Gender Peer Effects in Post-Secondary Vocational Education

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Abstract

This paper presents evidence that women benefit from having a higher percentage of female peers in post-secondary vocational STEM programs. I use idiosyncratic variation in gender composition across cohorts within majors within branches (campuses) for identification. A 10 percentage point increase in the proportion of women in a STEM major cohort has a statistically significant positive effect on female students. It decreases female dropout rates by 9.6% and increases GPA by 0.05 standard deviations. The evidence suggests the gender of the instructors mediates peer effects: as female students have fewer female instructors, the effect of having more female peers intensifies.

Does having more female peers increase achievement and persistence in Science, Technology, Mathematics, and Engineering (STEM)? Although educational attainment gender gaps have narrowed in many countries, and often reversed (Goldin, 2014; Duryea, Galiani, Nopo, & Piras, 2007; Goldin, Katz, & Kuziemko, 2006), gender gaps persist in STEM occupations, which are often dominated by men (Porter & Serra, 2020; Delaney & Devereux, 2019; Nollenberger, Rodríguez-Planas, & Sevilla, 2016; Schneeweis & Zweimüller, 2012). This gender imbalance can have lasting negative consequences for women, affecting their educational persistence and future income (Card & Payne, 2021; Kahn & Ginther, 2018). Consequently, studying the factors that make women persist (or desist) in STEM careers is relevant to closing gender gaps in education and the labor market.

Although the fact that women are underrepresented in STEM is consistent across different contexts (Jiang, 2021; Bordón, Canals, & Mizala, 2018; Arcidiacono, Aucejo, & Hotz, 2016), why these gaps originate and persist is a question that has not been fully answered. There is consensus in the economics literature about the importance of some factors like teacher bias and role models to secure female students' persis-

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tence in STEM (Carlana, 2019; Lavy & Sand, 2018; Dee, 2007; Sevilla, Bordon, & Ramirez-Espinoza, 2023; Griffith & Main, 2021; Porter & Serra, 2020) . But there is less agreement about how other mechanisms, like gender peer effects, can affect students' outcomes (Eisenkopf, Hessami, Fischbacher, & Ursprung, 2015).

In this paper, I study peer effects by answering the question: does having a higher percentage of female peers increase achievement and retention for vocational higher education STEM students? And, is this effect different for students who are assigned to a higher percentage of female instructors? Hypothetically, having a higher percentage of female peers could create a better learning environment or increase female students' sense of belonging in STEM, improving women's outcomes and persistence in STEM (Gong, Lu, & Song, 2021; Lavy & Schlosser, 2011; Hyde, Mertz, & Schekman, 2009). Furthermore, depending on the mechanism through which the gender peer composition affects educational outcomes, the effect could be different according to other characteristics of the student's educational production function, like instructor gender (Paloyo, 2020). I shed light on both questions by studying the case of vocational higher education students in Chile.

The identification strategy relies on the quasi-experimental variation in students' exposure to female peers. This approach helps to overcome the self-selection bias that stems from the fact that students could be choosing their peers motivated by unobservable characteristics that could be confounded with peer effects (Lavy & Schlosser, 2011). I use deviations from linear trends in the share of first-semester female peers within a given major in a particular branch (major-by-branch), drawing from a dataset of 129,378 students of Chile's biggest vocational educational institution. Moreover, the results are robust to using the deviations from the mean in gender peer composition within major-by-branch across the years. Using deviations from the linear time trends as idiosyncratic variation, I test the effect of gender peer composition on first-year dropout and Grade Point Average (GPA) and whether the effect is different for female and male students.

Estimation results suggest women's educational outcomes improve when they have a higher percentage of female peers. A 10-percentage point increase in the percentage of female peers within major-by-branch units, consistent with the mean idiosyncratic variation in the data, leads to a 9.6% reduction in female student dropout (equivalent to 1.9 percentage points) and a 0.05 standard deviation increase in GPA. For men, this relationship is both smaller and not statistically significant in relation to dropout rates and GPA. These results are robust, accounting for controls and major-by-branch time trends, and align with results from previous studies by De Giorgi, Pellizzari, and Woolston (2012). Additionally, the estimated effect on dropout for women is 60% larger compared to the gender peer effect calculated by Lavy and Schlosser (2011) in their seminal paper on gender peer effects in Israeli high schools.

Additionally, I run a heterogeneity analysis by instructor gender to explore a potential "substitution" effect between the proportion of female peers and female instructors in my setting. In other words, I test whether the effect of having a higher percentage of female peers varies depending on the percentage of female instructors students are exposed to. Results suggest that the percentage of female peers and instructors can act as substitutes: as women have a higher percentage of female instructors, the effect of having a higher percentage of female peers decreases. For instance, for women with 30% of female instructors, the effect of increasing the percentage of female peers in 10 p.p. is a decrease in probability of dropping out of 1.7 p.p, and it is significant at a 5% level of confidence. As the percentage of female instructors further increases, the female peer effect becomes smaller.

The economics of education literature agrees on the importance of some peer characteristics, like academic performance and classroom disruptive behavior, on students' outcomes (Feld & Zölitz, 2022; Busso & Frisancho, 2021; Antecol, Eren, & Ozbeklik, 2016; Mouganie & Wang, 2020; Ficano, 2012; Sacerdote, 2011; Hoxby, 2000). However, there is still debate on how peer gender composition affects middle and long-term outcomes (Paloyo, 2020; Eisenkopf et al., 2015). While some authors find evidence that women's educational outcomes are improved by having a higher percentage of female peers (Bostwick & Weinberg, 2022; Gong et al., 2021; Huntington-Klein & Rose, 2018; Booth, Cardona-Sosa, & Nolen, 2018; Hill, 2015; Eisenkopf et al., 2015; Schneeweis & Zweimüller, 2012; De Giorgi et al., 2012; Lavy & Schlosser, 2011), others find no significant effects (Anelli & Peri, 2019; Griffith & Main, 2019; Oosterbeek & van Ewijk, 2014). Furthermore, some authors find that having more female peers decreases women's participation in STEM (Brenøe & Zölitz, 2020; Zölitz & Feld, 2020; Hill, 2017).

This paper advances the literature by presenting new evidence on gender peer effects, studying not only the effect of gender peer composition on women but its relationship to other inputs of the educational production function, like the gender of female instructors. This exploration contributes to understanding how different elements of a student's educational experience can be conceptualized as complements or substitutes.

Furthermore, I analyze an underexplored population in the gender peer effect literature, focusing on higher education vocational students. Exploring this set of students is important for several reasons. Firstly, vocational students represent an important part of educational systems worldwide. For instance, in the United States, 38% of students in higher education are enrolled in vocational degrees (OECD, 2022), and in Chile, they account for 44.5% of higher education enrollment (Ministry of Education, Chile, 2023). Secondly, STEM vocational degrees are more gender polarized than other types of STEM degrees. Across OECD countries in 2020, women comprised 21% of STEM vocational education enrollment, rising to 31% at the bachelor's level (OECD, 2022). As women are more of a minority in vocational education compared to university education, the size and mechanisms of the gender peer effect may be different. In Chile, for instance, 79% of students from the lowest socioeconomic group pursued this type of education in 2020, while the remaining 21% enrolled in university (Ministry of Education, Chile, 2020). Consequently, finding ways to increase the persistence of women in vocational STEM degrees can be interesting to policymakers who are targeting women from disadvantaged backgrounds.

The paper is organized as follows. Section 1 summarizes the key features of the application process in the vocational education institution of interest, describes data sources and reports summary statistics. In Section 2, I describe the identification strategy used in this study and show evidence on the plausibility of the identifying assumption. I present the main results in Section 3, provide a heterogeneity analysis in Section 4, and present robustness checks in Section 5. I conclude in Section 6 by interpreting my findings in the context of gender peer effects.

1 Context and Data

1.1 Institutional Context

Chile's education system comprises four levels of education: pre-school, primary education, secondary education, and tertiary education (also known as higher education). Three types of institutions can provide higher education: Universities, Professional Institutes (IPs), and Centers for Technical Training (CFTs). The most significant difference between universities and IPs and CFTs is the type and length of training they provide. Universities focus on formal academic training, while IPs and CFTs are vocational and focus on developing practical work skills. This is reflected in the length of studies — the average minimum length of university degrees for incoming students is about nine semesters (Arango, Evans, & Quadri, 2016), whereas CFT and IP's programs are from four to six semesters. Students enrolling in universities or vocational institutions must choose a major when they are admitted, and most of their classes are with peers of the same or similar majors.

This paper uses information from DUOC UC [2], the largest vocational higher education institution in Chile, for the years 2014-2018. It tends to 19.3% of all vocational higher education students in the country, offering 72 majors in health, tourism, construction, and management. In 2018, they had 102,817 enrolled students in their 15 branches, with a presence in three regions of the country. Twelve of these branches are

[2] For more information, visit: http://www.duoc.cl/international-affairs

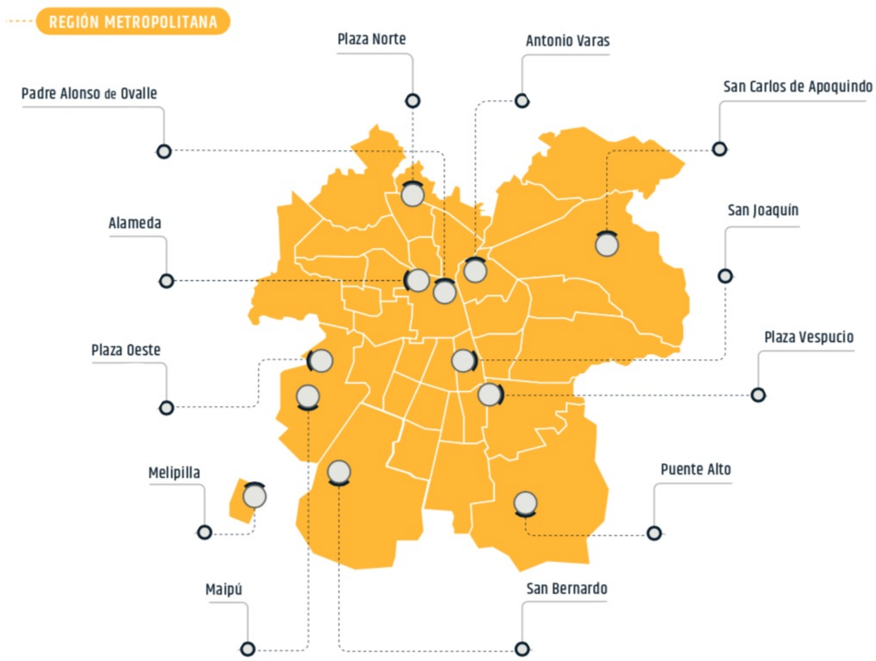


Figure 1: Map of DUOC branches in the Greater Santiago area

located in the Greater Santiago Area (Figure 1), covering an area similar to New York City with 6,257,516 inhabitants. Sixty-two out of the 72 majors are offered in more than one branch. Human resources administration and Business administration are the concentration are the majors taught at more branches. Each is taught at 10 branches in hybrid and in-person versions. There are 323 major-by-branch combinations, which will serve as the unit of analysis in this paper.

Although academic requirements to study at DUOC UC are not strict, the institution holds the highest level of accreditation — a standard shared only with three of the best universities in the system. According to this metric, DUOC UC is the highest-quality vocational higher education institution in the country.

1.2 The Enrollment Process

DUOC UC has a rolling admissions process that is "first-come, first-served." Besides some minimal academic requirements, there are no requisites for enrollment besides proof of payment (either self-funded or through government financial aid). Therefore, neither the students nor the institution can accurately forecast the percentage of female peers they will have during their first semester. In theory, only the last student who enrolls could know how many female peers she/he would be exposed to, but the characteristics of those who are already enrolled are not public, so the student does not have this information available when she/he makes the decision. Therefore, individual students cannot know the exact percentage of female peers they will encounter on their first year of studies.

Another essential institutional detail is how higher education majors are chosen in the Chilean context. Students enroll directly into specific majors one to three months before they start their higher education studies. This has two significant implications: First, if they wish to change majors, they must re-enroll in the new major and retake all coursework. The second and most important in the study context is that they always study with the same group of peers: those from the same year of entry, same major, and same branch. In other words, students within the same major-by-branch in the same year have the same peer group in their first year of studies. In subsequent years students might be exposed to students from other cohorts, potentially introducing endogeneity bias as students could self-select into a particular group of classmates. To address this issue, I only use first-year outcomes: dropout and GPA by the end of the first year. This approach ensures that the concentration of female peers is the same for all students in the same entry year, major, and branch, reducing the likelihood of inter-cohort gender peer influence, as sharing classrooms with students from other cohorts is unlikely.

As it was previously stated, DUOC UC has 15 branches in different parts of the country. Each of them offers a set of majors (e.g., Electrical Technician, Dental Technician, Gastronomy), and most of the majors are offered in more than one branch. For this study, I consider the relevant peer group as those studying in the same major-by-branch who enrolled in the same year. Therefore, a first-year Electrical Technician student in branch A in 2014 has a different peer group than a first-year Electrical Technician student in Branch B in the same year.

1.3 Data

I use data from all enrolled students in Duoc UC from 2014 to 2018. The dataset includes all individuals that studied one of the 72 majors continuously offered between 2014 and 2018 in its 15 branches. This dataset includes gender, age, and mothers' education information on 129,378 students. It also contains information about their working status, their scores on a mathematics diagnostic test all students take before the beginning of their first academic year, if they attend classes during the day or at night (night shift), the gender of their instructors, first-year dropout rates, and GPA. Finally, it includes the students' major at the time of enrollment and a variable that indicates if the major is STEM or non-STEM. The STEM majors with the most students are car auto-mechanics and construction technician. Most Non-STEM students are enrolled in the human resources administration and nurse technician majors. For more detail on the majors included in both categories, see Appendix A.

The dataset contains two educational outcome variables: students' first-year dropout and GPA. In my

Table 1: Summary Statistics for STEM and Non-STEM students

	STEM	Non-STEM	Difference	N
Dropout	0.201	0.170	0.032**	129378
			(0.002)	
GPA (SD)	-0.152	0.104	-0.256**	126088
			(0.006)	
Percentage Female	0.124	0.590	-0.467**	129378
			(0.001)	
Age	21.426	21.682	-0.256**	129257
			(0.028)	
Diagnostic score (SD)	0.086	-0.063	0.149**	107555
			(0.006)	
Mothers' education (SD)	-0.041	0.027	-0.068**	125412
			(0.006)	
Works	0.571	0.548	0.023**	127421
			(0.003)	
Has financial aid	0.646	0.654	-0.008**	129378
			(0.003)	
Night Shift	0.378	0.247	0.131**	129378
			(0.003)	
Female Instructor Percentage	0.298	0.437	-0.138**	127090
			(0.001)	

Source: Own elaboration with data from 2014-2018 cohorts. The significance of the difference was calculated by estimating a linear regression between the variable and a binary indicator for STEM majors. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

sample, 18.2% of students dropout in the first year. Additionally, as shown in Table 1, STEM majors have a higher dropout rate than non-STEM majors (20.1% vs. 17%) and are markedly male-concentrated. On average, they have 12.4% of women, whereas non-STEM majors have 59%. STEM majors students study on the night shift more than Non-STEM students due to the higher supply of night-shift spots for STEM majors. Additionally, STEM majors students are exposed to a lower share of female instructors compared to non-STEM majors (29.8% vs. 43.7%). STEM and non-STEM majors are similar in other characteristics like students' age, diagnostic test scores, education of the mother, and working status. Although the difference between STEM and Non-STEM majors is statistically significant, the magnitude is small, rendering the difference not practically meaningful.

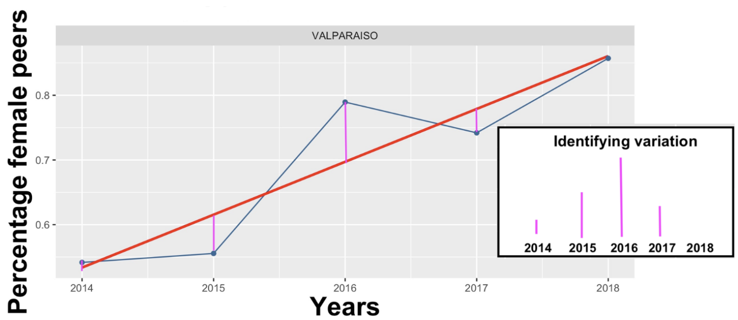
The "treatment" in this setting is each student's percentage of female peers in their first semester. This is calculated by taking the number of female peers over the number of total peers per major-by-branch in their first semester:

$$PercentageFemale_{itk} = \frac{\sum_{i' \neq i}^{n_{tk}} Female_{i'}}{n_{tk} - 1} \tag{1}$$

Where n_{tk} is student i's number of peers n in the major-by-branch k in cohort t and $Female_{i'}$ is a binary variable that takes the value of 1 if student i' is female.

The identifying variation used in this paper is the deviation from the long-term trend of the percentage of female peers students have within the 323 major-by-branches. Figure 2 illustrates the identifying variation of treatment within one major-by-branch over the years, using the major of "Technician in Agro-alimentary Quality and Safety" in the Valparaiso branch in the daytime shift as an example. Here, the dark blue line represents the yearly evolution of the percentage of female peers in this major-by-branch. The red line depicts the linear trend of the percentage of female peers for the major-by-branch. The difference between the predicted and actual percentage for each year is shown in purple, indicating the identifying variation of my model. To see the year-to-year variation for all majors, see Appendix B.

Figure 2: Identifying Variation Example: Within Major-by-Branch Yearly Percentage Female Variation



2 Causal Identification Strategy

In this context, the treatment is the major-by-branch deviation from the predicted percentage of women. Through a linear model that includes year-fixed effects, major-by-branch fixed effects, and major-by-branch time trends, I use year-to-year deviations from long-term trends in the percentage of female peers within major-by-branch to estimate the effect of interest. Given that treatment was not assigned randomly as it would be in the context of an experiment, the identifying assumption is that the deviations from the major-by-branch female peer percentage trends are as good as random and uncorrelated with any unobservables that could be affecting the outcomes of interest.

Besides testing if a gender peer effect exists in this context, understanding if the gender composition peer effect is different for women than for men is fundamental to my research question. To check if the effect of the percentage of female peers is different for men and women, I use an interaction term between gender and the treatment, percentage of female peers. The linear regression model I use to estimate the effect of the percentage of female peers on women and men is as follows:

$$Y_{itk} = \beta_0 + \beta_1 \% female_{itk} + \beta_2 Male_{itk} + \beta_3 \% female_{itk} * Male_{itk} + \beta_4 X_{itk} + \gamma_t + \delta_k + \delta_k * year_{it} + \varepsilon_{itk} \qquad (2)$$

Where Y_{itk} is the outcome of interest (dropout or standardized GPA) for student i in cohort t in major-by-branch k, $\% female_{itk}$ is the percentage of female peers for student i in major-by-branch k in cohort t, $Male_{itk}$ is a binary variable that takes value of 1 if the student i in cohort t in major-by-branch k is male and 0 otherwise, X_{itk} is a vector of student-level characteristics, γ_t are years fixed effects, δ_k are major-by-branch fixed effects, and δ_k multiplied by $year_{it}$ is a set of major-by-branch-specific linear time trends. X_{itk} includes age, diagnostic math test scores, mother education, working status, and an indicator variable for those studying on the night shift. X_{itk} also includes all controls interacted with the $Male_{itk}$ binary variable. The coefficient of interest is β_1, which indicates how the percentage of female peers is related to dropout for women. If the assumptions hold, then β_1 would identify the causal effect of the percentage of female peers on educational outcomes for women. β_3 indicates if the effect of the percentage of female peers in the outcome of interest is different for men in my sample. To check if there is a gender peer effect for men, I need to test that the linear combination of β_1 and β_3 is different from zero. If the gender peer effects are positive for women but negative for men, the evidence would suggest the existence of a trade-off between the benefits of improving the percentage of female peers for male versus female students. Conversely, if we observe that the effect for both male and female students is positive (negative), the evidence would suggest that there is no trade-off, and all students benefit (suffer) from a higher proportion of female peers.

Following Abadie, Athey, Imbens, and Wooldridge (2017), I take the perspective of an experimental design to decide the clustering of the errors. My setting can be conceptualized as the treatment (percentage of female peers) to be randomized to full cohorts within major-by-branch. If all the identifying assumptions hold, this setting is akin to randomizing the percentage of female peers each year to each cohort within a major-by-branch. Given that all students within a major-by-branch in a particular year are exposed to the same number of female peers[3], I posit that the unit of "randomization" is major-by-branch, and I cluster the errors to that level. This approach mirrors that of Lavy and Schlosser (2011), Mouganie and Wang (2020), Bostwick and Weinberg (2022), and others[4].

[3]The percentage of female peers in the same year-major-branch is mechanically different for women and men as described by equation 1, but comes from the same random number of female peers.

[4]Clustering at the major-by-branch-by-year level, maintains or improves the precision of the estimates.

Table 2: Balance Table

	Independent variable:		
	Percentage of Female Peers (Treatment)		
	STEM	Non-STEM	N
Age	-0.129	0.197	129257
	(0.908)	(0.396)	
Diagnostic score (SD)	-0.636*	0.076	107555
	(0.261)	(0.128)	
Mothers' education (SD)	-0.184	0.120	125412
	(0.157)	(0.087)	
Works	-0.179+	-0.039	127421
	(0.099)	(0.083)	
Has financial aid	-0.091	-0.033	129378
	(0.096)	(0.049)	
Night Shift	0.154*	-0.005	129378
	(0.070)	(0.032)	

Notes: Percentage of female peers ranges from 0 to 1. Control variables are in standard deviations units. Each coefficient is calculated estimating a regression of the control variable on the percentage of female peers, year fixed effects, major-by-branch fixed effects, and major-by-branch time trends, following the main specification of the paper. Errors clustered to the major-by-branch level. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

2.1 Evidence on the Feasibility of the Identifying Assumption Strategy

In the absence of a randomized treatment assignment, I need to assume that the major-by-branch deviations from the predicted percentage of women are not correlated with unobservables correlated with the outcome. As it involves unobservables, there is no definitive way to test this assumption. Nevertheless, I argue that the treatment is independent of potential outcomes and unobservables by analyzing how observables relate to treatment and extending this reasoning to unobservable characteristics.

I first check how the treatment is correlated to some of the observable covariates by regressing the covariate on the treatment using major-by-branch fixed effects and major-by-branch linear time trends. Results are shown in Table 2. Using a 10 p.p. increase on the percentage of female peers to interpret Table 2[5], the estimated coefficients can be interpreted as either insignificant or precise zeros. Although I will never be able to prove that unobservables are not correlated with treatment, the fact that the coefficients are either not significant or practically zero suggests that, at least in observables, the treatment is not systematically correlated with students' characteristics that could explain their educational outcomes.

As shown in Figure 3, the percentages of female peers are similar year to year for most STEM majors (in light blue). Nevertheless, the specification used is *conditional* on the major-by-branch and includes a major-

[5]See Section 2.2 for more detail on this benchmark.

by-branch specific time trend, meaning that although the average level of percentage female peers might be predictable, the deviations from the predicted percentage would be hard to predict by the students. In this context, it is hard for students to manipulate the percentage of female peers they are exposed to by unilaterally switching to other majors, both because they do not know the exact number until they start classes when the enrollment process is finished and because most majors do not have a substitute that is accessible to students. Therefore, assuming that the small deviations from the predicted treatment within major-by-branch year-to-year are random is plausible.

2.2 Relevant Variation in the Treatment for Interpretation

To validly interpret the results of my fixed effects model, I need to find a plausible hypothetical change in the percentage of female peers supported in the data. To do so, I use within-unit variation to motivate counterfactuals when discussing the substantive impact of the treatment (Mummolo & Peterson, 2018)

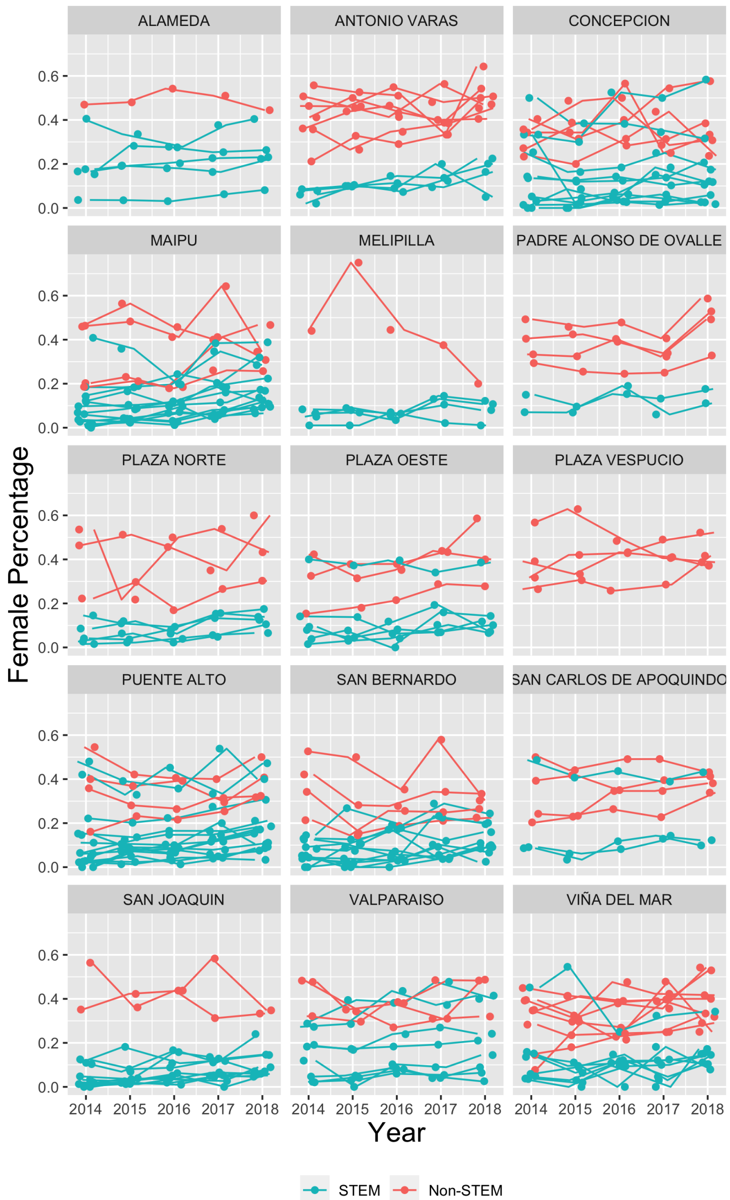
To identify a benchmark for an increase of female percentage that has support in the data, I analyze the within-unit ranges of treatment for the major-by-branch units. The range is defined as the difference between the maximum and minimum percentage of female peers within a major-by-branch across the years. Figure 4 shows the ranges of treatment for the 106 STEM major-by-branch units. The mean of the range, shown in blue, is 11 percentage points (p.p.), with a standard deviation of 6 p.p. To interpret the results, I use 10 p.p. as a benchmark for the change in the percentage of female peers.

2.3 Threats to Validity

As the treatment was not randomized, there is potential for bias in estimating the treatment effect. If the deviations from long-term trends of the percentage of women were somehow correlated with unobservables that are also correlated with the outcome, the estimate of treatment effect would be biased. In this subsection, I go over some of the most plausible threats to my identification strategy.

A threat would be for students to be able to manipulate the identifying variation: deviations from the predicted percentage of female peers. If groups of women that benefit (or suffer) from having female peers decide to strategically enroll in the same majors in the same branches, they could manipulate the treatment by increasing the percentage of female peers above the long-term time trends. An example would be female students that coordinate with female friends from high school to enroll in a major in a branch knowing that this will enhance their learning. In this situation, the unobservable that could threaten identification is having female friends in the cohort: it would be correlated with both a higher percentage of female peers and better educational outcomes. Although I do not have information on where students graduated from

Figure 3: Within Major-by-Branch Yearly Percentage Female Variation - Majors with more than 50% Male Students



for all of my sample so I can include it as a control variable in the model, I have high school information for the year 2018.

Figure 5 illustrates how prevalent is the concentration of women from the same high school in the same major-by-branch in the sample. In specific, it compares the distribution of the percentage of women in a major-by-branch versus the distribution of the percentage of women coming from the same high school in a major-by-branch in 2018. It shows the frequency of each percentage of women (binned at 0.01) for both

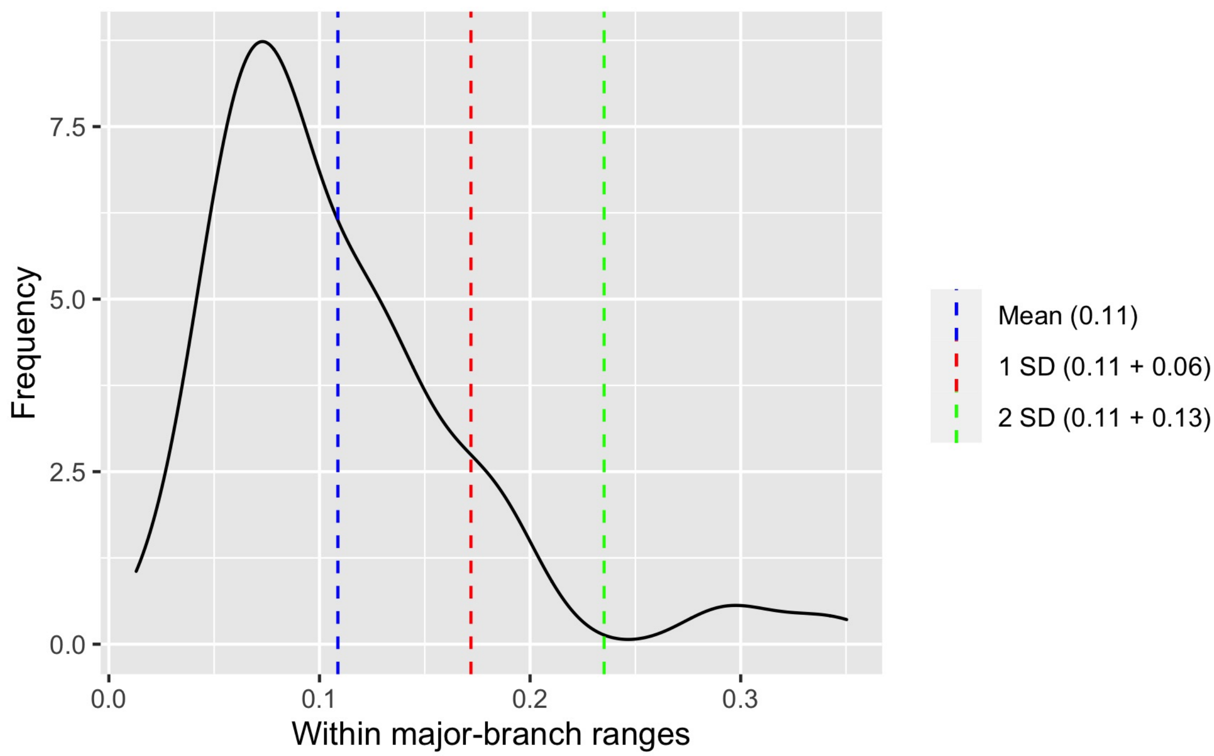


Figure 4: Within major-by-branch ranges of treatment

variables. As it can be seen in Figure 5, women from the same school represent low percentages of female peers in major-by-branches. For STEM majors, 92% of major-by-branches have less than 2% of women that come from the same high school, a small proportion compared to the mean 16% of female peers in STEM majors-by-branch. Although not conclusive, this evidence suggests that women who went to the same high school coordinating to go into the same major-by-branch is not a sizable threat to the identification strategy: even when we observe women from the same high school in the same major-by-branch, they represent a small portion of the percentage of female peers.

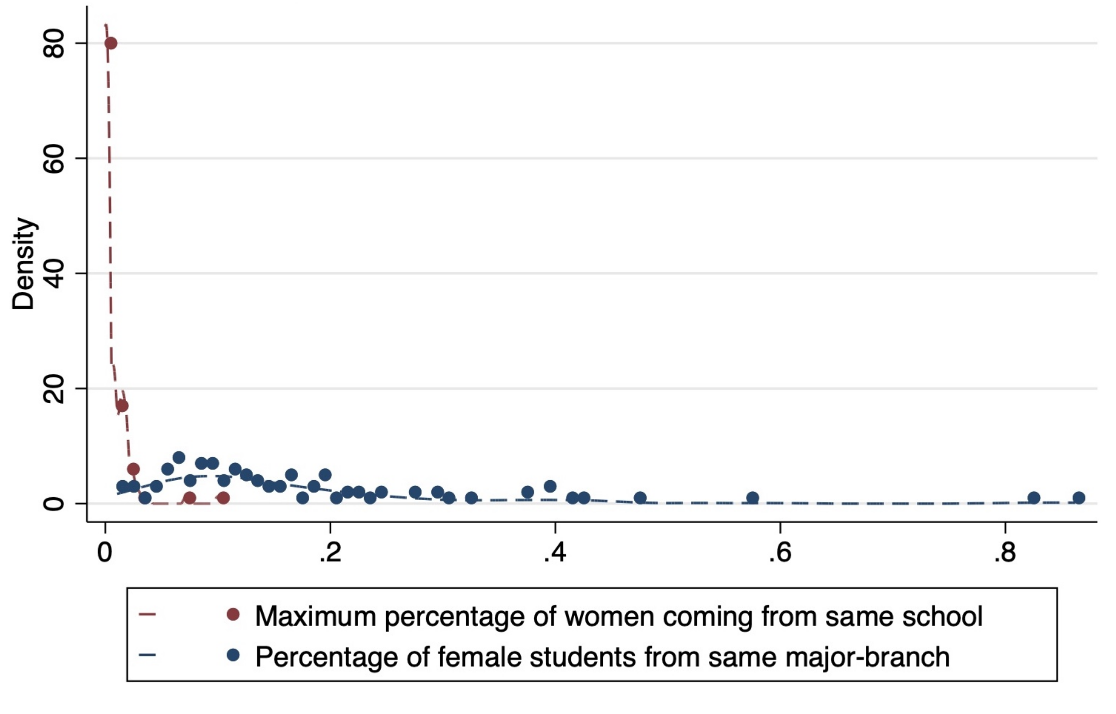


Figure 5: Percentage of women from same school vs. all women in major-by-branch

Another instance of an unobservable that could threaten the identification strategy is a program director concerned about gender imbalance making efforts to attract more women to STEM programs and implementing initiatives to reduce female dropout or improve their grades. The fact that I am using the variation that comes from deviations from trends in the percentage of female peers makes it unlikely for the "concerned director" to be a considerable threat, because of the temporality of the effort: the director should be able to differentiate which years she makes an effort to recruit more women and which years she makes an effort to improve their outcomes, as these two things (enrollment and educational outcomes) happen with a time difference of one year. Furthermore, she should be able to vary the intensity of her efforts so they are differentially bigger in years where women were admitted slightly more than what was expected – this is unlikely to happen because the efforts needed to make women succeed (change in syllabi, content programming, instructor training) require time to be planned and executed and cannot be fully deployed in one academic year.

3 Results

Tables 3 and 4 report the estimation of the model described in equation 2, for two outcomes: standardized GPA and first-year dropout. The sample includes 129,378 observations for dropout and 126,088 for standardized GPA, divided into STEM Major and Non-STEM Major students. Columns (3) and (6) show the estimation of the full model, that includes the major-by-branch time trends, major-by-branch and year fixed effects, and student-level controls (age, diagnostic test score, mother's education, working status, funding status, and night shift, and a dummy variable for each control that takes a value of 1 if the control is missing for that student and 0 otherwise). To evaluate the robustness of the results to alternative specifications, columns (1) and (4) show the simplest estimation with no controls or major-by-branch linear time trends, and columns (2) and (5) include controls but not major-by-branch linear time trends. The errors are clustered at the major-by-branch level. The interaction term allows comparing the coefficient for percentage female for men and women in each sample.

Using dropout as the outcome, the coefficient of interest for women in STEM majors is negative and significant at the 5% level. As shown in Table 3, the sign and significance of the coefficient for percentage of female peers for women in STEM is robust to the three specifications. Estimates for the model with controls and major by branch fixed effects and time trends (column 3) indicate that an increase of 10 p.p. on the percentage of women within a STEM major-by-branch causes a decrease of 1.8 percentage points in female students' dropout rate. This reduction represents a 9.6% decrease in dropout rates for women in STEM majors. For men in STEM majors, the effect of the percentage of women on dropout is small and is not statistically significant. Similarly, for students in Non-STEM majors, the coefficient of interest on dropout is small and non-significant. This suggests that gender peer composition does not affect dropout or GPA for Non-STEM major students.

In the case of standardized GPA as the outcome, the estimations in Table 4 suggest a positive effect on educational outcomes for STEM students, consistent with the improvement in dropout rates. For STEM majors, the coefficients of all models are positive and significant at the 10% level. For the model with all fixed effects and time trends (column 3), the coefficient of interest is significant to a 5% level. Here, a 10 p.p. increase of the percentage of female peers within the major-by-branch is related to a 0.05 standard deviation increase in GPA. The coefficient for percentage female is smaller but sill positive, but not statistically significant for men. For non-STEM majors the coefficients are small and not statistically significant.

It can be argued that the gender peer effect is not specific to STEM majors but male-concentrated majors, if the gender dynamics are only produced by women being in the minority. Examples of such dynamics could be increased classroom disruptions or discriminatory behavior by peers and instructor that only occur

Table 3: Estimates of the Effect of Percentage Female on Dropout

	STEM Majors			Non-STEM Majors		
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage Female	-0.208*	-0.200**	-0.179*	-0.006	0.006	0.014
	(0.082)	(0.071)	(0.083)	(0.032)	(0.033)	(0.035)
Male	-0.009	0.264*	0.252*	0.046**	0.111	0.104
	(0.013)	(0.122)	(0.123)	(0.012)	(0.100)	(0.101)
Percentage Female:Male	0.138*	0.145*	0.155*	0.001	0.019	0.026
	(0.060)	(0.055)	(0.059)	(0.019)	(0.017)	(0.017)
Mean outcome for women	0.186	0.186	0.186	0.146	0.146	0.146
Major by Branch and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Major by Branch Time Trend	No	No	Yes	No	No	Yes
Observations	52316	52316	52316	77062	77062	77062

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level.

Table 4: Estimates of the Effect of Percentage Female on GPA (SD)

	STEM Majors			Non-STEM Majors		
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage Female	0.419+	0.452+	0.555*	0.088	0.087	0.047
	(0.248)	(0.231)	(0.224)	(0.113)	(0.118)	(0.120)
Male	-0.066*	-0.225	-0.215	-0.294**	-0.667**	-0.606**
	(0.030)	(0.413)	(0.418)	(0.032)	(0.202)	(0.208)
Percentage Female:Male	-0.387**	-0.346*	-0.397**	0.093+	0.062	0.041
	(0.142)	(0.146)	(0.143)	(0.053)	(0.053)	(0.049)
Mean outcome for women	-0.047	-0.047	-0.047	0.225	0.225	0.225
Major by Branch and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Major by Branch Time Trend	No	No	Yes	No	No	Yes
Observations	50756	50756	50756	75332	75332	75332

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level.

Table 5: Estimates of the Effect of Percentage of Female Peers in Male-Concentrated Majors (40%)

	Dropout			**GPA (SD)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	STEM	Other	Δ	STEM	Other	Δ
Percentage Female	-0.206*	0.073	-0.279+	0.658**	-0.093	0.751
	(0.088)	(0.133)	(0.157)	(0.214)	(0.535)	(0.568)
Male	0.270*	-0.004	0.274	-0.264	0.074	-0.338
	(0.124)	(0.128)	(0.176)	(0.418)	(0.437)	(0.599)
Percentage Female:Male	0.187**	0.014	0.173+	-0.385**	0.220	-0.605*
	(0.063)	(0.081)	(0.101)	(0.123)	(0.280)	(0.301)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Observations	51060	11343		49537	11089	

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Only male-concentrated (less than .4 women) majors are included in the estimations. All regressions include major-by-branch specific time trends, major-by-branch and year fixed effects, and controls. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level. Δ represents the difference between the coefficients of the variable for STEM and non-STEM (other) students. P-values are calculated using a wald test testing the hypothesis that the coefficients are equal.

when men are in the majority. If this was the case, we would observe a decrease on dropout and increase in standardized GPA of a higher female percentage for women on male-concentrated non-STEM majors. This can be explored with the data, comparing estimates of the main specification for male concentrated STEM majors versus male concentrated non-STEM majors [6]. The results of estimating the main specification (equation 2) for STEM male-concentrated majors and non-STEM male concentrated majors are shown in Table 5 for both outcomes.

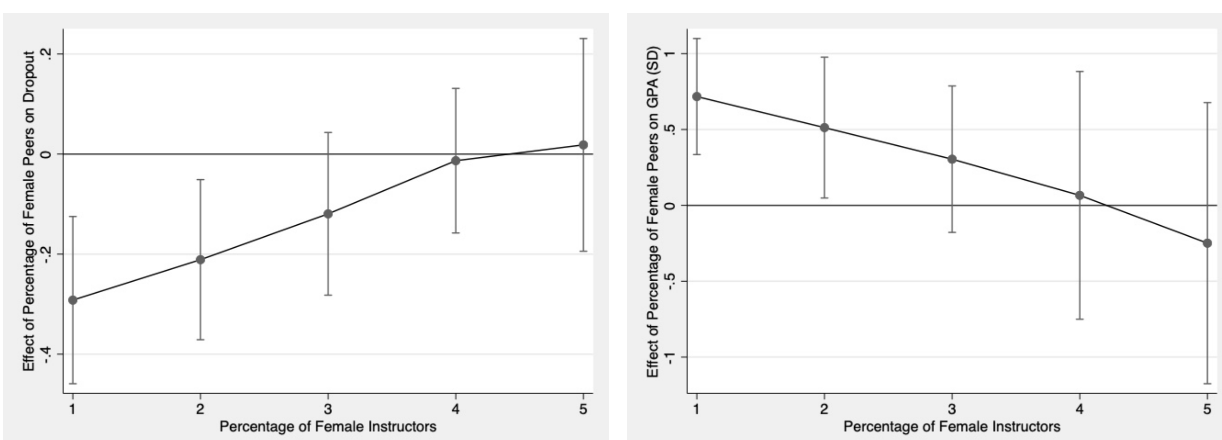
In the estimations for STEM male-concentrated majors, we observe that the sign of the effect reflected in the coefficient of the percentage of female peers remains the same and is still significant for both outcomes. On the other hand, for Non-STEM male-concentrated majors, the sign flips for both coefficients, and they are statistically insignificant. Given the possibility of this being an artifact of the smaller sample of non-STEM male concentrated majors, it is important to formally test if the coefficient is different for STEM and non-STEM male concentrated majors. To assess if the coefficients for both models are statistically different, I test the hypothesis that the coefficients are equal by doing a Wald test. For dropout, the difference between both coefficients is significant to the 5%, whereas that for GPA (SD), the difference is significant to the 11%. This suggests that even within male-concentrated majors, STEM majors are unique in relation to gender peer effects.

[6] Male concentrated majors are defined as majors that have less than 40% female students in their student body. Alternative definitions of male concentration are shown in Appendix C.

4 Heterogeneity Analysis

Gender peer effect, meaning the improvement of women's academic outcomes due to having a higher percentage of female peers, is one of many factors that can bolster women's trajectories in STEM. In this section, I study the relationship between the gender peer effect observed in this context and another factor that has been extensively studied in the literature: female role models. According to the literature of women in STEM, another way of improving female students' outcomes is to provide them with female role models (Porter & Serra, 2020; Paredes, 2014; Griffith, 2014; Carrell, Page, & West, 2010; Hoffmann & Oreopoulos, 2009; Bettinger & Long, 2005), particularly in vocational education (Sevilla et al., 2023). If being exposed to female role models improves women's education through the same mechanism as being exposed to female peers, there is a possibility for the gender peer effect to interact with the female role model effect. Conversely, if the gender peer effect is heterogeneous to female instructor exposure, these two factors can be conceptualized as complements or substitutes in the education production function (Attanasio, Meghir, & Nix, 2020). To explore this notion, I run a heterogeneity analysis of the gender peer effect by the percentage of female instructors that teach each student.

To shed light on the idea of gender peer composition and female role models being substitutes, I show estimates of the effects of the percentage of female peers on application behavior for all quintiles of percentage of female peers in Figure 6. Similar plots for deciles instead of quintiles are shown in Figure 9 in Appendix D. The trend in Figure 6a, shows that as the percentage of female peers is higher, the negative effect on dropout is smaller. For GPA, Figure 6b shows that as the percentage of female instructors is higher, the gender peer effect becomes smaller and it flips signs for higher deciles. The effects are significant for the lower quintiles of female instructors percent, which have more observations (as shown in Figure 7)



(a) Dropout

(b) GPA (SD)

Figure 6: Effect Heterogeneity by Percentage of Female Instructors

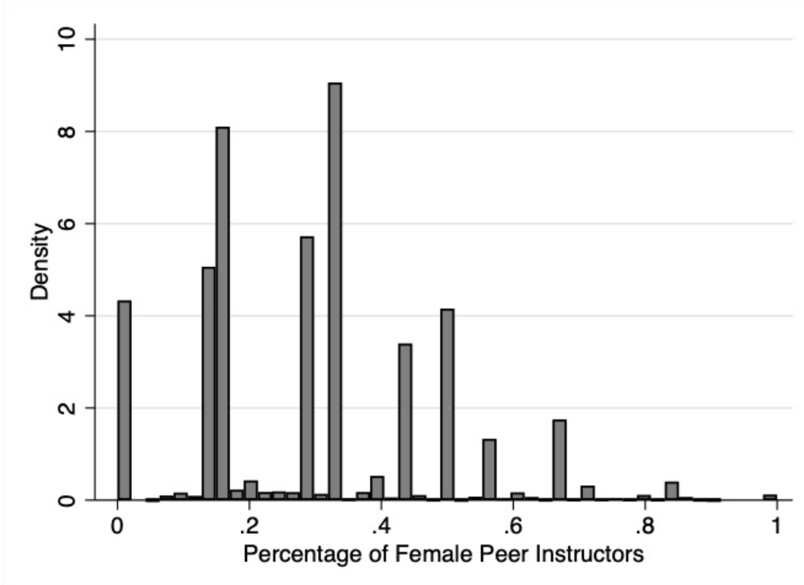


Figure 7: Percentage of Female Instructors in STEM majors

To test the hypothesis that the effect varies as the percentage of female instructors is higher, I estimate the original model, adding an interaction term between the percentage of female peers and the percentage of female instructors and another interaction term between the male dummy and the percentage of female instructors as shown in Equation 3. Given that this model includes a major-by-branch specific time trend, the variation used to identify the effect of female instructors are the deviations from the predicted percentage of female instructors. Similar to the empirical strategy to estimate gender peer effects, the assumption is that these deviations are not correlated with an unobservable characteristic that is also correlated to the outcome. An example would be a dean who makes an effort to improve female students' outcomes and hires more female instructors than could be predicted in the same year. While possible, it is unlikely that an interested dean will adjust their efforts depending on the deviation from the trend in female instructor hiring because the temporality of instructor hiring and the teaching of students is different: instructor hiring happens before students start the academic year.

$$\begin{aligned} Y_{itk} = \beta_0 + \beta_1 \% female_{tk} + \beta_2 Male_{itk} + \beta_3 \% female_{tk} \times Male_{itk} + \beta_4 \% femaleinstructors_{itk} + \\ \beta_5 \% female_{tk} \times \% femaleinstructors_{itk} + \beta_8 \% femaleinstructors_{itk} \times Male_{itk} + \beta_7 X_{itk} + \\ \gamma_t + \delta_k + \psi_k year_{st} + \varepsilon_{itk} \end{aligned} \tag{3}$$

Here, the coefficient of interest is the marginal effect of the percentage of female peers for women. For easier interpretation, I subtract the sample mean of percentage of female instructors in STEM from the $\%femaleistructors$ variable. This way, β_1 represents the effect of the percentage of female peers when female students are exposed to the mean percentage of female instructors in the sample. If having more female instructors is a substitute for having a higher percentage of female peers, then the coefficient on the interaction term (β_5) and the share of female peers coefficient (β_1) would have opposite signs. If, on the other hand, these are complements, then both coefficients would have the same sign as having a higher proportion of female instructors would magnify the effect of having a higher share of female peers.

The estimates of model 3 can be found in Table 6. For easier interpretation, I only show the coefficients relevant to female students. When female students are exposed to the mean percentage of female instructors for STEM (30%), the marginal effect of the percentage of female peers in women's dropout is -17 percentage points, and it is significant at the 5% level. The negative sign suggest that as women have a higher percentage of female instructors, the gender peer effect caused by having more female peers decreases: if instead of having 30% female instructors, women had 35% of female instructors, the marginal effect of the percentage of female peers in dropout would drop from -17 to -15.5 percentage points ($-0.17 + 0.05 * 0.309$) and it is significant to the 7% level. The estimates size and significance is robust to the exclusion of controls.

Table 6: Percentage of Female Instructor Interaction

	Dropout			GPA (Standardized)		
	New Model		Original Model	New Model		Original Model
% Female	-0.203**	-0.171*	-0.179*	0.501*	0.549*	0.555*
	(0.073)	(0.085)	(0.083)	(0.208)	(0.227)	(0.224)
% Female Instructors	-0.055+	-0.064*		0.125+	0.142*	
	(0.030)	(0.030)		(0.072)	(0.071)	
% Female:% Female Instructors	0.366**	0.309*		-0.948*	-0.400	
	(0.117)	(0.134)		(0.432)	(0.414)	
Mean outcome for women	0.186	0.186	0.186	-0.047	-0.047	-0.047
Major by Branch and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Major by Branch Time Trend	No	Yes	Yes	No	Yes	Yes
Observations	51256	51256	52316	49730	49730	50756

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. The means for STEM majors of percentage female peers (% Female) and percentage of female instructors (% Female Instructors) were substracted from the respective variables, so they are both centered at zero. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. The net % female Effect presented in row 4 is calculated by multiplying the coefficient of row 3 by 0.3 and adding the coefficient of row 1. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level.

This evidence suggests that a higher percentage of female instructors weakens the gender peer effect. If this was the case, what might be the underlying mechanism? A hypothesis that could explain both factors behaving as substitutes is that they both address the same active constraint on their outcomes. This constraint could stem from the fear of confirming the negative stereotype that women do not belong in

STEM, known as stereotype threat (Koenig & Eagly, 2005; Steele & Aronson, 1995). A less-male dominated environment could neutralize stereotype threat, as seeing more women studying a STEM major can foster a stronger sense of belonging among female students. According to the literature of women in STEM, another avenue for increasing women's sense of belonging is through the presence of female role models (Porter & Serra, 2020; Paredes, 2014; Griffith, 2014; Carrell et al., 2010; Hoffmann & Oreopoulos, 2009; Bettinger & Long, 2005).

Considering instructors as role models, and if students identify themselves more with same-sex role models (Basow & Howe, 1980), performance may be enhanced when students are taught by instructors of the same gender (Dee, 2007). If both factors function by lowering stereotype threat, we would expect for one factor to have a lower impact if the other is already present and has lowered the stereotype threat. In other words, for students that already feel that they belong in STEM because they find female role models in their instructors, having a higher percentage of female peers might not increase their sense of belonging as much as it would if they were not exposed to female role models. Another channel could be that both female instructors and female peers improve the learning environment for women, enhancing women's educational outcomes. Sadly, I do not have data on students' perception on stereotypes or learning environment. Given data limitations, I cannot test the channel for the substitution effect of female instructors and female peers in the context of this study.

Further research on this topic should focus on the mechanisms underlying the gender peer effect and its potential interaction with the presence of female role models. This exploration can be interesting to policymakers aiming to improve women's STEM educational experience. Furthermore, it would add to the scholarly debate about the complementarities among inputs in the educational production function.

5 Robustness Check

Without randomized treatment assignment, the identification strategy hinges on the assumption that the percentage of women is not correlated with unobservable variables correlated with the outcome. In this case, a threat would be any factor that would cause a simultaneous increase in the percentage of female students and female students' outcomes. A good placebo test would be to replicate the core analysis using lagged percentage of female peers as the treatment. If the change we observe in dropout and GPA was not a direct consequence of the idiosyncratic variation in the treatment but an unobservable that could affect the outcome around the time, it is likely that the unobservable is also correlated with the treatment of the previous year. To check for this possibility, I present estimations of the main specifications using the percentage of female peers of the previous year as treatment (and of the last year for the first cohort) in

Tables 7 and 8.

As shown in these tables, the relationship between the lagged treatment and the outcomes is of smaller magnitude and not statistically significant, supporting the idea that within major-by-branch, the change in the percentage of female peers is idiosyncratic. Furthermore, the effect of the percentage of female students on men is not significant for dropout or GPA.

Table 7: Placebo - Estimates of the Effect of Percentage Female on Dropout

	STEM Majors		
	(1)	(2)	(3)
Percentage Female (l)	-0.027	-0.034	-0.072
	(0.077)	(0.079)	(0.082)
Male	-0.007	0.267*	0.255*
	(0.011)	(0.122)	(0.123)
Percentage Female (l):Male	0.126*	0.124**	0.123*
	(0.051)	(0.046)	(0.048)
Mean outcome for women	0.186	0.186	0.186
Major by Branch and Year FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Major by Branch Time Trend	No	No	Yes
Observations	52316	52316	52316

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Placebo: treatment is that of the previous year, and for the first cohort the treatment is that of the last. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level.

Table 8: Placebo - Estimates of the Effect of Percentage Female on GPA

	STEM Majors		
	(1)	(2)	(3)
Percentage Female (l)	0.242	0.183	0.168
	(0.238)	(0.236)	(0.240)
Male	-0.051+	-0.209	-0.202
	(0.026)	(0.415)	(0.421)
Percentage Female (l):Male	-0.474**	-0.439**	-0.455**
	(0.117)	(0.110)	(0.113)
Mean outcome for women	-0.047	-0.047	-0.047
Major by Branch and Year FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Major by Branch Time Trend	No	No	Yes
Observations	50756	50756	50756

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Placebo: treatment is that of the previous year, and for the first cohort the treatment is that of the last. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level.

6 Discussion

The results presented in this paper support the hypothesis that there are gender peer effects in the vocational education system. In particular, having a higher percentage of female peers positively affects students in STEM majors, decreasing women's dropout rates and increasing GPA in vocational post-secondary education. For men, a higher percentage of female peers decreases dropout and increases GPA on a smaller scale, and the coefficients are not statistically significant. The evidence presented in this paper suggests that women benefit from having a higher percentage of female peers and men are, at least, not harmed by it. From a theory perspective, this paper proposes that in the case of vocational education, having a higher percentage of female students represents a Pareto improvement: both women and men benefit from it, or at the very least are not harmed by it. Although the literature has studied the effect on women extensively, there is little evidence on the impact that gender composition has on men, an important point when thinking about the general welfare of students. This has a two-fold implication: first, it supports the scholarship that has established that a higher share of female peers is associated with better outcomes (Lavy & Schlosser, 2011). Second, it challenges recent evidence that students' outcomes are hindered by having a higher share of opposite gender schoolmates (Hill, 2015).

In terms of policymaking, this paper presents evidence that gender peer effects exist in vocational education and that they might point to an intervention path to "stop the leaking" in the STEM pipeline. The heterogeneity analysis also suggests that increasing the percentage of female instructors could improve female students' outcomes by acting through similar channels as the percentage of female peers. Although post-secondary vocational institutions cannot directly control the gender composition of cohorts in this context, they do have discretion in instructor selection. Therefore, these results suggest that increasing the percentage of female instructors is an avenue to improve female students' outcomes when increasing the percentage of female peers is not feasible. Nevertheless, more causal evidence on this mechanism is necessary to affirm that role models will benefit women in this context. As scholars and institutions develop analyses of gender peer composition, collecting data and using causal inference methodologies will allow identifying levers to avoid gender polarization in STEM.

This paper builds on the gender peer effect literature, providing evidence for a novel context (a middle-income country in Latin America) for an education sector that has not been thoroughly studied: post-secondary vocational education. It provides strong evidence that the international trends of female student achievement and peer effects hold in this context and that actions geared toward improving gender balance within majors can positively affect students' outcomes. To understand better the actions that could improve gender balance in this context, the next step should be to explore the mechanisms at play that create these dynamics experimentally.

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Appendices

A STEM and non-STEM majors

The STEM/non-STEM classification used in this paper was developed by DUOC, following the guidelines of the Ministry of Education.

A.1 STEM majors

English translation

Telecommunications Technician

Computer engineering

Technician in electricity and industrial automation

Technician in auto mechanics and autotronics

Construction technician

Engineering in infrastructure and technological platforms

Architectural and structural drawing

Technician in installations and electrical projects

Automotive and autotrophic mechanical engineering

Computer Network Administration

Sound technology

Construction engineering

Computer programmer analyst

Network and connectivity engineering

Technician in renewable energies and energy efficiency

Engineering in electricity and industrial automation

Technician in geology and drilling control

Technician in machinery and heavy vehicles

Surveyor technician

Infrastructure and technology platform manager

Industrial design

Geomatics Technician

Technician in quality and agri-food safety

Engineering in machinery and heavy vehicles

Sound engineering

Original STEM major names

Técnico en telecomunicaciones

Ingeniería en informática

Técnico en electricidad y automatización industrial

Técnico en mecánica automotriz y autotrónica

Técnico en construcción

Ingeniería en infraestructura y plataformas tecnológicas

Dibujo arquitectónico y estructural

Técnico en instalaciones y proyectos eléctricos

Ingeniería en mecánica automotriz y autotrófica

Administración de redes computacionales

Tecnología en sonido

Ingeniería en construcción

Analista programador computacional

Ingeniería en conectividad y redes

Técnico en energías renovables y eficiencia energética

Ingeniería en electricidad y automatización industrial

Técnico en geología y control en sondaje

Técnico en maquinaria y vehículos pesados

Técnico topógrafo

Administrador de infraestructura y plataformas tecnológicas

Diseño industrial

Técnico en geomática

Técnico en calidad y seguridad agroalimentaria

Ingeniería en maquinaria y vehículos pesados

Ingeniería en sonido

A.2 Non-STEM majors

English translation

Acting

Business management, marketing diploma

Financial management

Human resources management

Hotel Management

Digital animation

Audit

Foreign trade

Audiovisual communication

General accounting, tax legislation diploma

Environment design

Costume Design

Graphic design

Ecotourism

Sports physiotherapist

Gastronomy

International gastronomy

Illustration

Biomedical informatics

Management Engineering

Human Resources Management Engineering

Logistics management engineering

Marketing engineering

Agricultural engineering

Environmental engineering

Foreign trade engineering

Risk prevention engineering

Physical trainer

Advertising

Public relations marketing mention

Heritage restoration

Agricultural Technician

Clinical laboratory and blood bank technician

Radiodiagnosis and radiotherapy technician

Nursing technician

Tourism and hospitality

Adventure trip

Technical tourism, mention of tourism companies

Technical tourism mention in aero-commercial services

Tourism and hotel

Audiovisual technician

Technician in graphic design

Logistics management technician

Dental technician

Risk prevention technician

Chemistry and Pharmacy Technician

Veterinary technician

Original non-STEM major names

Actuación

Administración de empresas mención marketing

Administración financiera

Administración de recursos humanos

Administración hotelera

Animación digital

Auditoria

Comercio exterior

Comunicación audiovisual

Contabilidad general mención legislación tributaria

Diseño de ambientes

Diseño de vestuario

Diseño grafico

Ecoturismo

Fisioterapeuta deportivo

Gastronomía

Gastronomía internacional

Ilustración

Informática biomédica

Ingeniería en administración

Ingeniería en administración de recursos humanos

Ingeniería en gestión logística

Ingeniería en marketing

Ingeniería agrícola

Ingeniería en medio ambiente

Ingeniería en comercio exterior

Ingeniería en prevención de riesgos

Preparador físico

Publicidad

Relaciones publicas mención marketing

Restauración patrimonial

Técnico agrícola

Técnico de laboratorio clínico y banco de sangre

Técnico de radiodiagnóstico y radioterapia

Técnico de enfermería

Turismo y hospitalidad

Turismo de aventura

Turismo técnico mención empresas turísticas

Turismo técnico mención en servicios aerocomerciales

Turismo y hotelería

Técnico audiovisual

Técnico en diseño grafico

Técnico en gestión logística

Técnico en odontología

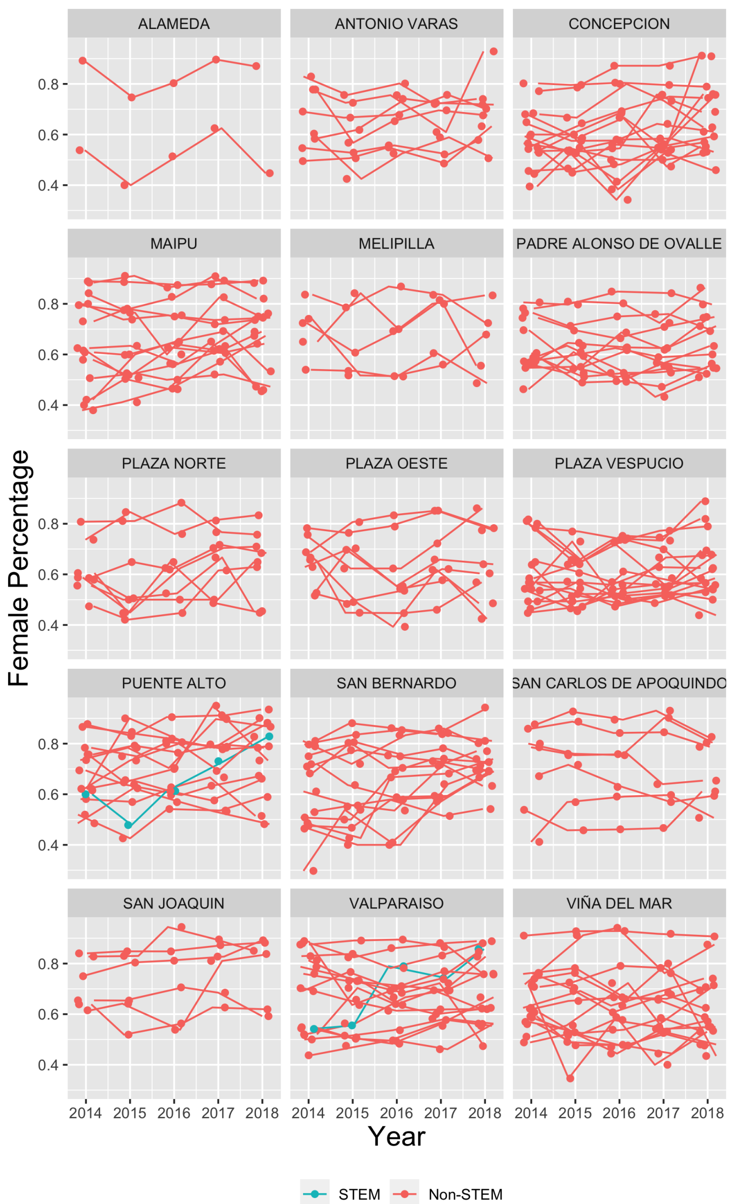
Técnico en prevención de riesgos

Técnico en química y farmacia

Técnico veterinario

B Identifying Variation Plots

Figure 8: Within Major-by-Branch Yearly Percentage Female Variation - Majors with 50% or more of Female Students



C Alternative Male Concentrations Estimations

Table 9: Estimates of the Effect of Percentage Female in Male-Concentrated Majors (35%)

	Dropout			GPA (SD)		
	(1)	(2)	(3)	(4)	(5)	(6)
	STEM	Other	Δ	STEM	Other	Δ
Percentage Female	-0.142	0.420	-0.562*	0.564*	-0.809	1.373
	(0.108)	(0.231)	(0.249)	(0.273)	(0.950)	(0.965)
Male	0.253	0.026	0.227	-0.135	-0.188	0.053
	(0.154)	(0.207)	(0.254)	(0.541)	(0.548)	(0.759)
Percentage Female:Male	0.129	-0.279+	0.408*	-0.309	0.763	-1.072*
	(0.090)	(0.139)	(0.163)	(0.209)	(0.512)	(0.541)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Observations	49127	8292		47677	8092	

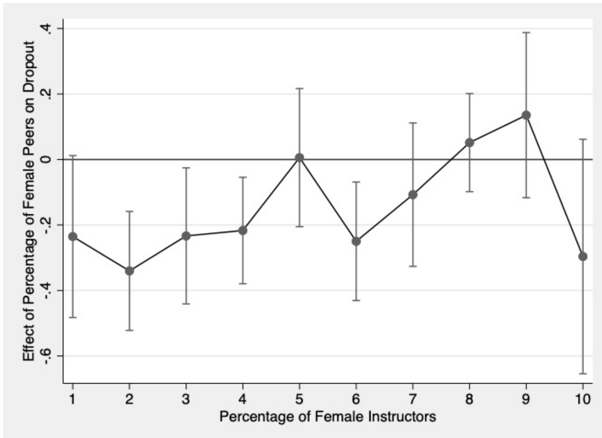
Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Only male-concentrated (less than .35 women) majors are included in the estimations. All regressions include major-by-branch specific time trends, major-by-branch and year fixed effects, and controls. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level. Δ represents the difference between the coefficients of the variable for STEM and non-STEM (other) students. P-values are calculated using a wald test testing the hypothesis that the coefficients are equal.

Table 10: Estimates of the Effect of Percentage Female in Male-Concentrated Majors (30%)

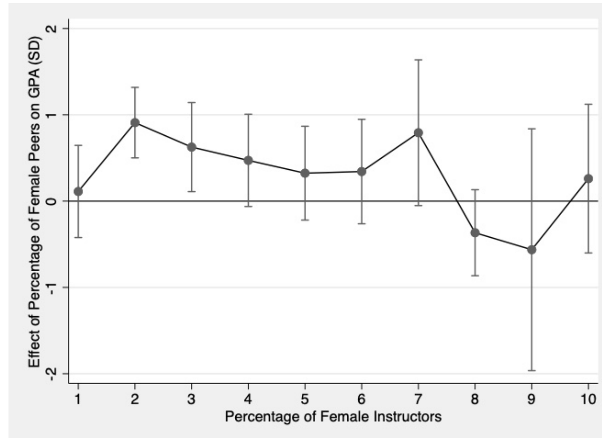
	Dropout			GPA (SD)		
	(1)	(2)	(3)	(4)	(5)	(6)
	STEM	Other	Δ	STEM	Other	Δ
Percentage Female	-0.106	0.642	-0.748*	0.493	-1.266	1.759
	(0.116)	(0.315)	(0.324)	(0.307)	(1.632)	(1.599)
Male	0.259+	-0.002	0.261	-0.146	-0.188	0.042
	(0.155)	(0.180)	(0.232)	(0.546)	(0.489)	(0.719)
Percentage Female:Male	0.056	-0.329	0.385	-0.170	0.891	-1.061
	(0.076)	(0.252)	(0.254)	(0.209)	(1.209)	(1.181)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Observations	48754	5862		47315	5709	

Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Only male-concentrated (less than .3 women) majors are included in the estimations. All regressions include major-by-branch specific time trends, major-by-branch and year fixed effects, and controls. Controls include age, diagnostic scores, mother's education, work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch level. Δ represents the difference between the coefficients of the variable for STEM and non-STEM (other) students. P-values are calculated using a wald test testing the hypothesis that the coefficients are equal.

D Heterogeneity by Percentage of Female instructors



(a) Dropout



(b) GPA (SD)

Figure 9: Effect Heterogeneity by Percentage of Female Instructors for STEM majors