Neighbors' Effects on University Enrollment*

Andrés Barrios Fernández †

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Abstract

This paper provides causal evidence that close neighbors significantly influence potential applicants' decision to attend university. I create a unique dataset combining detailed geographic information and individual educational records in Chile, and exploit the quasi-random variation generated by student loans eligibility rules. I find that potential applicants are significantly more likely to attend and complete university when their closest neighbor—defined as the closest individual applying to university one year before—becomes eligible for a student loan and enrolls in university. This increase in enrollment is mediated by an increase in the probability of taking the admission exam and applying to university. The closest neighbor typically lives 0.09 km away, and neighbors' influence decays with distance. My results highlight the importance of social influences for university enrollment decisions and suggest that financial aid and university access policies may have important spillover effects.

Keywords: Neighbors' effects, University access, Spatial spillovers.
JEL classification: I21, I24, R23, R28.

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†Centre for Economics Performance (LSE) and VATT Institute for Economic Research. andres.bafer@alumni.lse.ac.uk.

1 Introduction

Despite high individual returns to schooling and governmental efforts to improve educational attainment, university enrollment remains low among disadvantaged individuals. While not all of these individuals would benefit from a university education, enrollment is low even among those with high academic potential. This situation is partially explained by the absence of enough funding opportunities, but there is growing evidence that the lack of information, support, and encouragement also plays an important role in schooling decisions (Hoxby and Avery, 2013; Carrell and Sacerdote, 2017).[1] The barriers preventing students from taking full advantage of their education opportunities seem to be higher in areas where university attendance is low, suggesting that their neighborhoods and social networks matter. However, causally identifying how neighbors and other close peers affect educational choices is challenging and the evidence on the role they play in these consequential decisions is still scarce.

This paper provides causal evidence that close neighbors significantly influence potential applicants' decision to attend university. Specifically, I show that potential applicants are more likely to attend university when their closest neighbor—defined as the closest individual applying to university the previous year—becomes eligible for a student loan and enrolls in university. Although peer effects in education have been widely studied, this is among the first papers to investigate their influence in higher education decisions. This is an important margin to study. Attending university has positive average returns (Card, 1999; Barrow and Malamud, 2015) and, according to recent evidence, is beneficial even for marginal students (Zimmerman, 2014; Goodman et al., 2017). Furthermore, at the aggregate level it can drive economic growth and impact inequality (Goldin and Katz, 2008). This work also shows that neighborhood effects are at least partly driven by exposure to peers, in contrast to being driven only by exposure to different institutions (i.e., schools, health services, public infrastructure, security).

I conduct this study in Chile, taking advantage of the fact that eligibility for student loans depends on students scoring above a cutoff in the university admission exam, and

[1] Hoxby and Avery (2013) shows that high achieving individuals from areas with low educational attainment in the United States apply to less selective schools than similar students from other areas, despite the fact that better schools would admit them and provide them with more generous funding. This undermatching phenomenon has also been studied by Black et al. (2015); Griffith and Rothstein (2009) and Smith et al. (2013). There is also a vast literature looking at the role of information frictions in schooling investment. Attanasio and Kaufmann (2014), Hastings et al. (2015) and Jensen (2010) study these frictions in Mexico, Chile, and the Dominican Republic, respectively. Bettinger et al. (2012) and Hoxby and Turner (2015) analyse the same issues in the United States, and Oreopoulos and Dunn (2013) in Canada. Carrell and Sacerdote (2017), on the other hand, argues that interventions that increase university enrollment work not because of the information they provide, but because they compensate for the lack of support and encouragement. Lavecchia et al. (2016) discusses these frictions and different behavioral barriers that may explain why some individuals do not take full advantage of education opportunities.

that eligibility for this type of funding significantly increases university enrollment (Solis, 2017). Exploiting the discontinuity generated by this cutoff rule, I implement a fuzzy regression discontinuity (RD) design using potential applicants' enrollment as the outcome and instrumenting their neighbors' enrollment with an indicator of their eligibility for student loans.

To perform this analysis, I create a unique dataset that combines detailed geographic information and individual educational records collected from multiple public agencies. This allows me to identify potential applicants and their neighbors and to follow them throughout high school and during the transition to higher education.

A key challenge for the identification of neighbors' effects is distinguishing between social interactions and correlated effects. In this context, correlated effects arise because individuals are not randomly allocated to neighborhoods and because once in the neighborhood, they are exposed to similar institutions and local shocks. The fuzzy regression discontinuity (RD) design that I use in this paper helps me to overcome this challenge. Since potential applicants who have a close neighbor near the student loan eligibility cutoff are very similar, this design allows me to rule out that the estimated effects are a consequence of differences in individuals' or neighborhoods' characteristics.

In addition, if peers' outcomes have an effect on each other, this gives rise to what Manski (1993) described as the reflection problem. This paper focuses on potential applicants who decide whether or not to enroll in university one year after their neighbors. Thus, the neighbors' decisions should not be affected by what potential applicants do one year later. This lagged structure and the fact that the variation in neighbors' enrollment only comes from their eligibility for funding allows me to overcome concerns related to the reflection problem.

I show that student loans generate spillovers on younger peers of their direct beneficiaries. Having a close neighbor marginally qualifying for a student loan significantly increases university enrollment of younger potential applicants. Besides neighbors, other peers could influence university enrollment, so I also show that similar spillovers arise when an older sibling becomes eligible for funding.

By combining these reduced form effects on potential applicants with the first stage effects—i.e., the direct increase in university enrollment experienced by older neighbors—I show that having a close neighbor going to university with a student loan increases potential applicants' university enrollment by around 10 percentage points. As expected, I find that neighbors' influence quickly decays with distance. It also seems to decay with differences in age and in socioeconomic status, and seems weaker for potential applicants who are new or less attached to the neighborhood. I also show that in the absence of the neighbor shock, an important share of the potential applicants would not have enrolled in any higher education institution, and that their increase in university enrollment also translates into higher second-year enrollment and university completion rates, suggesting that an important fraction of the potential applicants benefit from following their neighbors' example. Using a similar strategy, I find that having an older sibling going to university with a student loan increases potential applicants' university enrollment between 12.5 and 16 percentage points. These effects are smaller than the sibling spillovers documented by Altmejd et al. (2021) on 4-year college enrollment, and are similar in size to the effects that high-touch interventions have achieved on college enrollment (Bettinger et al., 2012; Carrell and Sacerdote, 2017, see for instance).

Finally, I show that the increase in university enrollment generated by both older neighbors and older siblings is mediated by an increase in the number of potential applicants taking the university admission exam and applying to university. I only find a significant increase in applications for funding in the case of siblings, which likely reflects that households that have already sent a child to university rely more on external funding to finance their other children's studies.

I discuss and explore three broad classes of mechanisms, whose likelihood and relevance partially depends on the strength of the ties between potential applicants and their peers. Firstly, close peers may increase university enrollment of potential applicants by making them aware that university is accessible and potentially beneficial. This could be achieved simply by setting the example of going to university, but also by facilitating access to relevant information. Secondly, older peers could change the options available to potential applicants. They could either give potential applicants an advantage in terms of admission or help them with the admission exam and their applications. Finally, close peers could directly change potential applicants' preferences. Although I cannot perfectly distinguish between these alternative mechanisms, I argue that learning about close peers succeeding in their applications to funding and to university, and potentially receiving relevant information from them are important drivers of my results.

This paper contributes to the literature on neighborhood effects. This literature has shown that exposure to a better neighborhood as a child reduces teenage pregnancy, improves future earnings, and increases the probability of college enrollment (Chetty et al., 2014, 2016; Chetty and Hendren, 2018a,b).[2] However, from these results it is not possible to tell to what extent the effects are driven by exposure to better peers or to better institutions (i.e., schools, health services, infrastructure, security). The policy implications of these alternative explanations are very different. As Burdick-Will and Ludwig (2010) point out, if neighborhood effects are mainly driven by the quality of local institutions,

[2] This has been an active area of research in the last decade. Damm and Dustmann (2014); Fryer and Katz (2013); Kling et al. (2005, 2007); Ludwig et al. (2012) are examples of papers exploiting experimental or quasi experimental variation to study neighborhood effects on mental health, well-being, and criminal behavior, among others.

then educational attainment could be improved by investing in these institutions without having to move disadvantaged individuals to different areas. This paper focuses on the role of peers by exploiting a source of variation that allows the identification of neighbors' effects while keeping the characteristics of the neighborhood fixed; the results show that neighbors do indeed matter.

Secondly, it adds to the literature on peer effects in education. Despite all the research on peer effects—see Sacerdote (2011) and Sacerdote (2014) for a comprehensive review of this literature—we know little about how peers influence educational choices, especially in the context of higher education. This paper is among the first to study peer effects on university enrollment, and to the best of my knowledge, it is the first studying the role of close neighbors on this decision.

Most of the evidence on peer effects on educational choices comes from siblings and focuses on primary and secondary education. Two notable exceptions that study siblings' influence in higher education choices are Goodman et al. (2015) and Altmejd et al. (2021). Goodman et al. (2015) descriptively document that one-fifth of younger siblings follow their older siblings to the same college, and that younger siblings are more likely to enroll in any four-year college if an older sibling previously did so. Altmejd et al. (2021) investigate older siblings influence on the choice of college and major in Chile, Croatia, Sweden, and the United States. The variation they exploit only allows them to study sibling spillovers on the extensive margin—i.e., enrollment in any 4-year college—in the United States. This paper expands on their results by showing that older siblings also affect the decision to attend university in Chile, and that similar spillovers arise among close neighbors.

Finally, this paper informs the literature studying underinvestment in higher education and its implications for inequality. Recent evidence has shown that attending university is beneficial even for marginal students (Zimmerman, 2014; Goodman et al., 2017). Nevertheless, we observe vast differences in the higher education trajectories of individuals from different social groups, even when focusing on those with high academic potential (Hoxby and Avery, 2013; Patnaik et al., 2020). Differences in post-secondary education trajectories have been attributed to credit constraints, differences in the quality of primary and secondary education, and information frictions.[3] Recent work has shown that behavioral barriers also play a role in explaining why some individuals do not take full advantage of their education opportunities (Lavecchia et al., 2016).

[3] Papers studying credit constraints include Dynarski (2000); Seftor and Turner (2002); Dynarski (2003); Long (2004); van der Klaauw (2002); Belley and Lochner (2007); Lochner and Monge-Naranjo (2012); Solis (2017); Card and Krueger (1992); Goldin and Katz (2008); Chetty et al. (2014) discuss consequences of differences in the quality of teachers and schools; information frictions are studied in Bettinger et al. (2012); Busso et al. (2017); Dinkelman and Martínez A. (2014); Hastings et al. (2015, 2016); Hoxby and Turner (2015); Oreopoulos and Dunn (2013); Wiswall and Zafar (2013); Booij et al. (2012); Nguyen (2013); Castleman and Page (2015).

I build on this work by showing that there are causal links among the higher education decisions of close peers, and that shocks to the education trajectory of individuals propagate through their neighborhood and family networks.[4] This suggests that barriers to access can be amplified by social spillovers, exacerbating inequality in educational attainment and in long-term economic outcomes. My findings also indicate that financial aid and potentially other programs designed to increase access to university have greater effects than those typically estimated because they also benefit close neighbors and younger siblings of the direct beneficiaries.

The rest of the paper is organized into seven sections: the second section describes the Chilean higher education system; the third section describes the data; the fourth section discusses the identification strategy; the fifth section discusses the main results of the paper; the sixth section looks at siblings and investigates responses of potential applicants in other educational outcomes; the seventh section discusses mechanisms and relates the main results of the paper to previous findings; and finally, the eighth section concludes.

2 Higher Education in Chile

Despite the expansion experienced by the Chilean higher education system in recent decades, inequality in access to university remains high. According to the national household survey (CASEN), in 2015, individuals in the top decile of the income distribution were 3.5 times more likely to attend university than students in the bottom decile.

Although part of this inequality can be explained by differences in academic potential, Figure I shows that the gap in university enrollment persists along the ability distribution measured by students' performance in standardized tests in grade 10. This figure also shows that while on average low-income students are less likely to attend university, in some municipalities their enrollment rate is higher in comparison to wealthier students from other places.

To apply to university, students need to take a national level university admission exam (PSU). The PSU has four sections: language, mathematics, social sciences and natural sciences. Applicants need to take language and mathematics and at least one of the other sections.

All the public universities and 9 of the 43 private universities are part of the Council of Chilean Universities (CRUCH). The CRUCH universities, and since 2012 eight additional private universities, select their students through a centralized deferred acceptance admission system that only considers students' performance in high school and in a national

[4] Along this line, Bennett and Bergman (2020) documents large social spillovers among classmates in the context of a policy designed to prevent absenteeism in Chilean high schools.

level university admission exam (PSU). The universities that do not participate in the centralized system have their own admission processes. However, the PSU still plays an important role in the selection of their students, mostly due to strong financial incentives for both students and institutions.

In Chile, the majority of financial aid comes from the government. There are two student loan and multiple scholarship programs designed to fund studies in different types of higher education institutions. The allocation of these benefits is under the responsibility of the Ministry of Education.

Students who need financial aid have to apply for funding using an online platform a couple of months before taking the PSU. The Ministry of Education informs them about the benefits they are eligible once the results of the PSU are made public. This allows students to consider their available funding before applying and enrolling in higher education.

There are two student loan programs: solidarity fund credit (FSCU) and state guaranteed credit (CAE). The former can be used solely in CRUCH universities, while the latter can be used in any accredited higher education institution. In order to be eligible for these loans, students need to obtain an average PSU score (language and mathematics) of above 475 and come from households in the bottom 90% of the income distribution.[5]

Solis (2017) documents that eligibility for student loans creates a discrete jump in the probability of enrolling in university. This paper exploits the same discontinuity to study the effect of having a close neighbor or an older sibling going to university with a student loan.

The majority of the scholarships are allocated following a similar logic to loans; the main difference is that the academic requirements are higher (i.e., PSU average score above 550), and that they are focused on students from more disadvantaged backgrounds. This means that students eligible for these scholarships are also eligible for student loans. Thus, crossing the scholarships' eligibility threshold changes the generosity of the subsidy but not the availability of funding (the Online Appendix provides additional details and studies direct and indirect effects of scholarships on university enrollment).

Since Chilean universities have complete freedom to set their tuition fees, the government sets a reference tuition fee for each program and institution as a way to control public expenditure. These reference tuition fees define the maximum amount of funding that a student can receive from the government. At the university level, the reference tuition fee roughly covers 80% of the actual fee. This means that students need to fund the

[5] The FSCU is available for students from households in the bottom 80% of the income distribution. The CAE, on the other hand, initially focused on students in the bottom 90%; however, since 2014, the loan is available to anyone that satisfies the academic requirements.

additional 20% by using their own resources, by taking private loans or by applying for external support offered by their universities or other private institutions (see the Online Appendix for a more detailed description of the Chilean higher education system).

3 Data

This section describes the sources of the data collected and the sample used to study the effects of neighbors on potential applicants' probability of enrolling in university.

3.1 Data Sources

This paper combines rich administrative data from different public agencies, including the Chilean Ministry of Education and the Department of Evaluation, Assessment and Educational Records (DEMRE) of the University of Chile, which is the agency in charge of the PSU. In addition, it uses data from the Ministry of Social Development, the Education Quality Agency, and the Census.

This data allows me to follow students throughout high school and in the transition to higher education. The high school records contain information on students' demographic characteristics, attendance, academic performance (GPA), and household municipality in every grade. In addition, it registers the educational track chosen by students and schools' characteristics such as their administrative dependence (i.e., public, voucher, private) and location. All this information is available from 2002 onward, meaning that the first cohort that I can follow between grades 9 and 12 is the one that completed high school in 2005. I complement this data with anonymized codes of the last names of individuals provided by the Ministry of Education.

I also observe the universe of students who register for the PSU, starting from 2004. As discussed in Section 2, the PSU is free for students graduating from public and voucher high schools, so most students sign up for the test even if they do not plan to apply to university.[6] Apart from the scores that students obtain in each one of the sections of this admission exam, the data contains information on applications to the universities that are part of the centralized admission system (see Section 2 for more details). This includes the list of all the programs to which students apply and their admission status. The PSU registers also contain demographic and socioeconomic variables of the students and their families, including household income, parental education, parents' occupations and family size. These variables are later used to study whether the identifying assumptions of the regression discontinuity design (RD) are satisfied and to perform heterogeneity analyses. These registers also include students' addresses and a unique identifier of parents. This

[6] During the period of this study, more than 85% of high school graduates appear in the registers of the PSU.

information is used to identify neighbors and siblings.[7]

The Ministry of Education keeps records of all the applications and the allocation of financial aid. The type and amount of benefits are only observed for individuals who enroll in higher education, which means that it is not possible to know if students not going to higher education were actually offered funding. However, the eligibility rules are clear, and all the applicants satisfying the academic and socioeconomic requirements should be offered a student loan or a scholarship.

Finally, I also observe enrollment and higher education completion. These records contain individual-level data of students attending any higher education institution in the country (i.e., vocational higher education institutions and universities); they also report the programs and institutions in which students are enrolled each year. This data, like the data on financial aid, is available from 2006 onward.

Using all these data, I create two independent samples to investigate the role of neighbors and siblings. The first contains records of students appearing in the PSU registers between 2006 and 2012, and the second records of students appearing between 2006 and 2015. The difference in the years studied is purely driven by data availability. Next, I describe the neighbors' sample in detail; in the Online Appendix I describe the siblings' sample.

3.2 Sample Definition

This section describes the steps and restrictions imposed on the data to build the neighbors' estimation sample. The first step in this process consists in matching potential university applicants observed in time t, with close neighbors observed in $t-1$. Considering that the goal of the paper is to understand how the members of an individual's social network influence his/her decision to enroll in university, it seems natural to build the sample focusing on potential applicants. In addition, by proceeding in this way, I guarantee that each potential applicant appears only once in the sample. Older neighbors, on the other hand, can appear multiple times. This would be the case if they lived nearby more than one potential applicant.

To identify close neighbors of potential applicants, I first geocoded the addresses students provided when registering for the PSU. Since these addresses do not include postcodes, the geocoding process was very challenging, especially in regions with high levels of rural population, where street names are not always well defined. Thus, this study focuses on three regions where the identification of neighbors was easier. Together, these regions

[7] Information on demographic and socioeconomic variables, addresses and parents identifiers is not available for all the students in the registers. Some of it can be recovered from secondary and higher education registers. Although the baseline specifications do not use controls, observations with missing values in these dimensions are not used when performing heterogeneity analyses.

concentrate more than 60% of the total population of the country: *Metropolitana of Santiago* (7.1 million inhabitants), *Valparaíso* (1.8 million inhabitants), and *Bio-bío* (1.5 million inhabitants).[8] The Santiago and Valparaíso regions are located next to each other in the center of the country, while the Bio-bío region is located further south. While in the Santiago region there are 33 universities, in Valparaíso and the Bio-bío regions there are 12 and 9 universities, respectively.

After geocoding the addresses, potential university applicants of year t were matched to a large set of close neighbors registered for taking the PSU in $t-1$. Then, the demographic, socioeconomic, and academic characteristics of potential applicants and their neighbors were incorporated into the dataset. Finally, each individual was linked to their respective neighborhood unit. Neighborhood units correspond to subareas within a municipality and were defined by the Ministry of Social Development to decentralize certain local matters and to foster citizen participation and community-based management. This is the level at which I cluster standard errors in the main specifications of the paper, although in the Online Appendix, I show that the precision of the estimates does not suffer important changes when clustering at other levels.

To build the estimation sample, I apply some additional restrictions. I only keep individuals who are between 17 and 22 years old when registering for the PSU, and who finished high school through regular educational programs no more than three years before registering for the PSU. If an older neighbor registered more than once, then I use the record of the first time he/she actually takes the PSU. For potential applicants, I use the record of the first time they appear in the registers. Finally, I also drop pairs of potential applicants and neighbors that I suspect to be related. Thus, I drop from the sample observations in which potential university applicants and neighbors share any of their parents' national id numbers or any last name, independently of their order (in Chile, individuals have two last names). This procedure is likely to eliminate not only pairs of siblings and cousins from the sample but also non-related individuals who share the same last name. I follow this conservative approach to ensure that the effects I document later are not driven by family relations.

The main analyses of the paper focus on potential applicants and their closest neighbor applying for funding one year before they could apply to university. I also present results that pool together multiple neighbors to study how neighbors' effects evolve with distance. In the Online Appendix, I also present results looking at the effect of neighbors applying two or more years before, the same year, and after potential applicants. In all

[8] Even in these regions, it was not possible to geocode 100% of registered students' addresses. I identified addresses for nearly 85% of the sample. This implies that for some potential applicants, I was able to identify only a subset of close neighbors. Unless there is some sort of selection at the student loan eligibility threshold in missing neighbors, this should work against finding significant effects. The Online Appendix discusses this issue in greater detail.

these cases, I work only with potential applicants whose neighbors apply for financial aid because these are the only neighbors who could change their decision to enroll in university based on eligibility for student loans. Note that this restriction is only imposed on neighbors, and it does not affect potential applicants. This means that the sample includes potential applicants even if they do not take the PSU or apply for funding.

The restrictions applied to the sample do not affect the internal validity of the analysis but could affect the composition of the sample. Table I presents summary statistics for the sample of potential applicants and their closest neighbors. It also characterizes all the students in the PSU registers between 2007 and 2012.

Potential applicants and their closest neighbors are very similar. I only find relevant differences in academic variables. Neighbors, who by construction applied for financial aid, are more likely to have chosen the academic track during high school. They also obtain better scores in the PSU, a result that is partly driven by the fact that most of them actually take the test. Despite the restrictions imposed when creating this sample, potential applicants look very similar to the rest of the individuals in the PSU registers. There are some minor differences, that partly reflect that neighbors and potential applicants in the estimation sample come from three out of the sixteen regions of the country.

4 Identification Strategy

The identification of neighbors' effects is challenging (Manski, 1993; Angrist, 2014). Families are not randomly allocated to neighborhoods, and once in a neighborhood, they face similar circumstances, which makes it difficult to distinguish between social interactions and correlated effects. In addition, if peers' outcomes simultaneously affect each others' decisions, this gives rise to what Manski (1993) described as the "reflection problem".

This paper studies how having a close neighbor going to university in year $t-1$ affects individuals who could apply to university in year t. To identify this effect, I exploit quasi-random variation on neighbors' university enrollment generated by the rules determining eligibility for student loans. In Chile, eligibility for student loans depends on scoring above a threshold in the university admission exam (PSU). This allows me to estimate the effect of interest in a fuzzy regression discontinuity design (RD) setting, in which I instrument a neighbor's university enrollment (U_n) with an indicator variable that takes a value of 1 if their PSU score is above the student loan eligibility threshold (L_n).

Since older neighbors decide whether to enroll in university before the potential applicants, their decisions should not be affected by what potential applicants will do one year later. Even if this is not the case, my empirical strategy allows me to overcome the reflection problem. The variation that I exploit in older neighbors' university enrollment comes only from being above or below the student loan eligibility threshold, and thus it is not affected by the choices of potential applicants.

In addition, since potential applicants with a neighbor scoring around the student loan eligibility threshold are very similar, this approach also eliminates concerns related to correlated effects.

Thus, I estimate the following specification:

$$U_{at} = \alpha + \beta_n U_{nt-1} + f(PSU_{nt-1}) + \mu_t + \varepsilon_{at} \tag{1}$$

where U_{at} is the university enrollment status of potential applicant a in year t, U_{nt-1} is the university enrollment status of neighbor n in year $t-1$, and $f(PSU_{nt-1})$ is a linear or quadratic polynomial of the running variable whose slope is allowed to change at the cutoff.

Note that this specification only includes neighbor n. In order to interpret β_n as the direct local average treatment effect (LATE) of neighbor n on potential applicant a, in addition to the IV assumptions discussed by Imbens and Angrist (1994), we need to assume that the university enrollment of contemporaneous peers does not affect applicants' own university enrollment (see the Online Appendix for more details). If this last assumption is not satisfied, β_n can be interpreted as a reduced form parameter capturing not only the direct effect of neighbor n on potential applicant a but also the effects that other neighbors affected by n generate on a. This would be part of the mechanisms by which neighbors influence potential applicants' decisions, and would not affect the validity of the empirical strategy. In addition, from a policy perspective this still is a relevant parameter.

When estimating specification 1, I use optimal bandwidths computed according to Calonico et al. (2014b). I report parametric estimates, as well as robust estimates obtained following Calonico et al. (2014a) and Calonico et al. (2019). 2SLS estimates come from specifications that assume a flexible functional form for the running variable and instrument U_{nt-1} with a dummy variable that indicates whether neighbor n was eligible for student loans at $t-1$, L_{nt-1}.

The Online Appendix presents a series of analyses that investigate whether the assumptions required for the validity of the estimates are satisfied. Firstly, I show that there is no evidence of manipulation of the running variable around the cutoff; I implement the density discontinuity test suggested by Cattaneo et al. (2018) and show that the distribution of scores seems to be smooth around the cutoff. Secondly, I show that there are no discontinuities at the cutoff in a rich vector of demographic, socioeconomic, and academic characteristics of potential applicants and their neighbors. Then I perform multiple placebo exercises and show that as expected potential applicants' enrollment decision has no effect on their older neighbors, that older neighbors who do not apply for funding do not affect potential applicants' enrollment when crossing the student loan eligibility threshold, and that there are no effects around placebo cutoffs. I also show that the results are robust to different bandwidth choices, and conclude by studying whether my estimates are likely to be affected by endogenous PSU registration or by the effectiveness of the geocoding process. I show that the number of potential applicants living at different radius from a neighbor's address does not change when the neighbor crosses the eligibility threshold, and that the distance between a neighbor's address and their closest potential applicant is balanced at the eligibility threshold.

5 Results

This section discusses the main findings of the paper. It uses the definitions introduced in Section 4 according to which potential applicants are individuals who could apply to university in year t, while their neighbors are individuals who applied to university in year $t-1$. This section begins by looking at what happens with potential applicants' enrollment probability when their closest neighbor goes to university as a consequence of being eligible for a student loan. Then it incorporates other close neighbors into the analysis and studies how the effect evolves with physical and social distance. It concludes by investigating whether similar spillovers arise among siblings.

5.1 Effect of the Closest Neighbor on Potential Applicants' Enrollment

In order to study how potential applicants' enrollment probability changes when their closest neighbor goes to university, I estimate specification 1, instrumenting neighbors' university enrollment with a dummy variable that indicates if they are eligible for a student loan.

Panel (a) of Figure II illustrates the first stage of this exercise. It shows that neighbors' probability of going to university increases by around 18 percentage points (pp) when they become eligible for a loan. This figure, significantly different from zero, captures the direct effect of student loans on university enrollment. According to it, this type of funding roughly doubles the probability of going to university for individuals with PSU scores near the student loan eligibility threshold.

Panel (b), on the other hand, illustrates the reduced form effect. It shows that potential applicants whose closest neighbor is eligible for a student loan in year $t-1$, are around 2 pp more likely to enroll in university in year t. This figure is statistically different from zero and measures part of the indirect effect of offering university funding. According to this result, student loans not only have an effect on their direct beneficiaries but also on potential applicants who live near these beneficiaries. This indirect effect represents more than 10% of the direct effect of student loans on university enrollment.

If this reduced form effect works only through neighbors going to university with a student loan, the first stage and reduced form estimates can be combined to estimate the effect of having a close neighbor going to university with funding on potential applicant's enrollment. Table II presents estimates obtained using 2SLS and the robust approach suggested by Calonico et al. (2014b). According to these results, potential applicants' probability of going to university increases by more than 10 pp when their closest neighbor becomes eligible for a student loan and enrolls in university. This figure is statistically different from zero, and it represents around one third of the enrollment probability of potential applicants at the cutoff.

The 2SLS estimates in Table II would be an upper bound of the effect of neighbors' enrollment on potential applicants' probability of going to university if having a close neighbor eligible for funding would make them aware of these opportunities or of the benefits of going to university, independently of the enrollment decision of the neighbor.

Note, however, that having a neighbor going to university is more salient than having a neighbor eligible for a student loan. Indeed, to learn that a neighbor who does not enroll in university was eligible for a student loan requires quite a close relationship with him/her. In addition, if a neighbor decides against enrolling in university despite being eligible for funding, the signal sent to his/her social network would point in the opposite direction of the results that I find. The neighbor would be signaling that even if one has access to funding, pursuing university studies is not worth it.

If potential applicants only learn about financial aid when the neighbor takes it up and goes to university, this would be a mechanism through which exposure to these university going neighbors works and not a violation to the exclusion restriction.[9]

To further investigate how the decision to enroll in higher education is influenced by close neighbors, in Table III I present results that look at the type of institution in which potential applicants enroll. Firstly, in Column (1), I look at changes in the probability of enrolling in any higher education institution (i.e. vocational higher education institutions and universities). I find an increase of 6 pp in the probability of enrolling in any higher education institution, a number that represents around 60% of the increase that I find

[9] In the Online Appendix, I show that having a neighbor eligible for a more generous type of funding does not change university enrollment of neighbors or of potential applicants. Apart from working as a placebo test, this result is consistent with the idea that learning about funding opportunities alone does not change potential applicants' choices. The Online Appendix also shows that even potential applicants non eligible for student loans are more likely to enroll in university.

in university enrollment. This indicates that as shown in Column (2), in the absence of the neighbor's shock some potential applicants would have attended a vocational higher education institution instead of a university, but an important part of them would not have attended higher education at all.

Column (3) looks at the probability of enrolling in an accredited university. This coefficient is quite similar to the overall change in university enrollment, which suggests that most of the potential applicants who follow their neighbors to university enroll in accredited institutions. I find a smaller but significant increase in the probability of attending a CRUCH university (Column (4)). As discussed in Section 2, CRUCH universities include all the public universities and a group of traditional private universities. According to this result, around 70% of the effect on university enrollment is driven by an increase in enrollment in this type of institutions. Column (5) focuses on the program instead of the institution of enrollment. I find an increase of 5.2 pp in the probability of enrolling in an accredited program.

Finally, columns (6) and (7) look at changes in the share of applicants enrolling in the same or in a different university as the neighbor. Understanding if besides influencing the decision to enroll in university, neighbors also affect the institution to which potential applicants go, is an interesting question. I try to shed some light on this issue here, but these results need to be interpreted with caution. The increase in university enrollment documented earlier in this section generates a mechanic increase in the share of applicants going to the same university as their neighbor and to any other university. However, the fact that among always-takers the share of potential applicants going to the same university as their neighbors is 3.25% (0.01/0.31), and that among compliers whose neighbor is eligible for funding is 25.96% (0.027/0.104) suggests that to some extent neighbors also influence the choice of university.

Encouraging individuals to enroll in university is not necessarily something good, at least not for everyone. If the potential applicants who respond to their neighbors' enrollment do not have the skills required to succeed at university, then the neighbor's effect could be negative. Table IV explores this in more detail by investigating whether the difference in enrollment persists one year after the shock, and whether there is also a difference in higher education and university completion rates.

Columns (1) and (2) look at retention in the university system and in the same institution where potential applicants originally enrolled, respectively.[10] The estimates reported in these columns are very similar to the effects on enrollment, suggesting that compliers of the IV do not drop out at a higher rate than always-takers. In addition, columns (3)

[10] In both cases, the outcomes take value 1 for applicants who enroll in t and continue to be enrolled in $t+1$, and take value 0 for applicants who do not enroll in t or who enroll in t but dropout during the first year.

and (4) look at the probability of completing higher education or university before 2019. These results show that potential applicants with a close neighbor going to university one year before them, are 6.3 pp more likely to complete any higher education degree and 7.3 pp more likely to complete a university degree. These coefficients represent an important fraction of the effect on enrollment, suggesting that the neighbor shock experienced by the potential applicants is beneficial for an important fraction of them.

5.2 How do neighbors' effects evolve with distance?

Section 5.1 shows that close neighbors can play an important role in potential applicants' enrollment decisions. For these results to arise, close neighbors need to be part of the potential applicants' social network. Otherwise, they would not be able to learn about their neighbors' educational choices or to receive any information from them. This section studies how the influence of neighbors evolves with distance, social proximity, and attachment to the neighborhood. These variables are likely to affect the strength of social links, and therefore, the way in which neighbors affect potential applicants' choices.

The results discussed so far have focused on potential university applicants and their closest neighbor applying for university funding. However, other neighbors could also influence potential applicants' enrollment. To study this, I generate a new estimation sample that expands the original one by incorporating additional neighbors. To create this new sample, I first identify the closest 50 neighbors of each potential applicant, and then I retain all those who satisfy the conditions described in Section 3. Finally, I split the sample in four equal groups depending on the distance between the potential applicant and the neighbors. Thus, in the first group, the average distance between potential applicants and their neighbors is 98.8 meters, while in the last group it is 698.1 meters.

I then independently estimate specification 1 for each of these four groups. Since I am pooling together multiple neighbors, the same potential applicant could appear multiple times in the estimation sample. However, by splitting the sample into four groups and focusing on neighbors whose PSU scores are within the optimal bandwidth, the cases of duplicated potential applicants become less frequent.[11]

Figure III illustrates the results of this exercise. Each circle corresponds to the estimate obtained from the four independent regressions mentioned in the previous paragraph. In

[11] An alternative approach would be to use a specification including the enrollment status of multiple neighbors simultaneously. This would require having valid instruments for the enrollment status of each neighbor. However, this is not possible in this setting because the instruments that I have for neighbors' enrollment are valid only locally and after controlling by the running variable (i.e., near the cutoff). In addition, the instrument is relevant only for neighbors who apply for financial aid. Such approach would require finding potential applicants with many neighbors applying for funding and with PSU scores close enough to the eligibility threshold. Unfortunately, such potential applicants are scarce.

the horizontal axis, I report in parenthesis the average distance between potential applicants and their neighbors in each group. The estimates quickly decay with distance and the effect becomes non-significant already in the second distance quartile. In the third distance quartile, the coefficient is considerably smaller and definitely non-significant. In the fourth quartile, the coefficient is virtually zero.

Note that potential applicants do not necessarily appear in the four estimation samples. To appear in all of them, they would need to have neighbors who apply for university funding, live within the distance range that defines each group, and obtain PSU scores close enough to the eligibility cutoff. Thus, part of the differences between the coefficients in Figure III could be driven by changes in the composition of the sample. However, the pattern that arises is clear and suggests that the influence of neighbors quickly decreases with distance.

In the context of peer effects, these results highlight the importance of defining the reference group correctly. They suggest that interactions between neighbors occur at a very local level. Therefore, using an overly broad definition of neighborhood could dilute the effect of the relevant peers (i.e., what happens with individuals living more than 200 meters away from potential applicants does not seem to be very relevant).

The likelihood and strength of social links is not determined only by physical distance. In the rest of this section, I study how the effects evolve depending on proxies of social distance and on the time that potential university applicants, their closest neighbors, and some of their family members spend in the neighborhood. When performing these analyses, I come back to the original sample and focus only on the closest neighbor.

The results presented in Table V suggest that the effects are larger when potential applicants are closer to their neighbors in socioeconomic status and age.[12] Despite both differences being considerable in size, only the latter is statistically significant. The direction of these differences nevertheless suggests that social proximity matters.

When looking at differences by gender, the results seem to be stronger for pairs of potential applicants and neighbors of the same gender. This difference, however, is small and non-significant. The results in the Online Appendix show that this difference is driven by male potential applicants. Their response when the close neighbor is male is 10 pp larger than when the close neighbor is female. On the other hand, for female potential applicants, the neighbor's gender does not seem to be relevant. These patterns likely reflect differences in how male and female potential applicants are affected by their neighbors,

[12] Socioeconomic status is measured by an index that combines high school administrative dependence and the educational track chosen by individuals. The Online Appendix presents additional heterogeneity results, according to which students from highly disadvantaged backgrounds or who choose the vocational track in high school are less responsive. This suggests that the effects are driven by potential applicants who are better prepared for the PSU and for whom scoring above the student loan eligibility threshold and being admitted to university is easier.

rather than differences in how close they are.

Social links between neighbors might also depend on how attached they are to the neighborhood. In Table VI I show that the effect seems to be stronger for potential applicants who have lived in the neighborhood for longer and whose neighbors plan to remain in the neighborhood if they go to university.

Although I only observe the exact address of individuals at the end of high school, the student registers also report the students' municipality in each grade of high school. Using this information, I classify potential applicants as new to the neighborhood if they arrive to the municipality in which they register for the PSU while they were in high school. The effect seems to be completely driven by potential university applicants who have been living in the neighborhood for longer, but despite a significant difference in the size of the estimates—11.8 pp vs 1 pp—they are not precise enough to rule out them being equal.

The effect also seems to be larger when the neighbor plans to continue living in the neighborhood if they enroll in university. The estimated effect is 6.2 pp larger than when the neighbor intends to move to a different place. Although not statistically significant, this difference is consistent with social interactions being more likely to occur when the neighbor remains close. This is likely to also facilitate the transmission of relevant information about applications and the university experience.

Being part of the same social network does not imply being directly connected. Potential applicants might learn about close neighbors' educational choices through friends or family members. Columns (5) and (6) in Table VI show that the effect seems larger for potential university applicants whose mothers do not work outside the household. As these mothers are likely to spend more time in the neighborhood, they could play a role in making potential applicants aware of what neighbors do and in facilitating the transmission of relevant information.

Although not all the differences explored in this section are statistically significant, they suggest that the effects are driven by potential applicants and neighbors who are part of the same social network. The effects are stronger for individuals who live close to each other, and also seem to increase with social proximity and with the level of attachment to the neighborhood.

5.3 Siblings' Effects

In addition to close neighbors, there are other members of an individual's social network that could influence the decision of enrolling in university. In this section, I study whether having an older sibling qualifying for a student loan and going to university affects potential applicants' enrollment.

Although the siblings sample is similar to the neighbors sample, it covers a longer period of time —2006 to 2015— and contains potential applicants (i.e., younger siblings) who score higher in the PSU than the potential applicants in the neighbors sample. This is not surprising, as these potential applicants have at least one older sibling who already took the PSU and applied for funding. These differences do not affect the internal validity of the analysis, but they should be kept in mind when comparing the effects (the Online Appendix describes the siblings sample in more detail).

The top panel of Figure IV shows that older siblings eligible for student loans are around 16 pp more likely to enroll in university than those who are not eligible. This figure, statistically different from zero, represents the direct effect of student loans on this group of students.

The panel at the bottom illustrates the reduced form effect. It shows that potential applicants with an older sibling crossing the student loan eligibility threshold are more than 2 pp more likely to attend university than those whose older sibling fails to cross it. This result is interesting from a policy perspective. It means that offering funding for university generates spillovers on the younger siblings of the individuals receiving the offer.

Under the assumptions discussed in Section 4, the first stage and reduced form can be combined to estimate the effect of older siblings' loan-induced university enrollment on potential applicants' enrollment. Table VII summarizes these results. The first two columns present 2SLS estimates, while the third and fourth columns show estimates obtained using the robust approach suggested by Calonico et al. (2014b). According to these figures, having an older sibling going to university with a student loan increases their younger siblings' enrollment by between 12.5 and 16.5 pp.

These 2SLS estimates, however, need to be interpreted with caution. They would represent an upper bound of the effect of older siblings' loan-induced university enrollment on potential applicants if an older sibling's eligibility for student loans directly affected younger siblings' enrollment (see the Online Appendix for a detailed discussion).[13]

6 Other Educational Outcomes

This section looks at changes on the application decisions and the academic performance of potential applicants to identify the margins that they adjust and that mediate the increase in enrollment documented in the previous sections. To study this, I rely once more on specification 1, but this time to study how these other outcomes change when

[13] The Online Appendix also present additional results on siblings. It characterizes the type of institution in which they enroll, and studies persistence and higher education graduation.

the closest neighbor or an older sibling goes to university with a student loan.

According to the results presented in Table VIII, potential applicants with a close peer (i.e., the closest neighbor or an older sibling) going to university are more likely to take the PSU, and to actively apply to university. Since I only observe applications to universities that use the centralized admission system described in Section 2, these are the applications I use to define this outcome. While potential applicants are significantly more likely to apply to financial aid when an older sibling has gone to university with a student loan in the past (13.9 pp), they do not seem to significantly adjust this margin when the peer going to university is an older neighbor (3.6 pp). Potential applicants are more likely to qualify for a student loan both when an older sibling and when an older neighbor enroll in university. This result is partly driven by the increase in the number of potential applicants taking the PSU. While in the case of neighbors differences in the take up of financial aid represent roughly 50% of the effect on enrollment, in the case of siblings it represents more than 90%.

When focusing on differences in effort and academic performance during high school, I find no effects on attendance and a small increase in high school GPA.[14] I also find a significant improvement on potential applicants' performance in the PSU, although an important part of it is driven by the increase in the share of them who take the exam. Missing scores in the PSU were replaced by 0 (or -475 after centering the PSU scores around the student loan eligibility threshold). Thus, if potential applicants with neighbors or siblings going to university are more likely to take the admission test, this mechanically increases their average scores (i.e. they are less likely to have -475 points in the PSU). Although a formal analysis of performance in the PSU would require a selection model, I also present results that focus only on potential applicants that take the exam. The differences in this case are much smaller, and in the case of siblings, the difference is not statistically significant.

Although the coefficients of the application responses are not always precisely estimated, they represent an important fraction of the changes in potential applicants' enrollment. This suggests that an important part of the increase in enrollment is driven by a change in the decision to take the PSU and apply to university. This is consistent with the undermatching results discussed by Hoxby and Avery (2013) and Black et al. (2015), suggesting that there are students who despite having the potential to be admitted and to receive funding, do not apply to university.

[14] In Chile, the GPA scale goes from 1.0 to 7.0. The minimum GPA required to complete a grade is 4.0. The standard deviation of the GPA in grade 12 is 0.55. Average attendance in grade 12 is 89.8%.

7 Discussion

The results discussed so far show that close neighbors and older siblings significantly influence the educational trajectories of potential applicants.

The effects that I document are large in comparison to traditional college-going interventions. Most informational interventions fail to meaningfully affect higher education choices, unless they offer some type of individualized support.[15] Bettinger et al. (2012) and Carrell and Sacerdote (2017) for instance, find that providing information about funding opportunities or nearby colleges alone does not increase college enrollment. However, helping students to fill their funding and college applications generates large responses. Bettinger et al. (2012) shows that helping families to apply to financial aid increases college enrollment by 8 pp. Carrell and Sacerdote (2017) finds that offering a mentorship program to high school seniors increases college enrollment by 6 pp, an effect that is mostly driven by the women in the sample who experience a 15 pp increase in the likelihood of attending college. The effects that I find are similar in size to the most effective college-going interventions. In a recent paper, Altmejd et al. (2021) show that siblings influence different higher education choices in Chile, Croatia, Sweden and the United States. In the United States—the only country in which the paper studies effects on the decision to enroll in any 4-year college—the authors find an effect almost twice as large as the ones that I document, confirming that social influences can significantly affect individuals' education trajectories.

There are different mechanisms through which close neighbors' and older siblings' loan-induced university enrollment could affect the application and enrollment decisions of potential applicants. Their likelihood partially depends on the strength of their social links. While siblings typically live together and have strong social ties, neighbors are not necessarily part of the same social network. Section 5.2, however, suggests that the neighbors' effects are driven by neighbors who are more likely to have social ties with potential applicants. In addition, according to the results of the *Encuesta Bicentenario* more than 90% of low and mid SES individuals from the regions studied in this paper report to know the name of their immediate neighbors, and more than 75% report to have friends in the neighborhood.[16]

A first mechanism through which close peers could influence potential applicants' enrollment is by making them aware that university is accessible and potentially beneficial.

15 Low-touch informational interventions trying to tackle some of these frictions have not been very effective in increasing university enrollment (see for instance Gurantz et al., 2020; Busso et al., 2017; Bird et al., 2019; Hyman, 2019; Hurwitz and Smith, 2018).

16 The *Encuesta Bicentenario* is a national representative survey applied by AdimarkGFK and Pontificia Universidad Catolica de Chile (2007) every two years. The statistics I report were built using the data collected for the 2007 wave. This is the only year in which the survey included questions about relationships in the neighborhood.

Learning that someone close is going to university with funding could be enough to affect awareness, but close neighbors and siblings could also affect it by facilitating access to other relevant information. There is vast evidence that information frictions affect schooling decisions (see for instance Hoxby and Turner, 2015; Hastings et al., 2016). However, providing relevant information about higher education is challenging, and low-touch informational interventions have typically not been very effective. Thus, in order to be a relevant driver of my results, the information transmitted by close peers needs to be different. It could be different in its content, but also because it comes from someone close. Nguyen (2013) and Dinkelman and Martínez A. (2014) show that information provided by individuals of a similar background can have significant effects on effort and educational choices. In line with these results, Section 5.2 suggests that neighbors' influence is stronger when neighbors and potential applicants are similar in terms of socioeconomic status and age. In addition, the Online Appendix shows that the influence of neighbors seems to be stronger in neighborhoods where fewer people go to university. Potential applicants from these neighborhoods are likely to be less informed about funding, the admission process, and the overall university experience, which would make the example and information received from close neighbors more salient and relevant.

A second mechanism through which close peers could affect potential applicants' enrollment is by affecting their chances of being admitted in university. This would be the case if universities gave admission preferences to applicants related to their current students. This, however, is unlikely to be an important driver of my findings. Most potential applicants do not enroll in their neighbors' university. Siblings do enroll in their older siblings' university, but a large share of them enroll in universities that select their students through a centralized admission system that only considers high school gpa and PSU scores.

Help with the admission exam and with applications for funding and to university does not seem to be an important driver of my results either. I do not find large improvements on potential applicants' performance in the admission exam, and I only find an increase in applications for financial aid among siblings. In addition, considering that the student loans eligibility threshold is relatively low, the increase I find in student loans eligibility is likely to reflect an increase in the number of potential applicants who seriously consider applying to university and take the PSU.

Finally, a third mechanism through which close peers could influence potential applicants' enrollment is by directly affecting their preferences.[17] Preferences might change, for instance, if potential applicants experience utility gains from being near their neighbors or

[17] Preferences could also be indirectly affected. Learning that a close peer enrolls in university and potentially acquiring new information about funding, applications and the university experience could change potential applicants preferences in different ways. These indirect changes in preferences are part of the first class of mechanisms discussed in this section.

siblings. I find that only a small share of potential applicants follow their neighbors to the same university, and although this share is much larger among siblings, the Online Appendix shows that sibling spillovers on enrollment persist even when age differences make it unlikely that they will attend university at the same time. Therefore, this proximity channel does not seem to be an important driver of my results.

As discussed in this section, there are multiple mechanisms through which close peers could affect individuals' application and enrollment decisions. Although I cannot perfectly distinguish between them, my results and previous research suggest that learning about close peers succeeding in their applications to funding and to university, and potentially receiving relevant information from them are important drivers of my results. Nevertheless, more research is required to understand exactly what potential applicants learn from their neighbors and siblings, and whether other members of an individual's social network also affect human capital investment decisions.

8 Conclusions

Recent studies have shown that especially in disadvantaged contexts individuals face constraints that prevent them from taking full advantage of their education opportunities. These constraints significantly impact individuals' future earnings, and in the aggregate, can affect economic growth and inequality. The neighborhoods where individuals live and the social networks to which they are exposed seem to play an important role in shaping higher education choices. However, causally identifying how neighbors and other peers affect these consequential decisions is challenging.

This paper provides causal evidence that close neighbors and older siblings significantly influence potential applicants' university enrollment. Using rich administrative data from Chile and exploiting the quasi-random variation generated by the rules that define eligibility for student loans, I show that potential applicants are more likely to attend university when a close neighbor or an older sibling qualifies for a student loan and enrolls in university.

These results are important because they confirm the existence of causal links between the higher education decisions of individuals from the same social group. They show that shocks to the education trajectory of individuals propagate through their neighborhood and family networks, which suggests that social influences can amplify the effects of barriers and programs that affect access to university. Indeed, according to my results, financial aid and potentially other policies designed to expand access to university have larger effects than those typically estimated because they also benefit close neighbors and younger siblings of their direct beneficiaries.

I discuss three broad classes of mechanisms that could drive my findings. Firstly, close peers may increase university enrollment of potential applicants by making them aware that university is accessible and potentially beneficial. Secondly, older peers could change the available options for potential applicants, either by giving them some advantage in terms of admission or by helping them to prepare the admission exam and applications. Finally, close peers could directly affect potential applicants' preferences. Although I cannot perfectly distinguish between these alternative mechanisms, my results suggest that changes in awareness generated by learning about close peers succeeding in funding and university applications, and potentially receiving relevant information from them are important drivers of my results. Further research is required to understand exactly what potential applicants learn from their neighbors and siblings, and the full extent to which social networks affect this and other consequential human capital investment decisions.

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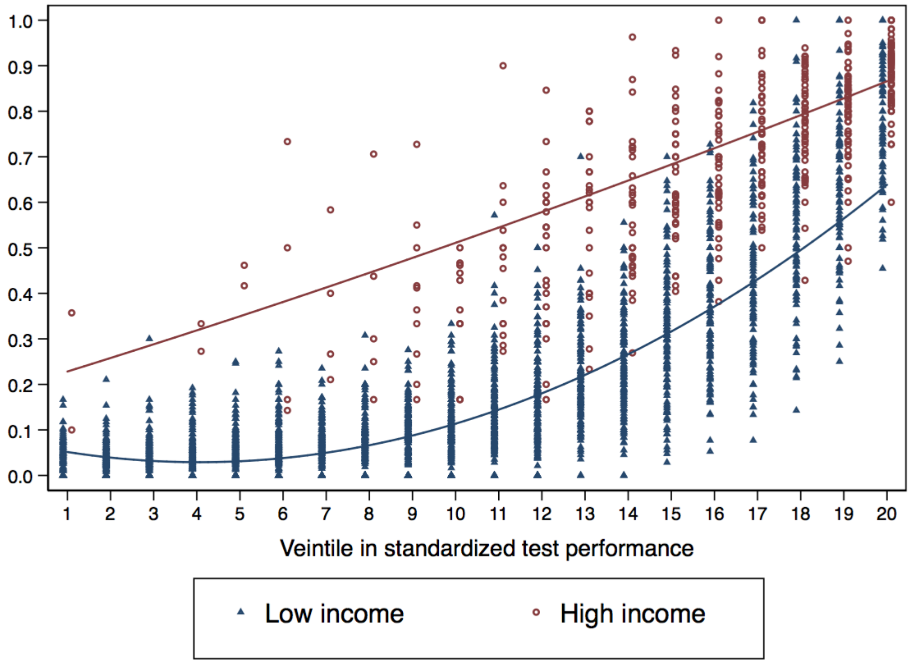
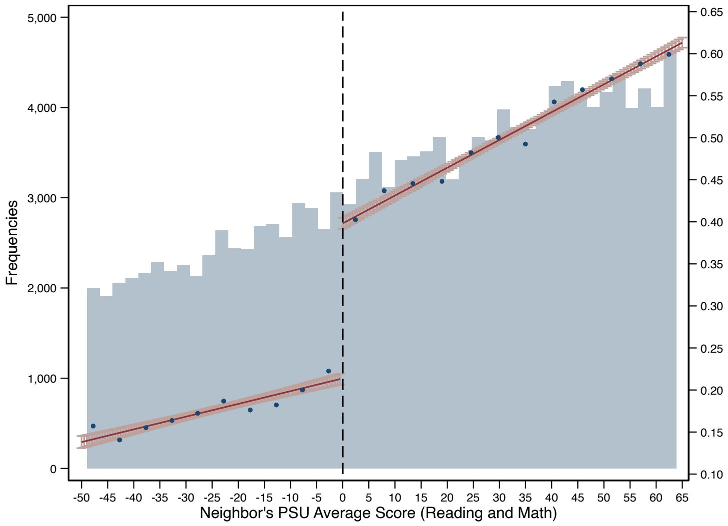
Figure I: University enrollment by household income, ability level, and municipality

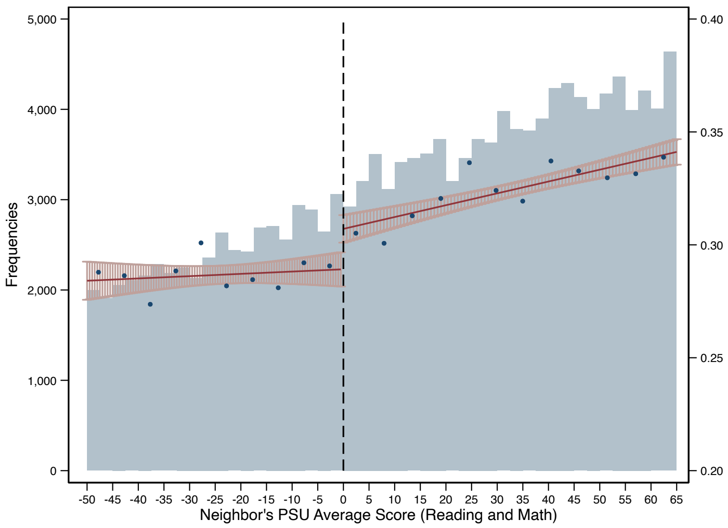


Notes: This figure illustrates the share of low and high income students enrolling in the university by ability level and municipality. Blue triangles represent the shares of low-income students, while red circles represent the shares of high-income students. The figure also presents quadratic fits of university enrollment on ability. The red line comes from a quadratic fit of high-income students attendance shares, while the blue from a similar exercise for low-income students. Ability is measured by students performance in grade 10 mathematics standardized test. University enrollment is measured 3 years later; if students do not repeat or dropout, this is one year after they complete high school. The sample includes students taking the standardized test in 2006, 2008, 2010 and 2012. Shares are computed only for municipalities for which at least 10 students were observed in each income-ability group.

Figure II: Effect of neighbors' eligiblity for student loans on their own and on potential applicants' enrollment



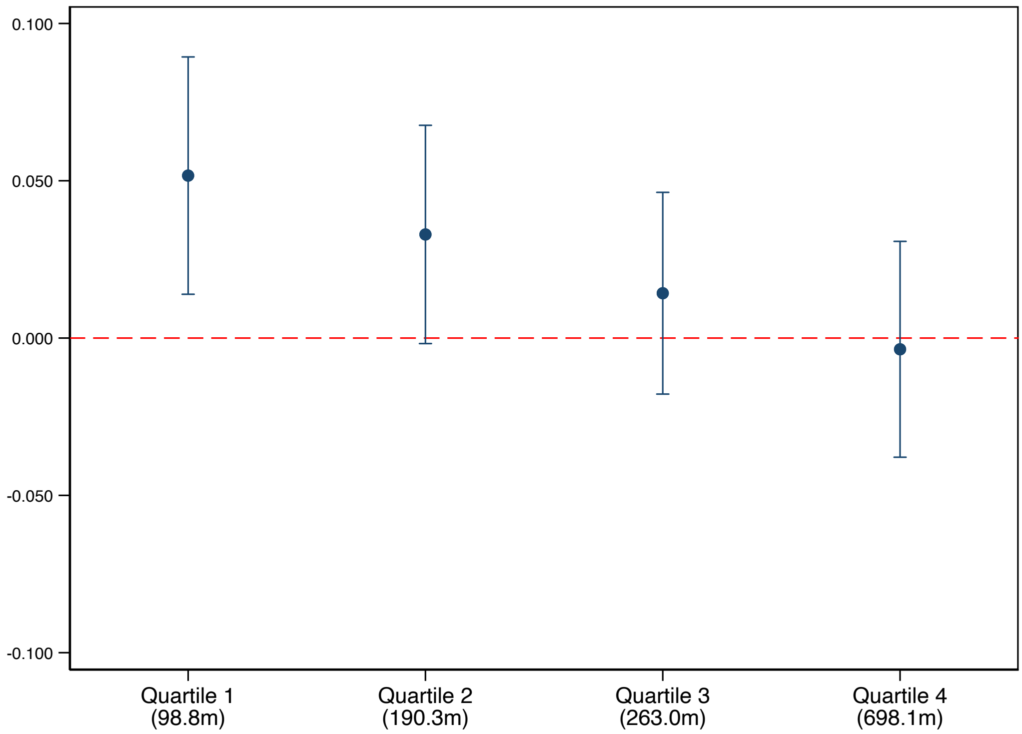
(a) First stage: Neighbors' own probability of going to university



(b) Reduced form: Potential applicants' probability of going to university

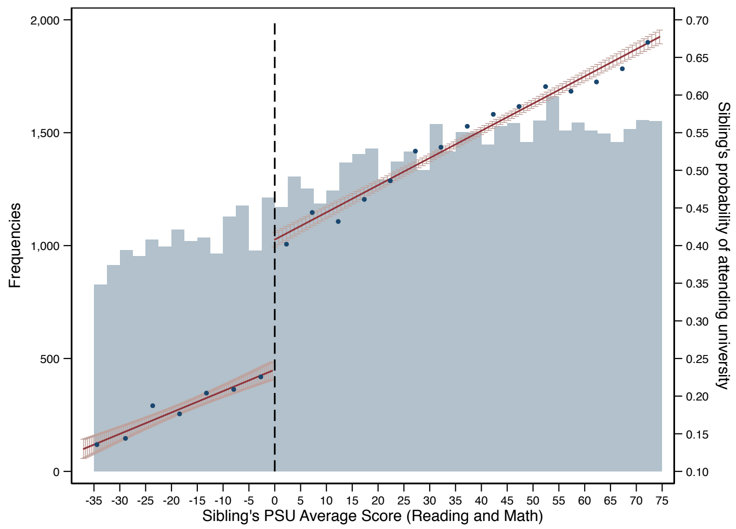
Notes: This figure illustrates the first stage and reduced form of the neighbors' RD. The first panel shows how neighbors' probability of going to university evolves with the score they obtain in the PSU. The second panel shows how potential applicants' probability of going to university evolves with the PSU score of their closest neighbor. The PSU score is centered around the student-loans eligibility threshold. Each dot represents the share of neighbors (panel 1) or potential applicants (panel 2) going to university at different ranges of neighbors' PSU scores. The red lines come from linear regressions of the outcome on the running variable on each side of the eligibility threshold, and the shadow around them to 95% confidence intervals. The blue bars in the background illustrate the distribution of the neighbors' scores in the PSU. The range used for these plots corresponds to optimal bandwidths computed following Calonico et al. (2014b).

Figure III: Effect of neighbors on potential applicants' university enrollment by distance

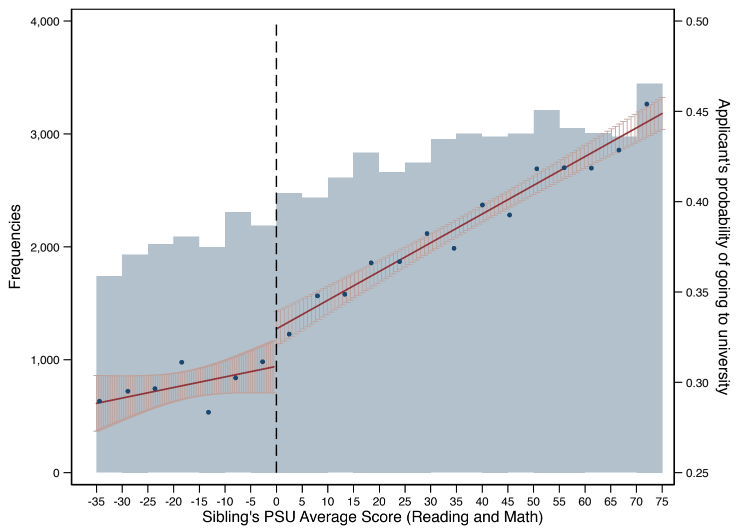


Notes: This figure illustrates how neighbors's effects on potential applicants' university enrollment evolve with distance. The sample used for this exercise includes all neighbors applying for funding among the 50 closest neighbors of each potential university applicant. The sample was divided in four quartiles depending on the distance between potential university applicants and their neighbors. Estimates come from the main specification independently estimated for each of this samples. It controls for a linear function of the running variable which slope is allowed to change at the cutoff. The estimation uses optimal bandwidths computed following Calonico et al. (2014b) for estimating the effect of the closest neighbor.

Figure IV: Effect of older siblings' eligiblity for student loans on their own and on potential applicants' enrollment



(a) First stage: Older siblings' own probability of going to univeristy



(b) Reduced form: Potential applicants' probability of going to university

Notes: This figure illustrates the first stage and reduced form of the siblings RD. The first panel shows how siblings' probability of going to university evolves with the score they obtain in the PSU. The second panel shows how potential applicants' probability of going to university evolves with the PSU score of their older sibling. The PSU score is centered around the student-loans eligibility threshold. Each dot represents the share of siblings (panel 1) or potential applicants (panel 2) going to university at different ranges of PSU scores. The red lines correspond come from linear regression of the outcome on the running variable on both sides of the eligibility threshold. The shadow around them to 95% confidence intervals. The blue bars in the background illustrate the distribution of the siblings' scores in the PSU. The range used for these plots corresponds to optimal bandwidths that were computed following Calonico et al. (2014b).

Table I: Summary statistics

	Neighbors (1)	Potential applicants (2)	Whole country (3)
1. Demographic characteristics			
Female	0.55	0.53	0.54
Age when taking the PSU	19.26	18.96	18.08
2. Socioeconomic characteristics			
Low Income ($\leq$ 288K CLP)	0.56	0.52	0.57
Mid Income ($\leq$ 864K CLP)	0.36	0.33	0.30
High Income ($>$ 864K CLP)	0.08	0.15	0.13
Parental ed. = primary ed.	0.07	0.09	0.13
Parental ed. = secondary ed.	0.52	0.52	0.52
Parental ed. = other	0.01	0.01	0.01
Parental ed. = vocational he	0.09	0.06	0.06
Parental ed. = professional he	0.08	0.10	0.05
Parental ed. = university	0.23	0.22	0.23
3. Academic characteristics			
Public high school	0.18	0.34	0.41
Charter high school	0.73	0.53	0.49
Private high school	0.09	0.13	0.10
Education track = academic	0.75	0.65	0.66
Education track = vocational	0.25	0.35	0.34
High school GPA (Grade 12)	5.76	5.58	5.48
Avg. score in the PSU (centered at the cutoff)	62.33	-4.51	-20.40
4. Family structure			
Family size	4.45	4.47	4.48
Household head = father	0.60	0.62	0.59
Household head = mother	0.32	0.30	0.28
Household head = other	0.08	0.08	0.13
Distance to closest neighbor (km)	0.09	0.09	
Age difference	1.30	1.30	
Observations	469,899	469,899	1,316,117

Notes: Columns (1) and (2) present summary statistics for potential applicants and their closest neighbors. Column (3) for all potential applicants in the country.

Table II: Effect of neighbors on potential applicants' university enrollment

	2SLS-1 (1)	2SLS-2 (2)	CCT-1 (3)	CCT-2 (4)
Neighbor goes to university (t-1)	0.104	0.127	0.116	0.138
	(0.031)	(0.040)	(0.043)	(0.051)
First stage	0.178	0.167	0.179	0.174
	(0.008)	(0.010)	(0.010)	(0.012)
Reduced form	0.019	0.021		
	(0.005)	(0.007)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	144,724	255,636	144,724	255,636
PSU Polynomial	1	2	1	2
Bandwidth	(49.09-64.35)	(67.04-124.88)	(49.09-64.35)	(67.04-124.88)
Kleibergen-Paap F statistic	449.63	260.11		
Outcome mean	0.31	0.33	0.31	0.33

Notes: The table presents the estimated effects of neighbors on potential applicants' university enrollment. Columns 1 and 2 present two stages least squares estimates using a linear and quadratic polynomial of PSU respectively. Columns 3 and 4 use instead the robust estimation approach suggested by Calonico et al. (2014b). Optimal bandwidths are used in all the specifications. In parenthesis, standard errors clustered at neighborhood unit level.

Table III: Effect of neighbors on potential applicants' enrollment by type of institution

	Pr. of Enrolling in:						
	Any HEI (1)	Vocational HEI (2)	Accredited university (3)	CRUCH university (4)	Accredited program (5)	Neighbor's university (6)	Other university (7)
Neighbor goes to university (t-1)	0.060	-0.046	0.101	0.068	0.052	0.027	0.077
	(0.032)	(0.026)	(0.031)	(0.023)	(0.019)	(0.005)	(0.031)
Reduced form	0.011	-0.008	0.018	0.012	0.009	0.005	0.014
	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.001)	(0.005)
First stage	0.178	0.178	0.178	0.178	0.178	0.178	0.178
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of students	144724	144724	144724	144724	144724	144724	144724
PSU Polynomial	1	1	1	1	1	1	1
Bandwidth	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)
Kleibergen-Paap F statistic	449.63	449.63	449.63	449.63	449.63	449.63	449.63
Counterfactual mean	0.51	0.20	0.30	0.15	0.11	0.01	0.30

Notes: The table presents the estimated effects of neighbors on potential applicants' enrollment in any higher education institution (column 1), in vocational higher education institutions (column 2), in accredited universities (column 3), in CRUCH universities (column 4), in accredited programs (column 5), in the neighbors' university (column 6), and in any other university (column 7). All specifications include a linear polynomial of the PSU which slope is allowed to change at the cutoff. Bandwidths are the same used in Table II. In parenthesis, standard errors clustered at neighborhood unit level.

Table IV: Effect of neighbors on potential applicants' second year enrollment and university completion

	Pr. of remaining in the:		Pr. of completing:	
	University system	Same institution	Higher education	University
	(1)	(2)	(3)	(4)
Neighbor goes to university (t-1)	0.100	0.091	0.063	0.074
	(0.030)	(0.029)	(0.031)	(0.028)
Reduced form	0.018	0.016	0.011	0.013
	(0.005)	(0.005)	(0.006)	(0.005)
First stage	0.178	0.178	0.178	0.178
	(0.008)	(0.008)	(0.008)	(0.008)
Years fixed effects	Yes	Yes	Yes	Yes
N. of students	144,724	144,724	144,724	144,724
Kleibergen-Paap F statistic	449.63	449.63	449.63	449.63
Outcome mean	0.28	0.26	0.53	0.26

Notes: The table presents estimated effects of neighbors on potential applicants' permanence in the system and in the university where they start one year after enrollment. It also present estimated effects on their probability of completing a higher education and a university degree. Column 1 looks at permanence in any university, column 2 at permanence in the same university in which applicants enrolled in their first year, column 3 at the probability of completing any higher education degree, and column 4 at the probability of completing a university degree. When looking at potential applicants' permanence, the outcome is 1 for potential applicants who enroll and remain enrolled one year later; it is 0 for applicants who do not enroll at all or who enroll but dropout after their first year. 2SLS estimates come from specifications that control for a linear polynomial of PSU which slopes are allowed to change at the cutoff. Bandwidths are the same used in the specifications presented in Table II. In parenthesis, standard errors clustered at neighborhood unit level.

Table V: Effect of neighbors on potential applicants by social distance

	Socioeconomic status		Gender		Age	
	Same	Different	Same	Different	≤1 year	>1 year
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor goes to university (t-1)	0.142	0.087	0.116	0.091	0.169	0.040
	(0.056)	(0.035)	(0.039)	(0.044)	(0.043)	(0.044)
Reduced form	0.024	0.016	0.022	0.016	0.028	0.008
	(0.010)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)
First stage	0.168	0.183	0.186	0.170	0.169	0.193
	(0.012)	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)
Difference in 2SLS	0.056		0.025		0.128	
	(0.065)		(0.055)		(0.060)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N. of potential applicants	50,485	94,239	73,540	71,184	79,661	59,730
Kleibergen-Paap Wald F Statistic	192.14	423.99	363.85	311.42	290.66	255.72
Outcome mean	0.35	0.29	0.31	0.31	0.31	0.33

Notes: The table presents the estimated effects of neighbors on potential applicants' university enrollment by different measures of social distance. Columns 1 and 2 study how the effects change with differences in socioeconomic status, columns 3 and 4 with gender and finally columns 5 and 6 with age. All specifications include a linear polynomial of the closest neighbor PSU score; its slope is allowed to change at the cutoff. Bandwidths are the same used in Table II. In parenthesis, standard errors clustered at neighborhood unit level.

Table VI: Effect of neighbors on potential applicants university enrollment by time at the neighborhood

	Time at the neighborhood		Neighbors remain-leave		Mother works outside the hh.	
	$\geq$ 4 years	< 4 years	Remain	Leave	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor goes to university (t-1)	0.118	0.009	0.102	0.040	0.115	0.074
	(0.033)	(0.082)	(0.037)	(0.073)	(0.041)	(0.046)
Reduced form	0.021	0.002	0.018	0.008	0.021	0.013
	(0.006)	(0.013)	(0.006)	(0.012)	(0.007)	(0.008)
First stage	0.176	0.182	0.176	0.187	0.179	0.175
	(0.009)	(0.017)	(0.010)	(0.021)	(0.009)	(0.010)
Difference in 2SLS	0.109		0.062		0.041	
	(0.085)		(0.081)		(0.059)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N. of potential applicants	121,160	19,313	104,889	26,204	65,414	69,893
Kleibergen-Paap F statistic	399.47	120.48	320.32	81.04	357.19	302.28
Outcome mean	0.31	0.35	0.31	0.33	0.29	0.34

Notes: The table presents the estimated effects of neighbors on potential applicants' university enrollment by different characteristics of potential applicants and their neighbors. Columns 1 and 2 show how the effects change depending on the time potential applicants have lived in the neighborhood. Columns 3 and 4 compare potential applicant whose neighbors say that they will remain or leave the neighborhood in case of going to university. Columns 5 and 6 compare potential applicants depending on mothers' occupation. All specifications include a linear polynomial of the closest neighbor or sibling PSU score; it is allowed to be different on both sides of the student-loans eligibility threshold. Bandwidths are the same used in Table II. In parenthesis, standard errors clustered at neighborhood unit level.

Table VII: Effect of older siblings on potential applicants' university enrollment

	2SLS-1 (1)	2SLS-2 (2)	CCT-1 (3)	CCT-2 (4)
Sibling goes to university (t-T)	0.126	0.165	0.140	0.165
	(0.053)	(0.068)	(0.064)	(0.079)
First stage	0.170	0.155	0.158	0.161
	(0.009)	(0.010)	(0.011)	(0.013)
Reduced form	0.021	0.026		
	(0.009)	(0.011)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	57,713	95,969	57,713	95,969
PSU Polynomial	1	2	1	2
Bandwidth	(37.0-74.5)	(60.0 - 132.0)	(37.0-74.5)	(60.0 - 132.0)
Kleibergen-Paap F statistic	362.60	223.08		
Outcome mean	0.37	0.40	0.37	0.40

Notes: The table presents the estimated effects of siblings on potential applicants' university enrollment. Columns 1 and 2 present two stages least squares estimates using a linear and quadratic polynomial of PSU respectively. Columns 3 and 4 use instead the robust approach suggested by Calonico et al. (2014b). Optimal bandwidths are used in all the specifications. In parenthesis, standard errors clustered at family level.

Table VIII: Effect of neighbors and siblings on potential applicants' academic performance and application decisions

	Neighbors (1)	Siblings (2)
	Panel A - Application Behavior	
Take PSU	0.045	0.048
	(0.022)	(0.029)
Active application to CRUCH universities	0.065	0.084
	(0.031)	(0.053)
Apply to financial aid	0.036	0.139
	(0.032)	(0.046)
Eligible for financial aid	0.095	0.117
	(0.035)	(0.049)
Take up financial aid	0.054	0.117
	(0.023)	(0.049)
	Panel B - Academic Performance	
High school attendance	0.007	0.013
	(0.007)	(0.010)
High school GPA at grade 12 (1-7)	0.094	0.095
	(0.044)	(0.058)
PSU Performance	29.614	25.550
	(11.956)	(15.299)
PSU Performance | Taking the PSU	17.381	5.820
	(7.508)	(9.677)

Notes: The table presents the estimated effects of neighbors and siblings on potential applicants' academic performance and application behavior. Column 1 presents the results for neighbors ($n = 144,724$) and column 2 for siblings ($n = 57,713$). All specifications include a linear polynomial of the closest neighbor or sibling PSU score; it is allowed to be different on both sides of the student-loans eligibility threshold. Bandwidths are the same used for the linear specifications presented in Tables II and VII. In parenthesis, standard errors clustered at neighborhood unit level.