observe that 57% of the students are interns at banks or other financial institutions, 19% work in research institutions, 10% at consulting firms, and 11% in private firms from different sectors. As mentioned above, the internships correlate with the industry choices over their career paths: 53% of graduates work in the financial industry, 20% at consulting firms, 17% in the public sector, and 9% in research institutions. Regarding occupational choices, 28% work as economists, while the remaining occupations are

[8] Students admitted into the daytime and evening streams have different characteristics (Table A.1). Daytime students have better admission scores, are younger, less likely to have enrolled at other USP majors before, and a higher percentage of them are female.

[9] Over the period 2000-2013, there were 72 professors at the Department of Economics on average. Turnover was between three and four per year on average, and 46% of departures were due to retirement or death. Even temporary lecturers are subject to a civil service examination and appointed for two years.

typically business-related or in other fields of study.[10]

2.1 Students' assignment to course sections

As mentioned before, students admitted into the Economics degree at USP are split into two alternative streams: daytime or evening classes. Each stream has two sections, each containing around 45 students (hereafter, sections 1 and 2). Conditional on the stream, the assignment criterion of students to sections is alphabetical order, which mimics the random assignment of students (Scoppa and Paola, 2010).[11]

We test whether the first letter of a student's given name correlates with a host of observables: gender, age, normalized admission scores, city of residence, previous experience at USP, and first admission list. Overall, results suggest orthogonality in our sample: the regressions of students' characteristics on the first letter of their given names lead to low R-squared and F-Statistics. In general, the coefficients of the regressions are not statistically significant at a 10% level. However, we find a correlation between the first letter of a student's name and gender, as some letters are associated with higher or lower probabilities of female names. Nevertheless, those gender differences spread across the alphabet. Table A.3 reports those results.

In Table 1, we test for whether there were differences in observable pretreatment characteristics for students assigned to section 1 or 2.[12] As students' assignment to sections is by admission year and stream, we control for cohort-stream fixed effects. There are no statistically significant differences between students assigned to section 1 compared to section 2 for most characteristics. However, in section 1, there is a lower percentage of female students (4 percentage points). This difference relates to Brazilian female first names being less concentrated in the first half of the alphabet (Lepine and Estevan, 2020).

Students' assignment to sections determines in which class the student attends compulsory courses. In first-semester courses, enrollment is centralized, and students cannot choose courses or professors. Since

[10] Following the Brazilian occupation classification, we categorize an individual as an economist if her principal occupation in the labor market data is economist, researcher, or professor in Economics. Students interested in business-related occupations typically opt for a Business undergraduate degree offered at USP, as explained in Section 2.

[11] In all admission years but one, all Economics students were assigned to classes by alphabetical order, except those at the waiting list or who transferred from other majors or universities. Only in 2008, student allocation did not follow the alphabetical order, and the criterion used to assign students to classes is unknown. We tested for whether USP used observable characteristics to assign students to sections in 2008, like age, admission scores, admission list, etc., and rejected those alternative criteria. We present in Table A.2 the randomization balance checking excluding the 2008 admission year, and we find evidence of orthogonality, as in Table 1. We also confirm that excluding the 2008 admission cohort from our sample does not change our estimates.

[12] In Table A.4, we test for differences between course sections 1 and 2 of all mandatory courses that our sample of students attended over the undergraduate studies, for each stream. In general, there are no differences between sections, although characteristics diverge for streams. The only noticeable difference between sections 1 and 2 is that there is a higher share of female students in course sections 2.

course attendance is mandatory and instructors/evaluations typically differ by course section, attending a course in the other section is unfeasible. Students may ask to change sections from the second semester on, but approvals depend on slot availability.

Thus, in the first semester, all students must take the same compulsory courses and attend lectures in randomly assigned course sections. To test whether the assignment to first-semester course sections is independent of the professor's gender, in Table 2, we follow Fairlie et al. (2014) and present regressions to check for differential sorting of high-achieving female students into course sections taught by female professors. The explanatory variables are a gender dummy, a female professor indicator, and the professor's and student's gender interaction. The dependent variables are students' average characteristics by course section and gender, to measure students' features related to their ability. We use the following students' characteristics: age, admission scores, and a dummy variable for whether they had previously enrolled at a USP major. In column (1), we do not insert control variables. In column (2), we add cohort fixed-effects, in column (3), we add a stream dummy variable, and in column (4), we include cohort-stream fixed-effects. The correlation between the instructor's gender and students' characteristics is small and statistically insignificant. We find no evidence of differential sorting by gender.

Moreover, to test for gender-specific selection into first-semester courses, in Table 3, we regress female students' share in the course section on a female instructor dummy variable. The professor's gender does not affect the percentage of female students enrolled in a first-semester course section.

We use the first-semester assignment to sections to determine exogenous variation in the gender composition of peers and professors and address potential selection issues. When evaluating the impacts of female classmates' share, the relevant peers for us are students from the same admission-cohort and stream, assigned to the same section in the first semester. Indeed, we expect friendships to be formed right after admission, a period of intense social activity at USP.[13] We calculate the student's share of female peers as the leave-me-out mean of female students in the assigned section. To analyze female professors' effects, we use the predicted percentage of female faculty members (we will discuss the specifications in more details in Section 4).

In Table 4, we analyze whether students comply with their assigned sections in compulsory courses.[14]

[13] In particular, freshmen students do not attend classes in the first week of the term but instead participate in several activities designed to promote integration.

[14] We exclude unified course sections from this analysis and restrict the sample to students attending classes in the regular schedule, excluding cases where the student failed a course or postponed the course enrollment to the following semesters.

In the first term, as expected, students enroll in their designated course sections (99%). In the subsequent semester terms, there is a decrease in students' compliance with the assigned sections. Nevertheless, adherence to the sections remains relatively high over the undergraduate program. Overall, in more than 85% of our student-course observations, students enroll in their initially assigned section.

To formally test the exogeneity of the share of assigned classmates and professors, in Table 5, we regress students' characteristics on those explanatory variables, conditional on admission year and stream (cohort-stream fixed-effects). The correlation between students' variables and the gender composition of peers and instructors is negligible for most variables and statistically insignificant in all cases. To avoid the negative mechanical correlation between female students and female classmates' share, we also control for the percentage of female peers in the cohort-stream, as suggested by Guryan et al. (2009).

3 Data

Our study uses detailed student, instructor, and course administrative data from the Department of Economics at the University of Sao Paulo. This dataset also includes admission data for these students.

Our data cover students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. The original sample contains 1,619 students. We exclude students who enrolled but did not attend any course from the Economics degree, which corresponds to 1.5% of the original sample. Finally, we drop 18 students with missing values on students' covariates (1% of the original sample). Our final sample consists of 1,576 students.

The university academic records contain information on course outcomes, including grades, whether the student passed the course, and credits obtained for every class offered by and every student enrolled in Economics at the University of Sao Paulo. We match each course section to the corresponding professor's full name, which allows us to assign the instructor's gender based on their given name.[15] This dataset contains several student identifiers, such as full name and date of birth and, for 65% of the sample (1,020 individuals), also the unique Brazilian tax identifier number, CPF.

We also use USP admission data that contain student-level pretreatment data. The data include information on gender, date of birth, city of residence, and students' scores at the admission process.

We obtain additional instructor data linking our administrative data with academic career measures,

[15]It is trivial to identify gender associated with most given names used in Brazil. In the few cases where there was some ambiguity, we checked the instructors' university webpage to confirm their gender.

collected from each instructor's curriculum vitae, available at Lattes Platform (CNPq, 2020).[16] For each instructor, we extract her publications, years since Ph.D., and Ph.D. granting institution (USP, another university in Brazil, or abroad). To assess the quality of the published papers, we use the *Qualis* ranking created by the Ministry of Education (CAPES, 2020).[17] *Qualis* ranks journals on a categorical scale (A1, A2, B1, B2, B3, B4, B5, C), where A1 defines papers published in the best journals and C papers published in the worst journals.

For labor market outcomes, we use *Relação Anual de Informações Sociais* (RAIS) from 2002 to 2017, a matched employer-employee dataset of the Brazilian formal labor market. RAIS contains information on the universe of formal employees and firms in Brazil, including individuals' tax identifiers. We first merge RAIS with our university academic records using students' full names and dates of birth to search for the tax identifier number for the remaining 35% of the sample (556 individuals). This procedure allows us to recover the tax identifier number for 98% of our initial sample. As shown in Table A.5, the success of the merge cannot be predicted by any student predetermined characteristics such as age, admission scores, stream, etc.

Using the tax identifier number, we then merge university academic records with each RAIS edition, allowing us to obtain yearly information on students' labor force participation, occupational and sector choice, career progression, and wages after graduation.

Instead of working as an employee at the formal labor market, some individuals may be partners in companies. To allow for this possibility when evaluating labor force participation rates, we include publicly-available information on firm partnership (ownership) gathered by the Brazilian Revenue Service (Receita Federal, 2020). The data contain partners' full name and six out of eleven digits of the tax identifier number, which allow us to merge it with the students' data.[18]

To identify students working during undergraduate studies, we combine RAIS with USP administrative dataset. RAIS provides us information on all workers at the Brazilian formal labor market but does not record data on internships. To obtain information on internships, we use administrative data from the Department

[16]The Lattes platform is a nationwide platform administered by the Brazilian Government, containing all Brazilian professors' and researchers' academic curricula.

[17]We use the 2013-2016 Qualis ranking, which is the most recent available at Sucupira Platform.

[18]The Brazilian Revenue Service updates the partnership database roughly every three months and does not keep previous versions online. For this study, we use all the updates we could obtain, starting from December 27, 2017, until February 2, 2020. Since the datasets include partners' entry date in a company, we can build panels for the duration of partnerships, except for those no longer partners on December 27, 2017.

of Economics, indicating that the student enrolled in an 'internship' discipline.[19]

Finally, we also obtain information on students' interest in attending a Brazilian Master's program in Economics by linking our administrative information to data from the Brazilian Association of Graduate Programs in Economics (ANPEC). As Brazil adopts a centralized admission for graduate studies in Economics, nearly all students pursuing a Master's program take the national exam. Thus, a dummy for whether the student took the ANPEC exam is a good measure of students' interest in graduate studies.

3.1 Variables and descriptive statistics

Table 6 provides summary statistics for students and professors. Panel A presents student-level characteristics for our sample of incoming students. Twenty-three percent of the students enrolled in Economics are female. Compared with their male counterparts, female students are younger and more likely to enroll in daytime classes. A higher percentage of male students have enrolled in another USP major before admission into the Economics degree.[20]

Panel B reports descriptive statistics for the sample of professors teaching mandatory courses to undergraduate students in Economics from 2000 to 2016. Female faculty members are more likely to have earned a Ph.D. degree from the University of Sao Paulo. Male professors are more likely to have received a Ph.D. from a foreign research institution. Differences in other instructors' characteristics are indistinguishable from zero.

Our main goal is to estimate the effects of gender composition on long-term outcomes related to career choices. When looking at career outcomes, we analyze labor force participation rates, career choice (occupation and industry), career progression, and wages after graduation. To investigate potential channels, we also evaluate the impact of female faculty members' and female classmates' percentages on academic performance, elective courses' selection, and work during undergraduate studies.

To assess labor force participation, we create dummies indicating whether the student works at the formal labor market or is a firm partner (owner). We consider that a student is part of the labor force if she is an employee in the formal sector or a firm partner.

[19]The creation of the internship subject took place in 2005, and students from the earlier cohorts (2000 and 2001) were only able to enroll in this course by the end of their undergraduate program. On average, students register for internships in their third year. Therefore, we restrict the sample to students admitted between 2002 and 2008 in this analysis.

[20]Figure A.3 plots the distribution of the admission exam scores, a pretreatment measure of academic performance, by gender. The distribution of admission scores is similar for both genders, although male students outperform female students in Phase 1 and female students outperform male students in Phase 2.

To investigate whether female professors and peers influence career occupations and industries, we focus on those outcomes most related to Economics. We define a dummy for whether the student worked as an economist, i.e., has economist, researcher, or professor in Economics as occupation, according to the students' occupation at the formal labor market, using the Brazilian Classification of Occupations (CBO - *Classificação Brasileira de Ocupações* 2002). In Panel A from Table A.6, we present all CBO codes considered as economists. Besides, we use the Brazilian Classification of Industries (CNAE - *Classificação Nacional de Atividades Econômicas*) to obtain information on which sector the student works at the formal labor market. We create a dummy for the following industries that typically employ economists: financial services, consulting firms, research institutions, and the public sector (see Panel B Table A.6).

Subsequently, we analyze gender composition effects on career advancement by investigating the impacts on the probability of holding managerial job positions. We look at two outcome variables: indicator variables for Top Manager and Middle Manager. We define the job position using the Brazilian Classification of Occupations. In Panel A, from Table A.6, we report the respective codes.

We also examine the effects of gender composition on wages one, two, or five years after expected graduation. Our wage measure is the average hourly salary in the months that the person had an active job contract at the formal labor market, considering all contracts that the individual holds in the month. We use real hourly wages in 2002 Brazilian *reais*. We normalize wages to have an average of zero and a standard deviation of one.

We analyze the following long-term educational outcomes: the probability of obtaining a bachelor's degree in Economics at USP; time to graduation (conditional on degree completion); grade point average in compulsory courses (GPA)[21]; the percentage of elective courses the student enrolled in the fields of Microeconomics, Macroeconomics, Finance and Humanities; a dummy variable for a female bachelor's thesis advisor; and a dummy for students' interests in graduate studies in Economics (i.e., whether they took the ANPEC exam). At the Department of Economics from USP, course grades and GPA vary from 0 to 10. The minimum course grade to pass a course is 5. We normalize the GPA, such as the variable has a mean of zero and a standard deviation of one.

Another intermediate outcome that we analyze is the likelihood of working during the undergraduate program. As explained above, an undergraduate can have a regular job in the labor market or undertake an

[21] As a robustness check, we run the regressions replacing GPA in core courses with GPA in all disciplines (including electives), and results remain similar.

internship. As an outcome variable, we include an indicator variable that equals one if the undergraduate work in the formal labor market or as an intern while at university, and zero otherwise.

Table 7 reports summary statistics for these outcome variables. The variables after graduation consider students' decisions at any moment of their career. For instance, the master's indicator variable equals one if the students applied for a Brazilian master's program in Economics at any moment (since admission into USP). Female students have a higher GPA, complete the undergraduate studies in fewer years, and have higher degree completion rates (87% for female students graduate versus 72% for the male students). Related to elective course choices, female students choose a higher percentage of Macroeconomics or Microeconomics courses. Female students also have a higher probability of having a female advisor (6 percentage points higher). There are no gender differences in the likelihood of applying for a Master's in Economics or labor force participation rates. However, female students are less likely to be firm partners and work in the public sector and more likely to work as economists. The share of students that hold managerial job positions after graduation is not different across genders.

We also evaluate the effects of labor market outcome variables (labor force participation rates and normalized wages), one, two, and five years after expected graduation.[22] We report descriptive statistics for such outcome variables in Table A.7.

Figure 1 presents career outcomes for female and male students from one to five years after the expected graduation. We verify that both participation in the Brazilian formal labor market and firm ownership increase after (expected) graduation. Although entrepreneurship rates are higher for male students five years after predicted graduation, we observe that labor force participation (the combination of formal labor work and firm partnership) is similar across genders. The percentage of students applying for master's programs in Economics is higher in the first two years following degree completion and decreases in the next years. Female students are more likely to apply for a Master's in Economics after graduating. The share of students that enroll in a master's program increases in the first three years after graduation and decreases in the following years, while the percentage of Ph.D. students steadily increases. A small percentage of students enroll in Ph.D. programs. A higher share of female students enroll in master's degrees, but the pattern is the opposite in doctorate programs.

[22] As the share of female peers and professors could affect time to graduation, we use the expected date of graduation to create those variables, instead of the actual date of graduation. The expected graduation year is when students would finish the undergraduate program if they graduate on time. Note that the expected graduation date varies by admission year and stream.

4 Empirical strategy

4.1 Female professors

Long-term outcomes

In our main specification, we investigate long-term effects, looking at students' outcomes after graduation. One advantage of focusing on long-term results is that professors cannot directly manipulate these outcomes. Therefore, they are more consistent with passive teacher effects (such as role-model effects) than with active teacher effects (Fairlie et al., 2014).

Students may attend lectures in a course section other than the one initially assigned starting in the second semester. To address this potential selection issue, we use the predicted share of female instructors, i.e., the percentage of female professors the student would have if she remained in the assigned course sections as our key explanatory variable.[23]

The econometric model to estimate the impacts of the instructor's gender is given by equation (1):

$$\begin{aligned} y_{ik} = \beta_0 + \beta_1 female_i + \beta_2 p\_share\_femaleprof_k + \\ \beta_3 female_i \times p\_share\_femaleprof_k + \alpha_{tm} + Z_i\omega + X_k\gamma + W_p\phi + \epsilon_{ik} \end{aligned} \tag{1}$$

where y_{ik} is the outcome variable of a student i randomly assigned to a class k (section, stream, and admission-cohort level). Our main response variables are labor force participation rates, occupational and industry choice, career development, and normalized hourly wages. To investigate potential channels, we also estimate equation (1) for the following outcome variables: graduation rates, normalized students' GPA, time to graduation, elective courses' choice (share of elective courses from Microeconomics, Macroeconomics, Finance, and Humanities fields), a dummy for a female advisor, whether the student applied for a Master' in Economics, and the probability of working during the undergraduate program. $p\_share\_femaleprof_k$ is the predicted share of female instructors teaching mandatory courses to section k, and $female_i$ is a gender dummy variable. Since our econometric models are at the student level, we will not include individual or course section fixed-effects. Still, we will control for a host of observables.[24] The vector Z_i includes

[23] As a robustness check, we use an instrumental variable estimator. The Two-Stage Least Squares (2SLS) estimations use female instructors' predicted share as an instrument for the students' actual percentage of female instructors in core courses. We report the first stage in Table A.8 and the estimates of professor effects in Tables A.9, A.10, A.11, and A.12.

[24] We may worry that the inclusion of professors' characteristics as control variables partially captures the impacts of higher female faculty members' shares. Reassuringly, our results are not sensitive to the inclusion of covariates. Results of the regressions

students' variables, X_k contains sections' characteristics, and W_p contains professors' characteristics. The vector Z_i contains Normalized admission scores, Previous USP enrollment, Student's age at admission, and Sao Paulo city of residence dummy. The variables included in X_k are Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Finally, in W_p, we add the following covariates: Percentage of professors with Ph.D. abroad, Professors' Experience, Share of A papers, Share of classified papers. We also control for cohort-stream fixed-effects (α_{tm}). The cohort-stream dummies are particularly relevant, since students from the daytime and evening streams differ in many observable characteristics (Table A.1). The fixed-effects inclusion allows us to control for any cohort-by-stream confounders as we compare students within the same cohort and stream (time-slot). Standard errors are clustered at the cohort-stream level. We estimate the model by Ordinary Least Squares (OLS).

Our main coefficient of interest is β_3, which measures the differential effect across female and male students of having more female versus male professors in compulsory courses. β_1 reflects average gender differences in outcome variables, and β_2 measures the effect on male students of higher shares of female instructors.

Since we test for several hypotheses simultaneously, both for outcomes and potential channels, we deal with multiple hypothesis tests using two approaches. The first is the randomization test based on Young (2019), which tests the null hypothesis that each treatment, i.e., gender composition of professors, classmates, and high-performing peers, does not affect any outcome. We apply this test for each table (group) of outcomes. The second approach consists of building a summary index of families of results that becomes the dependent variable of our specification, as suggested by Anderson (2008). To do so, we group findings that share a similar interpretation by computing the index by each table of results.[25] We then construct an aggregated index by combining data on multiple outcomes weighted by their covariance so that the index provides a maximum amount of information.

without controls are available upon request.

[25]We do not construct the summary index for occupational and industry choice, elective course choice, or female advisor, as the definition of a 'better' outcome is unclear. We are also unable to include course duration, which is conditional on degree completion.

First-semester courses

We also estimate own-gender instructor effects on first-semester course section level outcomes when students are randomly assigned to course sections. The main econometric model is given by:[26]

$$y_{ic} = \delta_0 + \beta female_i \times female\_instructor_c + \alpha_i + \theta_c + \epsilon_{ic} \tag{2}$$

where y_{ic} is the outcome variable for a student i in course section c, $female_i$ is a dummy variable for whether a student is female, $female\_instructor_c$ is an indicator variable for whether the course section professor is female, α_i are student fixed-effects, and θ_c are course section fixed-effects. By including course section fixed-effects θ_c, we are implicitly controlling for the professor, section, course, and term fixed-effects. We cluster standard errors at the course section level. We run OLS regressions.

The coefficient of interest is β, which measures the extent to which gender gaps depend on students' assignment to a female or male instructor. We will estimate equation (2) for two different outcome variables: a dummy variable for whether the student passed the course and normalized course grades.

4.2 Female classmates

The random assignment of students to classmates and the use of a pre-determined peer characteristic (gender) allow us to overcome empirical challenges of peer effects measurement, such as the endogenous formation of the peer group and the reflection problem (Sacerdote, 2001; Feld and Zölitz, 2017).

To investigate gender peer effects, we estimate the following specification, both for short-term and long-term outcomes:

$$\begin{aligned} y_{ik} = \beta_0 + \beta_1 female_i + \beta_2 share\_femaleclassmates_{ik} + \\ \beta_3 female_i \times share\_femaleclassmates_{ik} + \alpha_{tm} + Z_i\omega + X_k\gamma + W_p\delta + \epsilon_{ik} \end{aligned} \tag{3}$$

where i indexes student, k sections, and p professors. y_{ik} are the response variables, $female_i$ is a gender indicator, and $share\_femaleclassmates_{ik}$ is the percentage of female peers. As aforementioned, we define a student's classmates as the students assigned to the same section in first-semester courses. Indeed, course section composition is quite stable throughout the undergraduate program, as shown in Table 4, and

[26] Similar econometric models have been widely used by the economic literature, see e.g., Dee (2005, 2007), Fairlie et al. (2014), and Paredes (2014).

friendships are likely to be built at the beginning of the undergraduate degree, a period of intense social activities.

The model also includes individual-level control variables Z_i and classmates' and professors' covariates X_k and W_p. We also control for the predicted share of female professors. α_{tm} are cohort-stream fixed effects.[27] We estimate our model by Ordinary Least Squares (OLS). We cluster standard errors at the cohort-stream level.

Our primary variable of interest is the interaction term $female_i \times share\_femaleclassmates_{ik}$. The coefficient β_3 indicates the differential effect of having higher shares of female classmates for women. β_2 captures overall differences in outcome variables for classes with higher shares of female peers, and β_1 measures gender differences in response variables.

The undergraduate studies and career outcomes are the same analyzed when measuring professor effects. For academic results, we analyze impacts on elective course-taking behavior, normalized GPA, degree completion, time to graduate, advisor gender, students' likelihood of applying for a Master's in Economics, and working during the undergraduate studies. After graduation, the outcomes are labor force participation, probability of working at the formal labor market or being a firm partner, occupational choice, career progression, and normalized hourly wages at the formal labor market. For first-semester courses, the dependent variable y_{ik} is the normalized first-semester GPA (average course-grade in first-semester courses, weighted by course credits).[28] When measuring gender peer effects, we also perform the multiple hypothesis tests mentioned above.

Table A.13 examines the extent of variation in gender composition that is left after removing fixed effects and controlling for other explanatory variables, following Bifulco et al. (2011) and Lepine and Estevan (2020). Removing cohort-stream fixed effects reduces the total variation by 35%. The inclusion of students' and classes' covariates reduces the total variation by 45%. The inclusion of all control variables reduces the total variation by 52%. Compared to the previous studies, it seems that the remaining variation in our sample is sufficient to estimate peer effects.

We also estimate our main specification using an alternative measure of female classmates. Instead of using the share of female peers $share\_femaleclassmates_{ik}$, we replace with the percentage of females

[27] Both for peers' and professors' effects, we have also run regressions allowing for nonlinear impacts. We found no evidence of nonlinearity. Results are available upon request.

[28] Students will have the same classmates in all course sections. Therefore, when estimating gender peer effects, we cannot use equation (2), as our key explanatory variable will not vary by course section.

among high-performing students $HP\_femaleclassmates_{ik}$. We consider a student as high-performing if she ranked amongst the top 25% at the admission exam (by admission year).

5 Main results

We now investigate the impact of higher shares of female faculty members and classmates on future career choices, looking at outcomes after graduation. First, we analyze the effects of the gender composition on female labor force participation rates, and then we look at occupational and industry choice, career progression, and wages. As explained in Section 3, our labor force participation measure combines formal labor market participation with firm partnership data. Besides looking at labor force participation at any point in time, we also evaluate it one, two, or five years after expected graduation.

Panel A from Table 8 provides the results from estimating the effect of professor gender, measured by the proportion of mandatory courses taught by female faculty, on labor force participation. In general, we find no statistically significant impact on female students' labor force participation. Most coefficients are positive, but none of them is statistically significant at a 5% level. Both the Summary Index Test and the Westfall-Young suggest no professors' effects on female labor force participation.

Table 8 (Panel B) also displays estimates of the impacts of female classmates' share on female labor force participation rates. Higher percentages of female peers increase the likelihood that a female student works at the formal labor market two and five years after expected graduation. If female peers' share increases by seven percentage points (one standard deviation), female students relatively increase labor force participation rates by ten percentage points two years after expected graduation (0.21 standard deviations) and six percentage points after five years (0.15 standard deviations). The coefficient measuring effects on female labor participation in the year after students' expected graduation is also positive but smaller and not statistically significant.[29] Our multiple inference tests (summary index and randomization-t p-values) confirm that female classmates have a statistically significant impact on female labor force participation.

In Panel C from Table 8, we verify that high-performing classmates' gender composition positively impacts female labor force participation two and five years after graduation. An increase by one standard deviation (12 percentage points) in the share of high-performing female classmates results in an eight per-

[29] This pattern may emerge because students, on average, take longer to graduate than the coursework schedule recommends. The predicted duration of the undergraduate program in Economics is four years for the daytime and five for evening classes. Our sample's average time to graduation is five years for daytime students and 5.6 years for evening students.

centage point higher labor force participation (0.17 standard deviations) two years after graduation and a four percentage point larger participation (0.11 standard deviations) five years later. The multiple hypothesis tests reject the null hypothesis of no impacts of high-performing female peers at a 5% significance level (p-values 0.008 for summary index test and 0.034 for the randomization-t).

We also analyze whether women underrepresentation in Economics influences female students' occupations and activity in the formal labor market in Table 9. We only have information on students' occupations and sectors conditional on their Brazilian labor market participation. Therefore, the sample used in regressions presented in Table 9 is restricted to students that we observe at the administrative formal labor market data (RAIS dataset). Panel A presents the impacts of the share of female faculty members on career choice. Overall, we find little influence of female professors on women's occupation and activity choices. However, female instructors' share leads to a higher probability that a female student works at a consulting firm. If the female instructors' share increases by ten percentage points (one standard deviation), women are nine percentage points (0.21 standard deviations) more likely to work at a consulting company. However, the joint significance p-value does not reject the null hypothesis of the irrelevance of female professors' effects on occupational and industry choice at a 10% level.

Information on students' activity is only available for students working in the formal labor market (i.e., on RAIS data). As the impact of female faculty shares on labor force participation is limited, sample selection probably does not influence our estimates. However, we deal with the possible sample selection by running the regressions using a Heckman Two-Step Procedure. The instrument we use in the selection equation is the formal employment rate of higher education workers at Sao Paulo city by gender-age-graduation year cell.[30] We present results correcting for selection in Table A.14. Heckman estimates suggest lower coefficients, but the impact is still statistically significant at a 10% significance level.

Panel B in Table 9 presents estimates of female peer effects on career choice. We find that the share of female classmates has no impact on female students' choice of occupation or industry, and we observe that the joint-significance test confirms the absence of impacts. Nevertheless, we find significant effects of high-performing peers' gender composition on career choice (Panel C). A 12 percentage higher percentage

[30]To construct the instrument, we merge formal labor market data (RAIS), the Brazilian census, and municipal population estimates. We use RAIS data from Sao Paulo city between 2002 and 2017 to obtain information on the number of formal workers with a higher education degree, segmented by gender, age, and year. We use Census data to gather information on the city's percentage of people with a higher education degree by gender and age. As we only have Census data each decade, we used population estimates to obtain a yearly number of citizens with a higher education diploma (we multiply the shares by the population sizes). Finally, we divide the number of formal workers by population in the gender-age-year cell to obtain formal workers' share.

of high-ability peers (one standard deviation) increases by 8.5 percentage points the probability of a female student working as an economist (0.19 standard deviations). The joint significance randomization-t p-value rejects at a 5% significance level the hypothesis of no effects of high-performing female peers on occupational and sector choice. We checked if those results are robust to sample selection corrections (results shown in Table A.15). Coefficients are larger when we use the Heckman Two-Step Procedure.

To assess the effects of higher women's representation on career progression, we look at the probability of working as a top or middle manager at the formal labor market. As in the previous table, our sample is restricted to students observed in the formal labor market. Results shown in Panel A from Table 10 indicate that higher female faculty shares increase female students' likelihood of working as top managers. A ten percentage points higher share of female professors (one standard deviation) increases by four percentage points the likelihood of working as a top manager (0.16 standard deviations). The joint significance and summary index tests reinforce that female professors influence women's career progression (p-values 0.034). Results remain similar after correcting for sample selection, as shown in Table A.16. There is no impact of female classmates on women's career advancement (Panels B and C).

We also evaluate whether female professors and classmates impact future wages. We show results in Table 11. As explained in Section 3, we normalize real hourly wages (2002 prices in Brazilian *reais*), such as the wage variables have an average of zero and a standard deviation of one. We find no impact of the gender composition of classmates or high-performing female peers on women's relative real hourly wages after graduation. The predicted percentage of female instructors in compulsory courses does not impact hourly wages one or five years after graduation. Still, two years after, there is a positive and statistically significant impact on wages. An increase of ten percentage points (one standard deviation) results in a 0.2 standard deviation increase in normalized hourly wage. The multiple inference tests suggest that female professors' share impacts hourly wages (significant at a 5% level). Besides, once we consider selection into the formal labor market, using a Heckman Two-Step Procedure, the coefficients are similar and still statistically significant at a 5% level (Table A.17).[31]

Finally, we estimate heterogeneity effects for female students with different initial ability levels for our main response variables (results available upon request).[32] Previous studies, such as Hoffman and

[31] For the selection equation, we use a dummy variable for whether the student had information on the individual taxpayer number. As we explain in Section 3, for students that we do not have information on the individual taxpayer number, i.e., CPF, we used the full name and birth dates to link our administrative records to RAIS data, which reduces the probability of merging them.

[32] To do so, we expand equations (1) and (3) to allow for heterogeneous impacts. We include a triple interaction term with new dummy variables $Top\_25\%\_Admission\_score_i$ and $Bottom\_25\%\_Admission\_score_i$, which indicate if scores are in the top or

Oreopoulos (2009), Carrell et al. (2010), and Bottia et al. (2015), found that same-gender instructor effects are larger for high-achieving students. While female professors' share particularly influences top quartile female students to become top managers, our labor force participation effects are concentrated in the middle of the ability distribution.

In sum, a higher representation of women in a typically male-dominated environment, an Economics undergraduate program, influences female students in the job market. We observe that both an increase in the percentage of female classmates and high-performing female peers lead to higher female labor force participation rates. Moreover, female students who had higher shares of female instructors in core courses are more likely to be top managers in the formal labor market.

6 Potential Channels

In this section, we investigate possible channels that could be driving our estimated effects. First, we analyze whether female students' academic performance could explain gender differences in labor market outcomes. In this analysis, we evaluate impacts on first-semester academic performance and throughout the undergraduate program. We also assess peers' and professors' effects on the likelihood of choosing a female advisor and the probability of pursuing graduate studies in Economics. Second, we evaluate if the share of female peers and professors influence female students' elective course choice. Finally, we check if women's representation influences the decision to work while at university.

6.1 Academic achievement

In this subsection, we analyze how the gender composition of professors and classmates affects female students' performance. First, we will present results for having a same-gender instructor on first-semester course performance. We estimate same-gender instructor effects on first-semester course performance, a sample that consists of 6,713 student-course section observations. We will use two student outcome variables at the student-course-section level: normalized course grades and a dummy for whether the student passed the course.

Table 12 presents the estimates of gender interaction effects on normalized course grades and pass rates. In column (1), we include only the variables on which the randomization is conditional, i.e., cohort-stream

bottom quartile of the admission-year scores.

fixed-effects. In column (2), we add students' characteristics as explanatory variables. In column (3), we replace students' characteristics with individual fixed-effects. In column (4), we add professor fixed-effects. Finally, in column (5), we simultaneously include student and course section fixed-effects.

In the first panel, we present own-gender instructor impacts on course grades. The female professor dummy shows that students, on average, have lower grades in courses taught by female faculty members (0.3 standard deviation lower in column (2)).[33] Besides, we note that female students have course grades 0.17 standard deviation higher than male students, on average. Once we include student fixed-effects, the interaction term indicates female students relatively gain in course-sections taught by female vs. male instructors. In our preferred specification (column (5)), we verify that female students have a 0.1 standard deviation higher grade in course sections with female instructors. Conversely, male students have a 0.1 standard deviation lower achievement in courses taught by female vs. male professors.

In the second panel from Table 12, we report the effects of female professors on pass rates. Female students have pass rates, on average, 3 to 4 percentage points higher than male students, and course sections taught by female instructors have pass rates six percentage points lower. Female students have relatively higher pass rates in course sections with female instructors: their likelihood of passing a first-semester course is 4.1 percentage points higher than male rates when a female rather than a male professor teaches the course (0.14 of a standard deviation).

We verify that the own-gender professor impacts are driven by male students performing relatively worse in courses taught by female instructors, rather than by an increase in female students' performance (results similar to Hoffman and Oreopoulos, 2009). Figure 2 reports unconditional mean performance in courses by student and professor gender. Female students outperform male students, regardless of instructor gender. Students have lower performance in first-semester courses taught by female professors. However, this decrease in achievement is larger for male students.[34]

To examine the impact of the percentage of female classmates on average performance in first-semester

[33] Our empirical analysis shows that students from both genders have lower performance in courses taught by female instructors. In Table 6, we verify that female and male professors do not differ in many observable variables. Thus, differences in their characteristics do not seem to drive the results. At the Department of Economics from the University of Sao Paulo, the exams will differ by course section, and grading is not on a curve. A possible explanation is that female instructors hold students to higher standards than their male colleagues. Another possibility is the existence of students' behavioral responses to the professor's gender.

[34] The pattern shown in the figure is qualitatively similar to additional regression estimates available upon request. We estimate the impacts of female professors for female and male students separately (in this specification, we include individual fixed-effects, analogous to column (3) from Table 12). We find that having a female professor in a first-semester course reduces male students' pass rates but has no impact on female students' rates. Female professors decrease the course grade for both genders, but the effect is more substantial for male students.

courses, Table 13 presents estimates of model (3). In column (1), we control only for cohort-stream dummies. Column (2) includes students' characteristics. In column (3), we control for sections' and professors' characteristics. For the average student, the share of female classmates does not impact the first-semester GPA. In Panel B, we show estimates of the effects of females' share among high-performing peers (top admission scores quartile) on female students' first-semester GPA. Likewise, we find no impact of high-performing classmates' gender composition on students' performance in the first semester courses.

In Table 14, we present estimates of the impact of women representation in Economics on longer-term academic outcomes, looking at students' results throughout their undergraduate studies and after graduation. The undergraduate program variables are a dummy variable for degree completion (whether the student obtained a bachelor's degree in Economics), cumulative GPA, the duration of the undergraduate program, the gender of the bachelor thesis' advisor, and the probability of applying for a Master's in Economics. We control for cohort-stream fixed-effects and covariates for students, classes, and professors in all regressions.

In Panel A, we show the impact of the female faculty members' shares on academic performance. Female students are 17 percentage points more likely to graduate with an Economics degree and have a 0.27 standard deviation higher GPA. The share of female professors in core courses does not differentially impact long-term academic outcomes for female students. The percentage of female faculty members increases degree completion. A ten percentage points higher female instructors' share leads to a four percentage points higher graduation rate. Moreover, the percentage of female professors in compulsory courses does not affect female students' willingness to pursue a Master's in Economics. The share of female professors seems to reduce the probability of applying for a Master in Economics, but this coefficient is only marginally significant (at a 10% level). Furthermore, we cannot reject at a 10% significance level the hypothesis of no female professors' impacts on educational outcomes.

Panel B in Table 14 shows the impacts of female classmates' share on students' performance. The percentage of female peers decreases time to graduation for all students, but there is no additional effect for female students. We find no impacts of female classmates' share for the average female student for the other outcome variables. The percentage of high-performing female peers does not affect female students' educational outcomes differentially (Panel C).[35]

Our results suggest that an increase in female representation in Economics does not improve women's

[35] We pooled the variables normalized GPA, degree completion, and applied for a Master dummy, and conducted a summary index test. The summary index tests suggest that the gender composition of professors, classmates, and high-achieving classmates does not impact performance in undergraduate studies (p-values 0.510, 0.191, and 0.358, respectively).

performance throughout their undergraduate program. Female students have relatively better achievement in first-semester courses taught by female instructors, but a comparatively worse male performance drives the result. In the long term, female professors' share does not impact grades and degree completion rates for female students. Likewise, there is no female performance increase when assigned to classes with higher female classmates' shares. We find no impact of a broader women representation in Economics on the probability of having a female advisor or willingness to pursue graduate studies in Economics.

6.2 Elective courses' choice

In Table 15, we assess if higher female representation in Economics impacts elective courses' choice. As mentioned above, the coursework structure at the University of Sao Paulo is relatively rigid, as around 57% of credits are in mandatory courses. The remaining credits are elective courses from the Department of Economics (at least 29% of the total credits) and courses from other departments or universities (at most 13% of the credits). Our analysis's dependent variables are the shares of elective courses from the Department of Economics that the student enrolled in each field: Microeconomics, Macroeconomics, Finance, and Humanities (History, Sociology, and other humanities courses), considering all elective courses that the student enrolled as the denominator.

As in the previous tables, in Panel A, we present the effects of female instructors' share. In Panel B, we show the impacts of the percentage of female peers, and in Panel C, we display estimates for the proportion of high-achieving female classmates. Overall, we note that women's representation in Economics does not influence female students' course choices. None of the coefficients is statistically significant at a 5% level, and only one is significant at a 10% level (Finance coefficient in Panel B). Moreover, the Westfall-Young tests do not reject the null hypothesis of no impacts of the gender composition of classmates and professors.

6.3 Work during undergraduate studies

One of our main findings is that a greater women's representation in Economics increases labor force participation. This subsection investigates if the gender composition influences female students to make more career-oriented decisions already during undergraduate studies. More specifically, we will analyze if exposure to higher shares of female professors and peers impacts the likelihood of working while at university, either as an intern or as a regular employee.

As explained in Section 3, we restrict this analysis to cohorts admitted between 2002 and 2008.[36] We report the estimates in Table 16. In column (1), we control for cohort-stream dummies, and we gradually include students' (column (2)), instructors', and classmates' covariates (column (3)) in the subsequent columns.

In Panel A, we represent the impacts of the share of female professors in core courses. Although female instructors increase the probability of work during graduation, there is no differential impact on female students. In Panel B, we verify that female peers' share increases female students' likelihood of working during undergraduate studies. A six percentage point increase in the share of female classmates (one standard deviation in the 2002-2008 sample) results in a five percentage point higher likelihood of work during the undergraduate studies, which corresponds to a 0.15 standard deviations rise. Finally, in Panel C, we examine if the percentage of high-achievement female classmates influences females' decision to work during graduation and find no impact.

7 Conclusion

This paper estimates female peers' and instructors' effects in an undergraduate program in Economics. As Economics is a male-dominated and math-intensive field, higher women's representation in the profession is relevant for female students and could influence their future career outcomes.

We explore the random assignment of students to classes at the Department of Economics from the University of Sao Paulo (USP), a prestigious public Brazilian university. We merge detailed USP administrative data with Brazilian formal labor market and firm ownership data to obtain labor market outcomes.

Female students become more career-driven when exposed to higher shares of female classmates during their undergraduate studies, increasing their labor force participation rates five years after (expected) graduation. We also find suggestive evidence that female faculty members' share affects female students' career progression, raising their likelihood of working as top managers.

We investigate potential channels driving our results. First, we assess the effects of female professors and peers on students' achievement. Gender differences in academic performance, advisor's gender, or willingness to pursue graduate studies cannot explain our results. Second, we examine if the gender composition of classmates and instructors influences female students' choice of elective courses, and we find no impact.

[36] As a robustness check, we verified that our conclusions remain the same using all admission cohorts, i.e., 2000 to 2008.

Lastly, we show that classmates' gender composition affects the probability of work during undergraduate studies (at the formal labor market or as an intern). Our results show that a higher percentage of female peers increases women's likelihood of working during undergraduate studies. Since undergraduates at USP typically work on their degree areas, we interpret this finding as suggestive evidence of an early labor market attachment. More broadly, it is possible that other channels that we cannot measure, such as ambition, self-confidence, and persistence, mediate our effects.

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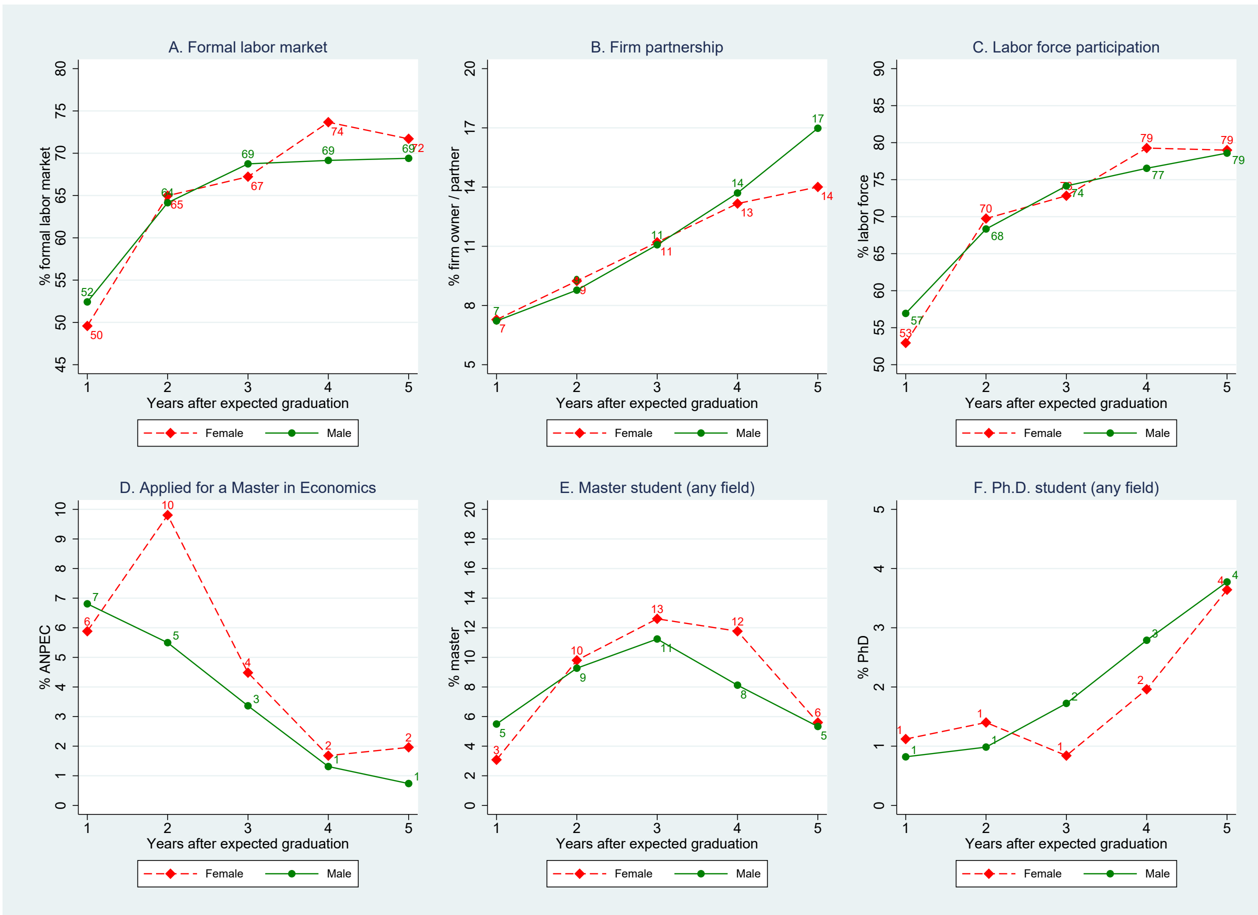
Figures and Tables

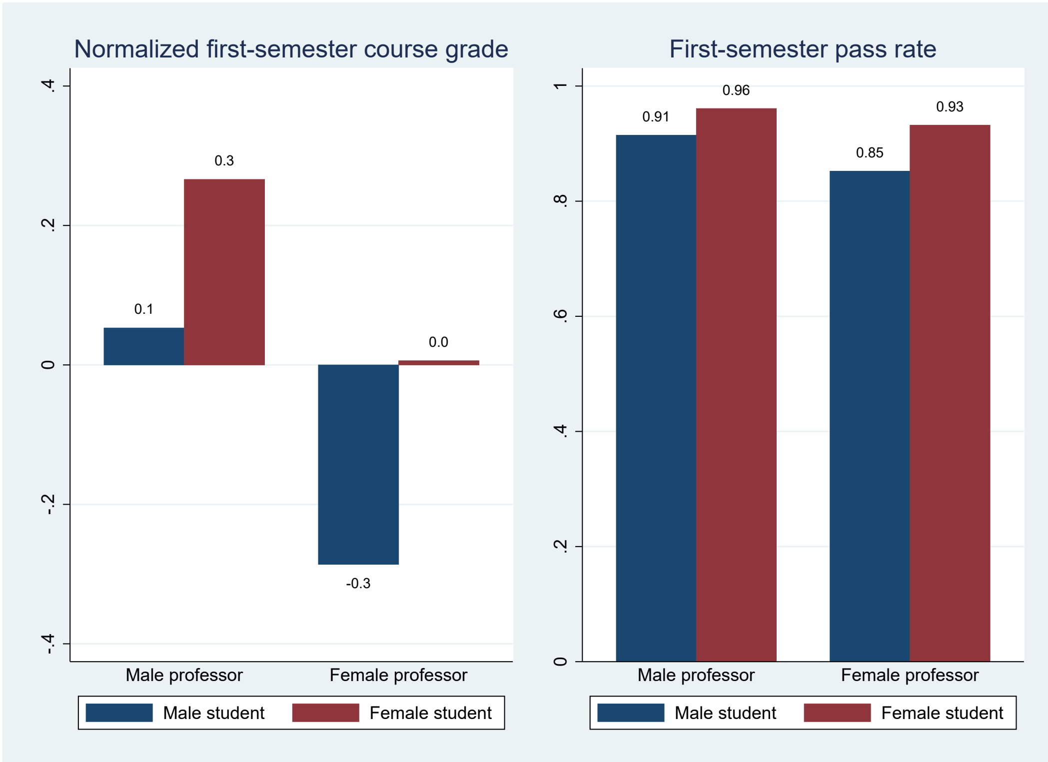
Figures

Figure 1: Career outcomes in the years after expected graduation, by gender



Notes: Labor force participation combines data on formal labor market participation and firm ownership (see Section 3 for more details). We use RAIS data for formal labor market participation, the Brazilian Revenue Service for firm ownership, ANPEC for students that applied for a Master's in Economics, and *Coordenacao de Aperfeicoamento de Pessoal de Nivel Superior* (CAPES) for Master and Ph.D. students in Brazil. We complement the Ph.D. student information with web scraped data on students enrolled in Ph.D. programs abroad collected by dos Santos (2020).

Figure 2: Unconditional mean performance, by student and professor gender



Notes: Table displays information on students' average performance in first-semester courses. Normalized first-semester course grade is the normalization of course grade (0 to 10 scale) to have an average of zero and standard deviation of one and first-semester pass rate is the average proportion of courses students passed.

Tables

Table 1: Randomization balance check

	Female	Admission scores	Previous USP enrollment	SP city	Age	First admission list
Section 1	-0.040*	0.016	0.009	0.009	0.066	0.018
	(0.019)	(0.038)	(0.018)	(0.020)	(0.165)	(0.016)
Observations	1576	1576	1576	1576	1576	1576
F Statistics	4.19	0.18	0.29	0.21	0.16	1.31
Mean of dependent variable	0.23	-0.00	0.14	0.84	19.46	0.85
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficients from separate OLS regressions. The dependent variables are: Female indicator; Normalized admission scores (mean zero, standard deviation one); Previous enrollment at USP dummy; Sao Paulo city of residence dummy; Student's age at admission; First admission list dummy. The key explanatory variable is a dummy variable for whether the student was assigned to section 1. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2: Sorting regressions Fairlie et al. (2014), First semester course sections

	(1)	(2)	(3)	(4)
Dependent variable: Student's average age				
Female professor × female	-0.024	-0.038	-0.004	-0.018
	(0.171)	(0.176)	(0.162)	(0.157)
Female professor	-0.048	-0.037	0.123	0.122
	(0.186)	(0.196)	(0.110)	(0.102)
Female	-0.883***	-0.896***	-0.752***	-0.745***
	(0.100)	(0.103)	(0.094)	(0.091)
Mean of dependent variable	20.05			
Standard deviation of dependent variable	1.09			
Dependent variable: Student's average admission scores				
Female professor × female	0.958	-1.005	-1.692	-1.684
	(2.561)	(2.208)	(2.204)	(2.176)
Female professor	8.930	3.655	0.405	0.953
	(6.928)	(3.146)	(0.917)	(0.863)
Female	1.974	-0.150	-3.073**	-3.129**
	(1.461)	(1.326)	(1.277)	(1.243)
Mean of dependent variable	646.69			
Standard deviation of dependent variable	34.45			
Dependent variable: Share of students with previous USP enrollment				
Female professor × female	0.017	0.014	0.015	0.014
	(0.021)	(0.021)	(0.021)	(0.020)
Female professor	0.016	0.011	0.017	0.014
	(0.013)	(0.012)	(0.012)	(0.010)
Female	-0.085***	-0.086***	-0.081***	-0.079***
	(0.011)	(0.011)	(0.011)	(0.011)
Mean of dependent variable	0.18			
Standard deviation of dependent variable	0.09			
# Observations	6713	6713	6713	6713
# Students	1576	1576	1576	1576
Cohort fixed-effects	No	Yes	Yes	No
Stream fixed-effects	No	No	Yes	No
Cohort-stream fixed-effects	No	No	No	Yes

Notes: We estimate OLS regressions. The dependent variables are the students' average age, admission scores and the share of students with previous enrollment at USP, by gender and course section. The explanatory variables are Female indicator; Female Professor dummy; and interaction term of the previous variables. Standard errors in parentheses, clustered at the course section level. P-values:* p<0.10, ** p<0.05, *** p<0.01.

Table 3: Gender specific selection

	(1)	(2)	(3)
Dependent variable: Share of female students			
Female professor	-0.001	-0.010	-0.009
	(0.012)	(0.010)	(0.010)
Daytime stream		0.074***	0.075***
		(0.010)	(0.009)
Mean of dependent variable	0.23		
Observations	137	137	137
F Statistics	0.01	28.28	35.06
Cohort fixed-effects	No	No	Yes

Notes: We estimate OLS regressions. The dependent variable is the Share of female students in first-semester (compulsory) course sections. The explanatory variables are Female professor dummy; Daytime stream dummy. Robust standard errors in parentheses. P-values * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Students' compliance to assigned sections in compulsory courses, by undergraduate program term

	Section 1		Section 2	
	Mean	Obs	Mean	Obs
Term				
1	0.99	2681	0.99	2534
2	0.90	2065	0.89	2052
3	0.87	2064	0.78	2397
4	0.79	1477	0.79	1352
5	0.74	778	0.78	638
6	0.77	343	0.71	427
7	0.55	119	0.55	181
Total	0.88	9527	0.85	9581

Notes: This table reports the percentage of students assigned to sections 1 or 2 enrolled in the designated section in compulsory courses by undergraduate program term (semester). We exclude unified course-sections to compute these descriptive statistics (courses with a single section, where students from both sections 1 and 2 enroll). We restrict the sample to students attending classes in the regular schedule, excluding cases where they failed a course or postponed the course enrollment to the following semesters. The number of observations decreases by term as the number of compulsory (elective) decreases (increases) over the undergraduate studies' terms. According to the ideal coursework plan, students from both streams should complete their core courses in the 7^{th} term (semester).

Table 5: Balance test - Female classmates and professors

	Female	Admission scores	Previous USP enrollment	SP city	Age	First admission list
Predicted % female professors	-0.012	0.313	-0.074	0.219	-0.129	0.128
	(0.207)	(0.293)	(0.156)	(0.127)	(1.035)	(0.115)
F Statistics	0.00	1.15	0.22	2.98	0.02	1.25
Share of female classmates	-0.009	-0.365	-0.039	-0.179	-1.415	-0.015
	(0.009)	(0.442)	(0.185)	(0.171)	(2.167)	(0.200)
F Statistics	-	0.68	0.04	1.10	0.43	0.01
% high-performing female classmates	-0.108	-0.012	0.008	-0.022	0.179	-0.089
	(0.108)	(0.186)	(0.090)	(0.081)	(0.507)	(0.053)
F Statistics	1.00	0.00	0.01	0.08	0.12	2.86
Mean of dependent variable	0.23	-0.00	0.14	0.84	19.46	0.85
Standard deviation	0.42	1.00	0.34	0.37	3.09	0.36
Observations	1576	1576	1576	1576	1576	1576
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficients from separate OLS regressions. The dependent variables are Female indicator; Normalized admission scores; Previous enrollment at USP dummy; Sao Paulo city of residence dummy; Student's age at admission; First admission list dummy. The key explanatory variables are the Predicted Share of female professors in compulsory courses in the first panel, the share of female classmates in the second panel, and the share of high-achieving female classmates in the third panel. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01. Following Guryan et al. (2009), when analyzing the correlation between the share of female classmates and the gender dummy, we also control for the share of female peers in the student's admission year and stream ("Leave-me-out share of female, urn"). In this specification, we do not include the F Statistics, which is large, as we include in the regression the "Leave-me-out share of female, urn".

Table 6: Summary statistics

	Female	Male	Difference
Normalized admission scores	0.02	-0.01	0.03
	(0.97)	(1.01)	
Age	18.86	19.63	-0.78***
	(2.14)	(3.30)	
Daytime classes	0.59	0.48	0.10***
	(0.49)	(0.50)	
First admission list	0.84	0.85	-0.01
	(0.36)	(0.36)	
Previous USP enrollment	0.09	0.15	-0.06**
	(0.28)	(0.36)	
Sao Paulo city	0.86	0.83	0.03
	(0.35)	(0.38)	
Sao Paulo state	0.99	0.99	0.00
	(0.11)	(0.12)	
N	357	1,219	1,576
	Female professor	Male professor	Difference
Panel B: Professor level (Compulsory courses)			
No Lattes CV profile	0.06	0.05	0.01
	(0.23)	(0.22)	
Ph.D. in Economics	0.41	0.58	-0.17
	(0.50)	(0.49)	
Ph.D. in other math-intensive field	0.35	0.28	0.07
	(0.49)	(0.45)	
Ph.D. in other fields	0.24	0.14	0.10
	(0.43)	(0.34)	
Ph.D. at USP	0.79	0.52	0.27**
	(0.41)	(0.50)	
Ph.D. abroad	0.18	0.42	-0.24**
	(0.39)	(0.49)	
Years since Ph.D. graduation	22.94	23.79	-0.85
	(9.82)	(11.30)	
# published papers	19.65	25.19	-5.54
	(19.76)	(25.70)	
# published A papers	2.59	4.86	-2.27
	(4.62)	(8.82)	
# published B papers	12.29	13.51	-1.21
	(13.40)	(15.62)	
# published C papers	0.59	0.86	-0.27
	(1.69)	(3.54)	
N	34	132	166

Notes: The table presents descriptive statistics of students', professors', and sections' characteristics. The column "Difference" reports the coefficient of a t-test of mean differences between groups. Panel A - Student-level variables: Normalized admission scores; Student's age at admission; Daytime stream dummy; First admission list dummy; Previous enrollment at USP dummy; Sao Paulo city and state of residence dummies. Panel B - Professor-level variables: Dummies for whether the professor earned a Ph.D. degree in Economics, other math-intensive fields, or other non-math-intensive fields; Dummies for whether the professor earned a Ph.D. degree from USP or a foreign institution; Dummy for whether the professor did not have the CV registered at Lattes Platform; Years since Ph.D. graduation; Number of published papers until 2016, by *Qualis* ranking. Standard deviations in parentheses. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7: Summary statistics: long-term students' outcomes

	Full sample	Female	Male	Difference
Normalized GPA compulsory courses	0.00	0.26	-0.07	0.33***
	(1.00)	(0.84)	(1.03)	
	[1576]	[357]	[1219]	
Time to graduation (in years)	5.23	5.10	5.28	-0.18*
	(1.19)	(1.07)	(1.22)	
	[1189]	[309]	[880]	
% elective courses - Microeconomics	0.24	0.26	0.23	0.03**
	(0.13)	(0.12)	(0.14)	
	[1576]	[357]	[1219]	
% elective courses - Macroeconomics	0.20	0.22	0.20	0.02**
	(0.12)	(0.11)	(0.12)	
	[1576]	[357]	[1219]	
% elective courses - Finance	0.13	0.13	0.13	-0.00
	(0.10)	(0.07)	(0.10)	
	[1576]	[357]	[1219]	
% elective courses - Humanities	0.28	0.26	0.28	-0.02
	(0.21)	(0.18)	(0.22)	
	[1576]	[357]	[1219]	
Work during undergraduate studies	0.87	0.90	0.86	0.04
	(0.34)	(0.30)	(0.35)	
	[1227]	[286]	[941]	
Degree completion	0.75	0.87	0.72	0.14***
	(0.43)	(0.34)	(0.45)	
	[1576]	[357]	[1219]	
Female advisor - Bachelor Thesis	0.16	0.20	0.14	0.06*
	(0.37)	(0.40)	(0.35)	
	[1080]	[272]	[808]	
Applied for a Master in Economics	0.18	0.21	0.17	0.04
	(0.38)	(0.41)	(0.37)	
	[1576]	[357]	[1219]	
Worker at the formal labor market	0.91	0.92	0.91	0.01
	(0.28)	(0.27)	(0.28)	
	[1576]	[357]	[1219]	
Firm partner	0.35	0.29	0.37	-0.07*
	(0.48)	(0.46)	(0.48)	
	[1576]	[357]	[1219]	
Labor force participation	0.94	0.95	0.94	0.00
	(0.23)	(0.22)	(0.23)	
	[1576]	[357]	[1219]	
Economist	0.28	0.35	0.26	0.09**
	(0.45)	(0.48)	(0.44)	
	[1441]	[329]	[1112]	
Financial services	0.53	0.50	0.54	-0.04
	(0.50)	(0.50)	(0.50)	
	[1441]	[329]	[1112]	
Public sector	0.17	0.13	0.19	-0.06*
	(0.38)	(0.33)	(0.39)	
	[1441]	[329]	[1112]	
Consulting firms	0.20	0.24	0.19	0.04
	(0.40)	(0.43)	(0.40)	
	[1441]	[329]	[1112]	
Research institutions	0.09	0.08	0.09	-0.01
	(0.28)	(0.27)	(0.28)	
	[1441]	[329]	[1112]	
Top manager	0.07	0.06	0.07	-0.01
	(0.25)	(0.24)	(0.25)	
	[1441]	[329]	[1112]	
Middle manager	0.30	0.31	0.30	0.01
	(0.46)	(0.46)	(0.46)	
	[1441]	[329]	[1112]	

Notes: The table presents descriptive statistics of students' outcome variables. All outcomes presented in the table consider variables at any point in students' careers. For example, the Economist dummy equals one if a student worked as an economist at any moment from 2002 to 2017. The column "Difference" reports the coefficient of a t-test of mean differences between groups. Variables: Normalized GPA: average grade in compulsory courses weighted by course-credits, normalized to have a mean of zero and standard deviation of one; Time to graduation: years from admission to graduation in Economics at USP, conditional on degree completion; % electives courses in Microeconomics, Macroeconomics, Finance, and Humanities: share of elective courses from each field that the student enrolled in; Work during undergraduate studies: dummy for whether the student was at the Brazilian formal labor market dataset before graduation (RAIS) or undertook an internship; Degree completion: dummy variable for whether the student majored in Economics at USP; Female advisor: dummy for whether the bachelor thesis' advisor is a female professor; Applied for a Master's in Economics dummy; Worker at the formal labor market: dummy for whether the student was at the Brazilian formal labor market dataset (RAIS). Firm partner: indicator variable equals one if a person is a firm partner/owner. Labor force participation: work at the formal labor market or own a firm. Economist: economist occupation at the formal labor market (conditional on being at the formal labor market). Sector dummies for financial services, public sector (government), consulting firms, and research institutions (CNAE codes). Top and middle manager, according to CBO 2002. Standard deviations in parentheses and the number of observations in square brackets. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 8: Long-term effects of women's representation on labor force participation

	Formal	Formal 1 +	Formal 2 +	Formal 5 +	Work	Work 1 +	Work 2 +	Work 5 +
Panel A: Predicted share of female professors in compulsory courses								
Female × Predicted % female professors	-0.154	0.427	0.474*	0.146	0.016	0.358	0.449	0.427*
	(0.177)	(0.354)	(0.243)	(0.235)	(0.152)	(0.438)	(0.347)	(0.213)
Predicted % female professors	0.111	-0.126	0.201	0.206	0.145	-0.259	0.111	0.132
	(0.158)	(0.326)	(0.299)	(0.328)	(0.115)	(0.247)	(0.217)	(0.279)
Female	0.044	-0.063	-0.061	-0.001	0.006	-0.061	-0.050	-0.063
	(0.030)	(0.052)	(0.062)	(0.047)	(0.023)	(0.062)	(0.068)	(0.044)
Observations	1576	1576	1576	1576	1576	1576	1576	1576
Summary Index Test (p-value)	0.297							
Westfall-Young multiple testing (randomization-t p-value)	0.282							
Panel B: Share of female classmates								
Female × % female classmates	0.363	0.290	1.419***	1.164**	0.312	0.164	1.407***	0.896**
	(0.307)	(0.432)	(0.460)	(0.402)	(0.270)	(0.407)	(0.438)	(0.382)
Share of female classmates	0.114	0.036	-0.366*	-0.354	0.006	0.015	-0.456**	0.026
	(0.152)	(0.282)	(0.193)	(0.296)	(0.130)	(0.198)	(0.161)	(0.250)
Female	-0.066	-0.052	-0.297**	-0.239**	-0.062	-0.034	-0.288**	-0.190*
	(0.079)	(0.109)	(0.120)	(0.103)	(0.064)	(0.101)	(0.117)	(0.097)
Observations	1576	1576	1576	1576	1576	1576	1576	1576
Summary Index Test (p-value)	0.039							
Westfall-Young multiple testing (randomization-t p-value)	0.027							
Panel C: Share of high-performing female classmates								
% high-performing female classmates × female	0.292*	0.651*	0.792***	0.596**	0.240	0.439	0.639***	0.366*
	(0.156)	(0.320)	(0.247)	(0.211)	(0.142)	(0.287)	(0.208)	(0.190)
% high-performing female classmates	-0.044	-0.078	-0.255*	-0.274*	-0.047	-0.026	-0.190*	-0.071
	(0.079)	(0.128)	(0.121)	(0.154)	(0.065)	(0.088)	(0.100)	(0.125)
Female	-0.043	-0.112	-0.127*	-0.089*	-0.039	-0.081	-0.089	-0.060
	(0.039)	(0.067)	(0.064)	(0.049)	(0.035)	(0.056)	(0.058)	(0.046)
Observations	1576	1576	1576	1576	1576	1576	1576	1576
Summary Index Test (p-value)	0.008							
Westfall-Young multiple testing (randomization-t p-value)	0.034							
Mean of dependent variable	0.91	0.52	0.64	0.70	0.94	0.56	0.69	0.79
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me-out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variables are Formal: formal labor market participation dummy, and Work: labor force participation, also considering firm ownership. 1+, 2+, 5+ state that the variable refers to one, two, or five years after expected graduation. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9: Long-term effects of women's representation on occupational and industry choice

	Occupation	Industry			
	Economist	Finance	Government	Consulting	Research
Panel A: Predicted share of female professors in compulsory courses					
Female × Predicted % female professors	-0.091	0.039	0.174	0.862**	-0.234
	(0.577)	(0.303)	(0.258)	(0.383)	(0.166)
Predicted % female professors	-0.263	0.151	-0.166	0.075	0.201
	(0.329)	(0.109)	(0.188)	(0.289)	(0.256)
Female	0.090	-0.050	-0.074	-0.116	0.037
	(0.118)	(0.073)	(0.048)	(0.081)	(0.035)
Observations	1441	1441	1441	1441	1441
Westfall-Young multiple testing (randomization-t p-value)	0.175				
Female × % female classmates	0.723	0.606*	-0.373	-0.014	-0.161
	(0.521)	(0.347)	(0.371)	(0.674)	(0.267)
Share of female classmates	0.456	0.292	-0.201	0.444	-0.070
	(0.360)	(0.219)	(0.201)	(0.308)	(0.212)
Female	-0.091	-0.181**	0.042	0.041	0.032
	(0.115)	(0.084)	(0.081)	(0.150)	(0.067)
Observations	1441	1441	1441	1441	1441
Westfall-Young multiple testing (randomization-t p-value)	0.409				
Panel C: Share of high-performing female classmates					
% high-performing female classmates × female	0.712***	0.008	-0.206	-0.405	0.053
	(0.233)	(0.194)	(0.176)	(0.349)	(0.117)
% high-performing female classmates	-0.135	0.077	0.076	0.053	-0.186**
	(0.154)	(0.089)	(0.087)	(0.175)	(0.080)
Female	-0.074	-0.050	0.002	0.110	-0.015
	(0.054)	(0.044)	(0.046)	(0.086)	(0.022)
Observations	1441	1441	1441	1441	1441
Westfall-Young multiple testing (randomization-t p-value)	0.038				
Mean of dependent variable	0.28	0.53	0.17	0.20	0.09
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variables are occupation dummies for economists, sector dummies for financial services, public sector (government), consulting firms, and research institutions. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008, conditional on working in the formal labor market (we only observe occupational choice for students who have RAIS information). Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 10: Long-term effects of women's representation on career progression

	Top Manager	Middle Manager
Panel A: Predicted share of female professors in compulsory courses		
Female × Predicted % female professors	0.400**	0.296
	(0.154)	(0.289)
Predicted % female professors	-0.251	-0.198
	(0.228)	(0.241)
Female	-0.075**	-0.037
	(0.033)	(0.062)
Observations	1441	1441
Summary Index Test (p-value)	0.034	
Westfall-Young multiple testing (randomization-t p-value)	0.034	
Panel B: Share of female classmates		
Female × % female classmates	0.229	0.279
	(0.216)	(0.499)
Share of female classmates	-0.168	0.305
	(0.270)	(0.197)
Female	-0.056	-0.048
	(0.060)	(0.124)
Observations	1441	1441
Summary Index Test (p-value)	0.314	
Westfall-Young multiple testing (randomization-t p-value)	0.518	
Panel C: Share of high-performing female classmates		
% high-performing female classmates × female	-0.015	0.041
	(0.112)	(0.292)
% high-performing female classmates	-0.053	0.201
	(0.097)	(0.119)
Female	0.001	0.003
	(0.027)	(0.061)
Observations	1441	1441
Summary Index Test (p-value)	0.978	
Westfall-Young multiple testing (randomization-t p-value)	0.986	
Mean of dependent variable	0.07	0.30
Cohort-stream fixed-effects	Yes	Yes
Students' covariates	Yes	Yes
Classes' covariates	Yes	Yes
Professors' covariates	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me-out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variables are occupation dummies for top manager and middle manager. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008, conditional on working in the formal labor market (we only observe occupational choice for students who have RAIS information). Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 11: Long-term effects on normalized real hourly wages (R$ 2002 Brazilian *reais*)

	Norm. Wages +1	Norm. Wages +2	Norm. Wages +5
Panel A: Predicted share of female professors in compulsory courses			
Female × Predicted % female professors	0.892	2.126**	0.680
	(0.962)	(0.767)	(0.630)
Predicted % female professors	-0.274	-1.071	-0.360
	(0.757)	(0.694)	(0.439)
Female	-0.144	-0.359**	-0.078
	(0.153)	(0.133)	(0.120)
Observations	787	992	1082
Summary Index Test (p-value)	0.032		
Westfall-Young multiple testing (randomization-t p-value)	0.027		
Female × % female classmates	-0.220	0.372	-0.208
	(1.154)	(0.869)	(0.938)
Share of female classmates	0.831	0.434	0.004
	(1.092)	(1.014)	(0.549)
Female	0.058	-0.058	0.091
	(0.254)	(0.215)	(0.255)
Observations	787	992	1082
Summary Index Test (p-value)	0.611		
Westfall-Young multiple testing (randomization-t p-value)	0.958		
Panel C: Share of high-performing female classmates			
% high-performing female classmates × female	-0.183	0.286	-0.588
	(0.805)	(0.622)	(0.483)
% high-performing female classmates	0.080	-0.104	-0.239
	(0.418)	(0.411)	(0.235)
Female	0.034	-0.036	0.157
	(0.178)	(0.153)	(0.157)
Observations	787	992	1082
Summary Index Test (p-value)	0.237		
Westfall-Young multiple testing (randomization-t p-value)	0.517		
Mean of dependent variable	0.00	-0.00	0.00
Std. dev. of dependent variable	1.00	1.00	1.00
Cohort-stream fixed-effects	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me-out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variable is the Normalized Average Hourly Wages, considering all labor contracts. We normalize the variable to have an average of zero and standard deviation of one. Wages' information is conditional on working in the formal labor market. 1+, 2+, 5+ state that the variable refers to one, two, or five years after expected graduation. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008, conditional on working in the formal labor market one, two or five year after predicted graduation. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Impact of having an own-gender professor on first-semester course performance

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Normalized course grade					
Female professor × female	0.067	0.086	0.108*	0.106**	0.097**
	(0.060)	(0.059)	(0.055)	(0.041)	(0.040)
Female professor	-0.298***	-0.304***	-0.283***		
	(0.078)	(0.077)	(0.089)		
Female	0.177***	0.173***			
	(0.037)	(0.036)			
Mean of dependent variable	-0.00				
Stand. dev. of dependent variable	1.00				
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Pass rate					
Female professor × female	0.031*	0.034**	0.042***	0.043***	0.041***
	(0.017)	(0.017)	(0.015)	(0.016)	(0.015)
Female professor	-0.059***	-0.060***	-0.055***		
	(0.018)	(0.017)	(0.021)		
Female	0.036***	0.030***			
	(0.008)	(0.008)			
Mean of dependent variable	0.91				
Stand. dev. of dependent variable	0.29				
Observations	6713	6713	6713	6713	6713
Number of students	1576	1576	1576	1576	1576
Cohort-stream fixed-effects	Yes	Yes	No	No	No
Professor fixed-effects	No	No	No	Yes	No
Course section fixed-effects	No	No	No	No	Yes
Student fixed-effects	No	No	Yes	Yes	Yes
Students' covariates	No	Yes	No	No	No

Notes: We estimate OLS regressions. The dependent variables are Normalized course grades and Pass rate dummy for whether students passed a course. We normalize the course grade, such as the variable has an average of zero and standard deviation of one. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. The individual fixed-effect absorbs admission cohort-stream fixed-effects. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy. Standard errors in parentheses, clustered at the course section level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 13: Effects of female classmates' share on normalized first-semester GPA

	(1)	(2)	(3)
Panel A: Share of female classmates			
Female × % female classmates	-0.586	-0.279	0.037
	(0.636)	(0.582)	(0.577)
Share of female classmates	-0.335	-0.414	0.336
	(0.921)	(0.804)	(0.877)
Female	0.366**	0.297*	0.251
	(0.171)	(0.148)	(0.151)
Observations	1576	1576	1576
	(1)	(2)	(3)
Panel B: Share of high-performing female classmates			
% high-performing female classmates × female	-0.145	0.134	0.404
	(0.420)	(0.472)	(0.378)
% high-performing female classmates	0.237	0.187	0.341
	(0.482)	(0.480)	(0.344)
Female	0.267***	0.215**	0.181**
	(0.092)	(0.087)	(0.071)
Observations	1576	1576	1576
Mean of dependent variable	-0.00		
Std.dev. of dependent variable	1.00		
Cohort-stream fixed-effects	Yes	Yes	Yes
Students' covariates	No	Yes	Yes
Classes' covariates	No	No	Yes
Professors' covariates	No	No	Yes

Notes: We estimate OLS regressions. In panel B, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variable is the GPA in first-semester courses, normalized to have a mean of zero and standard deviation of one. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy, First admission list dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Long-term effects of women's representation on academic performance

	Completion	Norm. GPA	Duration	Female advisor	Master
Panel A: Predicted share of female professors in compulsory courses					
Female × Predicted % female professors	-0.397	0.005	-0.170	0.009	0.002
	(0.243)	(0.701)	(1.013)	(0.420)	(0.229)
Predicted % female professors	0.439***	0.146	0.753	-0.098	-0.324*
	(0.138)	(0.378)	(0.446)	(0.184)	(0.178)
Female	0.174***	0.267*	-0.167	0.060	0.047
	(0.036)	(0.128)	(0.166)	(0.071)	(0.050)
Observations	1576	1576	1189	1080	1576
Westfall-Young multiple testing (randomization-t p-value)	0.441				
Panel B: Share of female classmates					
Female × % female classmates	-0.114	0.589	-0.884	0.111	0.670*
	(0.315)	(0.758)	(1.185)	(0.563)	(0.320)
Share of female classmates	0.054	0.672	-3.836***	-0.019	0.287
	(0.248)	(0.468)	(0.374)	(0.209)	(0.175)
Female	0.129	0.134	0.005	0.036	-0.105
	(0.083)	(0.218)	(0.293)	(0.131)	(0.082)
Observations	1576	1576	1189	1080	1576
Westfall-Young multiple testing (randomization-t p-value)	0.236				
Panel C: Share of high-performing female classmates					
% high-performing female classmates × female	0.126	0.626	-0.882	0.179	0.135
	(0.198)	(0.532)	(0.573)	(0.252)	(0.225)
% high-performing female classmates	-0.040	0.399	-1.231***	0.052	0.068
	(0.155)	(0.329)	(0.377)	(0.100)	(0.090)
Female	0.078	0.140	0.027	0.027	0.015
	(0.047)	(0.130)	(0.142)	(0.055)	(0.050)
Observations	1576	1576	1189	1080	1576
Westfall-Young multiple testing (randomization-t p-value)	0.529				
Mean of dependent variable	0.75	0.00	5.23	0.16	0.18
Std. dev. of dependent variable	0.43	1.00	1.19	0.37	0.38
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me out counts). High-performing: Top quartile (highest 25% admission scores). The dependent variables are Degree completion rates, Normalized GPA in compulsory courses, Duration: Time to graduation (conditional on obtaining a bachelor degree), Female advisor: Bachelor thesis' supervisor is a woman, Master dummy: applied for a Master's in Economics at any moment. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Duration and female advisor dummy are conditional on degree completion. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table 15: Long-term effects of women's representation on elective courses' choice

	Microeconomics	Macroeconomics	Finance	Humanities
Panel A: Predicted share of female professors in compulsory courses				
Female × Predicted % female professors	0.013	-0.012	-0.056	0.097
	(0.073)	(0.057)	(0.068)	(0.100)
Predicted % female professors	-0.025	0.108	0.059	-0.036
	(0.051)	(0.089)	(0.042)	(0.157)
Female	0.016	0.018	0.006	-0.026
	(0.016)	(0.011)	(0.012)	(0.021)
Observations	1576	1576	1576	1576
Westfall-Young multiple testing (randomization-t p-value)	0.782			
Panel B: Share of female classmates				
Female × % female classmates	-0.009	0.045	-0.010	0.094
	(0.083)	(0.104)	(0.073)	(0.141)
Share of female classmates	-0.001	0.047	0.106*	0.094
	(0.077)	(0.095)	(0.059)	(0.124)
Female	0.020	0.005	-0.002	-0.030
	(0.023)	(0.028)	(0.018)	(0.038)
Observations	1576	1576	1576	1576
Westfall-Young multiple testing (randomization-t p-value)	0.927			
Panel C: Share of high-performing female classmates				
% high-performing female classmates × female	-0.006	-0.046	0.041	-0.128
	(0.067)	(0.066)	(0.040)	(0.103)
% high-performing female classmates	0.026	0.070	0.045	-0.068
	(0.057)	(0.068)	(0.028)	(0.074)
Female	0.020	0.024	-0.013	0.014
	(0.017)	(0.017)	(0.010)	(0.025)
Observations	1576	1576	1576	1576
Westfall-Young multiple testing (randomization-t p-value)	0.614			
Mean of dependent variable	0.24	0.20	0.13	0.28
Std.dev. of dependent variable	0.13	0.12	0.10	0.21
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me-out counts). High-performing: Top quartile (highest 25% admission scores). The sample is restricted to students admitted into the Economics major between 2002 and 2008. The dependent variables are the share of elective courses that a student enrolled from each field: Microeconomics, Macroeconomics, Finance, and Humanities (History, Sociology, and other humanities). The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 16: Long-term effects of women's representation on the probability of working during the undergraduate program

	(1)	(2)	(3)
Panel A: Predicted share of female professors in compulsory courses			
Female × Predicted % female professors	-0.355	-0.337	-0.351
	(0.337)	(0.337)	(0.333)
Predicted % female professors	0.371**	0.351**	0.582***
	(0.142)	(0.138)	(0.120)
Female	0.108	0.100	0.108
	(0.068)	(0.064)	(0.063)
Observations	1227	1227	1227
Panel B: Share of female classmates			
Female × % female classmates	0.793**	0.805**	0.817**
	(0.314)	(0.309)	(0.312)
Share of female classmates	-0.403**	-0.384**	0.042
	(0.174)	(0.170)	(0.118)
Female	-0.142*	-0.149*	-0.142*
	(0.080)	(0.077)	(0.076)
Observations	1227	1227	1227
Panel C: Share of high-performing female classmates			
% high-performing female classmates × female	0.069	0.059	0.056
	(0.214)	(0.220)	(0.224)
% high-performing female classmates	-0.103	-0.101	0.009
	(0.088)	(0.087)	(0.077)
Female	0.030	0.028	0.031
	(0.048)	(0.048)	(0.050)
Observations	1227	1227	1227
Mean of dependent variable	0.87		
Cohort-stream fixed-effects	Yes	Yes	Yes
Students' covariates	No	Yes	Yes
Classes' covariates	No	No	Yes
Professors' covariates	No	No	Yes

Notes: In Panels A, B, and C, we run OLS regressions. In Panel C, Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me-out counts). High-performing: Top quartile (highest 25% admission scores). The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2002 and 2008. The dependent variable is a dummy that equals one if the student worked as an intern or regular worker during the undergraduate studies, and zero otherwise. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix – Figures and Tables

Figures

Figure A.1: Share of female students admitted into the Economics major

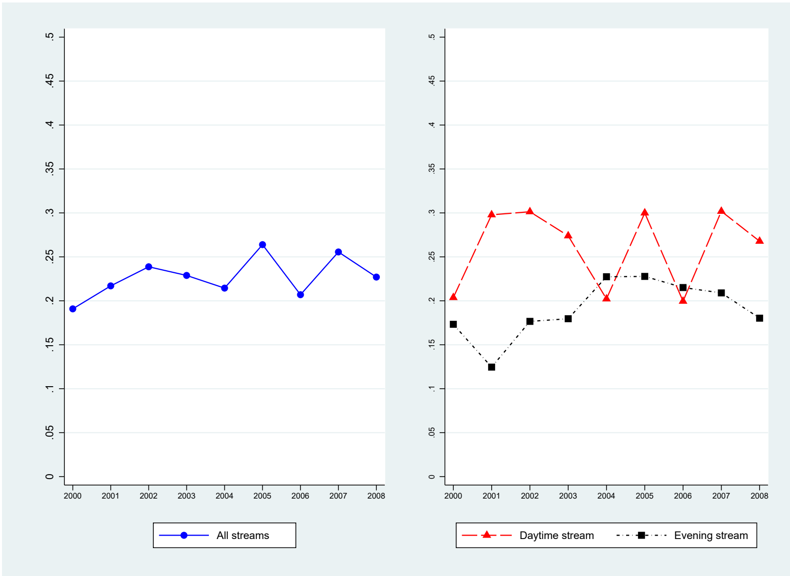


Figure A.2: Share of female professors in compulsory courses

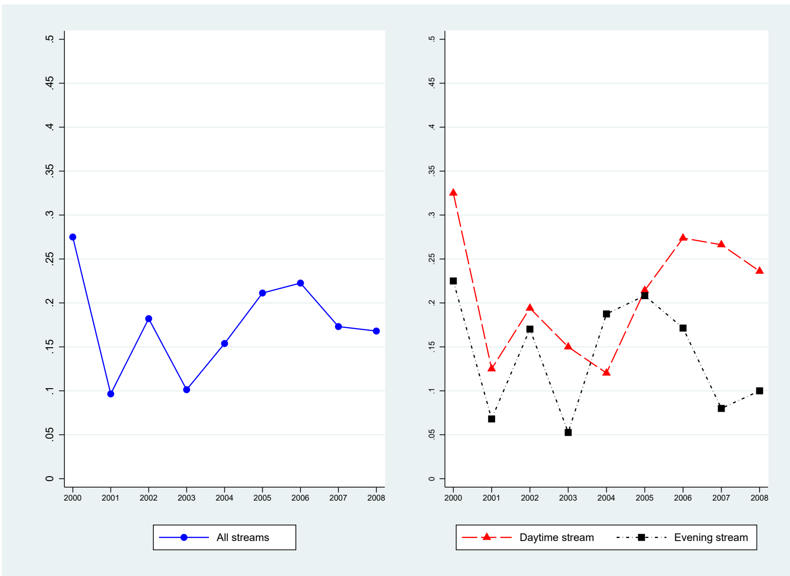
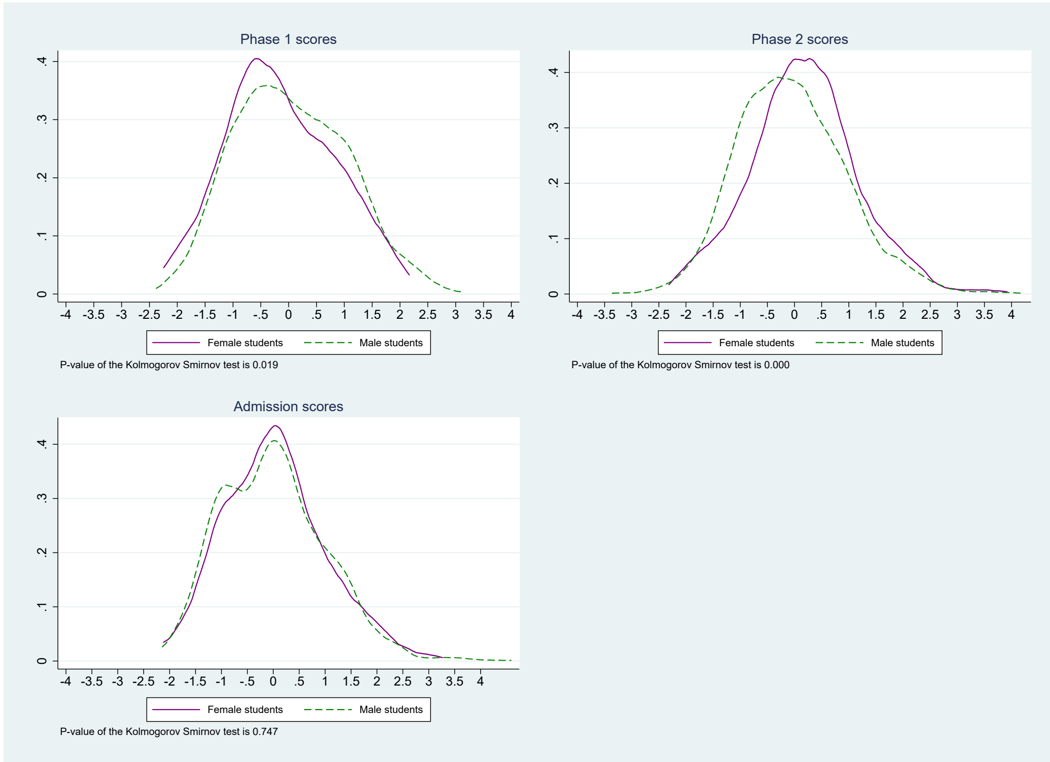


Figure A.3: Distribution of admission scores, by gender



Notes: We normalize Phase 1, Phase 2, and admission scores, such that all variables have a mean of zero and standard deviation of one.

Tables

Table A.1: Comparing students from daytime and evening streams

	Daytime	Evening	Difference
Normalized admission scores	0.31	-0.32	0.62***
	(0.98)	(0.92)	
Age	18.58	20.36	-1.77***
	(2.07)	(3.67)	
Female	0.26	0.19	0.07***
	(0.44)	(0.39)	
Previous USP enrollment	0.07	0.20	-0.13***
	(0.26)	(0.40)	
First admission list	0.88	0.82	0.07***
	(0.32)	(0.39)	
Sao Paulo city	0.83	0.85	-0.02
	(0.38)	(0.36)	
Sao Paulo state	0.98	0.99	-0.01
	(0.14)	(0.09)	
N	801	775	1,576

Notes: The table presents descriptive statistics comparing students from daytime and evening streams. The column "Difference" reports the coefficient of a t-test of mean differences between evening and daytime students. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.2: Randomization balance check excluding 2008 admission year

	Female	Admission scores	Previous USP enrollment	SP city	Age	First admission list
Section 1	-0.034	0.001	0.009	0.011	0.055	0.016
	(0.021)	(0.041)	(0.019)	(0.022)	(0.187)	(0.017)
Observations	1401	1401	1401	1401	1401	1401
F Statistics	2.47	0.00	0.23	0.23	0.09	0.89
Mean of dependent variable	0.23	-0.00	0.13	0.83	19.49	0.84
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents coefficients from separate OLS regressions. The dependent variables are Female indicator; Normalized admission scores (mean zero, standard deviation one); Previous enrollment at USP dummy; Sao Paulo city of residence dummy; Student's age at admission; First admission list dummy. The key explanatory variable is a dummy variable for whether the student was assigned to section 1. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.3: Testing whether students' characteristics correlate with their initials

	Female	Admission scores	Previous USP enrollment	SP city	Age	First admission list
initial==B	-0.075	-0.182	-0.073	0.024	-1.058***	-0.010
	(0.067)	(0.140)	(0.045)	(0.058)	(0.373)	(0.052)
initial==C	0.081	-0.263*	0.005	0.028	-0.286	-0.016
	(0.064)	(0.136)	(0.048)	(0.051)	(0.442)	(0.046)
initial==D	-0.172***	-0.306**	-0.019	0.034	-0.506	-0.086*
	(0.053)	(0.134)	(0.045)	(0.049)	(0.391)	(0.049)
initial==E	-0.191***	-0.241	0.038	0.062	0.056	-0.016
	(0.057)	(0.159)	(0.056)	(0.053)	(0.489)	(0.051)
initial==F	-0.197***	-0.127	0.040	0.077*	-0.165	-0.053
	(0.050)	(0.131)	(0.047)	(0.045)	(0.415)	(0.045)
initial==G	-0.256***	-0.108	-0.012	0.014	-0.770*	-0.018
	(0.046)	(0.123)	(0.044)	(0.048)	(0.392)	(0.043)
initial==H	-0.218***	0.147	0.091	-0.049	0.605	-0.009
	(0.069)	(0.240)	(0.086)	(0.087)	(0.777)	(0.070)
initial==I	-0.111	-0.151	-0.045	0.088	-0.685	-0.240**
	(0.102)	(0.271)	(0.077)	(0.078)	(0.544)	(0.115)
initial==J	-0.004	0.066	-0.079*	0.052	-0.702*	-0.013
	(0.065)	(0.136)	(0.041)	(0.051)	(0.403)	(0.048)
initial==K	0.133	-0.224	0.123	0.011	1.703	0.038
	(0.156)	(0.233)	(0.139)	(0.122)	(1.528)	(0.092)
initial==L	0.000	0.003	-0.016	0.041	-0.736*	0.021
	(0.060)	(0.122)	(0.044)	(0.048)	(0.391)	(0.041)
initial==M	0.012	-0.095	0.003	0.033	-0.121	0.004
	(0.056)	(0.121)	(0.043)	(0.046)	(0.444)	(0.040)
initial==N	0.366***	-0.155	-0.088	0.005	-0.093	-0.059
	(0.123)	(0.198)	(0.068)	(0.104)	(0.839)	(0.102)
initial==O	-0.196	-0.392	-0.150***	0.193***	-0.968	0.004
	(0.124)	(0.329)	(0.030)	(0.034)	(0.605)	(0.121)
initial==P	-0.124**	-0.017	-0.018	-0.018	-0.185	-0.016
	(0.061)	(0.142)	(0.049)	(0.058)	(0.580)	(0.050)
initial==R	-0.209***	-0.186	0.002	0.047	-0.551	-0.006
	(0.046)	(0.120)	(0.041)	(0.043)	(0.381)	(0.038)
initial==S	0.058	-0.376**	-0.116**	-0.083	-0.188	-0.044
	(0.099)	(0.183)	(0.046)	(0.090)	(0.746)	(0.076)
initial==T	-0.140**	-0.179	-0.059	0.011	-0.960***	-0.027
	(0.059)	(0.134)	(0.045)	(0.056)	(0.358)	(0.050)
initial==V	-0.081	-0.000	-0.070	0.013	-0.903**	-0.051
	(0.073)	(0.164)	(0.049)	(0.064)	(0.444)	(0.062)
initial==W	-0.321***	-0.850***	0.004	-0.038	3.311	-0.179
	(0.040)	(0.248)	(0.105)	(0.122)	(2.180)	(0.132)
initial==Y	-0.036	-0.108	-0.150***	-0.093	-1.129***	-0.014
	(0.176)	(0.409)	(0.030)	(0.175)	(0.411)	(0.136)
Mean of dependent variable	0.23	-0.00	0.14	0.84	19.46	0.85
Stand. dev of dependent variable	0.42	1.00	0.34	0.37	3.09	0.36
Observations	1576	1576	1576	1576	1576	1576

Notes: The table presents coefficients from separate OLS regressions. The dependent variables are: Female indicator; Normalized admission scores (mean zero, standard deviation one); Previous enrollment at USP dummy; Sao Paulo city of residence dummy; Student's age at admission; First admission list dummy. The explanatory variables are dummies for students' first names initials. Robust standard errors in parentheses. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: Comparing course sections 1 and 2

	Daytime stream			Evening stream		
	Section 1	Section 2	Diff.	Section 1	Section 2	Diff.
Female professor	0.22	0.23	-0.01	0.17	0.15	0.02
	(0.42)	(0.42)		(0.38)	(0.36)	
# students enrolled in course section	56.18	55.33	0.85	53.42	49.85	3.58*
	(13.21)	(14.74)		(14.05)	(13.19)	
Average grade	5.90	5.96	-0.06	5.31	5.51	-0.20
	(0.94)	(0.86)		(1.12)	(1.10)	
Average attendance rate	86.60	86.83	-0.24	82.97	84.49	-1.52
	(6.96)	(6.75)		(7.92)	(7.98)	
Average pass rate	0.82	0.83	-0.02	0.74	0.76	-0.03
	(0.13)	(0.11)		(0.17)	(0.15)	
Share of female students	0.25	0.28	-0.03***	0.19	0.21	-0.02**
	(0.06)	(0.05)		(0.06)	(0.06)	
Average admission score	660.39	658.85	1.54	632.38	635.48	-3.10
	(29.15)	(27.97)		(28.83)	(26.33)	
Share of students from daytime stream	0.91	0.93	-0.02**	0.09	0.08	0.01
	(0.07)	(0.06)		(0.13)	(0.12)	
Professor: Ph.D. in Economics	0.72	0.73	-0.01	0.70	0.67	0.03
	(0.45)	(0.45)		(0.46)	(0.47)	
Professor: Ph.D. in other math-intensive field	0.20	0.19	0.01	0.23	0.21	0.01
	(0.40)	(0.39)		(0.42)	(0.41)	
Professor: Ph.D. at USP	0.62	0.58	0.04	0.50	0.56	-0.06
	(0.49)	(0.50)		(0.50)	(0.50)	
Professor: Ph.D. abroad	0.33	0.37	-0.04	0.44	0.40	0.04
	(0.47)	(0.48)		(0.50)	(0.49)	
Professor's experience	18.37	16.21	2.16	16.45	14.52	1.93
	(10.00)	(9.17)		(9.07)	(8.83)	
Professor: # published papers	15.44	12.17	3.27*	13.48	12.08	1.39
	(13.44)	(10.95)		(14.11)	(10.36)	
Professor: % papers with *Qualis* classification	0.79	0.79	-0.00	0.71	0.69	0.02
	(0.28)	(0.28)		(0.33)	(0.31)	
Professor: % A papers	0.11	0.11	-0.01	0.12	0.09	0.02
	(0.14)	(0.18)		(0.20)	(0.17)	
N	148	144	292	125	125	250

Notes: The table presents descriptive statistics comparing sections 1 and 2 from the compulsory courses that our sample of students attend over the undergraduate studies, by the stream (time of day). We exclude unified course sections to compute these descriptive statistics (courses with a single section, where students from both sections 1 and 2 enroll). The column "Diff" reports the coefficient of a t-test of mean differences between section 1 and section 2. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.5: Subsample of students without individual taxpayer number (CPF) at USP data: Comparing students with or without CPF at our final data

	CPF	No CPF	Diff.
Normalized admission scores	-0.38	-0.36	-0.02
	(0.96)	(0.98)	
Age	19.36	19.38	-0.02
	(3.03)	(2.68)	
Daytime classes	0.52	0.59	-0.07
	(0.50)	(0.50)	
Previous USP enrollment	0.09	0.15	-0.07
	(0.28)	(0.37)	
Sao Paulo city	0.85	0.95	-0.10
	(0.36)	(0.22)	
Sao Paulo state	0.99	0.97	0.01
	(0.11)	(0.16)	
First admission list	0.80	0.82	-0.02
	(0.40)	(0.39)	
Female	0.25	0.21	0.05
	(0.43)	(0.41)	
Observations	517	39	556

Notes: For the subsample of students that USP did not provide us CPF information, we compare students' characteristics with or without the individual taxpayer information (CPF). We could partially obtain the CPFs by merging USP data with the labor market database using the full name and birth date. The column "Diff." reports the coefficient of a t-test of mean differences between groups. Variables: Normalized admission scores (mean zero, standard deviation one), Student's age at admission, Daytime stream dummy, Previous USP enrollment, Sao Paulo city of residence dummy, Sao Paulo state of residence dummy, First USP admission list, gender dummy. Standard deviations in parentheses. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.6: Brazilian Classification of Occupations and Industries

Panel A - Brazilian Classification of Occupations (CBO 2002)

Occupation/Position	*CBO*
Economist	Economist - 251205, Agroindustrial Economist - 251210, Financial Economist - 251215, Public Economics - 251225 , Environmental Economist - 251230, Urban Economics - 251235, Industrial Economist - 251220, Researcher in Economics - 203510, Professor in Economics - 234805
Top Manager	Top manager from the public service (CBO family 114); Top Manager - General (CBO family 121); Top Manager - Production and Operation (CBO family 122); Top Manager - Support services (CBO family 123); Top Manager Service (Health, Education, Cultural, Social) (CBO family 131).
Middle Manager	Middle Manager - Production and Operation (CBO family 141); Middle Manager - Support services (CBO family 142).

Panel B - Brazilian Classification of Industries (CNAE)

Industry	*CNAE 2.0*	*CNAE 1.0*
Financial services	Division 64 - Financial services, Division 65 - Insurance, Retirement plans, Health insurance, 66 - Subsidiary financial services	Division 65 - Financial services, Division 66 - Insurance, Retirement plans, Health insurance, 67 - Subsidiary financial services
Public sector	Division 84 - Public Administration, National Defense and Social Security	Division 75 - Public Administration, National Defense and Social Security
Consulting firms	Division 70 - Consulting firms	Subclass 74160 - Consulting firms
Research	Division 72 - Research and Development (R & D); Group 853 Higher Education Institutions	Division 73 - Research and Development (R & D); Group 803 Higher Education Institutions

Table A.7: Summary statistics: long-term students' outcomes, years after expected graduation

	Full sample	Female	Male	Diff.
Panel A: One year after expected graduation				
Formal labor market	0.52	0.50	0.52	-0.03
	(0.50)	(0.50)	(0.50)	
	[1576]	[357]	[1219]	
Firm partner	0.07	0.07	0.07	0.00
	(0.26)	(0.26)	(0.26)	
	[1576]	[357]	[1219]	
Labor force participation	0.56	0.53	0.57	-0.04
	(0.50)	(0.50)	(0.50)	
	[1576]	[357]	[1219]	
Normalized hourly real wages	0.00	-0.14	0.04	-0.18*
	(1.00)	(0.70)	(1.07)	
	[787]	[170]	[617]	
Panel B: Two years after expected graduation				
Formal labor market	0.64	0.65	0.64	0.01
	(0.48)	(0.48)	(0.48)	
	[1576]	[357]	[1219]	
Firm partner	0.09	0.09	0.09	0.00
	(0.28)	(0.29)	(0.28)	
	[1576]	[357]	[1219]	
Labor force participation	0.69	0.70	0.68	0.01
	(0.46)	(0.46)	(0.47)	
	[1576]	[357]	[1219]	
Normalized hourly real wages	-0.00	-0.11	0.03	-0.14
	(1.00)	(0.86)	(1.04)	
	[992]	[225]	[767]	
Panel C: Five years after expected graduation				
Formal labor market	0.70	0.72	0.69	0.02
	(0.46)	(0.45)	(0.46)	
	[1576]	[357]	[1219]	
Firm partner	0.16	0.14	0.17	-0.03
	(0.37)	(0.35)	(0.38)	
	[1576]	[357]	[1219]	
Labor force participation	0.79	0.79	0.79	0.00
	(0.41)	(0.41)	(0.41)	
	[1576]	[357]	[1219]	
Normalized hourly real wages	0.00	-0.02	0.01	-0.02
	(1.00)	(1.10)	(0.97)	
	[1082]	[252]	[830]	

Notes: The table presents descriptive statistics of students' outcome variables one, two, or five years after expected graduation. The column "Diff." reports the coefficient of a t-test of mean differences between groups. Variables: Formal labor market: dummy for whether the student was at the Brazilian formal labor market dataset (RAIS); Firm partner: indicator variable equals one if a person is a firm partner/owner; Labor force participation: work at the formal labor market or own a firm; Normalized hourly real wages: average hourly real wages, 2002 prices in Brazilian *reais* (conditional on being at the formal labor market), normalized such as to have a mean of zero and standard deviation of one. Standard deviations in parentheses and the number of observations in square brackets. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.8: Share of female professors, 2SLS Regressions: First stage estimations

	% female professors × female			Female professors		
Female × Predicted % female professors	0.780***	0.782***	0.781***	-0.019	-0.023	-0.025
	(0.049)	(0.049)	(0.050)	(0.041)	(0.041)	(0.041)
Predicted % female professors	0.006	0.005	0.014	0.837***	0.838***	0.790***
	(0.012)	(0.012)	(0.030)	(0.087)	(0.085)	(0.095)
Female	0.040***	0.040***	0.040***	0.001	0.003	0.003
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)
Observations	1576	1576	1576	1576	1576	1576
F Statistics	242.91	243.73	286.31	35.17	36.92	201.96
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	No	Yes	Yes	No	Yes	Yes
Classes' covariates	No	No	Yes	No	No	Yes
Professors' covariates	No	No	Yes	No	No	Yes

Notes: The table presents the first stage of our 2SLS regressions. We estimate OLS regressions. The dependent variables are female professors' share in compulsory courses and its interaction term with the gender dummy. Predicted % of female professors is the share of female professors assigned to a class (section, stream, and admission year group) in compulsory courses. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.9: IV estimates: Long-term effects of women's representation on labor force participation

	Formal	Formal 1 +	Formal 2 +	Formal 5 +	Work	Work 1 +	Work 2 +	Work 5 +
Female $\times$ % female professors	-0.192	0.541	0.614*	0.195	0.026	0.447	0.579	0.552*
	(0.222)	(0.464)	(0.340)	(0.297)	(0.199)	(0.560)	(0.471)	(0.280)
% female professors	0.144	-0.169	0.243	0.257	0.183	-0.336	0.129	0.157
	(0.207)	(0.415)	(0.379)	(0.422)	(0.156)	(0.318)	(0.275)	(0.357)
Female	0.051	-0.084	-0.086	-0.010	0.004	-0.078	-0.074	-0.086
	(0.037)	(0.069)	(0.076)	(0.056)	(0.031)	(0.083)	(0.087)	(0.056)
Observations	1576	1576	1576	1576	1576	1576	1576	1576
Mean of dependent variable	0.91	0.52	0.64	0.70	0.94	0.56	0.69	0.79
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We run 2SLS regressions. The dependent variables are Formal: formal labor market participation dummy, and Work: labor force participation, also considering firm ownership. 1+, 2+, 5+ state that the variable refers to one, two, or five years after expected graduation. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.10: IV estimates: Long-term effects of women's representation on occupational and industry choice

	Occupation	Industry			
	Economist	Financial services	Public sector	Consulting firms	Research institutions
Female × % female professors	-0.121	0.052	0.219	1.101**	-0.294
	(0.728)	(0.387)	(0.325)	(0.491)	(0.211)
% female professors	-0.334	0.193	-0.212	0.091	0.258
	(0.426)	(0.155)	(0.232)	(0.325)	(0.311)
Female	0.094	-0.051	-0.082	-0.155	0.048
	(0.144)	(0.086)	(0.058)	(0.094)	(0.042)
Observations	1441	1441	1441	1441	1441
Mean of dependent variable	0.28	0.53	0.17	0.20	0.09
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes	Yes	Yes

Notes: We run 2SLS regressions. The dependent variables are occupation dummies for economists, sector dummies for financial services, public sector (government), consulting firms, and research institutions. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.11: IV estimates: Long-term effects of women's representation on career progression

	Top Manager	Middle Manager
Female × % female professors	0.505**	0.374
	(0.197)	(0.374)
% female professors	-0.322	-0.254
	(0.306)	(0.313)
Female	-0.093**	-0.051
	(0.040)	(0.075)
Observations	1441	1441
Mean of dependent variable	0.07	0.30
Cohort-stream fixed-effects	Yes	Yes
Students' covariates	Yes	Yes
Classes' covariates	Yes	Yes
Professors' covariates	Yes	Yes

Notes: We run 2SLS regressions. The dependent variables are occupation dummies for a top manager or middle manager. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.12: IV estimates: Long-term effects on normalized real hourly wages (R$ 2002 Brazilian *reais*

	Norm.Wages+1	Norm.Wages+2	Norm.Wages+5
Female × % female professors	1.093	2.583**	0.872
	(1.212)	(0.899)	(0.794)
% female professors	-0.372	-1.391	-0.501
	(1.019)	(1.000)	(0.654)
Female	-0.174	-0.434**	-0.111
	(0.186)	(0.150)	(0.140)
Observations	787	992	1082
Mean of dependent variable	0.00	-0.00	0.00
Cohort-stream fixed-effects	Yes	Yes	Yes
Students' covariates	Yes	Yes	Yes
Classes' covariates	Yes	Yes	Yes
Professors' covariates	Yes	Yes	Yes

Notes: We run 2SLS regressions. The dependent variable is the normalized average hourly wages, considering all labor contracts. We normalized each dependent variable to have a mean of zero and standard deviation of one. Wages' information is conditional on working in the formal labor market. 1+, 2+, 5+ state that the variable refers to one, two, or five years after expected graduation. The regressions include the sample of students admitted through USP's admission exam into the Economics undergraduate degree between 2000 and 2008. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (Admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.13: Variation in the share of female classmates

	Mean	Standard deviation	Observations
Share of female classmates			
Raw variable	0.225	0.069	1576
Residuals after removing cohort-stream fixed-effects	-0.000	0.045	1576
Residuals students' covariates + cohort-stream FE	-0.000	0.045	1576
Residuals students' cov + classes' cov. + cohort-stream FE	-0.000	0.038	1576
Residuals students' cov + classes' cov. + professors' cov. + cohort-stream FE	-0.000	0.033	1576

Notes: In this table, we present the variation in the share of female classmates left after removing fixed effects and controlling for other explanatory variables, following Bifulco et al. (2011) and Lepine and Estevan (2020). We gradually remove cohort-stream fixed-effects, students', classes', and professors' covariates.

Table A.14: Heckman Selection Two-Step Procedure: Long-term effects of the predicted share of female professors on the probability of working in a consulting firm

	Positive values			Input Zeros			Heckman		
Female × Predicted % female professors	0.880**	0.891**	0.862**	0.779**	0.812**	0.794**	0.886**	0.815*	0.746*
	(0.369)	(0.375)	(0.383)	(0.340)	(0.354)	(0.361)	(0.399)	(0.398)	(0.408)
Predicted % female professors	0.057	0.056	0.075	0.045	0.040	0.089	0.059	0.028	0.149
	(0.320)	(0.324)	(0.289)	(0.294)	(0.296)	(0.258)	(0.318)	(0.324)	(0.293)
Female	-0.118	-0.127	-0.116	-0.101	-0.113	-0.103	-0.119	-0.105	-0.079
	(0.077)	(0.079)	(0.081)	(0.072)	(0.075)	(0.077)	(0.085)	(0.084)	(0.089)
Mean of dependent variable	0.20			0.19			0.20		
Observations	1441	1441	1441	1576	1576	1576	1441	1441	1441
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Professors' covariates	No	No	Yes	No	No	Yes	No	No	Yes
Classes' covariates	No	No	Yes	No	No	Yes	No	No	Yes

Notes: In 'Positive values,' we run OLS without considering selection into the formal labor market. In 'Input zeros,' we run OLS following Martorell and Isaac McFarlin Jr. (2011) and inputting zeros for students that we do not find at the formal labor market (i.e., we consider that the student is not working in a consulting firm). The remaining column presents estimates of a Heckman Two-Step procedure. In the first stage, we estimate the selection equations using a Probit model, and in the second stage, we use OLS regressions. Instrument: % working at the formal labor market at SP city, by age, gender, and expected graduation year. The dependent variable is a Consulting firm industry dummy variable. Students' covariates: Normalized admission scores, Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.15: Heckman Selection Two-Step Procedure: Long-term effects of high-performing female classmates on the probability of working as an economist

	Positive values			Input Zeros			Heckman		
% high-performing female classmates × female	0.638**	0.674**	0.712***	0.664**	0.687***	0.726***	0.386	0.761***	0.840***
	(0.252)	(0.251)	(0.233)	(0.232)	(0.231)	(0.212)	(0.264)	(0.256)	(0.233)
% high-performing female classmates	-0.101	-0.103	-0.135	-0.097	-0.100	-0.132	-0.074	-0.112	-0.160
	(0.163)	(0.160)	(0.154)	(0.152)	(0.151)	(0.149)	(0.160)	(0.158)	(0.152)
Female	-0.045	-0.067	-0.074	-0.049	-0.064	-0.071	-0.014	-0.078	-0.090*
	(0.057)	(0.057)	(0.054)	(0.054)	(0.054)	(0.051)	(0.056)	(0.053)	(0.050)
Mean of dependent variable	0.28			0.26			0.28		
Observations	1441	1441	1441	1576	1576	1576	1441	1441	1441
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Classes' covariates	No	No	Yes	No	No	Yes	No	No	Yes
Professors' covariates	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Share of high-performing female classmates = # female high-performing among peers ÷ # high performing among peers (leave-me out counts). High-performing: Top quartile (highest 25% admission scores). In 'Positive values,' we run OLS without considering selection into the formal labor market. In 'Input zeros,' we run OLS following Martorell and Isaac McFarlin Jr. (2011) and inputting zeros for students that we do not find at the formal labor market (i.e., we consider that the student is not working as an economist). The remaining column present estimates of a Heckman Two-Step procedure. In the first stage, we estimate the selection equations using a Probit model, and in the second stage, we use OLS regressions. Instrument: % working at the formal labor market at SP city, by age, gender, and expected year of graduation. The dependent variable is an economist occupation dummy variable. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.16: Heckman Selection Two-Step Procedure: Long-term effects of predicted female professors' share in compulsory courses on the probability of working as a top manager

	Positive values			Input Zeros			Heckman		
Female × Predicted % female professors	0.382**	0.386**	0.400**	0.328**	0.329**	0.337**	0.372**	0.398**	0.411**
	(0.152)	(0.153)	(0.154)	(0.127)	(0.130)	(0.129)	(0.160)	(0.159)	(0.159)
Predicted % female professors	-0.031	-0.039	-0.251	-0.033	-0.040	-0.214	-0.035	-0.035	-0.258
	(0.163)	(0.156)	(0.228)	(0.134)	(0.130)	(0.195)	(0.162)	(0.154)	(0.229)
Female	-0.071**	-0.070*	-0.075**	-0.063**	-0.061**	-0.065**	-0.068*	-0.073*	-0.079**
	(0.032)	(0.033)	(0.033)	(0.028)	(0.029)	(0.029)	(0.036)	(0.035)	(0.034)
Mean of dependent variable	0.07			0.06			0.07		
Observations	1441	1441	1441	1576	1576	1576	1441	1441	1441
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Professors' covariates	No	No	Yes	No	No	Yes	No	No	Yes
Classes' covariates	No	No	Yes	No	No	Yes	No	No	Yes

Notes: In 'Positive values,' we run OLS without considering selection into the formal labor market. In 'Input zeros,' we run OLS following Martorell and Isaac McFarlin Jr. (2011) and inputting zeros for students that we do not find at the formal labor market (i.e., we consider that the student is not working as a top manager). The remaining column presents estimates of a Heckman Two-Step procedure. In the first stage, we estimate the selection equations using a Probit model, and in the second stage, we use OLS regressions.Instrument: % working at the formal labor market at SP city, by age, gender, and expected year of graduation. The dependent variable is a Top manager occupation dummy variable. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * p<0.10, ** p<0.05, *** p<0.01.

Table A.17: Heckman Selection Two-Step Procedure: Long-term effects of the predicted share of female professors on normalized real hourly wages two years after graduation

	Positive values			Input Zeros			Heckman		
Female × Predicted % female professors	2.214***	2.126**	2.126**	2.000***	1.767***	1.764***	2.163**	2.109*	2.042**
	(0.705)	(0.771)	(0.767)	(0.593)	(0.554)	(0.555)	(0.924)	(1.000)	(0.955)
Predicted % female professors	-0.927	-1.101	-1.071	-0.475	-0.459	-0.329	-0.928	-1.101	-1.103
	(0.911)	(0.761)	(0.694)	(0.664)	(0.624)	(0.386)	(0.916)	(0.769)	(0.708)
Female	-0.470***	-0.363**	-0.359**	-0.397***	-0.301**	-0.299**	-0.464**	-0.360*	-0.348**
	(0.143)	(0.146)	(0.133)	(0.133)	(0.123)	(0.121)	(0.171)	(0.174)	(0.159)
Mean of dependent variable	-0.00			-0.00			-0.00		
Observations	992	992	992	1554	1554	1554	992	992	992
Cohort-stream fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Students' covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Classes' covariates	No	No	Yes	No	No	Yes	No	No	Yes
Professors' covariates	No	No	Yes	No	No	Yes	No	No	Yes

Notes: In 'Positive values,' we run OLS without considering selection into the formal labor market. In 'Input zeros,' we run OLS following Martorell and Isaac McFarlin Jr. (2011) and inputting zeros for students that we do not find at the formal labor market (i.e., we consider that the student is receiving a zero wage). The remaining column presents estimates of a Heckman Two-Step procedure. In the first stage, we estimate the selection equations using a Probit model, and in the second stage, we use OLS regressions. Instrument: Dummy equals one if students' had information on individual taxpayer number (CPF). The dependent variable is the normalized average hourly wages, considering all labor contracts. We normalized each dependent variable to have a mean of zero and standard deviation of one. Students' covariates: Normalized admission scores (mean zero, standard deviation one), Previous USP enrollment, Student's age at admission, Sao Paulo city of residence dummy; Classes' covariates: Class size, Share of female classmates, Average peers' ability (admission scores), Share of peers with previous USP enrollment, Peers' average age. Professors' covariates: Share of female professors, Percentage with Ph.D. abroad, Experience, Share of A papers, Share of classified papers. Standard errors in parentheses, clustered at the cohort-stream level. P-values: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.