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 peer effects are mediated by the gender of the instructors: as female students have fewer female instructors, the effect of having more female peers intensifies.

Although educational attainment gaps have narrowed, and often reversed, in many countries (Goldin, 2002; Goldin, Katz, & Kuziemko, 2006; Duryea, Galiani, Nopo, & Piras, 2007), occupational gaps remain. Men and women are still concentrated in different occupations (Schneeweis & Zweimüller, 2012). These occupational gaps originate in the

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subjects that men and women choose to study and partly explain gender wage differences. Consequently, studying the mechanisms through which women persist (or desist) in high-paying paths like STEM fields will likely contribute to closing gender pay gaps.

In this paper, I test whether having more female peers increases achievement and persistence in STEM majors in vocational education in Chile. The analysis is motivated by previous literature that suggests that peer effects exist and are particularly salient in the STEM fields, where women have lower participation than in other fields (Hoxby, 2000; Bostwick & Weinberg, 2018; Sacerdote, 2011).

The identification strategy uses quasi-experimental variation in students' exposure to female peers in Chile. I use variation over time, for a given major in a particular campus (major-by-branch), in the share of female peers. Moreover, the result is robust to using the deviation from linear trends in gender peer composition within major-by-branch across the years, instead of the deviations from the mean. Using this idiosyncratic variation, I test whether gender peer composition predicts first-year dropout and Grade Point Average (GPA), and whether the prediction is different for female and male students. I use observational data from 129,378 students of the largest post-secondary vocational institution in Chile in my estimations.

Estimation results suggest women's educational outcomes improve when they have a higher percentage of female peers. Here, a 10 percentage point in the percentage of female peers within major-by-branch units, close to the mean idiosyncratic variation in the data, reduces female student's dropout by 9.6% (1.9 percentage points) and increases their GPA by 0.05 standard deviations. For men, this relationship is of a smaller magnitude and not statistically significant for either dropout rate or GPA. These results are robust to the inclusion of controls and major-by-branch time trends.

The results here cannot be explained by STEM majors having a high concentration of male students. If this were the case, I would observe a similar effect for male-concentrated STEM and non-STEM majors. Instead, the coefficients for the percentage of female peers in male-concentrated STEM majors are statistically significantly different from non-STEM majors and of opposite sign.

There are several potential explanations of why women improve their outcomes when they are surrounded by more women. If, for instance, the increase in the percentage of female peers works by making STEM's gender stereotype less salient, we can hypothesize that having more female instructors could do something similar through a role model effect (Porter & Serra, 2020; Paredes, 2014). To test this idea, I run a heterogeneity analyses to determine 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 are 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 that have 30% 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. If the percentage of female instructors is higher (e.g. 35%), the effect of the same increase in the percentage of female peers (10 p.p.) is lower (decrease of 1.3 p.p.). Both of these effects are significant at a 5% level of confidence.

Many researchers and teachers have argued that peer composition is an important a determinant of student outcomes (Sacerdote, 2011). This issue seems to be particularly crucial for women: there is evidence that women respond more than men to peer influences, consistent with social psychology theories that peers affect female students more (Han & Li, 2009).

There is evidence that the gender composition of peers affects outcomes and that these effects are different for boys and girls (Busso & Frisancho, 2021; Mouganie & Wang, 2020; Zölitz & Feld, 2020). Lavy and Schlosser (2011) find large positive effects from the percent of girls within a classroom, and they also interpret these effects as working through more than merely increasing peer average test scores. Along the same lines, Hoxby (2000) finds modestly large effects of peer background on own test scores, using idiosyncratic gender variation. Paredes (2018) finds that single-sex classrooms reduce the math gender gap by more than half in the Chilean context. She finds that this effect is driven by the gender composition of the classroom itself.

Although the gender peer effect literature in primary and secondary education is robust, post-secondary education remains a less-explored area. Papers that study how culture may be connected to female underrepresentation have been published recently, like those authored by Lundberg (2017) and Wu (2017). Likewise, there are several studies on STEM graduate program admissions and persistence. For instance, Bostwick and Weinberg (2018) use a difference-in-difference approach and find that an increase in the percentage of female students differentially increases the probability of on-time graduation for women. This paper contributes to the emergent body of evidence of gender peer effects in post-secondary education.

Studies on gender peer effects in vocational education are almost non-existent, although it comprises a significant part of educational systems worldwide. In some developed countries, one-quarter of cohorts pursue professional programs. In the United States, certificate graduation rates are burgeoning — tripling in recent years (*Skills beyond school: synthesis report*, 2014). This study is situated in Latin America, where the post-secondary education sector is also growing fast. This trend is observed in countries with the highest secondary education completion rates, such as Colombia, Mexico, Brazil, Chile, and Peru. As other Latin American countries raise their secondary education completion rates, this paper sheds light on how gender peer effects play out in this specific context.

The causal identification strategy relies on the assumption that the variation in gender peer composition within major-by-branches is as good as random. To support this idea, I estimate an autoregressive model of gender peer composition with major-by-branch and year-fixed effects. In this context, peer composition in the previous year is not significantly correlated to gender peer composition in the current year, supporting the idea that the change of percentage of female peers is idiosyncratic within major-by-branch.

The paper is organized as follows. Section 1 summarizes the key features of the application process in the vocational education institution that will be studied, describes data sources, reports summary statistics, and tests for balance on the treatment variable and the plausibility of the identifying assumption. In Section 2, I describe the identification strategy used in this study. I present the main results in Section 3 and provide a heterogeneity analysis in Section 4. I conclude in Section 5 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 the vocational sector 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 courses — the average minimum length of university degrees for incoming students is about nine semesters (Arango, Evans, & Quadri, 2016). 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. Furthermore, students cannot choose their courses during their first year, so women cannot coordinate to concentrate in one section of a course. This is relevant, as section choice would be a possible mechanism for women to manipulate the percentage of female they interact with.

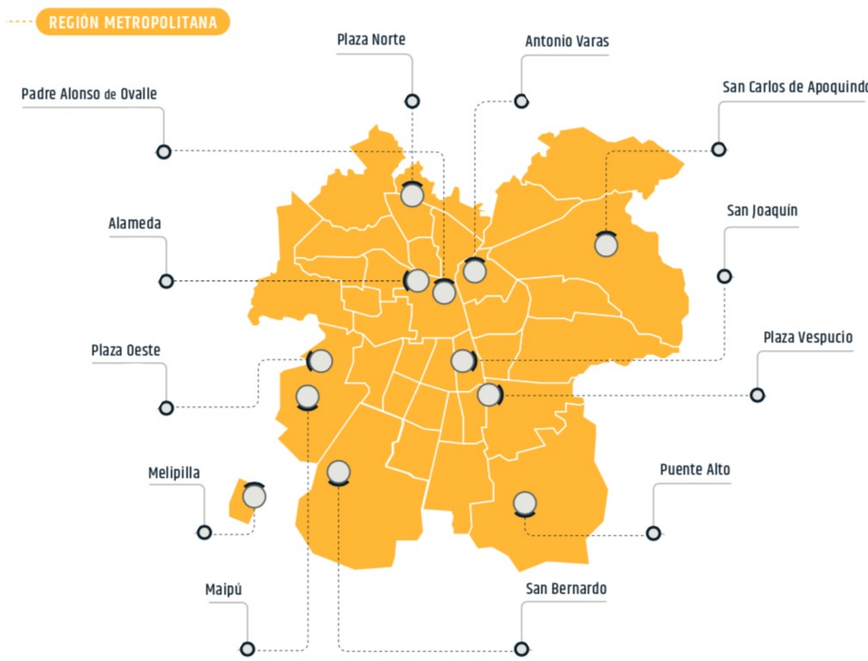


Figure 1: Map of DUOC branches in the Greater Santiago area

This paper uses information from DUOC UC [2], the largest vocational higher education institution in Chile. It tends to 19.3% of all vocational higher education students in the country, offering 75 majors in 9 areas of health, tourism, construction, and management. In 2018, they had 102,817 enrolled students in their 15 branches, present in three regions of the country. Twelve of these branches are located in the Greater Santiago Area (Figure 1), which covers an area similar to New York City and has 6,257,516 inhabitants. Given that some majors are taught in more than one branch, there are 323 Major-by-Branch combinations.

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

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

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 (first come-first served). 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 who are already enrolled are not public, so the student does not have this information available when she/he makes the decision. Therefore, individuals students cannot know exactly how many female peers they will have.

Another essential institutional detail is how higher education studies are taught in the Chilean context. For the higher education system in general and DUOC UC in particular, students enroll directly into specific majors. This has two significant implications: first, if they wish to change majors, they must re-enroll to the new major and start this second major from scratch. The second, and most important in the context of the study, is that they always study with the same group of peers: those from their same year-of-entry, same major and same branch. Therefore, the concentration of female peers is the same for all students in that major in a particular branch, and the opportunity for inter-major gender peer influence is less likely.

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 the same major at the same branch in the same year of entry. Therefore, a first-year Electrical Technician student in branch A has a different peer group than a first-year Electrical Technician student in branch B.

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 includes information on their working status, the scores on a mathematics diagnostic test all students take before the beginning of their first academic year, if they attend school during the day or at night (night shift), gender of their instructors, first year dropout rates, and GPA. Finally, it included the major students at time of enrollment, and a variable that indicates if the major is STEM or non-STEM. Appendix A shows a list of the majors included in both categories. All this information allows testing for the effects and heterogeneity described in Section 2.

The measurement of educational outcomes for this dataset is students' dropout during her first year of studies at Duoc UC and students' GPA. From the data, we get that 18.1% of students dropout in the first year. As shown in Table 1, STEM majors have a higher dropout rate than non-STEM majors (18.1% vs. 15.2%). STEM majors are markedly male concentrated: on average, they have 12.5% of women, whereas non-STEM majors have 60%. Compared to the mean, differences in the other covariates are small in magnitude, showing that the differences are not practically meaningful.

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

The identifying variation used in this paper is the variation of the average percentage of female peers students have within the 323 major-by-branches. Figure 2 illustrates the

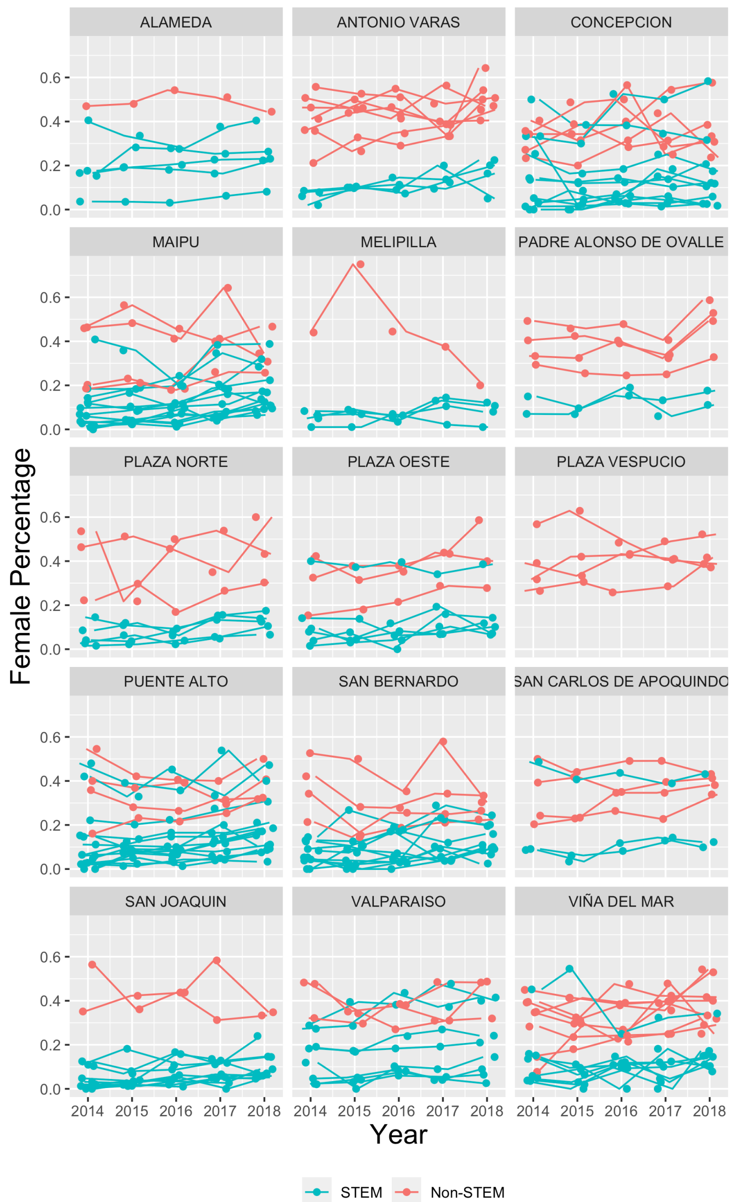
Table 1: Summary Statistics for STEM and Non-STEM students

	STEM	Non-STEM	Difference	N
Dropout	0.201	0.170	0.032**	129378
			(0.002)	
GPA (in 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	48.761	45.872	2.889**	107555
			(0.120)	
Mothers' education	3.888	4.036	-0.147**	125412
			(0.012)	
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)	

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. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

variation of treatment within major for each branch for majors with more than 50% men for all branches (for majors with 50% or less men, see Appendix B). The year-to-year variation plotted in Figure 2 is the identifying variation in this context.

Figure 2: Within Major-by-Branch Yearly Percentage Female Variation - Male Majority



2 Causal Identification Strategy

In this context, the treatment is the percentage of female peers a student has in their program, in their branch, in their entrance cohort. Through a linear model that includes year-fixed effects, major-by-branch fixed effects, and 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 treatment was assigned as good as randomly, conditional on the controls.

To estimate the effect, I use a linear regression model. Because I am interested in knowing the effect of the percentage of female peers and how this effect is different for men and women, I will use an interaction term between gender (male) and percentage of female peers. The linear regression model I will use to estimate the effect of the percentage of female peers on women and men is:

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

Y_{itk} is the outcome of interest (dropout or standardized GPA) for student i in cohort t in major-by-branch k, $\% female_{tk}$ is the percentage of female peers in major-by-branch k in cohort t, $Male_{itk}$ is a dummy that takes value of 1 if the student i in cohort t in major-by-branch k is male, X_{itk} is a vector of student's covariates, γ_t are years fixed effects, δ_k are major-by-branch fixed effects, ψ_k is a set of major-by-branch-specific linear time trends, and $year_{it}$ is the year when student i in cohort t studied. X_{itk} includes age, diagnostic math test scores, mother education, working status, and educational shift. X_{itk} also includes all controls interacted with the $Male_{itk}$ dummy. The coefficient of interest is β_1, that indicates how percentage of female peers is related to dropout for women. If the assumptions hold, then β_1 would identify the causal effect of percentage of female peers on educational outcomes for women.

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-by-year and I cluster the errors to that level.

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 percentage of women is 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. I do this by analyzing how observables relate to treatment and extend this reasoning to the unobservables. Additionally, I present an autoregressive model to check for within major-by-branch gender peer composition trends.

I first check how the treatment is correlated to some of the observable covariates in Table 2 by regressing the covariate on the treatment using major-by-branch fixed effects and major-by-branch linear time trends. Using a 10 p.p. increase on percentage of female peers to interpret Table 2[4], the estimated coefficients can be interpreted as either insignificant or precise zeros. Although I will never be able to prove that unobservables

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

Table 2: Balance Table

	Independent variable:		
	Percentage of Female Peers (Treatment)		
	STEM	Non-STEM	N
Age	-0.026	0.038	129257
	(0.150)	(0.065)	
Diagnostic score	-0.636**	0.076	107555
	(0.209)	(0.108)	
Mothers' education	-0.184	0.120+	125412
	(0.131)	(0.066)	
Works	-0.362*	-0.079	127421
	(0.176)	(0.130)	
Has financial aid	-0.189	-0.069	129378
	(0.164)	(0.081)	
Night Shift	0.318*	-0.011	
	(0.134)	(0.060)	129378
Major-by-branch & Year Fixed Effects	Yes	Yes	
Major-by-branch Time Trends	Yes	Yes	

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 Year and Major level. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

are not correlated with treatment, the fact that the coefficients are either not significant or practically zero suggests that, at least in observables, the exogeneity assumption holds.

As shown in Figure 2, the percentages of female peers are similar year to year. Nevertheless, the specification used is *conditional* on the major-by-branch, meaning that although the average level of percentage female peers might be predictable, the idiosyncratic change can be thought of as random. Therefore, as 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 the students), assuming that the small changes within major-by-branch

Table 3: Autocorrelation model for percentage of female peers

	Percentage Female (t)
Percentage Female (t-1)	-0.082
	0.056
Major by Branch and Year FE	Yes
Observations	424

Notes: The regression includes year and major-by-branch fixed effects. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

year-to-year are random is plausible. If this were not the case, we would see that the percentage of female peers in one year is a good predictor of the percentage of female peers in the next. To check if the idiosyncratic variation in gender peer composition within programs has any trends, I estimate an autoregressive model of gender peer composition with major-by-branch fixed effects:

$$\%female_{tk} = \beta_0 + \beta_1 \%female_{(t-1)k} + \delta_k + \varepsilon_{tk} \tag{3}$$

Table 3 shows the results from estimating equation 3. In this context, peer composition in the previous year is not significantly correlated to gender peer composition in the current year, supporting the idea that within major-by-branch, the change of percentage of female peers is idiosyncratic.

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 will 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. Figure 3 shows the ranges of treatment for all years: the mean difference between the maximum and minimum percentage of female peers within the 106 STEM Major-by-Branch units,

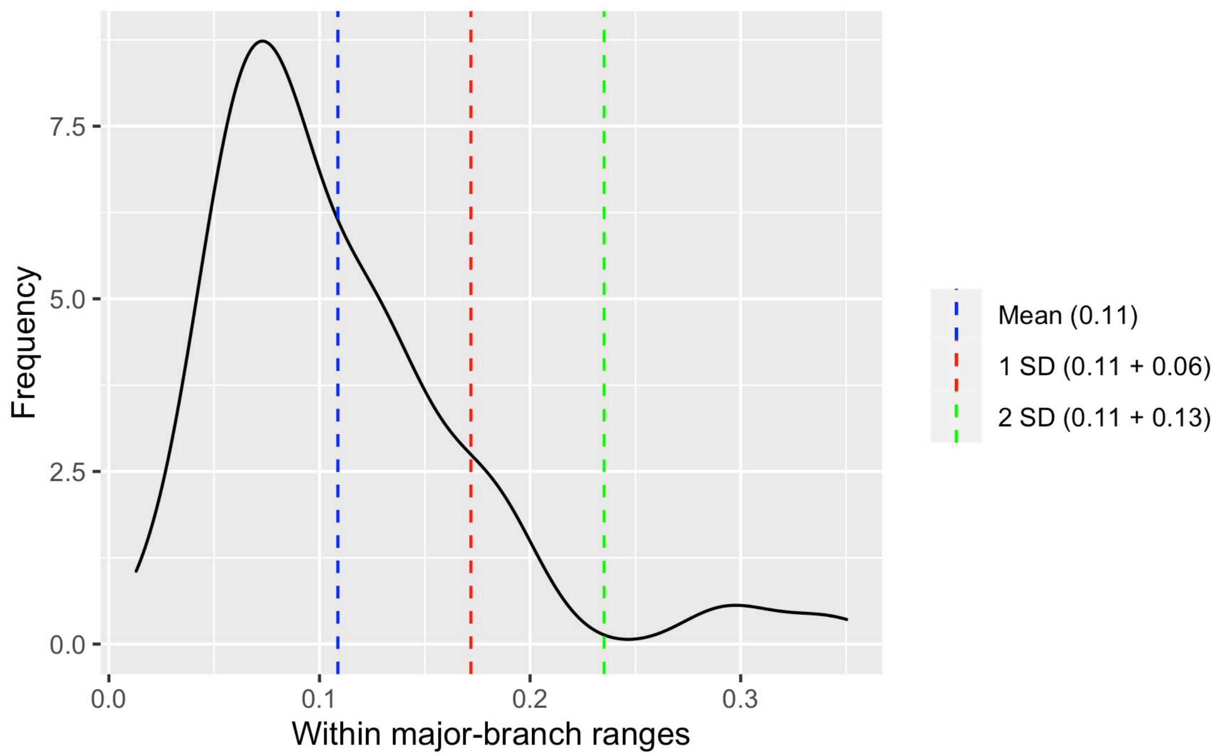


Figure 3: Within major-by-branch ranges of treatment

shown in blue, is 11 percentage points (p.p.), with a standard deviation of 6 p.p. To interpret the results, I will use 10 p.p. as a benchmark for change in treatment.

2.3 Threats to Validity

As the treatment was not randomized, there is the potential for bias in estimating the treatment effect. If the change of 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: changes in the percentage of female peers. If groups of women that benefit from feeling supported by friends decide to strategically enroll in the same majors in the same branches, they could manipulate the treatment. In this situation, the unobservable that could threaten identification is having 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 for all of my sample, I have high school information for year 2018.

Figure 4 compares the percentage of all women in a major-by-branch versus the percentage of women coming from the same school in a major-by-branches in 2018. It shows the frequency of each percentage of women (binned at the 0.01) for both variables. As it can be seen in Figure 4, 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 that 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.

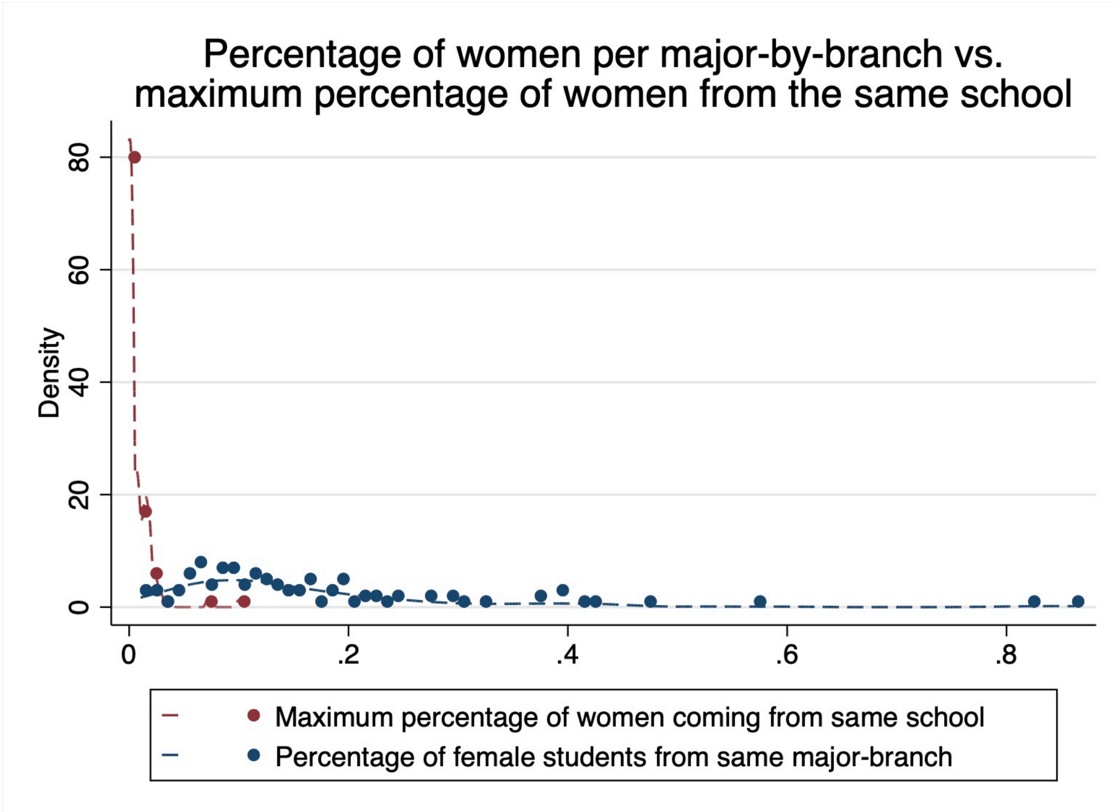


Figure 4: Percentage of women from same school vs. all women in major-by-branch

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 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 4 and 5 report the estimation of the fixed effects 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. Regressions shown in the columns (1) and (4) include Major-by-Branch and year fixed effects, but no controls or Major-by-Branch linear time trends. The rest of the estimations include 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. Besides controls and year fixed effects and Major-by-Branch fixed effects, columns (3) and (6) include Major-by-Branch linear time trends. The errors are clustered at the Major-by-Branch and year 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 4, the coefficient for percentage of female peers for women in STEM remains negative and significant for 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 1.9 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

Table 4: 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
	(0.068)	(0.070)	(0.069)	(0.028)	(0.029)	(0.028)
Male	-0.009	0.264*	0.252*	0.046**	0.111	0.104
	(0.011)	(0.122)	(0.124)	(0.011)	(0.100)	(0.100)
Percentage Female:Male	0.138**	0.145**	0.155**	0.001	0.019	0.026
	(0.050)	(0.048)	(0.048)	(0.018)	(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 by year level.

peer composition does not affect dropout or GPA for Non-STEM major students.

In the case of standardized GPA as the outcome, the estimations showed in Table 5 suggest a positive effect in educational outcomes, consistent with the improvement in dropout rates. For STEM majors, the coefficients of all models are positive and significant. For the model with all fixed effects and time trends (column (3)), the coefficient of interest is significant to the to the 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.

Some could argue that the problem is not some particular gender dynamic in STEM majors but male-concentrated majors, given dynamics produced by women being a minority. Examples of such dynamics could be increased classroom disruptions or discriminatory behavior by peers and instructor that only occur 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

Table 5: 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
	(0.213)	(0.212)	(0.192)	(0.097)	(0.099)	(0.096)
Male	-0.066*	-0.225	-0.215	-0.294**	-0.667**	-0.606**
	(0.030)	(0.415)	(0.417)	(0.029)	(0.215)	(0.221)
Percentage Female:Male	-0.387**	-0.346*	-0.397**	0.093+	0.062	0.041
	(0.145)	(0.140)	(0.128)	(0.048)	(0.047)	(0.046)
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 by year level.

concentrated STEM majors versus male concentrated non-STEM majors [5]. The results of estimating the main specification (equation 2) for STEM male-concentrated majors and non-STEM male concentrated majors are shown in Table 6 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. To formally compare both models, 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%.

[5] 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.

Table 6: 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
	(0.076)	(0.114)	(0.137)	(0.196)	(0.424)	(0.465)
Male	0.270*	-0.004	0.274	-0.264	0.074	-0.338
	(0.124)	(0.112)	(0.167)	(0.418)	(0.437)	(0.602)
Percentage Female:Male	0.187**	0.014	0.173+	-0.385**	0.220	-0.605*
	(0.060)	(0.078)	(0.098)	(0.128)	(0.278)	(0.304)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Major by Branch and Year FE	Yes	Yes		Yes	Yes	
Controls	Yes	Yes		Yes	Yes	
Major by Branch Time Trend	Yes	Yes		Yes	Yes	
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. 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 by year 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.

This piece of evidence suggests that having a higher percentage of female peers is associated with higher GPA, and lower dropout is not an artifact of majors being mostly male-concentrated but of other mechanisms that seem to be unique to STEM majors.

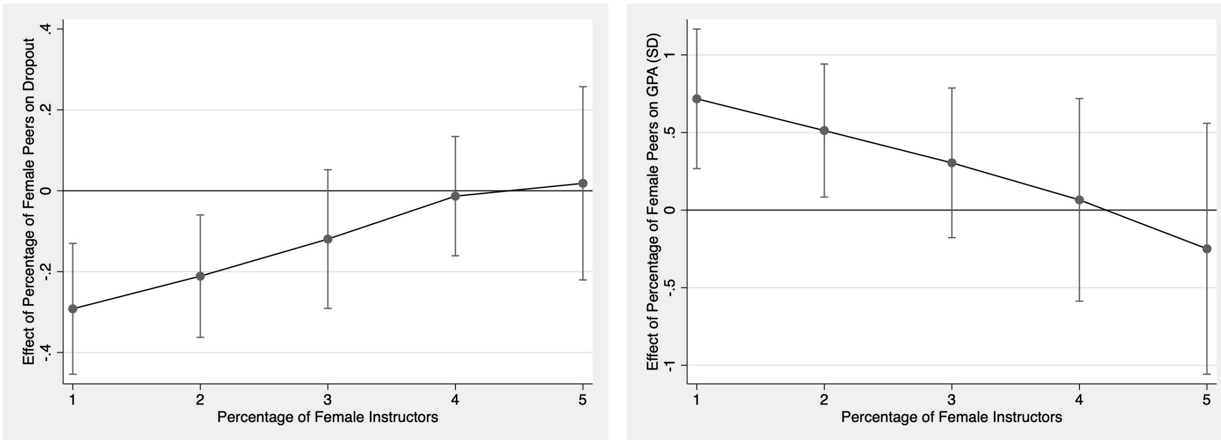
4 Heterogeneity Analysis

There are several potential explanations of why women improve their academic outcomes when surrounded by more women. One of them is that experiencing STEM as less male-dominated might lower stereotype threat: the fear of confirming the negative stereotype that women do not belong in STEM (Koenig & Eagly, 2005; Steele & Aronson, 1995). According to the literature of women in STEM, another way of lowering this threat is to have female role models (Porter & Serra, 2020; Paredes, 2014; Bettinger & Long, 2005). If we think of 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 assigned to a same gender teacher (Dee, 2007).

If that was the case, then the gender peer effect I observe in this context is different depending on the percentage of female instructors of the student. To shed light on this idea, 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 5. Similar plots for deciles instead of quintiles are shown in Figure 8 in Appendix D.

The trend in Figure 5a, shows that as the percentage of female peers is higher, the negative effect on dropout is smaller. For GPA, Figure 5b 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 quintieles that have more observations (as shown in Figure 6)

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



(a) Dropout (b) GPA (SD)

Figure 5: Effect Heterogeneity by Percentage of Female Instructors

female peers and percentage of female instructors and another interaction term between the male dummy and percentage of female instructors as shown in Equation 4. If having more female instructors is a substitute for having a higher percentage of female peers, then the coefficient on the interaction term and the share of female coefficient 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.

$$Y_{itk} = \beta_0 + \beta_1 \% female_{tk} + \beta_2 Male_{itk} + \beta_3 \% female_{tk} \times Male_{itk} + \beta_4 \% femaleinstructors_{itk} + \\ \beta_5 \% female_{tk} \times \% femaleinstructors_{itk} + \beta_8 \% femaleinstructors_{itk} \times Male_{itk} + \beta_7 X_{itk} + \\ \gamma_t + \delta_k + \psi_k year_{st} + \varepsilon_{itk} \tag{4}$$

Here, the coefficient of interest is the marginal effect of the percentage of female peers for women, which will include a component of the percentage of female instructors:

$$\frac{\partial Y_{itk}}{\partial \% female_{tk}} = \beta_1 + \beta_5 \% femaleinstructors_{itk} \tag{5}$$

The estimates of model 4 can be found in Table 7. For easier interpretation, I only show the coefficients relevant to female students. When female students are exposed

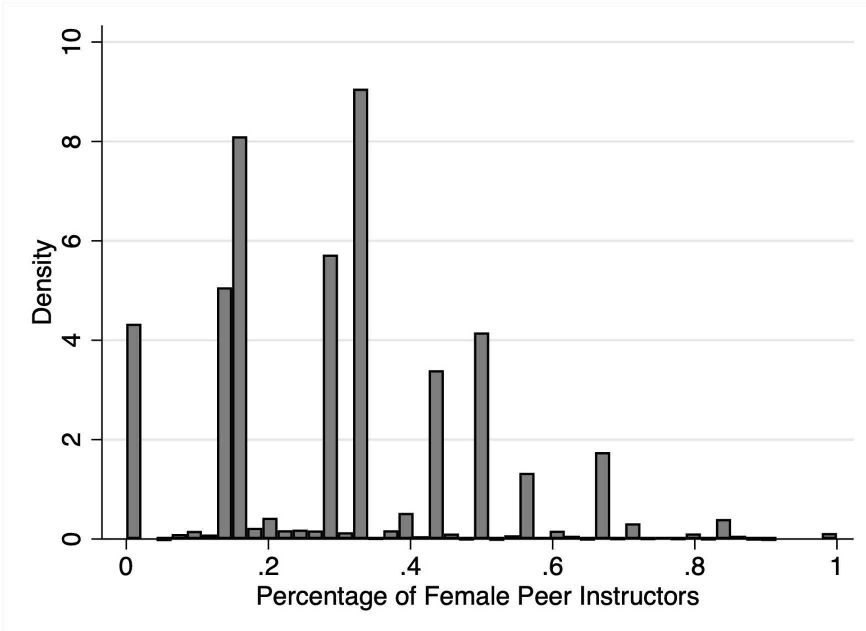


Figure 6: Percentage of Female Instructors in STEM majors

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 ($-0.263 + 0.3 * 0.309$), 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 ($-0.263 + 0.35 * 0.309$) and it is significant to the 5% level.

In the case of GPA, we also observe that the percentage of female instructors seems to be a substitute for having a higher share of female peers. Here, when women are exposed to 30% of female instructors, the marginal effects of *%Female* in GPA is 0.55 standard deviations ($0.668 - 0.3 * 0.4$), and it is significant at the 1% level. Similarly to what I observe in dropout, the opposite signs suggest that as students 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, the students had 35% of female instructors, the marginal effect of *%Female* in GPA would decrease from 0.55 to 0.53 percentage points ($0.668 - 0.35 * 0.4$), and it is significant to the 1% level.

Table 7: Percentage of Female Instructor Interaction

	Dropout			GPA (Standardized)		
	New Model		Original Model	New Model		Original Model
% Female	-0.312**	-0.263**	-0.179*	0.783**	0.668**	0.555**
	(0.084)	(0.081)	(0.069)	(0.243)	(0.245)	(0.192)
% Female Instructors	-0.100**	-0.102**		0.242*	0.191*	
	(0.035)	(0.036)		(0.096)	(0.097)	
% Female:% Female Instructors	0.366**	0.309*		-0.948*	-0.400	
	(0.122)	(0.135)		(0.407)	(0.440)	
Net % Female Effect	-0.2023**	-0.1702*		0.4991*	0.5479**	
	(0.0705)	(0.0696)		(0.2048)	(0.1932)	
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: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. 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. The coefficient of row 3 is multiplied by 0.3 because the mean percentage of female instructors in STEM majors is 30%. All controls are interacted with the gender dummy. Errors are clustered at the major by branch by year level.

5 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 GPA in vocational post-secondary education. For men, a higher percentage of female peers decreases dropout and increases GPA on a on a smaller scale, and the coefficients are not statistically significant. The evidence presented in this paper suggests that both women benefit from having a higher percentage of female peers and men are, at least, not harmed by it. 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, 2017).

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 sector. The heterogeneity analysis also suggests that increasing the percentage of female instructors could improve female students' outcomes by substituting 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. 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 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.

References

Abadie, A., Athey, S., Imbens, G., & Wooldridge, J. (2017, November). *When Should You Adjust Standard Errors for Clustering?* (Tech. Rep. No. w24003). Cambridge, MA: National Bureau of Economic Research. Retrieved 2020-04-20, from http://www.nber.org/papers/w24003.pdf doi: 10.3386/w24003

Arango, M., Evans, S., & Quadri, Z. (2016, January). *Education Reform in Chile* (Tech. Rep.). Woodrow Wilson School of Public Policy.

Basow, S., & Howe, K. (1980, June). Role-Model Influence: Effects of Sex and Sex-Role Attitude in College Students. *Psychology of Women Quarterly*, *4*(4), 558–572. doi: 10.1111/j.1471-6402.1980.tb00726.x

Bettinger, E. P., & Long, B. T. (2005, April). Do Faculty Serve as Role Models? The Impact of Instructor Gender on Female Students. *American Economic Review*, *95*(2), 152–157. Retrieved 2020-07-25, from https://pubs.aeaweb.org/doi/10.1257/000282805774670149 doi: 10.1257/000282805774670149

Bostwick, V., & Weinberg, B. (2018, September). *Nevertheless She Persisted? Gender Peer Effects in Doctoral STEM Programs* (NBER Working Paper No. 25028).

Busso, M., & Frisancho, V. (2021, May). Good Peers Have Asymmetric Gendered Effects on Female Educational Outcomes: Experimental Evidence from Mexico. *IDB Working Papers Series*(1220).

Dee, T. S. (2007). Teachers and the Gender Gaps in Student Achievement. , 27.

Duryea, S., Galiani, S., Nopo, H., & Piras, C. C. (2007). The Educational Gender Gap in Latin America and the Caribbean. *SSRN Electronic Journal*. Retrieved 2018-12-01, from http://www.ssrn.com/abstract=1820870 doi: 10.2139/ssrn.1820870

Goldin, C. (2002, April). *The Rising (and then Declining) Significance of Gender* (Tech. Rep. No. w8915). Cambridge, MA: National Bureau of Economic Research. Retrieved 2018-11-05, from http://www.nber.org/papers/w8915.pdf doi: 10.3386/

w8915

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The Homecoming of American College Women: The Reversal of the College Gender Gap. *Journal of Economic Perspectives*, *20*(4), 133–156.

Han, L., & Li, T. (2009, February). The gender difference of peer influence in higher education. *Economics of Education Review*, *28*(1), 129–134. Retrieved 2018-11-05, from http://linkinghub.elsevier.com/retrieve/pii/S0272775708000575 doi: 10.1016/j.econedurev.2007.12.002

Hill, A. J. (2017, January). The positive influence of female college students on their male peers. *Labour Economics*, *44*, 151–160. Retrieved 2019-10-14, from https://linkinghub.elsevier.com/retrieve/pii/S0927537117300581 doi: 10.1016/j.labeco.2017.01.005

Hoxby, C. M. (2000, August). Peer Effects in the Classroom: Learning From Gender and Race Variation. *NBER Working Paper Series*, *7867*. Retrieved from https://www.nber.org/papers/w7867.pdf

Koenig, A. M., & Eagly, A. H. (2005, April). Stereotype Threat in Men on a Test of Social Sensitivity. *Sex Roles*, *52*(7-8), 489–496. Retrieved 2020-05-15, from http://link.springer.com/10.1007/s11199-005-3714-x doi: 10.1007/s11199-005-3714-x

Lavy, V., & Schlosser, A. (2011, April). Mechanisms and Impacts of Gender Peer Effects at School. *American Economic Journal: Applied Economics*, *3*(2), 1–33. Retrieved 2018-05-04, from http://pubs.aeaweb.org/doi/10.1257/app.3.2.1 doi: 10.1257/app.3.2.1

Lundberg, S. (2017). CSWEP Annual Report to the Ameri- can Economic Association. , 16.

Mouganie, P., & Wang, Y. (2020). High-Performing Peers and Female STEM Choices in School. *Journal of Labor Economics*, *38*(3), 805–841.

Mummolo, J., & Peterson, E. (2018, October). Improving the Interpretation of Fixed Effects Regression Results. *Political Science Research and Methods*, *6*(04), 829–835. Retrieved 2018-12-20, from https://www.cambridge.org/core/product/identifier/S2049847017000449/type/journal_article doi: 10.1017/psrm.2017.44

Paredes, V. (2014, April). A teacher like me or a student like me? Role model versus teacher bias effect. *Economics of Education Review*, *39*, 38–49. Retrieved 2018-05-04, from http://linkinghub.elsevier.com/retrieve/pii/S0272775713001684 doi: 10.1016/j.econedurev.2013.12.001

Paredes, V. (2018, September). Gender Gaps in Single-Sex Classrooms. *Serie de Documentos de Trabajo, FEN*, 32.

Porter, C., & Serra, D. (2020, July). Gender Differences in the Choice of Major: The Importance of Female Role Models. *American Economic Journal: Applied Economics*, *12*(3), 226–254. Retrieved 2020-11-29, from https://pubs.aeaweb.org/doi/10.1257/app.20180426 doi: 10.1257/app.20180426

Sacerdote, B. (2011). Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far? In *Handbook of the Economics of Education* (Vol. 3, pp. 249–277). Elsevier. Retrieved 2018-11-05, from http://linkinghub.elsevier.com/retrieve/pii/B9780444534293000041 doi: 10.1016/B978-0-444-53429-3.00004-1

Schneeweis, N., & Zweimüller, M. (2012, August). Girls, girls, girls: Gender composition and female school choice. *Economics of Education Review*, *31*(4), 482–500. Retrieved 2018-11-05, from http://linkinghub.elsevier.com/retrieve/pii/S0272775711001749 doi: 10.1016/j.econedurev.2011.11.002

Skills beyond school: synthesis report. (2014). Paris: OECD Publishing. (OCLC: ocn891126521)

Steele, C. M., & Aronson, J. (1995). Stereotype Threat and the Intellectual Test Performance of African Americans. *Journal of Personality and Social Psychology*, *69*(5), 797–811.

Wu, A. H. (2017). Gender Stereotyping in Academia: Evidence from Economics Job Market Rumors Forum. *SSRN Electronic Journal*. Retrieved 2018-11-05, from https://www.ssrn.com/abstract=3051462 doi: 10.2139/ssrn.3051462

Zölitz, U., & Feld, J. (2020, March). The Effect of Peer Gender on Major Choice in Business School. *Management Science*, mnsc.2020.3860. Retrieved 2021-09-29, from http://pubsonline.informs.org/doi/10.1287/mnsc.2020.3860 doi: 10.1287/mnsc.2020.3860

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

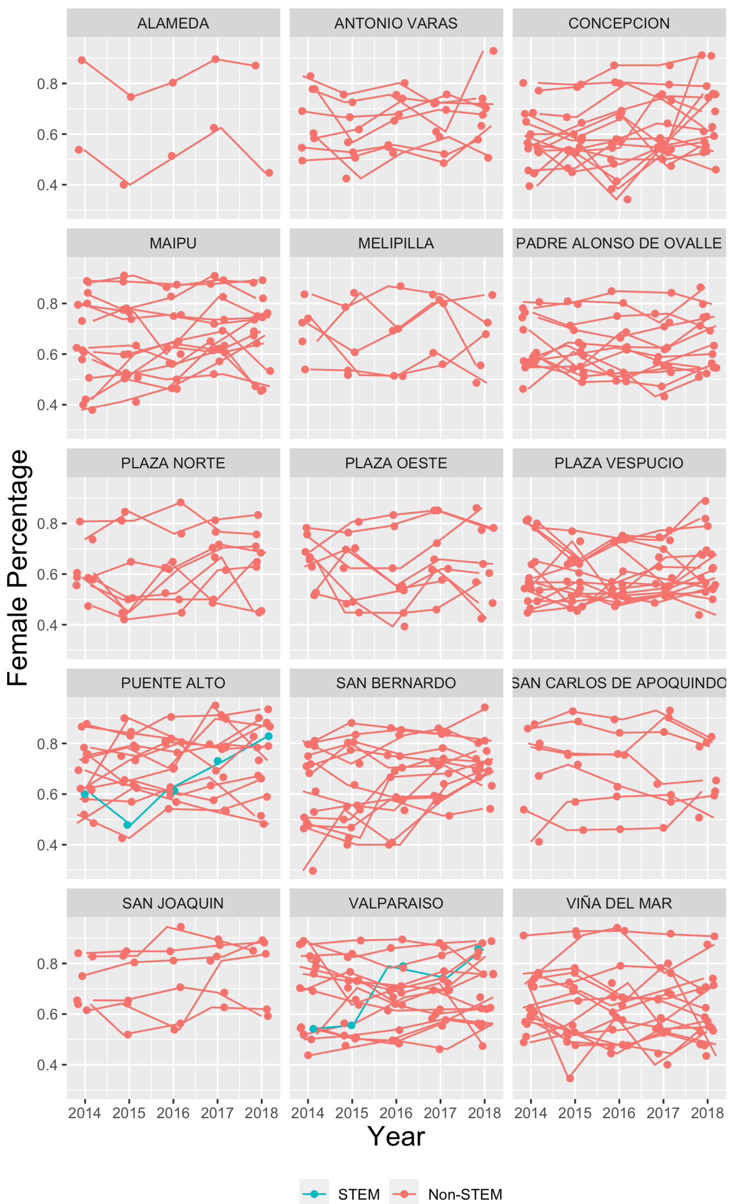
Técnico en prevención de riesgos

Técnico en química y farmacia

Técnico veterinario

B Identifying Variation Plots

Figure 7: Within Major-by-Branch Yearly Percentage Female Variation - Female Majority



C Alternative Male Concentrations Estimations

Table 8: 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*
	(0.094)	(0.166)	(0.190)	(0.251)	(0.648)	(0.690)
Male	0.253	0.026	0.227	-0.135	-0.188	0.053
	(0.161)	(0.170)	(0.232)	(0.541)	(0.570)	(0.781)
Percentage Female:Male	0.129	-0.279*	0.408**	-0.309	0.763	-1.072*
	(0.083)	(0.127)	(0.150)	(0.199)	(0.466)	(0.503)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Major by Branch and Year FE	Yes	Yes		Yes	Yes	
Controls	Yes	Yes		Yes	Yes	
Major by Branch Time Trend	Yes	Yes		Yes	Yes	
Observations	49127	8292		47677	8092	

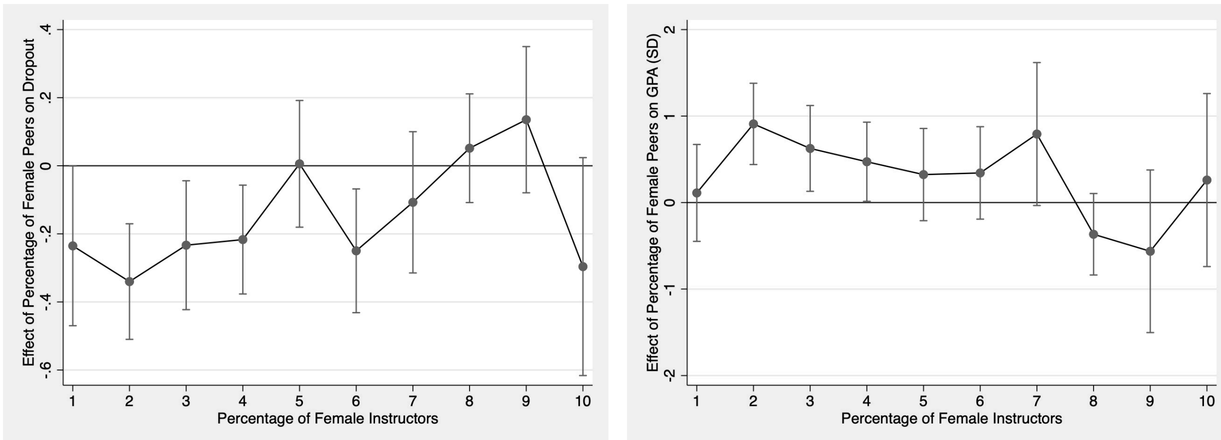
Notes: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Only male-concentrated (less than .35 women) majors are included in the estimations. Controls include age, diagnostic scores, mother's education work status, financial aid status, education shift, and missing dummies for all the variables. All controls are interacted with the gender dummy. Errors are clustered at the major by branch by year 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 9: 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
	(0.100)	(0.236)	(0.254)	(0.282)	(1.099)	(1.122)
Male	0.259	-0.002	0.261	-0.146	-0.188	0.042
	(0.161)	(0.178)	(0.238)	(0.547)	(0.563)	(0.780)
Percentage Female:Male	0.056	-0.329	0.385+	-0.170	0.891	-1.061
	(0.086)	(0.214)	(0.228)	(0.224)	(0.998)	(1.012)
Mean outcome for women	0.186	0.146		-0.047	0.225	
Major by Branch and Year FE	Yes	Yes		Yes	Yes	
Controls	Yes	Yes		Yes	Yes	
Major by Branch Time Trend	Yes	Yes		Yes	Yes	
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. 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 by year 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 8: Effect Heterogeneity by Percentage of Female Instructors for STEM majors