"Classroom composition and network effects: Evidence from a college special admission program in Chile"

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Research idea

Using administrative data about the grades of Business and Economics undergraduate students from Chile, and exploiting the fact that students are randomly assigned to their first semester classes, I want to examine the existence of peer effects among students, and to study how different class compositions affect their outcomes. In 2012, the University of Chile implemented a college special admission program that targets high achieving vulnerable students from public schools, and I want to see how students that belong or don't belong to this program interact within their own group and with the other group, and how students should be assigned to classes in order to maximize their academic outcomes.

Besides the fact that in this context the peers of the students are determined in an exogenous way, another advantage of this setup is these college students are assigned on average to 6 classes during their first semester, and they interact with different students in each of these classes, so this allows me to use instrumental variables in a similar fashion to Bramoulle et al. (2009), computing measures of the outcomes or characteristics of the peers of the peers of a student, in contrast to other type of studies where all students belong to the same peer group, as it is the case with roommate or classroom studies. Besides that, the network structure can be exploited to compute network characteristics that could be able to explain how the interactions between these groups might determine the outcomes of the students in this context.

Motivation

S. Zimmerman (2019) studied how elite colleges help students reach top positions in the economy in Chile. He identified 3 highly selective, business-oriented majors dictated at the 2 most selective universities in Chile, and found that 1.8% of their graduates account for 41% of leadership positions in major companies and the same share accounts for 39% of top 0.1% incomes. One of these programs is the Business Engineering program at the University of Chile, for which I have administrative data, so I want to study what happens when vulnerable students from public high schools interact in the classroom with high achieving students from expensive elite high schools, and how these students affect people in their same group, and how exposure to people from a different group can affect them.

In this context, besides estimating peer effects on their own, another objective is to study how students *should be* assigned to classes in order to maximize their outcomes. We can look at classroom compositions and the overall structure of our peer's network to see what are desirable traits in a design either for the students that are part of the affirmative action program, or for all the members of the student body. The affirmative action implemented in this school was also implemented in other schools at the University of Chile, so what we learn here could have educational policy implications for an important number of students.

Context

In Chile there is a centralized admission system through which students apply to multiple programs and universities. In order to apply to the vast majority of accredited programs and universities, students need to take the "University Selection Test" ("Prueba de Seleccion Universitaria" in Spanish or **PSU**)[1], a battery of 4 standardized tests to test their competencies in Mathematics, Spanish, Natural Sciences and History. After knowing their scores, students apply to several programs through a unique platform, submitting a ranked list of preferences over up to 10 pairs of program/universities. Students and their applications are ranked by universities based on a weighted average of their PSU scores, high school GPA and high school within-cohort ranking, with weights that are specific to each program. After ranking the applicants, universities select students based on their weighted scores using a deterred acceptance algorithm.

In this context, during the year 2012 the University of Chile implemented the **SIPEE** program (Priority Entry System for Educational Equity, or "Sistema de Ingreso Prioritario de Equidad Educativa" in Spanish), a special admission mechanism to admit high achieving students from public high schools that applied to programs at the university but were below the admission cutoff score. These students have to comply with the following requisites to be able to apply through this special mechanism:

- Taking their university selection test the same year they graduate from high school.
- Having completed all their high school education in a public school.
- Studying during their senior high school year in a high school with a vulnerability score (how many of their students are socioeconomically vulnerable) above 30%.
- Being below the 60th percentile in the Social Household Registry (the registry ranks household mostly according on their per capita income).
- Having a GPA above 5.5 (in a scale from 1 to 7) during all high school.

The SIPEE program started offering 131 reserved seats, but has been scaled up since 2012, and now offers 500 reserved seats per year, with 50 of them belonging for programs in the School of Economics and Business. The seats are filled by the eligible students below the admission cutoff score, ranking them on their score.

At the moment, I'm evaluating this program together with the supernumerary seat program for **BEA**[2] students. This program guarantees seats to students vulnerable students from public schools within the top 10% of their promotions that received a scholarship from the government, but that are below the admission cutoff score. These seats are also assigned to eligible students ranked based on their admission scores. During 2012 the School of Economics and Business offered 30 supernumerary seats for BEA students, but they increased the number of seats during

[1] Some artistic programs require special tests that replace the PSU

[2] BEA stands for "Beca de excelencia academica" in Spanish, which can be translated as "Scholarship for Academic Excellence"

time, reaching 45 during 2019.

I'm evaluating together the SIPEE and BEA programs since there is a significant overlap between their eligibility criteria, so in the end both programs target similar groups of students.

I'm going to study the peer effects within and between groups for students that were admitted through regular admission and students of the SIPEE and BEA programs using data for the 3 careers imparted at the School of Economics and Business:

- **Business engineering**: 5 year program that leads to a bachelor degree in Economics or Business. Accounts for approximately 70% of enrollment in the School of Economics and Business, and it is the most selective of the 3 careers (it has the highest admission cutoff score every year).
- **Information and Control Management Systems engineering**: 5 year program that accounts for approximately 25% of enrollment.
- **Accounting**: 5 year program that accounts for approximately 5% of enrollment.

During the 2012-2020 period, the 3 careers in the School of Economics and Business have undergone 2 reforms in their academic curriculum, with the first curriculum being valid until 2012, the second one was current between 2013 and 2019, and the third being implemented during 2020. There are some common characteristics in these 3 curricula: during the first semester, students always take between 5 and 7 classes depending on their curriculum, one of them being an English class. For their English classes, students take an ETS' TOEIC English test at the moment of enrolling to determine their English proficiency, and based on that they are assigned to a certain class. Students of all 3 careers are then randomly assigned to English classes conditional on their English proficiency.

For the rest of the classes, which generally include Algebra, Business and Economics introductory classes, students from the 3 careers are randomly assigned to classes. Almost all the classes are common across all 3 careers for all curricula, so students can be assigned to classes where students from other careers may be enrolled, but there are 1 or 2 classes that are career-specific in some of the curricula.

Related literature

There is a wide body of literature concerned with peer effects in general, starting with Manski (1993) and followed later by Bramoulle et al. (2009) and others. When looking at peer effects in an educational context, we have articles that study peer effects in school classrooms without random assignment to classes, like Hoxby (2000), McEwan (2003), Hanushek et al. (2003) and Hoxby and Weingarth (2005). There are also several studies focusing on peer effects associated to roommates in colleges , like Sacerdote (2001), D. Zimmerman (2003) and Kremer and Levy (2008).

There are also several papers that study educational peer effects in contexts with random assignment: Whitmore (2005) studies the effect of gender composition of classroom over the achievement of students using Tennessee's project STAR data, and finds that being in a classroom where the majority of the students are women has a positive impact over achievement, but the size of the effect decreases over time, and by the time students are in grade 3, the effect turns negative. Ammermueller and Pischke (2006) estimates peer effects for fourth graders in 6 European countries, finding positive peer effects overall, but there is significant heterogeneity across countries. Kang (2007) finds moderate yet positive peer effects in the math scores of middle school students in South Korea, using an instrumental variables approach. We also have Carrell et al. (2009), a study where they look at peer effect for college students that are randomly assigned to groups that live nearby and interact among themselves heavily.

There are not a lot of studies with college data and randomly assigned peers, and to the extend of my knowledge there are no articles with a peer structure quite the one presented in this paper.

Empirical strategy

Given the nature of my data, a very simple starting point is to estimate the effect of classroom composition and network structure over the outcomes of the student at the class level. To do this, I estimate the following equation:

$$y_{i,c} = a_i + CK_{i,c}\beta_1 + CK_{i,c} \times S_i + \varepsilon_{i,c} \tag{1}$$

Where $y_{i,c}$ is the outcome of student i in class c, a_i is a student level fixed effect, CK_c is a classroom composition variable (measured either as the share SIPEE students in the classroom or as the homophily for student i in the classroom[3]), and S_i is an dummy indicating if student i is part of the SIPEE program or not. The idea with this equation is that our student level fixed effect should be a very strong predictor of the outcomes of a student, so if we find an effect of class composition over outcomes even after this, that would provide initial evidence that the interactions between individuals in our 2 groups are important.

Next I study the effect of some characteristics of the network over the outcomes at the student level:

$$y_{i,t} = a_t + f(N, S_i)\beta + \varepsilon_{i,t} \tag{2}$$

Where $y_{i,t}$ is an outcome of student i from cohort t over several classes, a_t is a cohort level fixed effect and $f(N, S_i)$ is some network characteristic for student i. Here I use the degree of student i (the number of peers she has) and their clustering coefficient (the share of her peers that are also peers among themselves). I also compute these 2 measures for students within each of the 2 groups, so I can obtain differential effects between groups. This equation can help us design classrooms: we can see how beneficial for a student is to belong to a group that interacts in several contexts, if there are benefits to have very closed peer circles within their own group,

[3] Defined as the share of students in the same group (SIPEE or non-SIPEE) as student i.

and to see how clustered are my peers in the other group could affect me. It would be plausible to think that having a very clustered peer circle of people in your own group would be a good thing, since students would spend a lot of their time together, maybe form study groups or share notes. Regarding the peers on the other group, it is probably more beneficial for a student if they are not very clustered, since the other group being very close would make it harder for the student to interact with them.

After that, I want to look for the existence of peer effects in our sample. To do this, we can follow Bramoulle et al. (2009) and De Giorgi et al. (2010), and estimate the following equation (in matrix form):

$$y = \alpha + Gy\beta + X\gamma + GX\delta + \varepsilon \tag{3}$$

Where y is a $N \times 1$ vector of outcomes, X is a $N \times K$ matrix of covariates, G is a $N \times N$ adjacency matrix and ε is an $N \times 1$ error vector. For our adjacency matrix G we can define element G_{ij} as the number of times individuals i and j took a class together over the total number of interactions that individual i had. We are also going to define $G_{ii} = 0$ for all $i \in N$. Given this, G is a block diagonal right stochastic matrix. In this context, β is capturing endogenous peer effects and δ captures exogenous peer effects.

Bramoulle et al. (2009) showed that this model is identified as long as I, G and G^2 are linearly independent. De Giorgi et al. (2010) does something similar, studying the effect of peers over major choice in college in Italy, also defining peers based on randomly assigned first semester classes, and relying on the existence of excluded peers (students that are peers of the peers of student i, but that are not peers of i themselves) and a 2SLS strategy to identify peer effects. Here, we are going to do something similar to estimate equation (3). In this context, we also need our matrix G to be exogenous: conditional on their English level, students in my sample are randomly assigned to first semester classes, so their peers are indeed exogenous.

Data

I use administrative data for the 2012 to 2020 cohorts of the 3 programs imparted at the School of Economics and Business at the University of Chile. The data includes information about gender, birth date, program, academic situation, admission system, admission score, commune of residency, current GPA[4] and classes taken during their first semester. I'm currently dropping from my sample transferred students and students from other special admission programs (sport scholarships, international students and others), and pooling together students from the SIPEE and BEA programs. In Table 1 I summarize the number of students by cohort and career: we can see that Business Engineering accounts for most of the enrollment per cohort, and that enrollment has increased over time for all 3 careers.

[4]This GPA includes all passed and failed classes during the complete career of graduated students, and the current GPA for students that were still enrolled during 2020

Table 1: Students by career

Year	Program		
	Business Engineering	Information Engineering	Accounting
2012	340	107	18
2013	349	89	37
2014	367	109	62
2015	377	124	59
2016	377	133	67
2017	378	138	70
2018	410	141	66
2019	400	140	76
Total	2,998	981	455

In Table 2 I separate enrollment by type of admission, where we can that the SIPEE and BEA students represent in every cohort roughly 10% of enrollment.

Table 2: Students by type of admission

Year	Type of admission	
	SIPEE & BEA	Regular
2012	50	415
2013	69	406
2014	76	462
2015	62	498
2016	76	501
2017	60	526
2018	71	546
2019	65	551
Total	529	3,905

Next, in Table 3 we can see some descriptive statistics for our SIPEE and non-SIPEE students: around 40% of students are women in both samples, but females are more prevalent in the SIPEE group. By construction, SIPEE students have lower admission scores (since they are students who were below the admission cutoff score). The standardized major GPA is the same in both groups, but SIPEE students have a lower first semester GPA than non-SIPEE students. Finally, the passing rate of first semester classes is around 90% for non-SIPEE students, while SIPEE students likelihood to pass their classes is 81%.

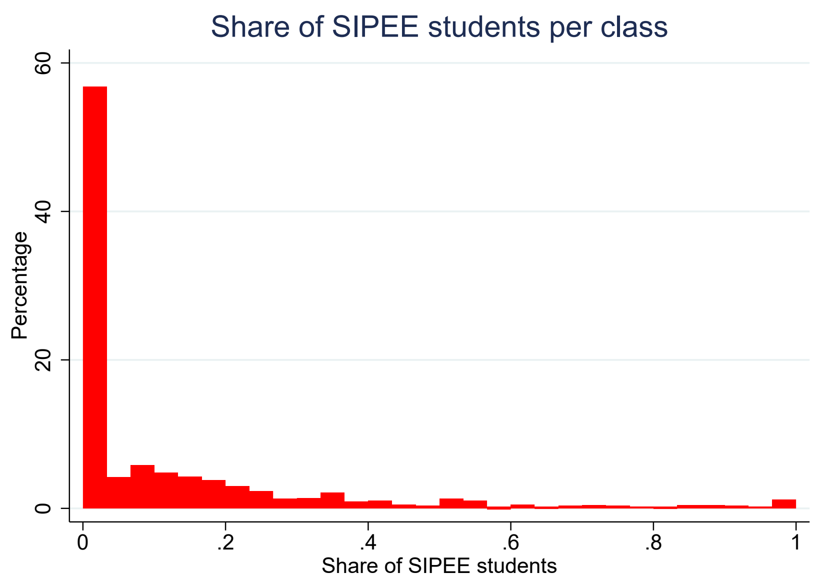
Now we can focus on describing the peer network: in Figure 1 we can see the distribution of the share of SIPEE students within each of the 1,229 classes present in our dataset. There is a lot of variation in SIPEE shares: while around 55% of all the first semester are completely made of non-SIPEE students, in the remaining 45% we observe almost all possible compositions. In fact,

Table 3: Student level descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
SIPEE students:					
Female	0.47	0.50	0.00	0.00	1.00
Admission score	-1.02	0.63	-3.16	-1.00	0.07
Major GPA	0.03	0.97	-5.86	0.21	1.76
First semester GPA	-0.12	0.62	-3.59	-0.05	1.25
1st semester passing rate	0.81	0.19	0.00	0.86	1.00
non-SIPEE students:					
Female	0.39	0.49	0.00	0.00	1.00
Admission score	0.14	0.96	-2.93	0.21	4.49
Major GPA	0.03	0.98	-5.41	0.23	2.38
First semester GPA	0.04	0.64	-4.35	0.11	2.11
1st semester passing rate	0.89	0.16	0.00	1.00	1.00

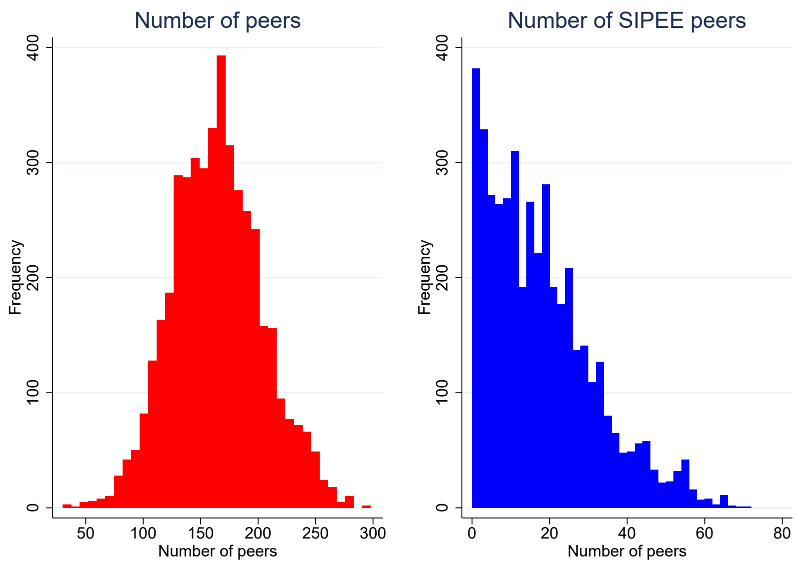
there were even 13 classes were all the students were part of the SIPEE program.

Figure 1: Distribution of SIPEE share per class



Next in Figure 2 we can see the distribution of the degree of the students, where I counted the links rather than adding the intensity of the links. We observe that most of the students have a substantial number of peers, with most of the mass of students having around 165 peers, and no students without peers (which is to be expected, since all students take classes with at least 1 other person in them). If we look at the number of SIPEE peers, now we see that a considerable number of students don't have SIPEE peers, but some of them are exposed to around 70 SIPEE peers. This was to be expected, since the SIPEE students per cohort are always around 10% of the total student body.

Figure 2: Distribution of the degree of students



In Figure 3 we can now observe the individual clustering coefficients of all the students in our sample. Here I also ignore the intensity of the link between students, and only considered if they are or not connected. Our clustering coefficient indicates what share of my peers are also peers themselves. We observe a wide range of clustering among individuals, with most students having around 60% of their peers being peers themselves.

Finally, in Table 4 we see more detailed information about the network characteristics by group. The average non-SIPEE student has around 166 peers, while an average SIPEE student has around only 146 peers. Students are more likely to have peers in the non-SIPEE group, due to the fact that around 10% of students belong to the SIPEE group. However, it is interesting to note that SIPEE students seem to have a much bigger share of the peers of other SIPEE students. If we look at overall clustering coefficients, both groups are very similar. However, if we separate clustering by group, we can see that non-SIPEE students have more clustered SIPEE peers, and SIPEE students have more clustered non-SIPEE peers.

Figure 3: Distribution of student's clustering

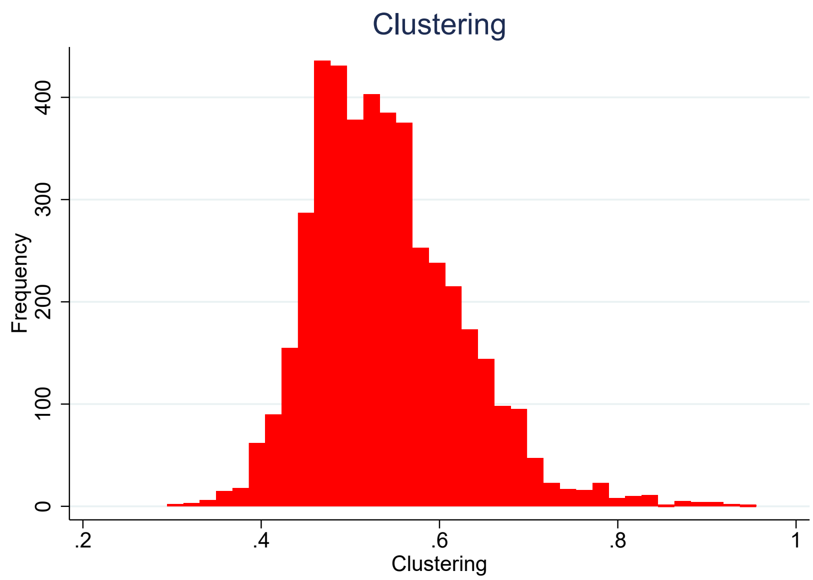


Table 4: Network characteristics by group

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
SIPEE students:					
Number of peers	146.17	34.26	54	146	263
Peers in the same group	35.26	14.16	4	36	72
Peers in the other group	110.91	39.71	17	111	237
Clustering	0.53	0.08	0.31	0.52	0.96
Clustering with the same group	0.25	0.13	0.03	0.22	0.89
Clustering with the other group	0.50	0.09	0.29	0.49	0.88
non-SIPEE students:					
Number of peers	166.81	38.82	30	166	298
Peers in the same group	151.79	38.28	21	149	280
Peers in the other group	15.02	11.70	0	13	69
Clustering	0.54	0.08	0.29	0.53	0.93
Clustering with the same group	0.53	0.09	0.28	0.52	0.93
Clustering with the other group	0.65	0.30	0.00	0.67	1.00

Preliminary results

In Table 5 I report the estimates of equation (1). I study the effect of class composition over class level outcomes: the outcomes here are the grades obtained by students in each class, and whether they passed a class or not. All regressions include student level fixed effects. I measure class composition with the share of SIPEE students in a class. I estimate an equation only using classroom composition, and then I add an interaction with the SIPEE dummy. We see a positive and statistically significant effect of the SIPEE share over grades, and no interaction effect, but the net effect for SIPEE students (sum of coefficients) is still positive and significative. Regarding passing rates, the share of SIPEE students has no statistically significant effect on its own, but when we include the SIPEE interaction we see a positive net effect of this share for SIPEE students, and a negative effect for non-SIPEE students. All this means that increasing the share of SIPEE students in a classroom would improve grades for everyone, but at the same time it would make SIPEE students more likely to pass, and non-SIPEE students more likely to fail, which seems counter intuitive, since their grades improving should make both groups more likely to pass.

Table 5: Effects of class composition over per class outcomes

Variable	**Class grade**		**Passed class**	
Share of SIPEE students in the class	0.2660***	0.2692***	-0.0260	-0.0959***
	(0.0420)	(0.0549)	(0.0257)	(0.0300)
SIPEE × Share of SIPEE students		-0.0091		0.2014***
		(0.0982)		(0.0614)
Sum of coefficients		0.2600***		0.1055**
		(0.0755)		(0.0503)
Observations	28,778	28,778	28,819	28,819

Note: Model includes student level fixed effect. Double clustered at the student and class levels standard errors are reported in parentheses.

Next, in table I study the effects of classroom composition, in the same setup, but now I separate it by subject, considering only 4 core first semester subjects: Economics, Mathematics, Business and English. I add English level fixed effects so we can have results of students randomly assigned to classes conditional on their English level. Here I only report the specification with classroom composition and a SIPEE interaction. For the Economics classes, we see that having more SIPEE peers improves grades in both groups, and it has no effect over their likelihood of approving for either group. For Mathematics we see again see a positive effect over grades for both groups, but now non-SIPEE students are more likely to pass the class. For business classes we only see a statistically significant effect of the SIPEE share over grades for non-SIPEE students, but no effect for SIPEE students, and no effects when we look at passing rates. Finally, we see no effect whatsoever for English classes.

Table 6: Classroom composition effects per subject

Variable	Economics	Mathematics	Business	English
Panel A: Effect over grades				
Share of SIPEE students in the class	0.3704***	1.0287***	0.2565**	0.0338
	(0.1216)	(0.1400)	(0.1108)	(0.1266)
SIPEE $\times$ Share of SIPEE students	0.0402	-0.3704	-0.1828	0.1720
	(0.2323)	(0.2299)	(0.2256)	(0.2303)
Sum of coefficients	0.4107**	0.6583***	0.0738	0.2058
	(0.1851)	(0.1807)	(0.1713)	(0.1775)
Panel B: Effect over passing classes				
Share of SIPEE students in the class	-0.0141	0.1267**	-0.0112	-0.0983
	(0.0764)	(0.0616)	(0.0319)	(0.0642)
SIPEE $\times$ Share of SIPEE students	0.1342	-0.1685	-0.0458	0.0248
	(0.1176)	(0.1436)	(0.0759)	(0.1012)
Sum of coefficients	0.1201	-0.0418	-0.0569	-0.0735
	(0.0966)	(0.1263)	(0.0598)	(0.0934)
Observations	3,374	3,327	3,402	3,482

Note: Model includes English level fixed effects, controls for gender, SIPEE status and admission scores. Standard errors clustered at the class level are reported in parentheses.

Even if we found statistically significant effects even after having student level fixed effects, and we have results that are consistent between the 2 panels, there is still no clear evidence on what kind of composition would be the best in the classroom, specially because the results imply that non-SIPEE students improve their grades, yet they are more likely to fail their classes, which make no logical sense.

Our next step here is repeating the previous exercise, but now I include classroom composition effects across subjects. I estimate the following equation, where I use the composition for all 4 subjects in the same equation:

$$y_{i,c} = \sum_{c=1}^{4} (\beta_{1c} CK_c + \beta_{2c} CK_c \times S_i) + X_i \gamma + \varepsilon_{i,c} \tag{4}$$

I present the results of estimating equation (4) in table 7 using grades as an outcome, and then in table 8 I present the results over passing classes. Here I don't find anything too interesting: most of the coefficients are non-significant in both tables, and the few significant coefficients are effects of the classroom composition of the same subject over outcomes, so we find no evidence of cross-subject effects.

Table 7: Classroom composition effects per subject over grades

Variable	Economics	Mathematics	Business	English
Economics composition	0.3527**	0.1145	0.2033	0.1057
	(0.1509)	(0.1331)	(0.1308)	(0.1563)
SIPEE × Economics composition	0.1425	0.1633	-0.1886	-0.1995
	(0.2408)	(0.2235)	(0.2332)	(0.2241)
Mathematics composition	0.0078	1.0436***	0.0302	0.0834
	(0.1226)	(0.1461)	(0.1305)	(0.1391)
SIPEE × Mathematics composition	0.1711	-0.4960*	-0.0000	-0.1287
	(0.2129)	(0.2689)	(0.1807)	(0.2651)
Business composition	0.0551	-0.0883	0.2206*	-0.0387
	(0.1349)	(0.1214)	(0.1197)	(0.1226)
SIPEE × Business composition	-0.2322	0.2560	-0.1844	-0.0713
	(0.2772)	(0.3104)	(0.2549)	(0.2550)
English composition	-0.0078	-0.2670	0.0842	0.0519
	(0.1849)	(0.1623)	(0.1682)	(0.1406)
SIPEE × English composition	-0.3964	0.0526	-0.0815	0.2242
	(0.2771)	(0.3122)	(0.3289)	(0.2538)
Observations	3,265	3,265	3,265	3,236

Note: Model includes English level fixed effects, controls for gender, SIPEE status and admission scores. Standard errors clustered at the class level are reported in parentheses.

Next, in Table 9 we estimate equation (2) and study student level effects of network characteristics over outcomes. Here the possible outcomes are the GPA of the student during their first semester, the overall GPA of the student during their whole stay in the university and the passing rate of the student for their first semester classes. This model includes controls for the admission score of the student, the weighted average admission score of the peers, and cohort and English level fixed effects. As network characteristics we use the degree of the student (number of peers) and their clustering coefficient. In one specification we use these overall network characteristics, but in the other we separate them per group.

Table 8: Classroom composition effects per subject over passing classes

Variable	**Economics**	**Mathematics**	**Business**	**English**
Economics composition	-0.0568	-0.0442	0.0281	0.0326
	(0.0856)	(0.0641)	(0.0316)	(0.0474)
SIPEE × Economics composition	0.2003*	0.0746	0.0245	-0.0196
	(0.1032)	(0.1457)	(0.0515)	(0.0858)
Mathematics composition	0.0732	0.1593**	0.0178	0.0375
	(0.0682)	(0.0663)	(0.0333)	(0.0456)
SIPEE × Mathematics composition	0.0779	-0.1774	0.0404	-0.0112
	(0.1382)	(0.1710)	(0.0557)	(0.0940)
Business composition	0.0036	-0.0007	-0.0109	0.0090
	(0.0510)	(0.0460)	(0.0323)	(0.0403)
SIPEE × Business composition	-0.1434	0.0242	-0.0741	-0.1004
	(0.1425)	(0.1348)	(0.0704)	(0.1033)
English composition	0.0966	-0.0540	-0.0302	-0.0976
	(0.0839)	(0.0844)	(0.0392)	(0.0628)
SIPEE × English composition	-0.1614	-0.2350	-0.0377	0.0464
	(0.1390)	(0.1653)	(0.1013)	(0.1052)
Observations	3,265	3,265	3,265	3,265

Note: Model includes English level fixed effects, controls for gender, SIPEE status and admission scores. Standard errors clustered at the class level are reported in parentheses.

Table 9: Effects of network characteristics over student outcomes

Variable	**1st semester GPA**		**1st semester passing rate**		**Major GPA**	
Panel A: Degree						
Number of peers	-0.0147		0.0039		-0.0046	
	(0.0092)		(0.0034)		(0.0274)	
Number of peers in own group		-0.0097		0.0057		0.0198
		(0.0134)		(0.0042)		(0.0369)
Number of peers in other group		0.0389**		0.0063*		0.1310***
		(0.0178)		(0.0034)		(0.0443)
Panel B: Clustering						
Clustering among peers	0.0021		-0.0021		-0.0105	
	(0.0077)		(0.0023)		(0.0167)	
Clustering in own group		-0.0317***		-0.0027		-0.0849***
		(0.0101)		(0.0024)		(0.0196)
Clustering in other group		-0.0042		0.0031		-0.0074
		(0.0065)		(0.0025)		(0.0137)
Observations	3,482	3,482	3,482	3,482	3,482	3,482

Note: Model includes controls for the admission score of the student, the average admission score of the peers, English level and cohort level fixed effects. Standard errors clustered at the cohort level are reported in parentheses.

In panel A of Table 9 we observe the effects of the degree of a student. I find no effect of the overall number of peers over any outcome, and the same is valid for the number of peers in the same group of the student. However, I find a positive and statistically significant effect of the composition of the other group over all 3 outcomes, but the effects for the first semester GPA and passing rate are very small in magnitude.

On the other hand, in panel B of Table 9 we find again that there are no effects for the overall number of peers, now there is no effect of the clustering in the other group over outcomes, and now we find a negative and statistically significant effect of the clustering in the same group of the student over 1st semester GPA and overall major GPA.

Despite the fact that in the different panels we find effects for different groups, the results indicate that there is a benefit when interacting with people in the other group: interacting with more peers in the other group leads to better outcomes, while students that interact in a circle too closed and that mostly interacts within the same group can worsen outcomes.

In Table 10 we observe the estimates of equation (3) using OLS and student level data. Here again the possible outcomes are the first semester GPA of a student, the GPA of the student over all his time studying (some cohorts have graduated, some are still studying), and the passing rate of the classes taken during the first semester. I control for gender, admission type and admission scores. All the models have English level fixed effects, and in the even columns I also add cohort level fixed effects.

First we can notice that for the first semester GPA and passing rates we find a negative and statistically significant endogenous effect regardless of the inclusion of cohort level fixed effects, but there is no effect over major GPA. The only exogenous effects we find are negative effects for the share of SIPEE peers, and the admission scores of peers, and these are only valid for the overall GPA major of students. Finally, in all specifications there is a positive effect of being a woman, of having a higher admission score, and for major GPA there is a positive effect for SIPEE students.

The previous results cannot be trusted too much, since this model is not identified, thus we should not care much about their results. Because of that, we are going to estimate again equation (3), but now we are going to use the generalized 2SLS technique described in Bramoulle et al. (2009) and Lee (2003), where we take advantage of the network structure to build an instrument for the endogenous effects. I implemented the routines of Bramoulle et al. (2009) for models of the same form of equation (3) that can include network fixed effects.

Table 10: Peer effects OLS estimates

Variable	**1st semester GPA**		**1st semester passing rate**		**Major GPA**	
Outcome of peers	-0.4335**	-0.4352**	-0.4376**	-0.3894**	-0.1371	-0.1363
	(0.1751)	(0.1752)	(0.1792)	(0.1782)	(0.1664)	(0.1665)
Share of female peers	0.0609	0.0707	-0.0613	-0.0472	-0.1005	-0.1038
	(0.1934)	(0.1937)	(0.0512)	(0.0509)	(0.2972)	(0.2977)
Share of SIPEE peers	-0.1806	-0.1852	-0.0358	-0.0413	-0.4747*	-0.4521*
	(0.1630)	(0.1633)	(0.0434)	(0.0432)	(0.2517)	(0.2521)
Adm. Score of peers	-0.1117	-0.1076	-0.0313	-0.0300	-0.4241***	-0.4200***
	(0.0885)	(0.0886)	(0.0234)	(0.0233)	(0.1348)	(0.1350)
Female	0.1873***	0.1871***	0.0144***	0.0144***	0.3265***	0.3253***
	(0.0202)	(0.0202)	(0.0054)	(0.0053)	(0.0311)	(0.0311)
SIPEE student	0.1726	0.1821	-0.0074	0.0013	0.4086**	0.3876**
	(0.1270)	(0.1277)	(0.0339)	(0.0338)	(0.1958)	(0.1968)
Admission score	0.1914***	0.1913***	0.0376***	0.0378***	0.3447***	0.3457***
	(0.0108)	(0.0109)	(0.0029)	(0.0029)	(0.0167)	(0.0168)
Constant	-0.0938	-0.0752	0.0224	0.0418*	-0.0711	0.0056
	(0.0784)	(0.0827)	(0.0207)	(0.0217)	(0.1206)	(0.1273)
Observations	3,482	3,482	3,482	3,482	3,482	3,482
Cohort level fixed effects	No	Yes	No	Yes	No	Yes

Note: Standard errors are reported in parentheses. All the models include English level fixed effects.

In Table 11 we observe the estimates obtained using the generalized 2SLS approach. All models control for English level by residualizing the outcomes against English level fixed effects, and some of the even columns include cohort level fixed effects: first we can see that we don't have endogenous peer effects for any outcome, and our only exogenous peer effect is a negative effect of the admission scores of my peers over the first semester passing rate, but only when we don't include cohort level fixed effects. The direct effects of our covariates are practically the same as the ones we found in table 10.

Again we cannot trust much our results, since we have no formal way of testing for weak instruments, so we can't tell if our generalized 2SLS results are more reliable than our OLS results.

Table 11: Peer effects Generalized 2SLS estimates

Variable	**1st semester GPA**		**1st semester passing rate**		**Major GPA**	
Outcome of peers	0.9522	2.1750	0.4912	-0.5239	2.6951	0.8491
	(1.5481)	(5.0448)	(1.0830)	(8.6805)	(2.8175)	(7.0987)
Share of female peers	-0.2596	-0.2493	-0.0703	-0.0381	-0.5042	-0.1451
	(0.2848)	(0.7501)	(0.0930)	(0.1612)	(0.4256)	(2.1085)
Share of SIPEE peers	-0.1112	-0.0808	0.0020	0.0220	-0.9777	-0.2287
	(0.2418)	(0.7362)	(0.0434)	(0.2720)	(0.9430)	(2.5885)
Adm. Score of peers	-0.2020	-0.3240	-0.0500**	-0.0227	-0.8222	-0.3615
	(0.2035)	(0.8042)	(0.0240)	(0.1833)	(0.6934)	(1.8609)
Female	0.1927***	0.1971***	0.0156***	0.0157**	0.3390***	0.3350***
	(0.0203)	(0.0288)	(0.0054)	(0.0076)	(0.0319)	(0.0326)
SIPEE student	0.1088	0.0956	-0.0285	-0.0403	0.3806**	0.3201
	(0.1136)	(0.1311)	(0.0298)	(0.0314)	(0.1789)	(0.2382)
Admission score	0.1933***	0.1957***	0.0383***	0.0380***	0.3497***	0.3467***
	(0.0107)	(0.0150)	(0.0027)	(0.0046)	(0.0176)	(0.0221)
Constant	0.0256		0.0246		0.1558	
	(0.1009)		(0.0394)		(0.2681)	
Observations	3,482	3,482	3,482	3,482	3,482	3,482
Cohort level fixed effects	No	Yes	No	Yes	No	Yes

Note: Standard errors are reported in parentheses. The generalized 2SLS procedure doesn't allow us to use English level fixed effects, so the outcomes are regressed against English level dummies and then we use the residuals as our new outcomes.

Concluding remarks

In this paper I use network data from undergraduate students in Chile for a school that implemented an affirmative action program, and I try to study how these specially admitted students interact with their peers that got in the school through regular admission, and how their peer network (determined through random assignment to classes) can shape their outcomes and their interactions as well. At the student/class level I found that the class composition matters, with the number of SIPEE students in classroom increasing the grades of everyone, increasing the passing rates of other SIPEE students, but decreasing the passing rates of non-SIPEE students.

Regarding network characteristics, there is limited evidence of its importance, I only found that the number of peers in the opposite group to the one where a student belongs affects positively their career GPA and negatively their passing rate, while the clustering of the peers in the same group where a student belongs affects negatively their career grades and positively their passing rates. Models with peer effects so far have not yielded consistent results, but the generalized 2SLS estimates that there is no evidence of endogenous peer effects, and there is little to no evidence supporting the existence of exogenous peer effects in this context.

The results here are only a starting point, since more complex models are needed here to try to shred some light about the existence of peer effects, classroom composition effects and network characteristics effects.

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