Neighbors' Effects on University Enrollment*

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Abstract

Educational trajectories vary substantially across neighborhoods, suggesting that the local networks of individuals could play a relevant role in human capital investment decisions. However, causally identifying how neighbors and other close peers affect these important choices is challenging. This paper provides causal evidence that close neighbors significantly influence potential applicants' decision to attend university. To identify these effects 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 a close neighbor becomes eligible for a student loan and enrolls in university. The increase in enrollment is mediated by an increase in the probability of taking the admission exam and applying to university. As expected, neighbors' influence decays with distance. These results confirm that there are causal links between the higher education decisions of individuals from the same social group. In addition, they show that financial aid and potentially other policies designed to expand access to university have spillover effects on close peers of their direct beneficiaries.

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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 the neighborhoods where individuals live and the social networks they are a part of 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 a potential applicant's close neighbors significantly influence the decision to attend university. Specifically, I show that potential applicants are more likely to attend university when a close neighbor 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 that eligibility for this type of funding significantly increases university enrollment (Solis,

[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) do so 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.

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 being driven by 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, these neighbors' decisions should not be affected by what potential applicants do one year later. The lagged structure and the fact that the variation in neighbors' enrollment only comes from eligibility for funding allows me to overcome concerns related to the reflection problem.

Based on this empirical analysis, I provide three sets of results. Firstly, 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, there are other peers that could influence university enrollment. I also investigate whether similar spillovers arise when an older sibling becomes eligible for funding. I find that sibling spillovers are slightly larger than neighbor spillovers.

Secondly, 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. (2020) 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 existing research in several ways. Firstly, it 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

[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.

explanations are very different. As Burdick-Will and Ludwig (2010) point out, if neighborhood effects are mainly driven by the quality of local institutions, 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. Qureshi (2018), for instance, shows that an increase in oldest sisters' schooling in Pakistan also increases their younger brothers' schooling. Gurantz et al. (2020) find that in the United States, younger siblings are more likely to take an advanced end-of-year exam if an older sibling previously passed the same exam. Similarly, Joensen and Nielsen (2018) and Dahl et al. (2020) show that older siblings influence the type of courses that their younger siblings take in high school in Denmark and Sweden, respectively. Finally, Dustan (2018) finds that students from Mexico City are more likely to enroll in a particular high-school if an older sibling enrolled there in the past.

There is little evidence of siblings' influence on higher education choices. 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. (2020) 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).

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

This section describes the higher education system in Chile. It begins by characterizing the institutions that offer this level of education, continues by explaining the university admission system, and finishes by discussing the main financial aid programs available in the country, emphasizing the rules that generate the identifying variation.

2.1 Institutions and Inequality in the System

In Chile, higher education is offered by three types of institutions: vocational centers, professional institutes, and universities. Out of these, only universities can grant academic degrees, and in 2017, they attracted 48.1% of the students entering higher education.

[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).

[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.

Despite the expansion experienced by the 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 measured by students' performance in standardized tests in grade 10, Figure I shows that the gap in university enrollment persists along the ability distribution. 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.

2.2 University Admission System

In Chile, there are public and private universities. All the public universities and 9 of the 43 private universities are part of the Council of Chilean Universities (CRUCH), an organization that was created to improve coordination and to provide advice to the Ministry of Education in matters related to higher education. For-profit universities are forbidden under the Chilean law.

The CRUCH universities, and since 2012 eight other private universities, select their students through a centralized deferred acceptance admission system that only considers students' performance in high school and in a national level university admission exam (PSU). The PSU assesses students in four areas: language, mathematics, social sciences and natural sciences. To apply to university, students need to take language, mathematics, and at least one of the other sections. Universities are free to set the weights allocated to each sections for selecting students. Students apply to their programs of interest using an online platform. They are asked to rank up to 10 programs according to their preferences. Places are then allocated using an algorithm of the Gale-Shapley family that matches students to programs using their preferences and scores as inputs. The PSU is conducted in December, at the end of the Chilean academic year, but students typically need to register before mid-August. Since 2006, all students graduating from public and voucher schools, who roughly represent 93% of high school students in the country, are eligible for a fee waiver that makes the PSU free for them.

Universities that do not participate in the centralized system have their own admission processes. Although they could use their own entrance exams, the PSU still plays an important role in the selection of their students, mostly due to strong financial incentives that exist for both students and institutions.[5] For instance, the largest financial aid

[5] Firstly, creating a new test generates costs for both the institutions and the applicants. Secondly, part of the public resources received by higher education institutions depends on the performance of their first-year students in the PSU. This mechanism was a way of rewarding institutions that

programs available for university studies require students to score above a cutoff in the PSU.

2.3 Financial Aid

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. This section briefly describes the programs that fund university degrees, emphasizing the rules that generate the discontinuities exploited in this paper.

Students who need financial aid must apply using an online platform a couple of months before taking the PSU. After verifying the validity of the information provided by the applicants, the Ministry of Education informs them about the benefits they are eligible for. Something similar occurs once the PSU scores are published; the Ministry of Education incorporates this new information to the system and updates the list of benefits that students could receive based on their performance. This allows students to consider their funding options 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. Although both programs are currently very similar, during the period under study they had several differences; for instance, while the annual interest rate of the FSCU was 2%, for the CAE it varied between 5% and 6%. On top of that, while repayment of the FSCU has always been income contingent, the CAE used to have fixed installments. In order to become 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.[6]

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, but this time to study the effect of having a close neighbor or an older sibling going to university with a student loan.

The majority of the scholarship programs are allocated following a similar logic; 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. Stu-

attracted the best students of each cohort. Although it was eliminated in 2016, it was in place during the period covered by this study.

6 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% of the income distribution; however, since 2014, the loan is available to anyone that satisfies the academic requirements.

dents eligible for one of these scholarships are also eligible for student loans. Since scholarships do not need to be repaid, crossing the scholarships' eligibility threshold changes the generosity of the subsidy but not the availability of funding (appendix D provides additional details and illustrates direct and indirect effects of scholarships on university enrollment). There are also a few programs that instead of requiring a minimum score in the PSU, allocate funding based on performance in high school. These programs are relatively small, both in terms of beneficiaries and of the support they offer.

Since Chilean universities have complete freedom to decide 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.[7] At the university level, the reference tuition fee roughly covers 80% of the actual fee. This means that students need to fund the 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.

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.

[7] The only exception to this rule is given by the CAE. In this case, students still cannot receive more than the reference tuition fee through the CAE, but they can use it to complement scholarships or the FSCU, up to the actual tuition fee.

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.[8] 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 information is used to identify neighbors and siblings.[9]

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; appendix A describes 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 po-

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

9 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.

tential 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 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).[10] 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 appendix C, 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

[10] 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. Appendix C discusses this issue in greater detail.

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 appendix G, 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 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 university 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 exploited 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 or not 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 is not affected by the choices of potential applicants.

In addition, since neighbors 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 (Section B in the appendix discusses this in detail). 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. Indeed, by going to university, a neighbor could influence multiple members of the social network of potential university applicants. This would be part of the mechanisms by which neighbors influence potential applicants' decisions, and would not affect the validity of the empirical strategy proposed in this section. In fact, since social interactions in a neighborhood do not take place only between two individuals, from a policy perspective this seems to be 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}.

Appendix C presents a series of analyses that investigate whether the assumptions required for the validity of the estimates are satisfied. First, it shows that there is no evidence of manipulation of the running variable around the cutoff. In this setting, it is not easy to think of a way in which potential applicants could manipulate the running variable. The whole PSU process, from the creation to the correction of the tests, is carried out under strict security measures. In addition, the final scores are the result of a transformation that adjusts the raw scores so that they follow a normal distribution. This makes it difficult to know ex ante the exact number of correct answers needed to be just above the cutoff. Although it seems very unlikely that potential applicants or their neighbors could manipulate PSU scores, 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.

Second, appendix C shows that there are no discontinuities at the cutoff in a rich vector of demographic, socioeconomic, and academic characteristics of potential applicants and their neighbors.

In addition to the aforementioned robustness checks, I also perform multiple placebo exercises. First, I study whether potential applicants' decision to go to university has an effect on their older neighbors. As discussed earlier, there ought to be no effect, something that is corroborated by the results of this exercise. Second, I show that there are no changes in the enrollment probability of neighbors or potential university applicants when focusing on the subset of neighbors who do not apply for funding. To them, being above or below the student loan eligibility cutoff does not make any difference; therefore, this does not change their decision to enroll. It is comforting not finding a jump in potential applicants' enrollment either. I also show that there are no jumps like the ones observed at the student loan eligibility cutoff at other points where there should not be any, and that the results are robust to different bandwidth choices.

Finally, in appendix C, I also study whether my estimates are likely to be affected by endogenous PSU registration or by the effectiveness of the geocoding process. As explained in Section 3, to identify potential university applicants and their neighbors, I rely on the addresses that students provide when they register for the PSU. Even though most high school graduates register for the PSU, since registration is not mandatory, this could generate some selection issues. Failures in the geocoding process might generate similar concerns. Relying on a fuzzy regression-discontinuity design (RD) for identification mitigates some of these concerns and offers opportunities to investigate them in greater detail. A first comforting result is that the number of potential applicants living at different radius from neighbors' addresses does not change when neighbors cross the eligibility threshold. I complement this result by also showing that the distance between neighbors' addresses and their closest potential applicant is balanced at the eligibility threshold. This evidence suggests that eligibility for student loans does not affect potential university applicants' registration for the PSU. It also indicates that any problem affecting the geocoding process is balanced at the cutoff, thereby alleviating concerns about the internal validity of my analyses. Indeed, considering these results, any problem in the geocoding process of neighbors should work against finding significant effects.[11]

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.

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

[11] Missing the closest neighbor, for instance, would mean that my main analysis is not estimating the effect of the closest neighbor but instead of other close neighbors. Mistakenly classifying someone as a close neighbor who actually lives far away would make finding effects more difficult. Problems in the geocoding process could also affect the external validity of the results. However, the summary statistics in Table I suggest that the potential university applicants in my sample are very similar to the other potential university applicants in the country.

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 funding for university. 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 of 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.[12]

[12] In appendix D, 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 appendix also shows that even potential applicants non eligible for student loans are more likely to enroll in university.

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 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 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. The coefficient I find in this case 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 of the country 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 neighbors also influence the choice of university to some extent.

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.[13] The estimates reported in these columns are very similar to the effects on enrollment, suggesting that the compliers of the IV do not drop out at a higher rate than always-takers. In addition, columns (3) 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.[14]

[13] 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.

[14] 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

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 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. 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.[15] 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 poten-

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.

15 Socioeconomic status is measured by an index that combines high school administrative dependence and the educational track chosen by individuals. Table F.I in the 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.

tial applicants and neighbors of the same gender. This difference, however, is small and non-significant. The results in appendix F 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, rather than differences in how close they are to them.

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 close 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.

6 Siblings and Other Educational Outcomes

This section starts by investigating whether indirect effects as the ones documented among neighbors also arise among siblings. It then studies how university enrollment of a close neighbor or an older sibling affect other educational outcomes of potential applicants.

6.1 Siblings' Effects

In addition to close neighbors, other members of an individual's social network 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.

As discussed in Section 3, I identify siblings through their parents' national id number. Using these data, I estimate the same specification used to investigate the influence of close neighbors, but now focusing on older siblings.

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 (appendix A describes the siblings sample).

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 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.

Since siblings usually live together, a potential applicant could learn about the availability of student loans even if his/her older sibling does not enroll in university. However, this is true for potential applicants whose older siblings score marginally above and marginally below the student loan eligibility threshold. In both scenarios, younger siblings are likely to be aware of the existence of funding opportunities and their rules before they need to decide whether to apply or not to university.

While neighbors do not usually share household budgets, siblings do. Thus, an additional concern that arises in this case is that the eligibility of an older sibling for funding could affect the resources available to finance the education of younger siblings. The importance of this threat greatly depends on the generosity of the funding to which older siblings have access. As discussed in Section 2, student loans only cover a share of the tuition fees. This means that even when older siblings are eligible for a student loan, they and their families have to cover part of the tuition fees as well as commuting, maintenance and study materials costs. Thus, irrespective of the availability of funding, households in which the older sibling enrolls in university are likely to face a tighter budget constraint than those in which the older sibling does not.[16]

Although I cannot completely rule out that the effect is partly driven by changes in household resources, it is unlikely that this is the whole story. There is a significant difference in the share of older siblings going to university at both sides of the cutoff, and as discussed in the previous paragraph, student loans cover only a part of the expenses of sending a child to university.[17] In addition, my results are in line with the findings of Altmejd et al. (2020). In this work, the authors exploit college specific admission cutoffs—instead of student loan eligibility cutoffs—and find even larger sibling spillovers in 4-year college enrollment.

To further investigate how older siblings influence the university choices of potential ap-

[16] In appendix D, I show that older siblings eligible for a scholarship are not more likely to enroll in university than those eligible for a student loan. Scholarships change the generosity of the subsidy that older siblings receive, but I find no spillovers on younger siblings' enrollment. Apart from working as a placebo test, this result is consistent with the idea that older siblings' funding alone is not enough to change their younger siblings' choices.

[17] Appendix H shows that average expenditure in older siblings' higher education fees does not change at the student loan eligibility cutoff. This suggests that on average younger siblings with an older sibling marginally above or below the cutoff come from households that face similar budget constraints.

plicants, in Table VIII, I present the results of additional exercises that look at the type of institutions in which potential applicants enroll. Columns (1) and (2) indicate that around 60% of the difference that I find in university enrollment is driven by potential applicants that otherwise would not have enrolled in any higher education institution; the other 40% corresponds to potential applicants who otherwise would have attended vocational higher education. Column (3) shows that most potential applicants enroll in accredited universities, column (4) shows that roughly half of them choose a university that is part of the CRUCH, and column (5) shows that a similar proportion attends an accredited program. Finally, Columns (6) and (7) indicate that the majority of potential applicants who decide to enroll in university choose the same institution as their older sibling. This last set of results suggests that older siblings not only affect the decision to attend university but also the specific university that their younger siblings attend. This result, however, needs to be interpreted with caution, as part of this increase is a mechanic consequence of the increase in younger siblings' enrollment documented earlier. Nevertheless, the size of the coefficient suggests that older siblings do influence their younger siblings' choice of university. This is consistent with the findings of Altmejd et al. (2020), who address this specific question in more detail.

I conclude this section by showing that the increase in younger siblings' university attendance persists a year later and also leads to an increase in university completion. Columns (1) and (2) of Table IX look at differences in retention in the university system and in the same institution where they originally enrolled. These estimates are similar in size to the effects documented for first year enrollment, indicating that the majority of younger siblings who decide to go to university following the example of an older sibling, remain enrolled in their second year.[18] In addition, columns (3) and (4) look at the probability of completing higher education or university before 2019. To study this outcome, I restrict the sample to observations in which the younger sibling registers for the PSU no later than 2013. These results show that potential applicants with an older sibling going to university before them, are 12.3 pp more likely to complete a university degree before 2019. I find no difference in the probability of completing higher education, which suggests that potential applicants whose older siblings do not enroll in university are more likely to attain a vocational higher education degree.

6.2 Effects on Applications and Academic Performance

This section looks at changes on the application decisions and on the academic performance of potential applicants. This allows me to identify the margins that they adjust and that mediate the increase in enrollment documented in the previous sections. To

[18] The outcomes take value 1 for applicants who enroll in t and continue 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.

study this, I rely once more on specification 1, but this time to study how these other outcomes change when the closest neighbor or an older sibling goes to university with a student loan.

According to the results presented in Table X, 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.[19] 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, it 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 for funding and 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.

19 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.[20] 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. (2020) 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*, strong social relationships are not rare in the setting that I study.[21] In fact, 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.

A first mechanism through which close peers could influence potential applicants' enroll-

[20] 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).

[21] 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.

ment is by making them aware that university is accessible and potentially beneficial. 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 relevant information.

There is vast evidence that information frictions affect schooling decisions. Hoxby and Turner (2015) shows that in low income areas of the United States, even high achieving students know little about costs, quality and the overall college experience. Hastings et al. (2016) documents similar information frictions in Chile, where students from disadvantaged groups have limited and imprecise information about costs and returns to education. These results suggest that university enrollment could be increased by tackling these information frictions. However, providing relevant information about higher education is challenging, and as discussed earlier, low-touch informational interventions have 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.[22] Nguyen (2013) finds that individuals process information on returns to education in a sophisticated way, and that they respond differently depending on who provides the information. Dinkelman and Martínez A. (2014) finds that providing information and showing low-income Chilean 8th graders a video of adults from similar backgrounds who succeed in higher education, decreased absenteeism and increased enrollment in the academic track of high school. This suggests that learning about a success story of someone similar can increase effort and affect relevant educational choices. These results suggest that information provided by similar peers could boost university applications and enrollment. Along this line, Section 5.2 suggests that neighbors' influence is stronger when neighbors and potential applicants are similar in terms of socioeconomic status and age. Being similar could make them more likely to interact, but could also make the example and information they provide more relevant. The heterogeneous results by gender, however, indicate that being similar is not the only element that matters. I find no important differences in the response of female potential applicants to female and male close neighbors. For male potential applicants the gender of neighbors seems to be more important. These results suggest that the example set by a neighbor and potentially the information he/she transmits affects differently male and female potential applicants.

In the context of this study, the results presented in Section 6.2 indicate that potential applicants with close peers going to university slightly improve their academic performance in high school, and are more likely to take the admission exam and to apply to

[22] Receiving the information from someone close could make it more salient and meaningful. Hastings et al. (2015) show that returns to higher education can be very different depending on the characteristics of individuals and institutions. Thus, learning about the experience of someone similar could inform potential applicants about what higher education offers for individuals like them.

university. This is consistent with close peers making potential applicants realize that they could also go to university and potentially benefit from it. Along this line, appendix E shows that the influence of neighbors seems to be stronger in neighborhoods where typically fewer people go to university.[23] 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. The result suggesting that the effect is stronger when neighbors remain living with their parents is also consistent with this mechanism. Remaining in the neighborhood makes them more accessible to potential applicants and facilitates the transmission of information. Note that information does not need to be directly transmitted by the neighbors or the older siblings. It could also be transmitted by other peers or family members, who could then encourage potential applicants to apply and enroll in university.[24]

Although I cannot exactly tell what potential applicants learn from their peers who go to university, the results in Section 6.2 shed some light on this question. Having a close neighbor enrolling in university does not make an important difference in applications to financial aid, which suggests that the neighbors' effects are not entirely driven by learning about funding opportunities. In the case of siblings, I do find a relevant increase in applications to financial aid. However, in this case it is unlikely that individuals whose older siblings marginally fail to get a student loan ignore their existence. Thus, for siblings, the increase in applications to financial aid might simply reflect that households that already sent a child to university are under a higher budgetary pressure. This does not mean that funding does not matter. Indeed, learning that someone close was successful in securing funding for university could be the trigger of the increase in PSU taking and university applications. A second mechanism through which close peers could affect potential applicants' enrollment is by changing their available options.[25]

This would be the case if as in other settings, universities gave admission preferences to applicants related to their current students. This, however, is not likely to be an important driver of my findings. Identifying neighbors of current students is not trivial, and since in my sample less than 7% of close neighbors attend the same high school, the effects are unlikely to be driven by policies that favor applications from specific high schools. In addition, most potential applicants do not enroll in their neighbors' univer-

[23] The differences across neighborhoods are not statistically significant, but they are large in size. See appendix E for additional details.

[24] Finding that the effects are stronger for individuals whose mothers are housewives and presumably have stronger ties to the neighborhood is consistent with this hypothesis (see Table VI).

[25] Since the variation in older peers' university enrollment comes from eligibility for student loans, the could affect the options available for potential applicants by making available additional resources for them. This is unlikely to be the case among neighbors. See Section 6.1 for a detailed discussion about this among siblings.

sity. Younger siblings do seem to follow their older siblings to the same university, but considering that a large share of them enrolls in universities that select their students through a centralized admission system, a legacy enrollment mechanism seems unlikely.

Close peers could affect the options available for potential applicants by directly helping them to prepare the admission exam and to apply for funding and to university. This type of support, though, would require a strong relationship between potential applicants and their older peers, something that is not necessarily true among neighbors. In addition, not finding large improvement on potential applicants' performance in the admission exam suggests that this is not the main driver of my results. As explained in Section 6.2, the differences that I report on potential applicants' PSU performance are mostly driven by their decision to actually take the exam. Conditioning on taking the exam the differences are much smaller. In addition, since the student loan eligibility threshold is relatively low, peers scoring around it are not the best suited to provide academic support.

Neighbors and siblings could also help with applications to financial aid and to university. Nevertheless, these applications are much simpler in Chile than in other contexts.[26] Thus, once potential applicants decide to apply, additional support is less likely to make a difference in university enrollment than in other settings (it might still make a difference in the institution and field of study they choose). In addition, as mentioned earlier, I only find a difference in applications for financial aid among siblings; and considering that the student loan eligibility threshold is relatively low, the increase I find in eligibility is likely to reflect an increase in the number of potential applicants who seriously consider applying to university and taking the PSU.

Finally, a third mechanism through which close peers could influence potential applicants' enrollment is by directly affecting their preferences.[27] Preferences might change, for instance, if potential applicants experience utility gains from being near their neighbors or siblings.[28]

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, appendix F shows that sibling spillovers on enrollment persist even when age differences make it unlikely that

[26] As explained in section 2, in Chile applications for financial aid are done through an online platform that shows individuals all the benefits to which they are eligible. In addition, around half of the universities select students through a centralized admission system that allocates students to programs only based on their performance in high school and in the admission exam. Applying to these universities is free of charge and the applications are also submitted through an online platform.

[27] 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 aspirations in different ways. These indirect changes in preferences are part of the first class of mechanisms discussed in this section.

[28] This could be the case if potential applicants enjoy their older peers company or if they believe these peers could make their university experience easier.

they will attend university at the same time. These results suggest that this proximity channel is not the main 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 earning 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 what exactly 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 what exactly 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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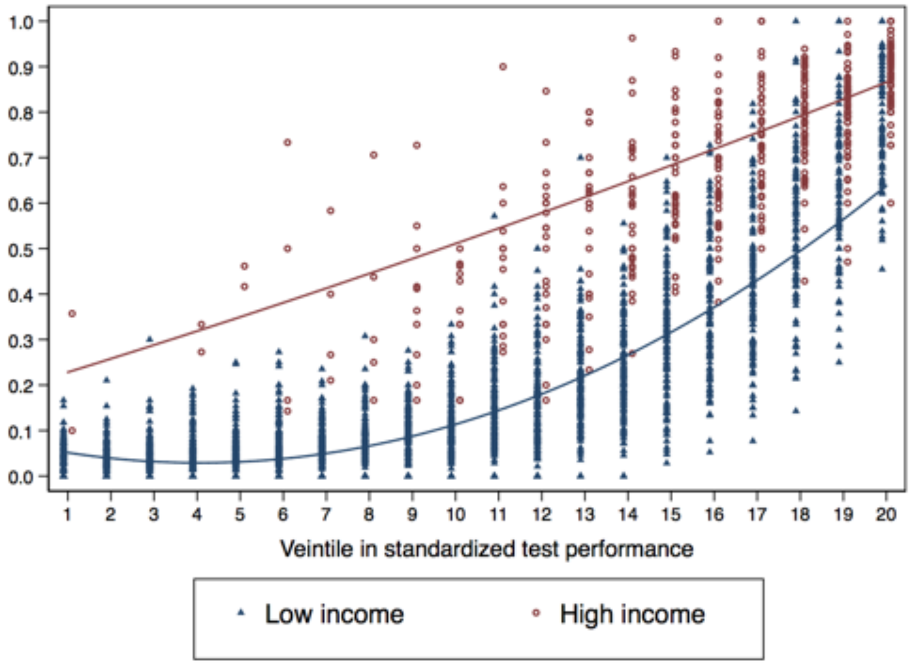
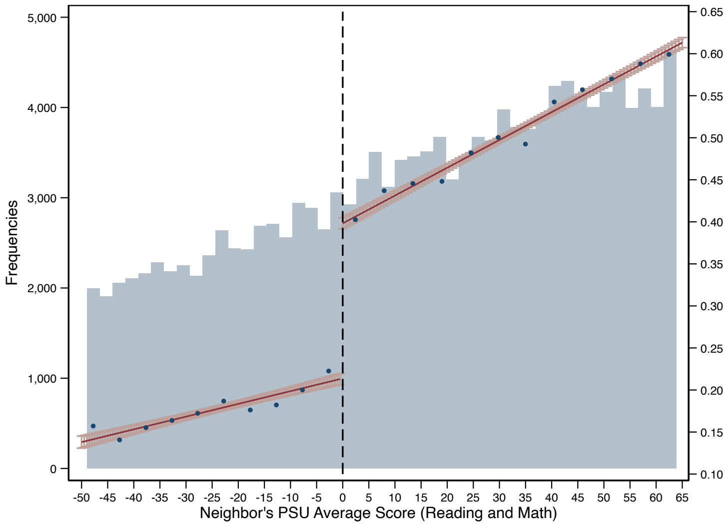
Figure I: University enrollment by household income, ability level, and municipality

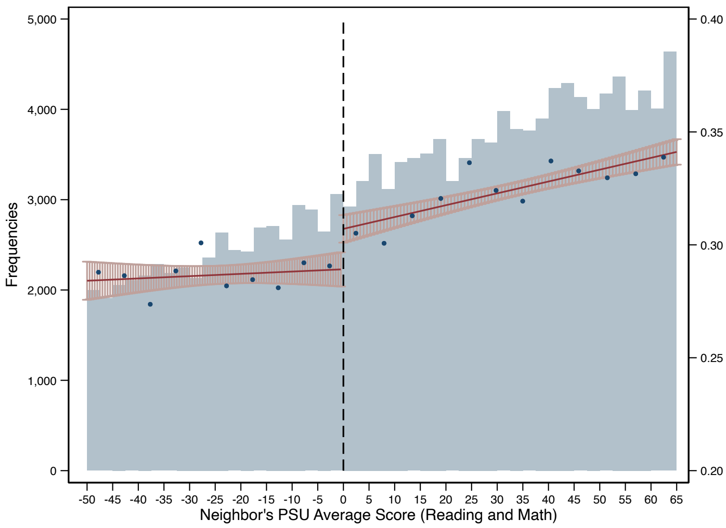


Notes: This figure illustrates the share of low and high income students enrolling in the university by ability level and municipality. Blue triangles represent the shares of low-income students, while red circles represent the shares of high-income students. The figure also presents quadratic fits of 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



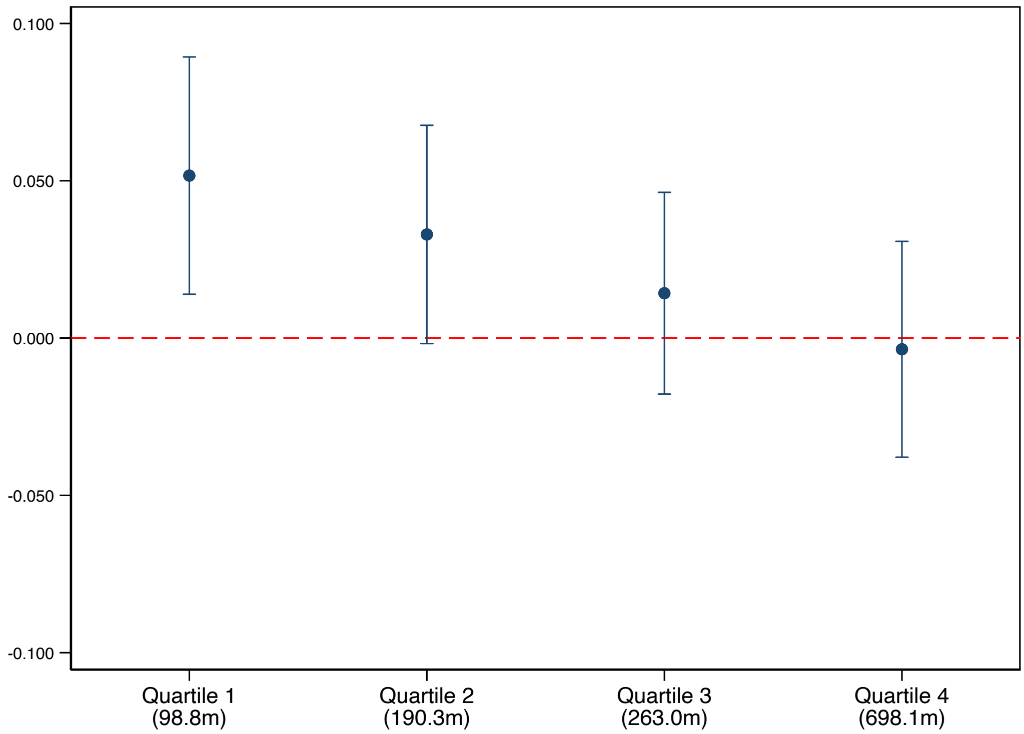
(a) First stage: Neighbors' own probability of going to university



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

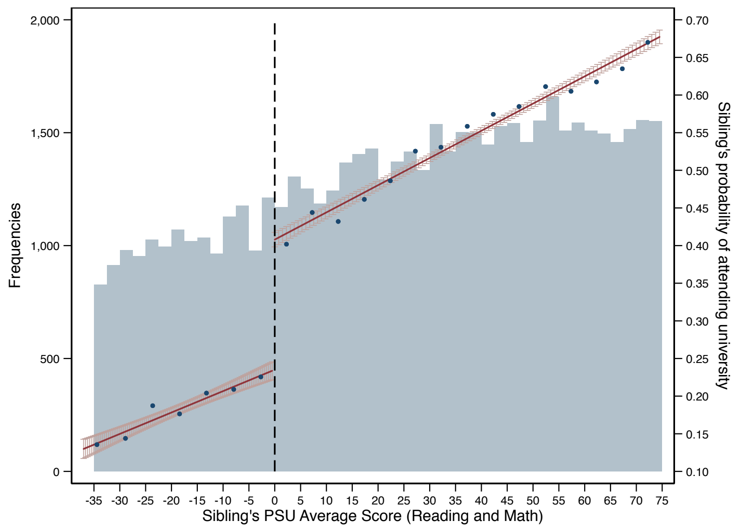
Notes: This figure illustrates the first stage and reduced form of the neighbors' RD. The first panel shows how neighbors' probability of going to university evolves with the score they obtain in the PSU. The second panel shows how potential applicants' probability of going to university evolves with 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

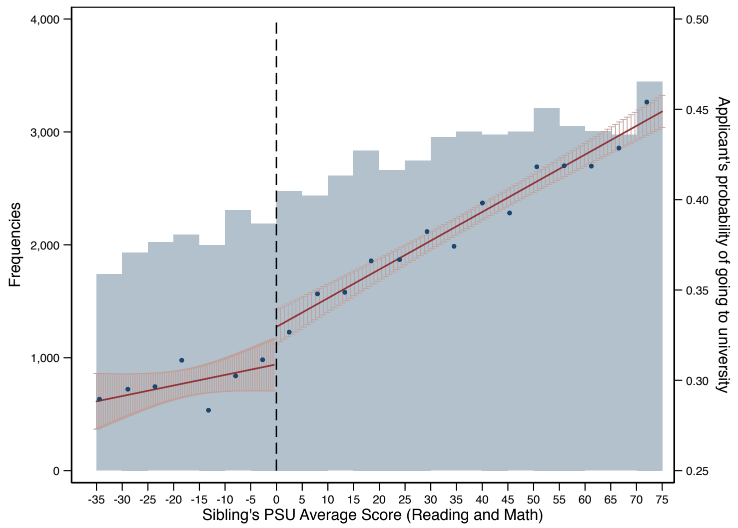


Notes: This figure illustrates how neighbors's effects on potential applicants' university enrollment evolve with distance. The sample used for this exercise includes all neighbors applying for funding among the 50 closest neighbors of each potential university applicant. The sample was divided in four 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. Optimal bandwidths for university enrollment are used in all the specifications. 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	$\leq$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. All specifications use optimal bandwidths computed according to Calonico et al. (2014b) for the main specification presented 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. All specifications use optimal bandwidths computed according to Calonico et al. (2014b) for the main specification presented 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 (0.053)	0.165 (0.068)	0.140 (0.064)	0.165 (0.079)
First stage	0.170 (0.009)	0.155 (0.010)	0.158 (0.011)	0.161 (0.013)
Reduced form	0.021 (0.009)	0.026 (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 older siblings 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)	Sibling's university (6)	Other university (7)
Older sibling goes to university (t-T)	0.073	-0.053	0.118	0.069	0.058	0.098	0.028
	(0.057)	(0.046)	(0.052)	(0.044)	(0.039)	(0.020)	(0.051)
Reduced form	0.012	-0.009	0.020	0.012	0.010	0.017	0.005
	(0.010)	(0.008)	(0.009)	(0.008)	(0.007)	(0.004)	(0.009)
First stage	0.170	0.170	0.170	0.170	0.170	0.170	0.170
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of students	57,713	57,713	57,713	57,713	57,713	57,713	57,713
PSU Polynomial	1	1	1	1	1	1	1
Bandwidth	(37.0-74.5)	(37.0-74.5)	(37.0-74.5)	(37.0-74.5)	(37.0-74.5)	(37.0-74.5)	(37.0-74.5)
Kleibergen-Paap F statistic	362.60	362.60	362.60	362.60	362.60	362.60	362.60
Counterfactual mean	0.56	0.19	0.36	0.17	0.22	0.06	0.31

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. Optimal bandwidths are used in all the specifications. In parenthesis, standard errors clustered at family level.

Table IX: Effect of siblings 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)
Sibling goes to university (t-1)	0.097	0.083	0.025	0.123
	(0.046)	(0.045)	(0.068)	(0.062)
Reduced form	0.016	0.014	0.004	0.021
	(0.008)	(0.008)	(0.012)	(0.011)
First stage	0.170	0.170	0.172	0.172
	(0.009)	(0.009)	(0.011)	(0.011)
Years fixed effects	Yes	Yes	Yes	Yes
N. of students	57,713	57,713	36,923	36,923
Kleibergen-Paap F statistic	362.60	362.60	243.30	243.30
Outcome mean	0.25	0.23	0.59	0.32

Notes: The table presents estimated effects of siblings 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 potential 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 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. When looking at degree completion I focus on potential applicants who register for the PSU no later than 2013. 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 VII. In parenthesis, standard errors clustered at family level.

Table X: 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.

Appendix

A Siblings Sample

Although this paper focuses on neighbors, I also investigate what happens with potential university applicants when an older sibling enrolls in university T years before him/her. The sample used for this purpose is similar to the one used to study neighbors effects, but it includes students that appear in the PSU registers between 2006 and 2015.

When registering for the PSU, potential applicants report their parents national id number. Using this information, I identify 273,806 pairs of siblings. I restrict the sample to 17-22 years old students completing high school in regular educational programs no more than 3 years before registering for the PSU. If an older sibling registers more than once, I use the first time he/she takes the PSU. For younger siblings I use the first time they appear in the registers. These restrictions reduce the sample size by 13.8%. I further restrict the sample to potential applicants whose siblings apply to financial aid; they are the only ones that could change their decisions based on student-loans eligibility. As before, this restriction is not imposed on potential applicants, but it reduces the sample size and I end up working with roughly half of the original sample. Table A.I presents the summary statistics for this sample.

As in the case of the neighbors sample, these students come from relatively low-income households and in the majority of the cases their parents did not attended higher education. Although there are some small differences, potential applicants and their siblings report very similar socioeconomic characteristics. I do not observe important differences in the type of school or educational track chosen by siblings, but older siblings seem to perform better on the PSU. Finally, siblings report some differences in the structure of the household. These differences are consistent with some parents leaving the household.

Table A.I: Summary statistics - Siblings' sample

	Older siblings (1)	Potential applicants (2)
1. Demographic characteristics		
Female	0.55	0.54
Age at PSU registration	18.06	17.75
2. Socioeconomic characteristics		
Low Income	0.52	0.51
Mid Income	0.38	0.38
High Income	0.09	0.11
Parental ed. = primary ed.	0.07	0.07
Parental ed. = secondary ed.	0.51	0.51
Parental ed. = other	0.01	0.01
Parental ed. = vocational he	0.09	0.08
Parental ed. = professional he	0.09	0.12
Parental ed. = university	0.23	0.21
3. Academic characteristics		
Public high school	0.40	0.34
Charter high school	0.55	0.60
Private high school	0.05	0.05
Education track = academic	0.77	0.76
Education track = vocational	0.23	0.24
High school GPA	5.84	5.75
Score in the PSU (centered at the cutoff)	52.89	20.90
4. Household structure		
Household size	5.03	4.77
Household head = father	0.73	0.70
Household head = mother	0.23	0.26
Household head = other	0.04	0.04
Age difference	3.89	3.89
Observations	135,658	135,658

Notes: Columns (1) and (2) present summary statistics for potential applicants and their older siblings.

B Identification Strategy: Further Discussion

Traditionally, peer effects have been modeled using a linear-in-means function. This implicitly assumes that all peers are equally important. Since in this case, a measure of proximity between peers is available, it is possible to assume a more flexible functional form:

$$U_{at} = \alpha + \sum_{n \in N_a} \beta_{n\tau} U_{n\tau} + \varepsilon_{it} \tag{2}$$

Where, N_a is the set of relevant neighbors for potential university applicant a and U_{nt} is a dummy variable indicating whether the $n-th$ neighbor goes to university in t.

As discussed in Section 4, neighbors decide whether to enroll or not into university before potential university applicants. Thus, their decision should not be affected by what potential university applicants do after them. This implies that N_a does not include younger neighbors (i.e., neighbors that could potentially apply to university in the future).

This paper focuses on the effects of neighbors going to university one year before potential university applicants. To highlight this, equation 2 can be rearranged as follows:

$$U_{at} = \alpha + \beta_{mt-1} U_{mt-1} + \sum_{n \in N_a \setminus U_{mt-T}} \beta_{n\tau} U_{n\tau} + \varepsilon_{it} \tag{3}$$

The coefficient β_{mt-1} can be consistently identified if $Cov(U_{mt-1}, \varepsilon_{it}) = 0$. This implies that there are no correlated effects, and that potential university applicant a_t does not affect the decision of neighbor $mt-1$.

There are many reasons why we could want to estimate a more parsimonious function. For instance, if we do not observe all the relevant neighbors, or if the type of variation used to identify these effects imposes some restrictions that prevent us from including all the observed neighbors in the analyses.

Consider the following simplified specification:

$$U_{at} = \alpha + \beta_{mt-1} U_{mt-1} + v_{it} \tag{4}$$

In this case, to consistently estimate β_{mt-1} we need $Cov(U_{mt-1}, v_{it}) = 0$. This means that in addition to the conditions discussed for equation 3, we need $Cov(U_{at}, U_{n\tau}) \cdot (Cov(U_{mt-1}, U_{n\tau}) = 0 \; \forall \; \{n, \tau\} \neq \{m, t-1\}$. To discuss the implications of this additional condition we can analyze three cases:

- Contemporaneous applicants: $\tau = t$
- Neighbors in t-1: $\tau = t-1$

- Neighbors in t-T: $\tau = t - T$ (with $T > 1$).

Note that for the first two cases, the absence of contemporaneous peers' effects is sufficient.[29] To satisfy the assumption in the third case we would need to assume that neighbors applying two or more years before potential university applicants do not directly affect them (i.e. they are not part of the structural equation).

This last assumption can be relaxed if as in this case we have an instrument for university enrollment. Instead of assuming that neighbors two or more years apart do not enter the structural equation, we would need to assume that $(Cov(Z_{mt-1}, U_{n\tau-T})) = 0$.

If the decisions of contemporaneous and younger peers enter equation 2, β_n can still be interpreted as a reduced form parameter capturing not only the effect of the $n-th$ closest neighbor on a, but also the effects that other neighbors affected by n could have generated on a. This is still a relevant parameter from a policy perspective.

A fuzzy regression discontinuity (RD) design can be thought as a particular case of IV. By abstracting from its local nature, this means that my estimates will be consistent under the following assumptions:

A1. Independence:
The instrument L_n needs to be independent of the enrollment decision of both, the potential university applicant and his/her neighbor. In my setting, this will only be true around the student loan eligibility threshold and after conditioning on neighbors' performance in the PSU.

A2. Relevance:
The instrument L_n needs to change the enrollment decision of neighbors U_n. First-stage regressions in section 5 show that this is indeed the case.[30]

A3. Exclusion:
The instrument only affects potential university applicants enrollment U_i through the change it induces in neighbors' university attendance. This implies that neighbors eligibility for student loans does not have a direct effect on the enrollment decision of potential university applicants.

A4. Monotonicity:
Finally, the monotonicity assumption requires eligibility for student loans to weakly increase neighbors enrollment. In this setting, it is difficult to think of any reasons that would induce individuals to not enroll in university because they are eligible for financial aid. Even if for some reason individuals dislike student loans or other types of funding, they could reject them and pay the tuition fees with their own resources.

[29] We are already assuming that younger applicants' decisions are not part of the equation 2.

[30] In line with the results of Solis (2017) I find that being eligible for student loans roughly doubles the probabilities of going to university at the eligibility cutoff.

According to Imbens and Angrist (1994), under this set of assumptions the IV estimates are consistent and can be interpreted as a local average treatment effect (LATE). In this fuzzy regression discontinuity (RD) design setting, this means that my estimates will have a double local interpretation. First, they are local in the sense that they are valid only for individuals whose neighbors are near the student loan eligibility threshold. Second, they are local in the sense that they are capturing the effect on the population of compliers; this is individuals whose neighbors decide to enroll at university because of their eligibility for funding.

C Robustness Checks

In this section, I study whether the identification assumptions of the empirical strategy used in the paper are satisfied. I start by investigating if there is evidence of manipulation of the running variable. Then, I check whether other variables that could be related to the decision of enrolling in university present jumps around the student loan eligibility threshold. I continue by showing the results of different placebo exercises and the robustness of my estimates to different bandwidths choices. Next, I discuss concerns related to endogeneity in PSU registration and in geocoding success. I finish this Section presenting figures that illustrate reduced form results using a second degree polynomial of the running variable.

C.1 Manipulation of the running variable

A common concern in the context of a regression discontinuity design (RD) is whether individuals can strategically manipulate the running variable affecting in this way their treatment status.

In this case, it would mean that potential university applicants have the ability to affect the average PSU score of their older neighbors and siblings. As discussed in Section 2, the PSU is a national level exam whose application and marking processes are completely centralized. This means that the teachers or the high school of a potential university applicant do not play any role in the process. In addition, given that the scores of students in each section of the test are normalized, students do not know ex ante the exact number of correct answers they would need to score above the eligibility cutoff.

All this makes manipulating scores around the threshold very difficult, even for individuals taking the exam. Considering this, it seems very unlikely that potential university applicants could strategically affect it.

In the context of this paper, a way in which potential university applicants could manipulate the score obtained by their neighbors would be to move to a different neighborhood. However, the results on movers and no-movers presented in Section 5 do not support this hypothesis. In addition, in the next Section I show that there are no jumps in neighbors' characteristics around the cutoff; so, if potential university applicants are moving to areas where neighbors are more likely to be eligible for student loans, they are not using any of the socioeconomic and academic variables I study to choose their new neighborhood.

I further investigate manipulation by looking at the density of the PSU scores around the eligibility threshold implementing the test suggested by Cattaneo et al. (2018). Figures C.I and C.II show that there is no evidence to reject the null hypothesis of a continuous density of neighbors' PSU scores around the eligibility threshold. In the case of neighbors, the p-value of the test is 0.7759, whereas in the case of siblings it is 0.5968. Therefore, the results that I find do not seem to be driven by manipulation of the running variable.

C.2 Discontinuities in potential confounders

A second concern in the context of a fuzzy regression discontinuity design (RD), is the existence of discontinuities in potential confounders around the cutoff that could explain the differences that we observe in the outcome of interest.

Taking advantage of a rich vector of demographic, socioeconomic and academic variables, I study whether there are discontinuities around the threshold in any of them.

Figure C.III summarizes these results for neighbors, and figure C.IV for siblings. They illustrate the estimated discontinuities at the cutoff and their 95% confidence intervals. To estimate these discontinuities, I use the optimal bandwidths estimated for the main specification following Calonico et al. (2014a). In both figures, the left panel looks at characteristics of potential university applicants, and the right panel at characteristics of their older peers (i.e., neighbors or siblings).

I do not find any significant difference in potential university applicants', neighbors' or older siblings' characteristics around the threshold. In addition, the magnitudes of the coefficients are small in all cases.

C.3 Placebo exercises

This section presents the results of a set of placebo exercises designed to investigate if responses like the ones documented in the main body of the paper arise in cases in which they should not.

I start by investigating if university enrollment of a younger applicant has any effect on older neighbors or siblings. Since older peers apply and decide to enroll in university before potential university applicants, their decision to enroll in university should not be affected by what potential university applicants do.

Figures C.V and C.VI illustrate the results of an exercise in which I study whether potential university applicants' eligibility for student loans changes the probability of going to university of their older neighbors and siblings. As expected, I find no discontinuity in older peers' university enrollment at the eligibility threshold; both the levels and slopes seem to be continuous around it.

The second placebo exercise that I implement consists in studying whether significant discontinuities can be found in points different to the student loan eligibility threshold. Since in these points there is no first stage (i.e., older peer's probability of going to university does not change), we should not find jumps around these placebo cutoffs. Figure C.VII presents these results for neighbors and siblings. None of the jumps at placebo cutoffs is statistically different from 0.

Finally, I investigate whether there are discontinuities around the student loan eligibility threshold for potential university applicants whose closest neighbor does not apply for funding. Since the neighbor does not apply for funding, being above or below the eligibility threshold does not change his/her likelihood of going to university. I show that this is indeed the case in Table C.I. As can be appreciated, there is no first stage. As expected, in the absence of a first stage I find no effect on potential university applicant's applications, enrollment or academic performance.

C.4 Different bandwidths

In this section, I study how sensitive my results are to the choice of bandwidth. Optimal bandwidths try to balance the loss of precision suffered when narrowing the window of data points used to estimate the effect of interest, with the bias generated by using points that are far from the relevant cutoff.

Figures C.VIII and C.IX present the estimated coefficients using bandwidths that go from 0.5 to 1.5 times the optimal bandwidths computed according to Calonico et al. (2014b). These results correspond to specifications that control for a first degree polynomial of the running variable whose slope is allowed to change at the cutoff. As shown in the figures, the estimated effects do not experience important changes when varying bandwidths.

C.5 Selection in PSU Registration and Geocoding Success

This section discusses threats related to endogenous registration in the PSU and endogenous geocoding success. As explained in Section 3, I identify potential university entrants and their close neighbors using the information that individuals provide when registering for the PSU. Thus, if the university enrollment of a close neighbor affects the PSU registration of potential university applicants, the estimated effects could be biased. Something similar could happen if the university enrollment of a close neighbor affects the probability of successfully geocoding an address.

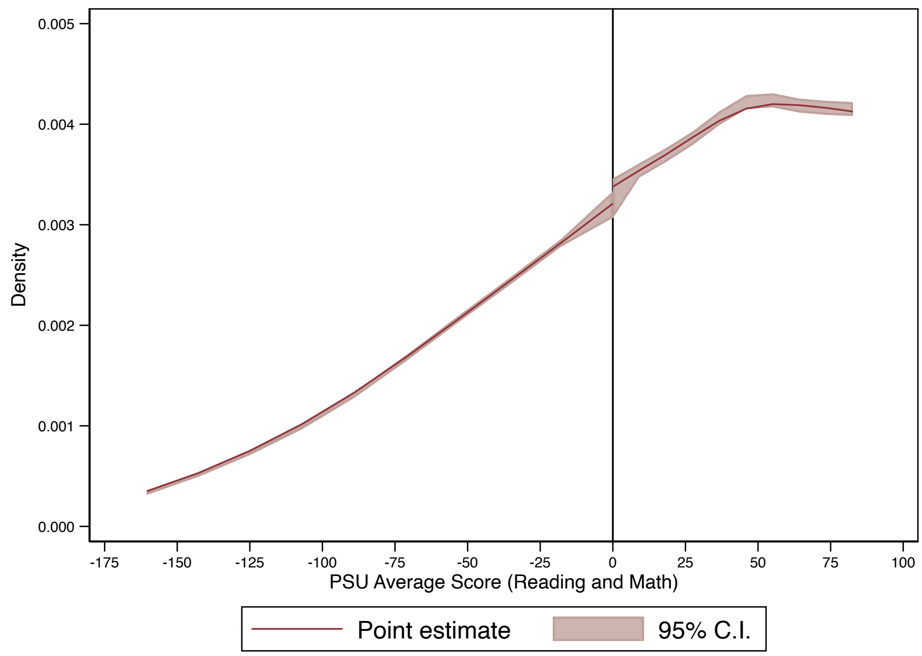
A first element that attenuates concerns respect endogenous PSU registration is that registering for the PSU is free for students completing secondary education in subsidized schools (93% of high school graduates). This results in more than 85% of high school graduates registering for the PSU even if they end not taking it. I formally investigate whether university enrollment driven by funding eligibility affects PSU registration or geocoding success in Table C.II and Figure C.XII. These exercises study whether a neighbor marginal eligibility for student loans changes the distance to the closest individual registered for the PSU the following year, and the number of individuals registered for the PSU the following year at 50m, 100m, 150m and 200m from the neighbors' address. To implement this exercise, I created a new sample using older neighbors as reference and identifying all the potential university entrants living at 200m or less from them and who appear in the PSU registers one year after the older neighbors. As shown in Table C.II, there is no significant difference in the distance between older neighbors and their closest potential university applicant at the cutoff. Similarly, Figure C.XII shows that the number of potential university applicants registered for the PSU living at 50m, 100m, 150m and 200m from the neighbor does not changes at the cutoff. These results suggest that older neighbors' eligibility for funding does not change PSU registration nor affects the probability of successfully geocoding addresses.

To further study how differences in geocoding success rates could affect my results, I present an additional exercise that replicates the main analysis just focusing on the Metropolitan Region of Santiago, as in this area the geocoding rate of success was higher than in the other two studied regions. Table C.III presents the results of this exercise. The obtained estimates are slightly larger than the ones I present in the main body of the paper.

C.6 Statistical Inference Approach

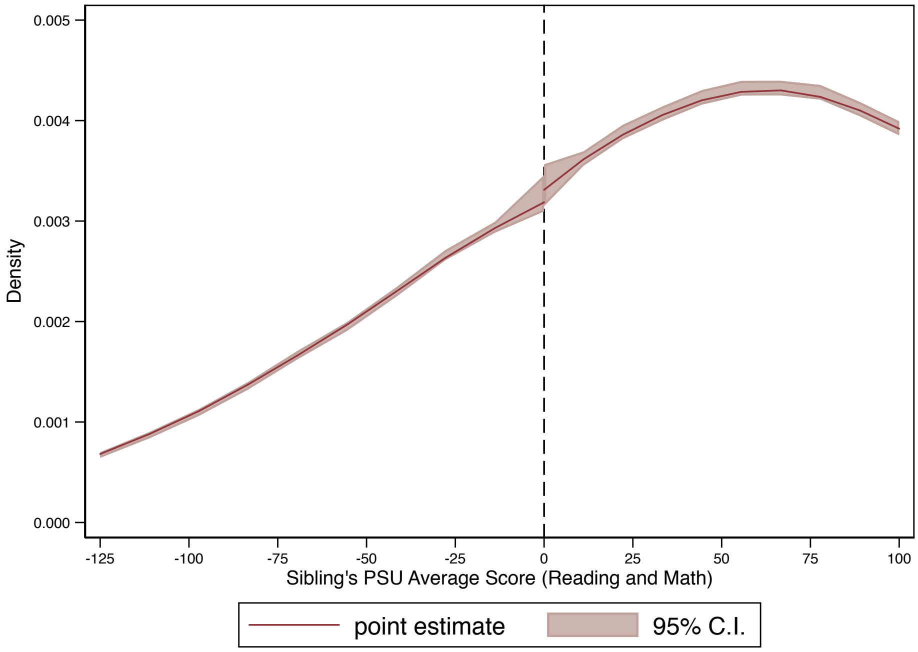
The results presented in the main body of the paper cluster standard errors at the neighborhood unit level. As explained in Section 3, neighborhood units correspond to subareas within a municipality and were defined by the Ministry of Social Development to decentralize certain local matters and to foster citizen participation and community-based management. In Table C.IV I show that the precision of the estimates does not suffer major changes when modifying the clustering level. Column (1) replicates the results presented in the paper. In the rest of the columns standard errors are computed clustering at the closest neighbor (column 2), potential applicants' high school (column 3), and potential applicants' municipality level (column 4). In all cases the estimated effects are statistically different from zero.

Figure C.I: Density of neighbors' PSU scores around the student loans eligibility threshold)



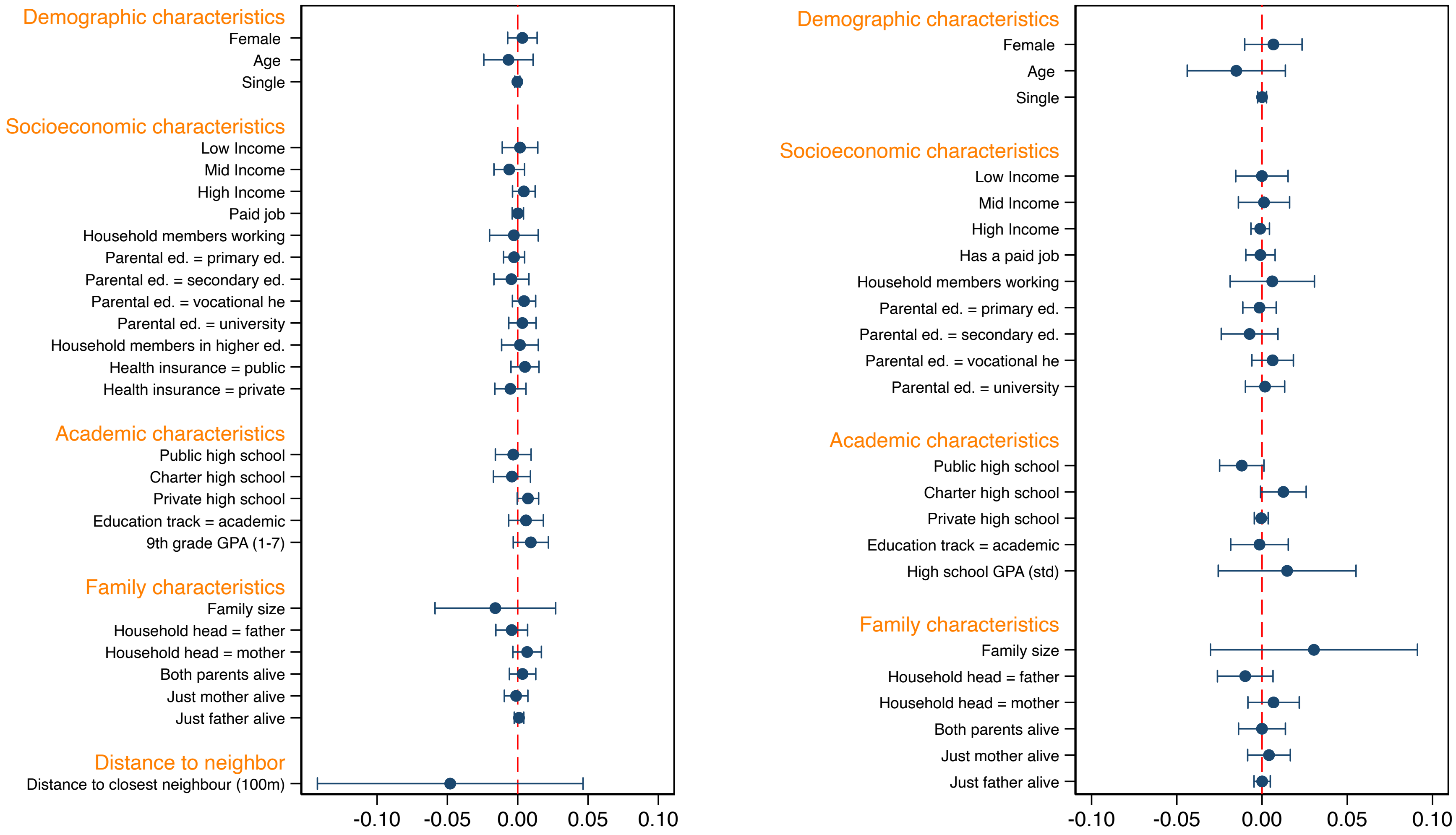
Notes: This figure illustrates the density of neighbors PSU scores around the student loans eligibility thresholds. The density and its confidence intervals on each side of the cutoff were estimated following Cattaneo et al. (2018). This chart complements the formal test they suggest to study discontinuities in the distribution of the running variable around the relevant threshold. In this case its $p-value$ is 0.7791. This means there is no statistical evidence to reject the null hypothesis of a smooth density around the threshold.

Figure C.II: Density of older siblings' PSU scores around the student loans eligibility threshold)



Notes: This figure illustrates the density of siblings PSU scores around the student loans eligibility thresholds. The density and its confidence intervals on each side of the cutoff were estimated following (Cattaneo et al., 2018). This chart complements the formal test they suggest to study discontinuities in the distribution of the running variable around the relevant threshold. In this case the test statistic is 0.4479 and the $p-value$ is 0.5968. This means there is no statistical evidence to reject the null hypothesis of a smooth density around the threshold.

Figure C.III: Discontinuities in potential confounders at the cutoff (neighbors)

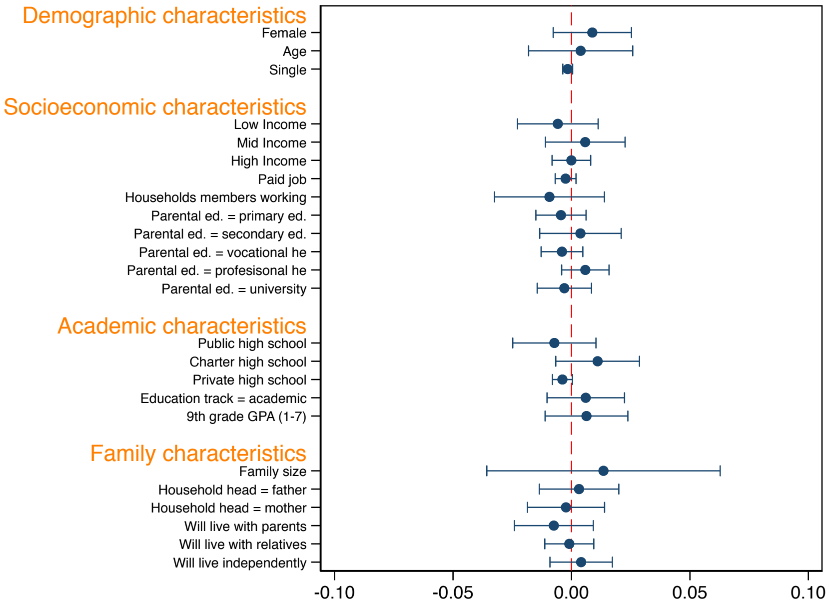


(a) Potential applicants

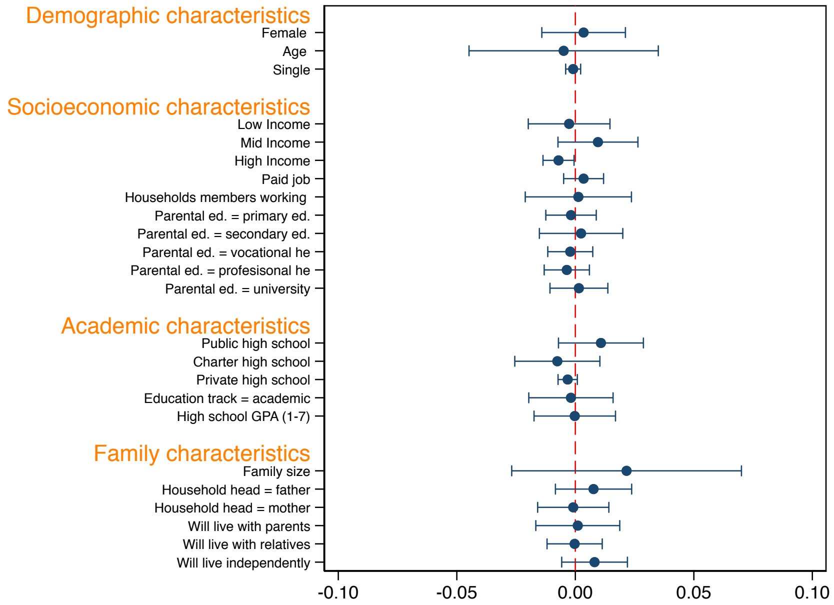
(b) Neighbors

Notes: This figure illustrates the coefficients obtained when studying discontinuities in other variables that could potentially affect the outcome of interest. The left panel presents the results for potential applicants, while the right panel for neighbors. Apart from the coefficients, the figures illustrate 95% confidence intervals. The dashed red line correspond to 0. The coefficients were obtained using optimal bandwidths that were computed following Calonico et al. (2014b).

Figure C.IV: Discontinuities in potential confounders at the cutoff (siblings)



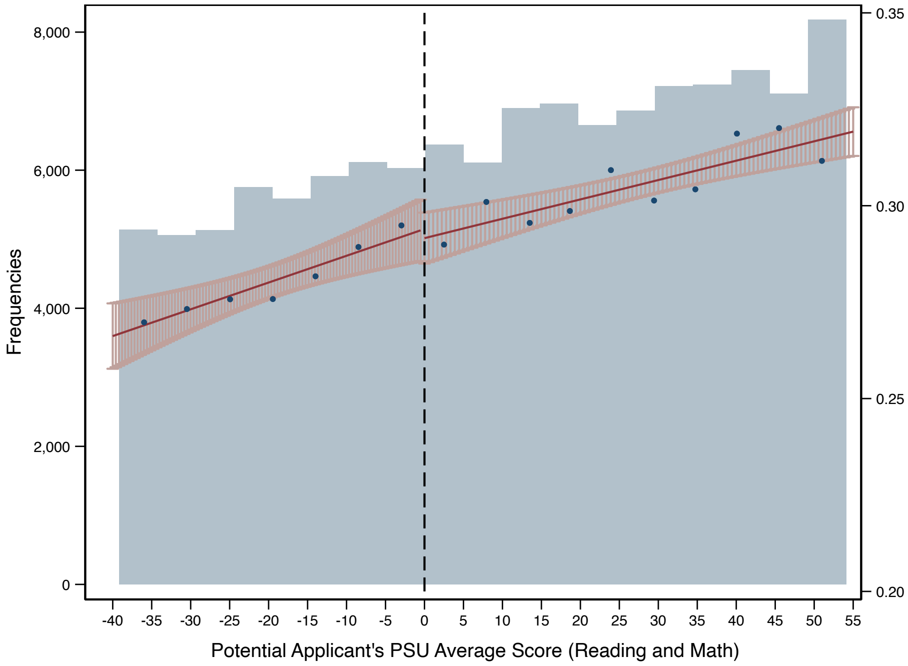
(a) Potential applicants



(b) Siblings

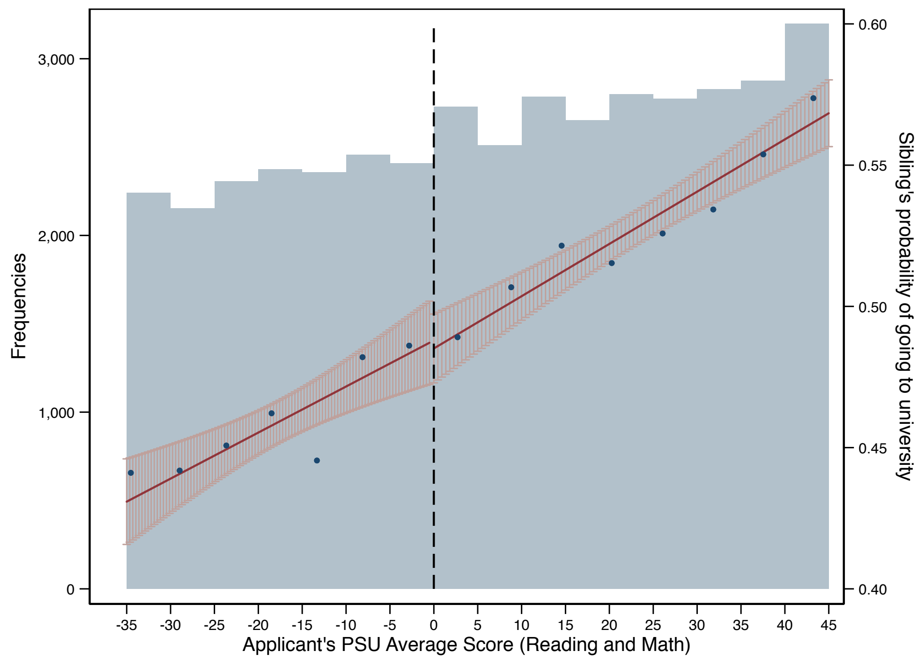
Notes: This figure illustrates the coefficients obtained when studying discontinuities in other variables that could potentially affect the outcome of interest. The left panel presents the results for potential applicants, while the right panel for siblings. Apart from the coefficients, the figures illustrate 95% confidence intervals. The dashed red line correspond to 0. The coefficients were obtained using optimal bandwidths that were computed following Calonico et al. (2014b).

Figure C.V: Placebo exercise: Effect of potential applicants (t) on neighbors (t-1)



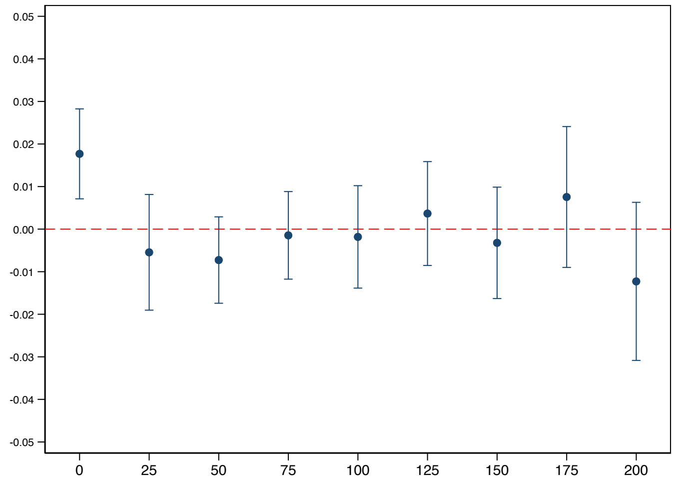
Notes: This figure illustrates the reduced form of a placebo exercise. It shows how neighbors' probability of going to university evolves with the PSU score of potential applicants. The PSU score is centered around the student-loans eligibility threshold. Each dot represents the share of neighbors going to university at different ranges of potential applicants PSU scores. The red lines correspond to linear approximations of these shares, and the shadow around them to 95% confidence intervals. The blue bars in the background illustrate the distribution of the potential applicants' scores in the PSU. The range used for these plots corresponds to optimal bandwidths that were computed following Calonico et al. (2014b).

Figure C.VI: Placebo exercise: Effect of potential applicants (t) on older siblings (t-T)

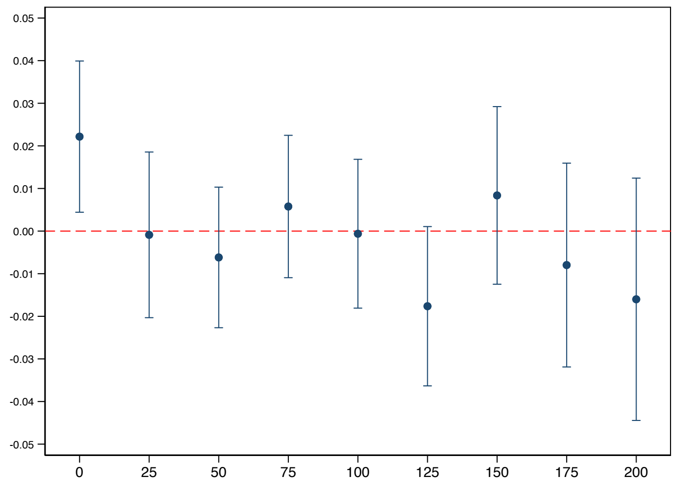


Notes: This figure illustrates the reduced form of a placebo exercise. It shows how siblings' probability of going to university evolves with the PSU score of potential applicants. The PSU score is centered around the student-loans eligibility threshold. Each dot represents the share of siblings going to university at different ranges of potential applicants PSU scores. The red lines correspond to linear approximations of these shares, and the shadow around them to 95% confidence intervals. The blue bars in the background illustrate the distribution of the potential applicants' scores in the PSU. The range used for these plots corresponds to optimal bandwidths that were computed following Calonico et al. (2014b).

Figure C.VII: Neighbors' and siblings' effects at placebo cutoffs



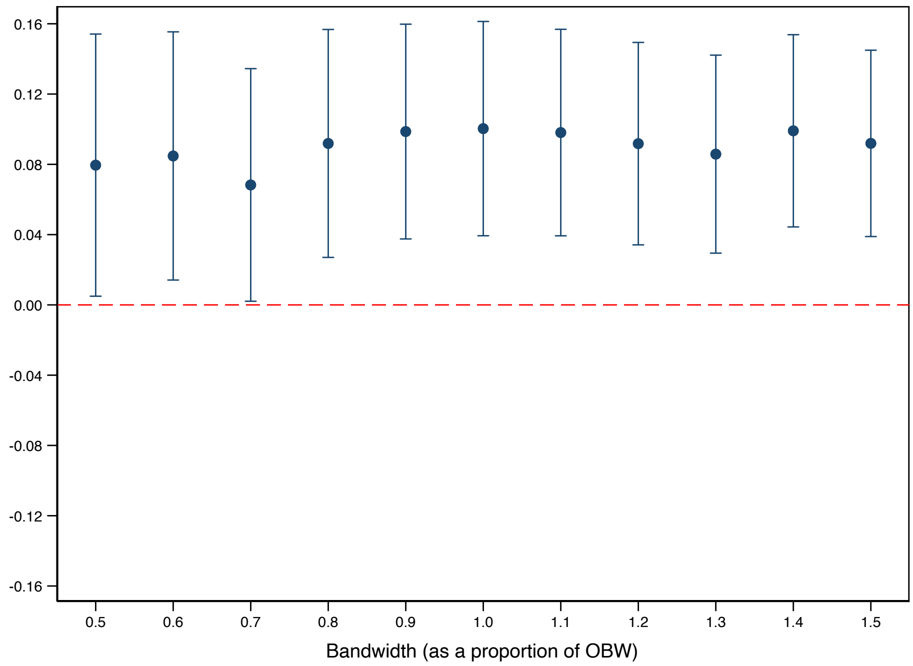
(a) Neighbors



(b) Siblings

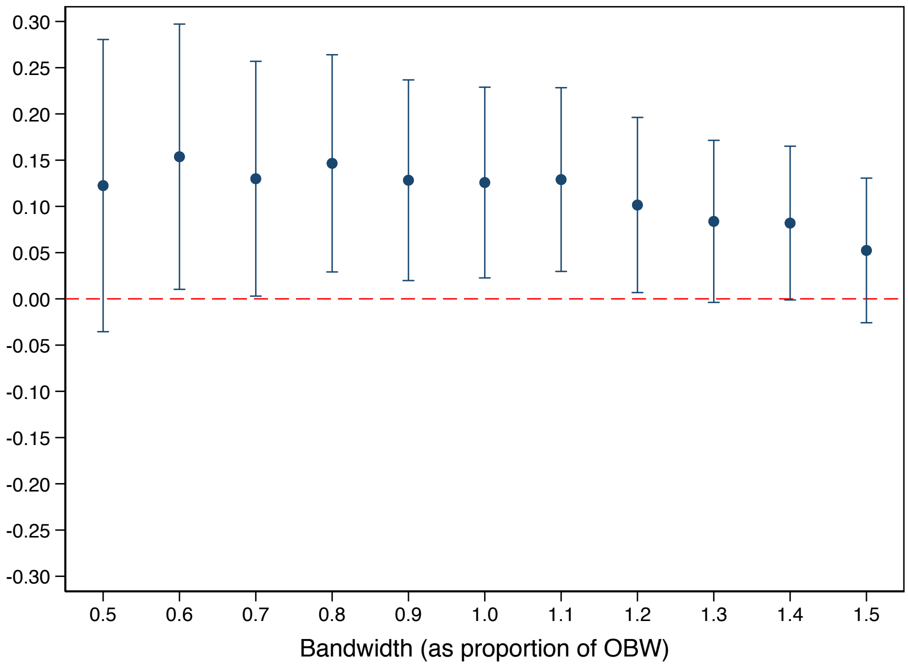
Notes: This figure illustrates the reduced form coefficients for the different cutoffs. The top panel illustrates the results for neighbors, and the panel at the bottom for siblings. Apart from the coefficients, the figures illustrate 95% confidence intervals. Standard errors are clustered at the neighborhood unit level.

Figure C.VIII: Neighbors' effects on potential applicants' university enrollment using different bandwidths



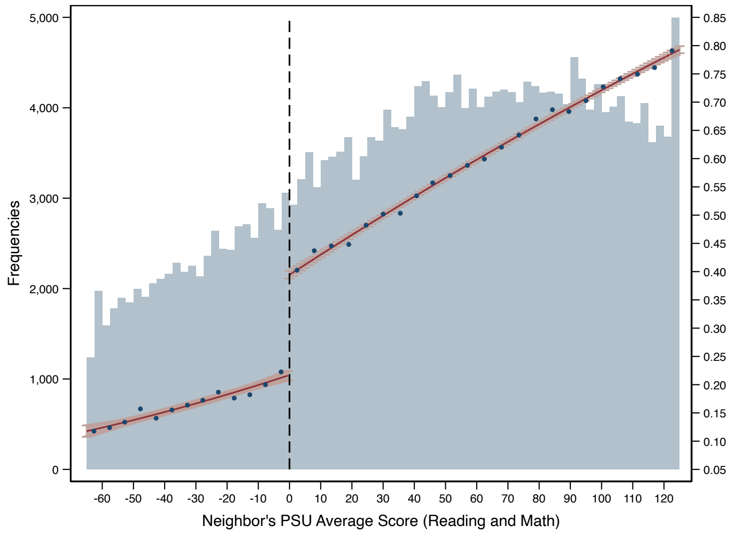
Notes: This figure illustrates the coefficients obtained when studying neighbors' effects using different bandwidths. The dots represent the coefficients, and the lines illustrate 95% confidence intervals.

Figure C.IX: Older siblings' effects on potential applicants' university enrollment using different bandwidths

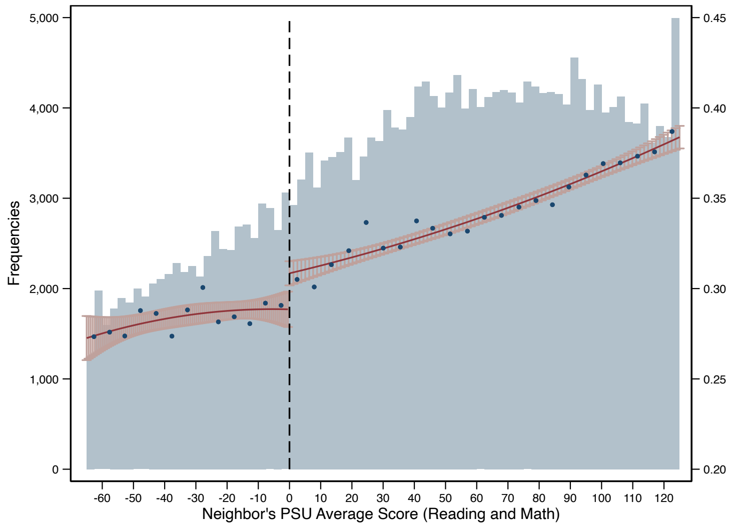


Notes: This figure illustrates the coefficients obtained when studying siblings' effects using different bandwidths. The dots represent the coefficients, and the lines illustrate 95% confidence intervals.

Figure C.X: Effect of neighbors' eligiblity for student loans on their own and on potential applicants' enrollment (second degree polynomial)



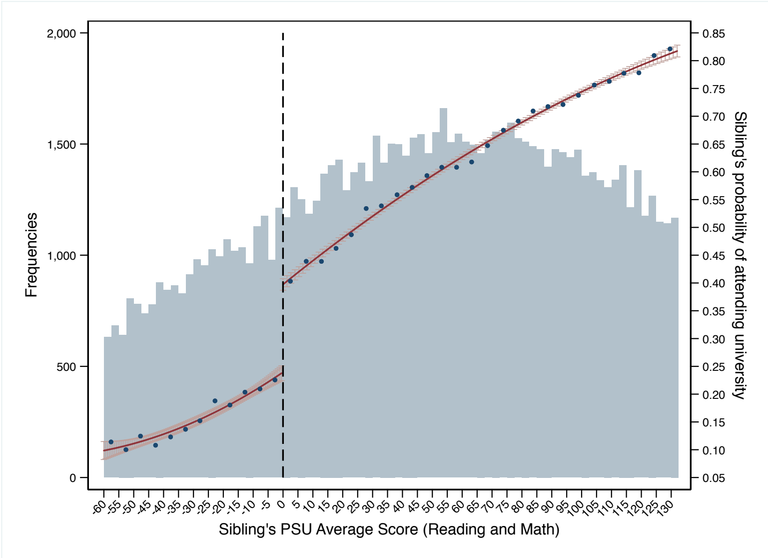
(a) First stage: Neighbors' own probability of going to univeristy



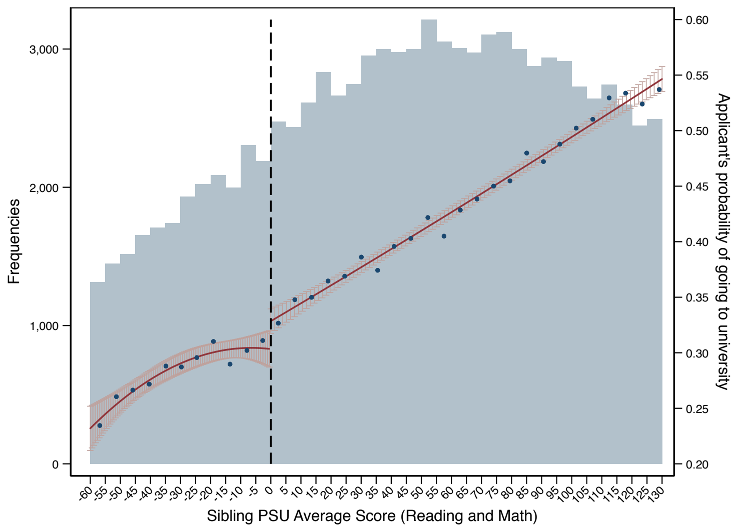
(b) Reduced form: Potential applicants' probability of going to university

Notes: This figure illustrates the first stage and reduced form of the 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 PSU scores. The red lines correspond to quadratic approximations of these shares, 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 that were computed following Calonico et al. (2014b).

Figure C.XI: Effect of older siblings' eligiblity for student loans on their own and on potential applicants' enrollment (second degree polynomial)



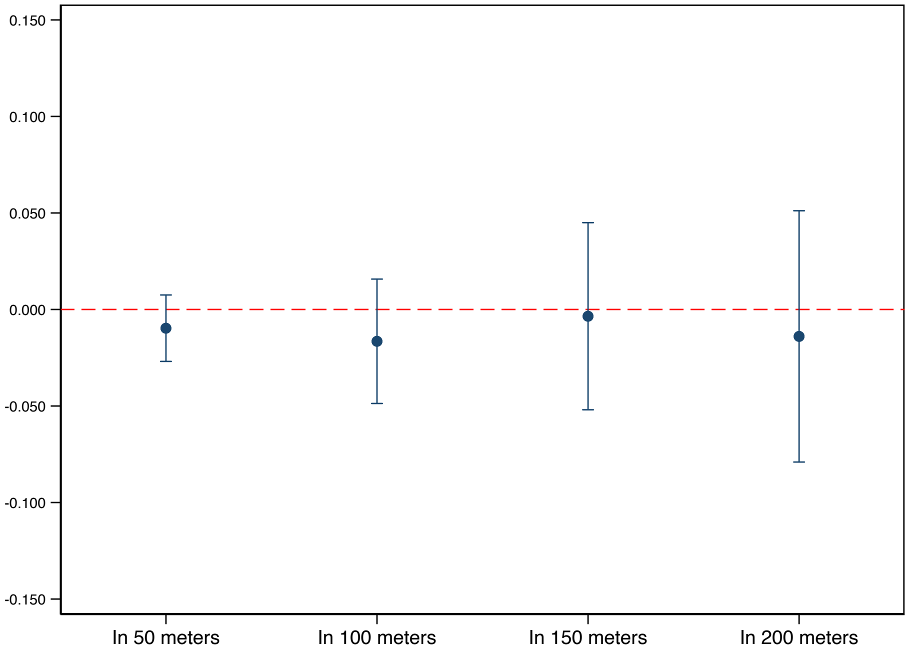
(a) First Stage: Siblings' Probability of going to Univeristy



(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 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 to quadratic approximations of these shares, and 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).

Figure C.XII: Effect of neighbor's eligibility for student loans on the number of potential applicants registered for the PSU in $t + 1$



Notes: This figure illustrates the effect of the closest neighbor eligibility for funding on the number of potential applicants registered for taking the PSU within 50m, 100m, 150m and 200m. The dots illustrate the coefficients and the bars 95% confidence intervals. Standard errors are clustered at the neighborhood unit level. Each coefficient was independently estimated and optimal bandwidths were computed following Calonico et al. (2014b).

Table C.I: Placebo effect of neighbors on potential applicants' outcomes (Neighbors not applying for student loans)

	Attends university (1)	Takes the PSU (2)	Applies for financial aid (3)	PSU score | Taking the PSU (4)	High school GPA (5)
Neighbor scores above student loans cutoff (t-1)	-0.003	0.004	0.003	0.039	0.002
	(0.006)	(0.004)	(0.006)	(1.316)	(0.008)
First Stage (neighbor enrolls in university)	0.007	0.007	0.007	0.007	0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N. of students	142311	142311	142311	129027	135354
PSU Polynomial	1	1	1	1	1
Bandwidth	(67.34-56.65)	(67.34-56.65)	(67.34-56.65)	(67.34-56.65)	(67.34-56.65)
Counterfactual mean	0.33	0.89	0.59	21.73	5.54

Notes: The table presents the estimated effects of neighbors scoring above the financial aid threshold on potential applicants' enrollment in university (column 1), probability of taking the PSU (column 2), probability of applying for financial aid (column 3), performance in the PSU (column 4), and performance in high school (column 5). The sample only includes older neighbors not applying for financial aid; thus, scoring above the student loans eligibility threshold does not change their enrollment status. All specifications include a linear polynomial of the PSU which slope is allowed to change at the cutoff. Optimal bandwidths are used in all the specifications. In parenthesis, standard errors clustered at neighborhood unit level.

Table C.II: Effects of close neighbors' eligibility for student loans on distance to the closest potential applicant registered for the PSU in $t + 1$

	Distance to closest potential applicant
Neighbor eligible for student loans	0.0015
	(0.002)
Running variable polynomial	Yes
Bandwidth	(46.75-76.39)
N. of students	73208
Outcome mean	0.099

Notes: The table presents results for a specification that studies how the distance to the closest potential applicant registered for the PSU changes at the cutoff. It controls for a linear polynomial of PSU which slope is allowed to change at the cutoff. Optimal bandwidths computed according to Calonico et al. (2014b) are used. In parenthesis, standard errors clustered at neighborhood unit level.

Table C.III: Effect of neighbors on potential applicants' university enrollment (Metropolitan Region of Santiago)

	2SLS-1 (1)	2SLS-2 (2)	CCT-1 (3)	CCT-2 (4)
Neighbor goes to university (t-1)	0.114	0.135	0.119	0.143
	(0.041)	(0.052)	(0.060)	(0.069)
First stage coefficient	0.160	0.154	0.161	0.161
	(0.010)	(0.013)	(0.013)	(0.017)
Reduced form coefficient	0.018	0.021		
	(0.006)	(0.008)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	97,104	174,469	97,104	174,469
PSU Polynomial	1	2	1	2
Bandwidth	(54.48-63.47)	(70.30-124.78)	(54.48-63.47)	(70.30-128.78)
Kleibergen-Paap F statistic	236.33	142.19		
Outcome mean	0.29	0.30	0.29	0.30

Notes: The table presents the results of analysis similar to those presented in table II but only focusing in the Metropolitan Region of Santiago. 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 neighborhood unit level.

Table C.IV: Effect of neighbors on potential applicants' university enrollment (Different clustering levels)

	Neighborhood Unit	Closest Neighbor	Potential Applicant's High School	Potential Applicant's Municipality
	(1)	(2)	(3)	(4)
Neighbor goes to university (t-1)	0.104	0.104	0.104	0.104
	(0.031)	(0.032)	(0.028)	(0.028)
Reduced form coefficient	0.019	0.019	0.019	0.019
	(0.005)	(0.006)	(0.005)	(0.005)
First stage coefficient	0.178	0.178	0.178	0.178
	(0.009)	(0.009)	(0.009)	(0.009)
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	97,104	174,469	97,104	174,469
PSU Polynomial	1	1	1	1
Bandwidth	(49.14-64.35)	(49.14-64.35)	(49.14-64.35)	(49.14-64.35)
Kleibergen-Paap F statistic	449.63	396.47	1077.31	426.04
Outcome mean	0.31	0.31	0.31	0.31

Notes: The table presents the results of analysis similar to those presented in table II but using different statistic inference approaches. Columns 1 replicates the main results and clusters at the neighborhood unit level, column 2 clusters at the closest neighbor level, column 3 at the potential applicant's high school level, and column 4 at the potential applicant's municipality level.

D Discontinuities at the Scholarships Eligibility Threshold

The main results of the paper exploit variation generated by eligibility for student loans. As explained in Section 2, to be eligible for a student loan individuals need an average score of 475 or more in the PSU (average between reading and math). Apart from student loans, the government offers a variety of scholarships. Eligibility for most of them depends on an eligibility rule similar to the one used for student loans. The main difference is that the cutoff that determines eligibility for scholarships is higher (i.e., 550).[31] This means that individuals marginally missing the scholarships cutoff are still eligible for student loans. Thus, crossing the scholarships cutoff changes the generosity of the subsidy for which individuals are eligible, but not their overall eligibility for government funding.

Since Chilean universities have complete freedom to define their tuition fees, the government sets a reference tuition fee for each program and institution that defines the maximum amount of funding that a student can receive from the government.[32] At the university level, the reference tuition fee covers around 80% of the actual fee. This means that students need to cover the additional 20% using their own resources, by taking a private loan, or by applying to scholarships offered at their higher education institutions if available.

In this section, I first study how crossing the scholarship eligibility threshold affects older neighbors' and older siblings' own outcomes. Then, as in the main body of the paper, I study whether it affects potential university applicants as well.

Figure D.I illustrates reduced form results for neighbors. Panel (a) indicates that neighbors eligible for a scholarship rely significantly less in student loans to fund their university studies. Some of them still use student loans, but since part of their funding is a scholarship, they are likely to accumulate a smaller debt. However, as shown in Panel (b) this change in the generosity and structure of the funding does not affect neighbors' own enrollment in university. This result is not surprising. If the expected returns to university studies accounting for the costs of student loans are positive, then crossing the scholarships eligibility threshold should not affect enrollment. Panels (c) and (d) focus instead on potential applicants' outcomes. They show that having an older neighbor marginally eligible for a scholarship does not affect potential applicants' probability of applying for financial aid or of attending university. This finding is consistent with the idea that learning about funding opportunities alone does not change enrollment.

[31] There are also a few programs that instead of requiring a minimum score in the PSU, allocate funding based on high school performance. These programs are relatively small, both in terms of beneficiaries and of the support they offer.

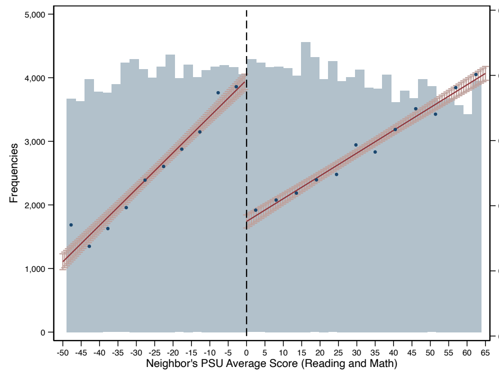
[32] The only exception to this rule is given by the CAE. In this case, students can still receive at most an amount equal to the reference tuition fee through the CAE loan, but they can use it to complement scholarships or the FSCU loan, up to the actual tuition fee.

Figure D.II replicates these results, but this time focusing on siblings. Panel (a) of Figure D.II shows that older siblings eligible for a scholarship are less likely to use a student loan to pay for their studies. Despite the change they experience in the generosity and structure of the funding, crossing the scholarships threshold does not make them more likely to enroll in university (Panel (b)). When focusing on the outcomes of potential university applicants (i.e., younger siblings), I find that having an older sibling eligible for a scholarship does not affect potential university applicants' applications for funding or enrollment at university (See Panels (c) and (d)). This seems to suggest that learning about funding opportunities alone does not change enrollment decisions of younger siblings.

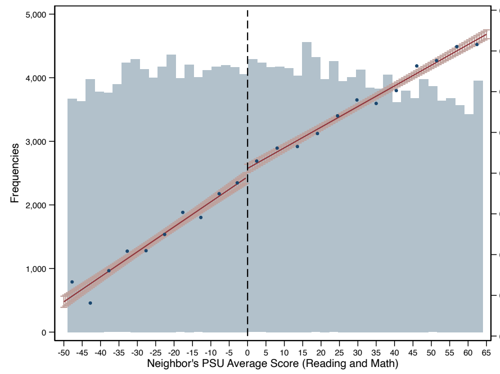
To further explore the role of funding on the effects documented in the main body of the paper, I present next an analysis studying how the responses vary depending on potential applicants' eligibility for student loans. Considering that that student loan eligibility is a potential outcome of the treatment this exercise has some problems, but it is still useful to shed some light about the drivers of the effect. An additional consideration worth having in mind is that the loan eligibility cutoff is quite low—i.e., percentile 40 of the PSU distribution—and therefore the number of students with scores below this cutoff that are admitted into university quickly decreases. With these caveats in mind, in Table D.I I present the results of an exercise that focus on potential applicants scoring below 0, -10, -20, -30, -40 and -50 (i.e., non-eligible for university funding). The last figure corresponds to the percentile 24 of the PSU distribution.

According to these results even potential applicants who are not eligible for funding are affected by having a neighbor going to university with funding. The effect decreases along columns, but this is not surprising. When we move from columns (1) to (6) we leave out of the sample students close to the percentile 40 of the PSU distribution and we give more importance to students in lower percentiles. Since PSU scores affects university admissions, it is natural to observe that the effects decrease. The fact that even the coefficients in the first columns are smaller than the ones obtained using the full sample is not surprising. First, the restrictions I applied leave out of the sample candidates that are more attractive for universities. Second, universities in Chile are relatively expensive. This means that many individuals need support from government in order to enroll. By focusing on individuals who are not eligible for government funding, we are focusing on a group of students for whom it is more difficult to enroll even if they want to. Even for individuals in this group I find large effects, especially if we consider that the baseline probability of attending university for them is much lower than in the whole sample.

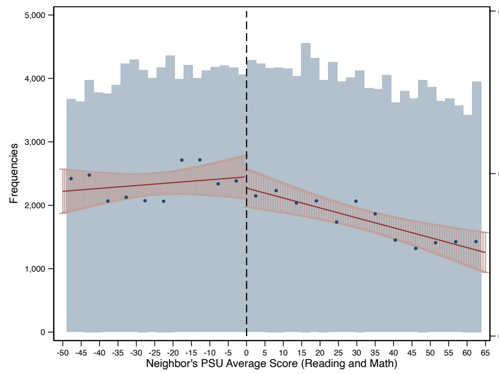
Figure D.I: Changes in neighbor's and applicant's outcomes at the scholarships eligibility cutoff



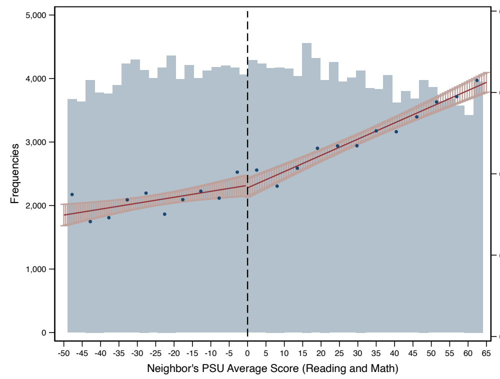
(a) Pr. of using a student loan (n)



(b) Pr. of going to university (n)



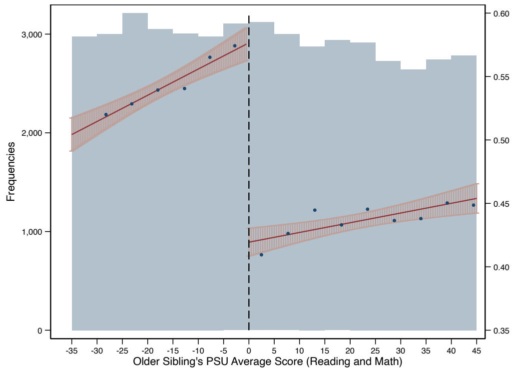
(c) Pr. of applying for financial aid (a)



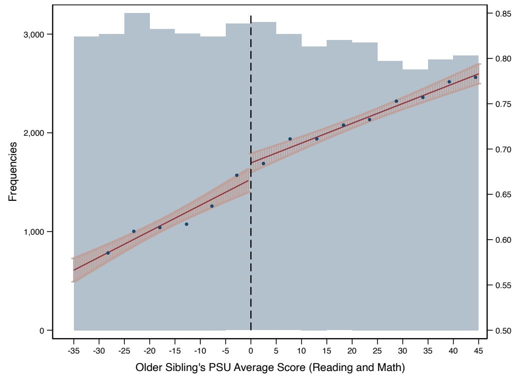
(d) Pr. of going to university (a)

This figure illustrates how neighbor's (n) and potential applicant's (a) outcomes change around the cutoff that defines eligibility for the largest scholarship programs in Chile. This cutoff is higher than the one defining eligibility for student loans, what means that individuals below the scholarship cutoff still qualify for other sources of funding. Panel (a) illustrates the drop in the share of neighbors funding their university studies with student loans at the scholarship threshold, while Panel (b) shows that neighbor's enrollment remains unchanged. Panel (c) illustrates how potential applicants' probability of applying for funding changes when a close neighbor qualify for a scholarship and Panel (d) does something similar but focusing on potential applicants' enrollment probability. Red lines and the shadows in the back of them represent linear polynomials and 95% confidence intervals. Blue dots represent sample means of the dependent variable at different values of neighbors' average score in the PSU.

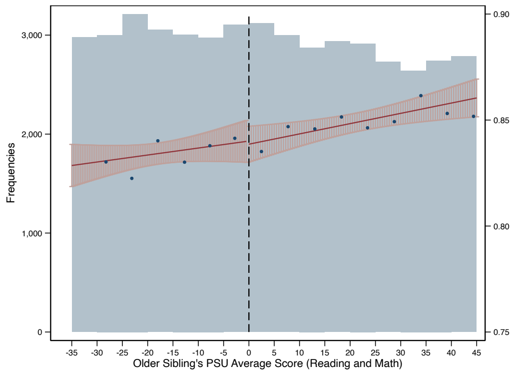
Figure D.II: Changes in older sibling's and applicant's outcomes at the scholarships eligibility cutoff



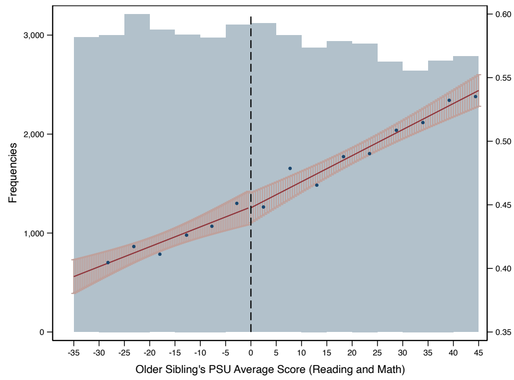
(a) Pr. of using a student loan (o)



(b) Pr. of going to university (o)



(c) Pr. of applying for financial aid (y)



(d) Pr. of going to university (y)

This figure illustrates how older (o) and younger (y) siblings' outcomes change around the cutoff that defines eligibility for the largest scholarship programs in Chile. This cutoff is higher than the one defining eligibility for student loans, what means that individuals below the scholarship cutoff still qualify for other sources of funding. Panel (a) illustrates the drop in the share of older siblings funding their university studies with student loans at the scholarship threshold, while Panel (b) shows that older siblings' enrollment remains unchanged. Panel (c) illustrates how younger siblings' probability of applying for funding changes when their older sibling qualifies for a scholarship, and Panel (d) does something similar but focusing on younger siblings' enrollment probability. Red lines and the shadows in the back of them represent linear polynomials and 95% confidence intervals. Blue dots represent sample means of the dependent variable at different values of older siblings' average score in the PSU.

Table D.I: Neighbor Effects on University Enrollment for Potential Applicants Non-Eligible for Funding

	Potential Applicant's Score					
	< 0	< -10	< -20	< -30	< -40	< -50
	(1)	(2)	(3)	(4)	(5)	(6)
Closest neighbor enrolls in university (t-1)	0.046	0.046	0.041	0.050	0.032	0.015
	(0.022)	(0.022)	(0.023)	(0.024)	(0.023)	(0.022)
Closest neighbor is eligible for funding (t-1)	0.008	0.008	0.007	0.008	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
First stage	0.181	0.180	0.176	0.167	0.166	0.171
	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Observations	65,444	60,376	50,512	51,609	48,829	46,040
Kleibergen-Paap Wald F-Statistic	316.75	274.35	223.01	204.08	213.80	227.63
Outcome mean	0.07	0.06	0.06	0.05	0.05	0.04

Notes: The table presents the estimated effects of neighbors on potential applicants' university enrollment. All specifications contro for a linear polynomial of the running variable which slope is allowed to change at the cutoff. Optimal bandwidths computed according to Calonico et al. (2014b) are used in all the specifications. In parenthesis, standard errors clustered at neighborhood unit level.

E Urban Segregation and Inequality in University Enrollment

As discussed in Section 2, access to university is very unequal in Chile. Given the high levels of urban segregation in the country, this also translates into spatial inequality. The map in Figure E.I illustrates this for Santiago, Chile's capital city. Figures E.II and E.III present similar maps for Valparaíso and Concepción, the two major cities of the other regions studied in the paper.

Since I do not have a formal definition of neighborhood, in order to create these areas I use a k-cluster algorithm to classify individuals according to their geographic coordinates in 1150 clusters (i.e., an average of 10 neighborhoods per each municipality). Then, using university attendance rates of individuals that could have gone to university before the first cohort of potential university applicants in my sample, I classify these areas in three groups.[33] The red areas in the maps correspond to neighborhoods where on average 33.0% of potential applicants go to university, yellow areas to neighborhoods where on average 52.2% of individuals go to university, and green areas to neighborhoods where more than 72% of potential applicants go to university.

The results discussed in the main body of the paper indicate that programs that expand access to university generate indirect effects on the close peers of the direct beneficiaries. The estimates obtained when looking at potential applicants and their closest neighbor indicate that the indirect effects of student loans represent a little more than 10% of their direct effect. In order to estimate the full extent of these indirect effects, we would need to investigate whether they also emerge among other peers[34] In addition, we would need to consider that potential applicants who enroll in university as a consequence of these indirect effect could also affect university enrollment of other individuals in the future. Although, the results presented in Section G suggest that at least in the case of neighbors, these effects quickly decay with time.

So far, the analyses have assumed that direct and indirect effects are constant across different areas. However, they may change depending on the level of exposure to individuals going to university. To investigate this in greater detail, I estimate the direct and indirect effect of student loans independently for low, mid and high exposure neighborhoods.

Figure E.IV presents the results of this exercise. The top panel shows the first stage estimates, the middle panel the reduced form estimates, and the bottom panel the results obtained when combining them to obtain 2SLS estimates. Under the assumptions discussed in Section 4, these last estimates capture the effects of neighbors' enrollment

[33] The cohorts used to build the measures of attendance are not included in the main analyses of the paper because these old cohorts did not have the main loan program available. Thus, I do not have exogenous variation on their university enrollment.

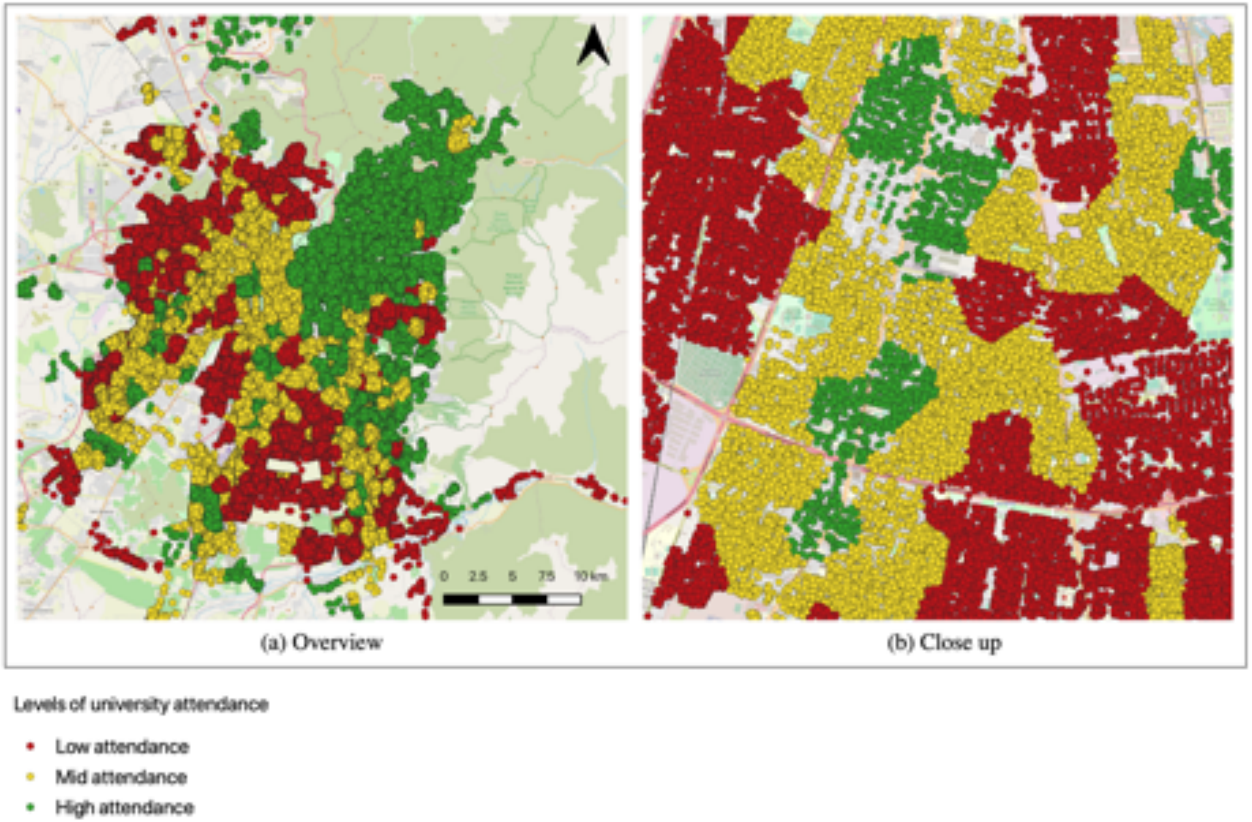
[34] According to the results discussed in Section 5.2, in the context of neighbors these spillover seem to be very local. Section 6.1 shows that similar indirect effects arise between siblings.

on potential applicants' enrollment.

The pattern illustrated in this figure shows that the direct effect (i.e., the share of individuals who take up student loans and go to university) does not change much across the three types of neighborhoods. However, the reduced form results and the 2SLS estimates seem stronger in low and mid attendance areas. Indeed, in high attendance areas these coefficients are small and not statistically different from 0.

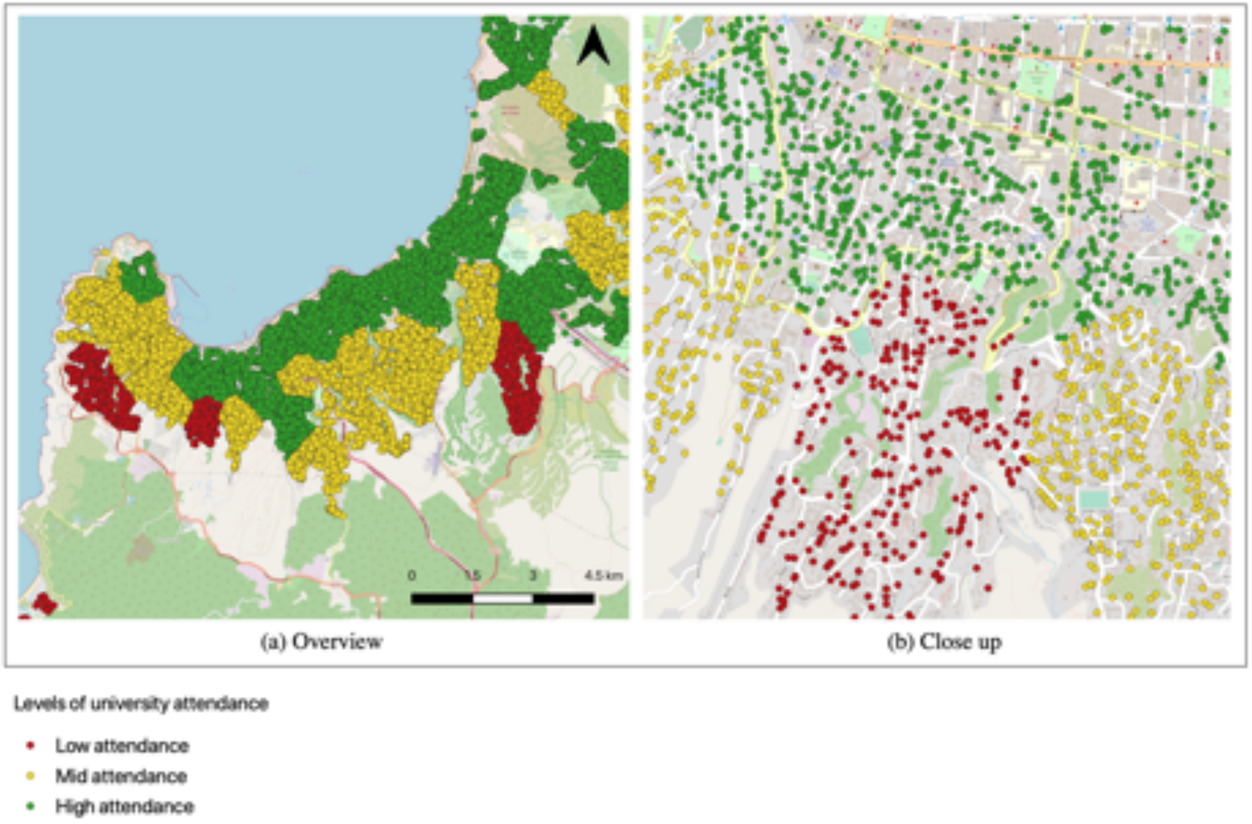
Although the standard errors of these estimates do not allow me to conclude that they are statistically different, these results show that indirect effects are relevant in low and mid attendance areas. This suggests that in areas where university attendance is relatively low, policies expanding university access would not only affect their direct beneficiaries, but also other individuals living close to them.

Figure E.I: University attendance across neighborhoods in Santiago



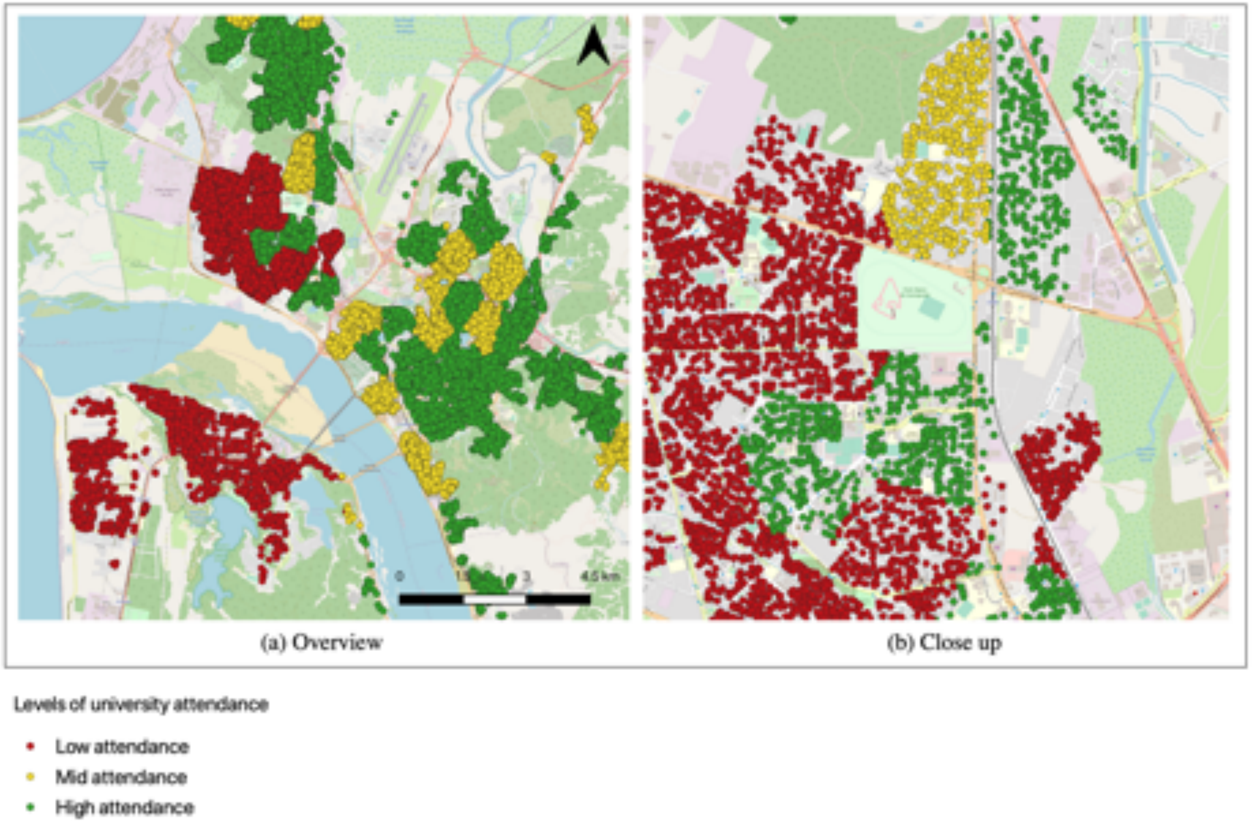
Notes: The figure illustrates potential applicants from Santiago and classifies them in three groups according to the share of individuals from their neighborhood going to university before the first cohort of potential applicants that I observe in my sample. The figure in the left presents an overview of the whole city, while the figure in the right zooms in around a specific area. In red neighborhoods average university attendance is 33.0%, in yellow neighborhoods 52.2% and in green neighborhoods 72.2.1%. Neighborhoods were defined using a k-cluster alorithm that grouped individuals according to the geographic coordinates of their household addresses in 1,150 clusters (i.e., on average 10 per municipality in the sample)

Figure E.II: University attendance across neighborhoods in Valparaíso and Viña del Mar



Notes: The figure illustrates potential applicants from Valparaíso and Viña del Mar and classifies them in three groups according to the share of individuals from their neighborhood going to university before the first cohort of potential applicants that I observe in my sample. The figure in the left presents an overview of the whole city, while the figure in the right zooms in around a specific area. In red neighborhoods average university attendance is 33.0%, in yellow neighborhoods 52.2% and in green neighborhoods 72.2.1%. Neighborhoods were defined using a k-cluster alorithm that grouped individuals according to the geographic coordinates of their household addresses in 1,150 clusters (i.e., on average 10 per municipality in the sample)

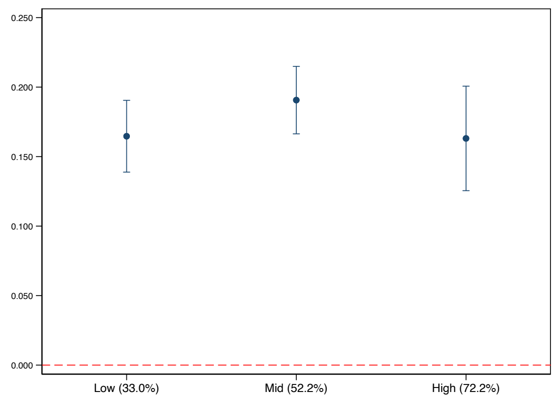
Figure E.III: University attendance across neighborhoods in Concepción and Talcahuano



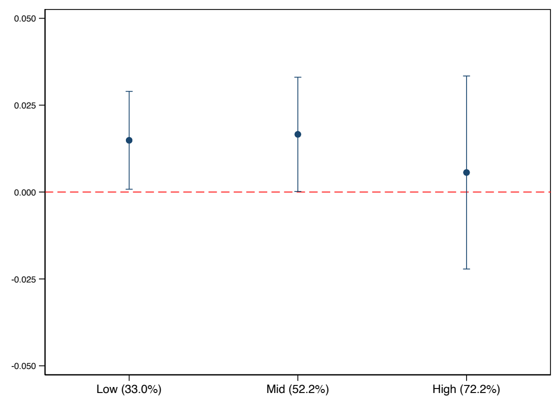
(a) Overview (b) Close up

Notes: The figure illustrates potential applicants from Concepción and Talcahuano and classifies them in three groups according to the share of individuals from their neighborhood going to university before the first cohort of potential applicants that I observe in my sample. The figure in the left presents an overview of the whole city, while the figure in the right zooms in around a specific area. In red neighborhoods average university attendance is 33.0%, in yellow neighborhoods 52.2% and in green neighborhoods 72.2.1%. Neighborhoods were defined using a k-cluster alorithm that grouped individuals according to the geographic coordinates of their household addresses in 1,150 clusters (i.e., on average 10 per municipality in the sample)

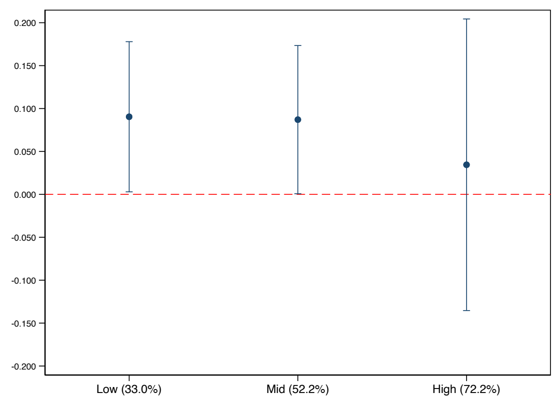
Figure E.IV: Neighbors' effects on potential applicants university enrollment by attendance level in the neighborhood



(a) First Stage



(b) Reduced Form



(c) 2SLS Estimates

Notes: The figure illustrates how neighbors' effects evolve depending on the level of university attendance of the neighborhood of potential applicants before they decide whether or not to apply. The dots represent coefficients from three different samples: low, mid and high attendance neighborhood. The lines represent 95% confidence intervals. The specification used for this exercise controls for a linear polynomial of the running variable which slope is allowed to change at the cutoff. The bandwidth correspond to optimal bandwidths computed according to Calonico et al. (2014b) for the whole sample. Standard errors are clustered at the neighborhood unit level.

F Other Heterogeneity Analyses

This section extends the heterogeneity analyses presented in the paper.

First, I study if the effects differ by potential applicants' household income, high school track, and gender. The table also looks at heterogeneous effects depending on the difference in academic potential between potential applicants and their closest neighbors. The difference in academic potential is computed using GPA in grade 9.[35] According to the results in Table F.I, potential university applicants from households with very low monthly incomes are less responsive than those coming from middle income households. Indeed, potential university applicants from households with monthly incomes between CLP 270,000 and CLP 834,000 seem to be the ones driving the effects.[36]. There are not many potential applicants from the top income category in my estimation sample, which results in very imprecise estimates for this category. Potential applicants in the vocational track of high school seem less responsive than those in the academic track. This suggests that potential applicants who are better prepared for the PSU and for university in general are more likely to successfully respond. There are no major differences by gender, and when looking at academic potential the effects seem slightly larger when potential applicants perform better than the neighbors in high school.

Second, I expand the analyses of heterogeneity by potential applicants' and neighbors' gender. According to the results in Table F.II, independently of their gender, potential university applicants seem to be more responsive to male than to female neighbors. This difference is more clear for male potential university applicants, who are 10 pp more likely to follow a male than a female neighbor. The difference for female potential applicants is smaller (i.e., 3 pp) and not statistically significant.

I conclude this section by studying whether the influence of older siblings on potential applicants depends on the age difference between siblings. To study this I split the sample in to groups of similar size. The first one includes siblings who were born no more than four years apart, while the second includes siblings who were born between four and twelve years apart. Table F.III indicates that the effects are very similar for both groups of siblings. If anything, the effect seems larger for siblings with larger age differences. This is the group of siblings less likely to attend university at the same time.

35 I do not use the GPA in grade 12 because it could be affected by learning that a close neighbor enrolls in university. Students' grades in high school depend on their teachers and on grade policies within establishments. Considering that only 6% of potential applicants attend their closest neighbor's high school, their GPA are not directly comparable. Unfortunately, I do not observe any standardized measure of ability that could be used in this exercise.

36 This income range is equivalent to around USD 280 to USD 1170 in 2015

Table F.I: Heterogeneity in the effects of closest neighbor on potential applicants' university enrollment

	Household income			High school track		Gender		Difference in academic ability	
	$\leq$ CLP 270K	CLP 270K - CLP 834K	$>$ CLP 834K	Academic	Vocational	Male	Female	≥ 0	< 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Neighbor goes to university (t-1)	0.051	0.234	-0.050	0.108	0.067	0.100	0.109	0.117	0.083
	(0.030)	(0.061)	(0.148)	(0.044)	(0.030)	(0.040)	(0.043)	(0.047)	(0.034)
Reduced form	0.010	0.037	-0.007	0.019	0.012	0.018	0.020	0.020	0.016
	(0.006)	(0.009)	(0.021)	(0.008)	(0.005)	(0.007)	(0.008)	(0.008)	(0.006)
First stage	0.192	0.160	0.142	0.179	0.176	0.175	0.181	0.169	0.188
	(0.009)	(0.011)	(0.030)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
N. of potential applicants	84689	48512	11507	86445	58279	77385	67339	74347	70377
Kleibergen-Paap F statistic	422.13	203.06	21.73	325.32	260.81	331.00	343.61	251.97	312.32
Outcome mean	0.22	0.39	0.67	0.45	0.12	0.31	0.32	0.43	0.19

Notes: The table presents the estimated effects of neighbors on potential applicants' university enrollment depending on socioeconomic, academic and demographic variables. Columns 1 to 3 study how the effect of neighbors and siblings on potential applicants change depending on the household income of potential applicants. Columns 4 and 5 do the same, but distinguishing by the high school track followed by potential applicants. Columns 6 and 7 look at heterogeneous effects by gender. Finally, columns 8 and 9 look at heterogenous effects depending on the difference in grade 9 gpa between potential applicants and their closest neighbor. All specifications include years fixed effects and a linear polynomial of the closest neighbor or sibling PSU score which slope is allowed to change at the cutoff. Optimal bandwidths computed according to Calonico et al. (2014b) for the main specification presented in table II are used. In parenthesis, standard errors clustered at neighborhood unit level.

Table F.II: Effects of close neighbors on potential applicants' university enrollment by gender

	Older Neighbor: Female		Older Neighbor: Male	
	Potential Applicant:		Potential Applicant	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Neighbor goes to university (t-1)	0.091	0.077	0.121	0.171
	(0.045)	(0.049)	(0.088)	(0.082)
Reduced form	0.018	0.015	0.016	0.027
	(0.009)	(0.010)	(0.011)	(0.013)
First Stage	0.201	0.198	0.131	0.155
	(0.013)	(0.013)	(0.015)	(0.016)
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	45942	39741	31443	27598
Bandwidth	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)
Kleibergen-Paap F statistic	244.16	244.99	71.75	100.01
Outcome mean	0.31	0.32	0.31	0.32

Notes: The table presents results for specifications that study the effect of close neighbors on potential applicants' university enrollment depending on gender. All specifications include a linear polynomial of PSU which slope is allowed to differ at both sides of the cutoff. Optimal bandwidths are the same used in table II. In parenthesis, standard errors clustered at neighborhood unit level.

Table F.III: Effects of older siblings on potential applicants' university enrollment by age difference

	Age Difference < 5 (1)	Age Difference ≥ 5 (2)
Older sibling goes to university (t-1)	0.114	0.136
	(0.070)	(0.067)
Reduced form	0.018	0.025
	(0.012)	(0.013)
First Stage	0.157	0.181
	(0.012)	(0.012)
Year fixed effects	Yes	Yes
N. of students	28615	29098
Bandwidth	(37.0-74.5)	(37.0-74.5)
Kleibergen-Paap F statistic	175.47	220.43
Outcome mean	0.36	0.38

Notes: The table presents results for specifications that study the effect of older siblings on potential applicants' university enrollment depending on age difference. All specifications include a linear polynomial of the older sibling's PSU which slope is allowed to change at the cutoff. Bandwidths are the same used in table VII. In parenthesis, standard errors clustered at family level.

G Other Neighbors Definitions

The results discussed in Section 5 focus on the closest neighbor applying to university one year before the potential university applicant. However, there could be other neighbors also affecting potential university applicants' decisions. Here, I expand the results discussed in the paper by looking at the effects of close neighbors applying to university two or more years before, the year before, the same year, one year after, and two or more years after the potential applicant. Figure G.I summarizes these results. As expected, college applications in the future do not affect choices today ($T+1, \geq T+2$). Given the nature of the exploited variation, not finding contemporaneous effects is not surprising either ($T+0$). The shock on the neighbor's education trajectory takes place at a point in the academic year in which the potential applicants have limited ability to respond. When the shock affecting the neighbor takes place one year before the potential applicant could apply, the effects are large and significant ($T+1$). However, they decline and become non-significant when looking at neighbors applying two or more years before. This suggests that age plays a particularly important role in social interactions among young neighbors, but it could also indicate that individuals only pay attention to this type of shocks when they are very close to deciding whether or not to enroll in college.[37]

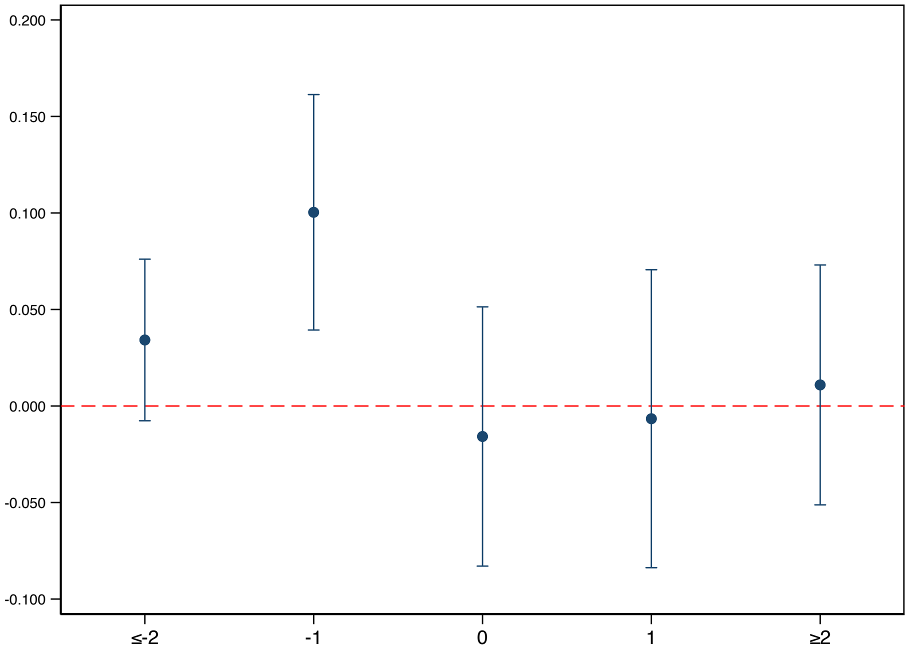
I further investigate how the effects evolve depending on the different definitions of close neighbors. The main specification in the paper focuses on the closest one. Here I look at the effect of the best neighbor applying to university in $T-1$ within different radius (i.e., best within 100m, 125m, 150m, 175m, 200m). The best neighbor is defined as the one for whom the running variable (i.e. average PSU score) takes the highest value.

When implementing these exercises, the sample size decreases with the size of the group being analyzed. The student loans cutoff is relatively low (percentile 40 in the PSU distribution); making it more difficult to find individuals that are at the same time the best of a group and close enough to the cutoff. This not only affects the precision of the estimates, but also the composition of the sample used to estimate the effects of interest.

The characteristics of areas where the best neighbor within 100m is close enough to the cutoff could be different from those where the best neighbor within 200m is close to the cutoff. By expanding the radius, the average distance to the neighbor also changes. However, since the composition of the sample is also changing, these results do not tell us much about how neighbors effects evolve with distance. Table G.I presents the results of these analysis. I find effects similar—if anything slightly larger—than the ones documented in the main body of the paper.

[37] Each coefficient comes from an independent sample focusing on potential university applicants and their closest neighbors applying to college in $T \leq -2, T-1, T, T+1, T \geq T+2$. Since for neighbors I only observe applications and enrollment in university between 2006 and 2012, I use a different group of cohorts in each specification.

Figure G.I: Neighbors' effects on potential applicants university enrollment by differences in the application year



Notes: This figure illustrates the effect of the closest neighbor applying to university between two years before and two years after the potential applicant. The dots represent 2SLS coefficients and the bars 95% confidence intervals. As in the rest of the paper standard errors are clustered at the neighborhood unit level. Each coefficient was independently estimated and optimal bandwidths were computed following Calonico et al. (2014b).

Table G.I: Effects of other close neighbors on potential applicants' university enrollment

	Best neighbor within:				
	100m	125m	150m	175m	200m
	(1)	(2)	(3)	(4)	(5)
Neighbor goes to university (t-1)	0.136	0.172	0.125	0.135	0.106
	(0.053)	(0.054)	(0.058)	(0.066)	(0.073)
Reduced form	0.023	0.033	0.026	0.028	0.023
	(0.009)	(0.010)	(0.012)	(0.014)	(0.016)
First Stage	0.173	0.189	0.205	0.210	0.218
	(0.012)	(0.014)	(0.016)	(0.018)	(0.021)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N. of students	64504	56905	47367	38695	31543
Bandwidth	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)	(49.09-64.35)
Kleibergen-Paap F statistic	204.19	190.46	169.83	128.98	108.88
Outcome mean	0.30	0.30	0.31	0.32	0.32

Notes: The table presents results for specifications that study the effect of other close neighbors on potential applicants' university enrollment. Column 1 looks at the effect of the best neighbor within 100m, column 2 at the best within 125m, column 3 at the best within 150m, column 4 at the best within 175m and column 5 at the best within 200m. All specifications include a linear polynomial of PSU which slope is allowed to differ at both sides of the cutoff. Bandwidths are the same used in table II. In parenthesis, standard errors clustered at neighborhood unit level.

H Older Siblings' Expenditure in Higher Education

This section investigates how the household budget constraint is affected when an older sibling becomes eligible for a student loan. As discussed in Section 2, in Chile universities set their own tuition fees. To control public expenditure the Ministry of Education sets a reference tuition fee that limits the maximum amount of funding that an individual can receive from government. This reference tuition fee is specific to each college and program, and at university level represents roughly an 80% of the actual tuition fees. Thus, even if an individual is eligible for financial aid, families typically have to finance a share of the tuition fees, in addition to study materials, and commuting and living expenses.

Unfortunately, I do not have information on all these costs. I do observe, however, reference and actual tuition fees from 2008 onward. I also observe an additional fee that some institutions charge to their students when they enroll in first year. By combining this information with the registers on funding recipients and higher education enrollment I can study how expenditure in tuition fees changes at the student loan eligibility cutoff. For this analysis, I focus on older siblings who appear in the main estimation sample and apply to higher education after 2007. If they do not enroll in higher education, I assume their expenditure in tuition fees is 0.

Table H.I summarizes the results of this exercise. First, it shows that being eligible for a student loan significantly increases attendance to higher education. It also shows that having access to a student loan for university moves some individuals from vocational higher education to universities. This explains why the effect of student loans on university enrollment is twice their effect on higher education enrollment.

Eligibility for student loans and scholarships to fund vocational higher education does not depend on PSU scores. In this level, most benefits are allocated based on high school performance. This explains why crossing the student loans university threshold results in a small decrease in take up of scholarships. This result reflects that some of the individuals who choose to take up a loan and enroll in university were eligible for scholarships in vocational higher education institutions.

The changes in enrollment decisions discussed in the previous paragraphs result on no significant differences in tuition fees expenditure at the cutoff. If anything, the households of individuals who are eligible for a student loan spend more in tuition fees than the households of individuals who are non-eligible. This difference reflects that individuals to the right of the eligibility threshold are more likely to enroll in higher education, and to attend more expensive institutions (i.e., universities). Although not statistically significant, this difference is likely to represent a lower bound. It ignores all costs apart from tuition fees and to compute it I focused only on the first year of studies. University degrees, however, are longer than vocational higher education degrees which implies that the difference in total expenditure will be larger.

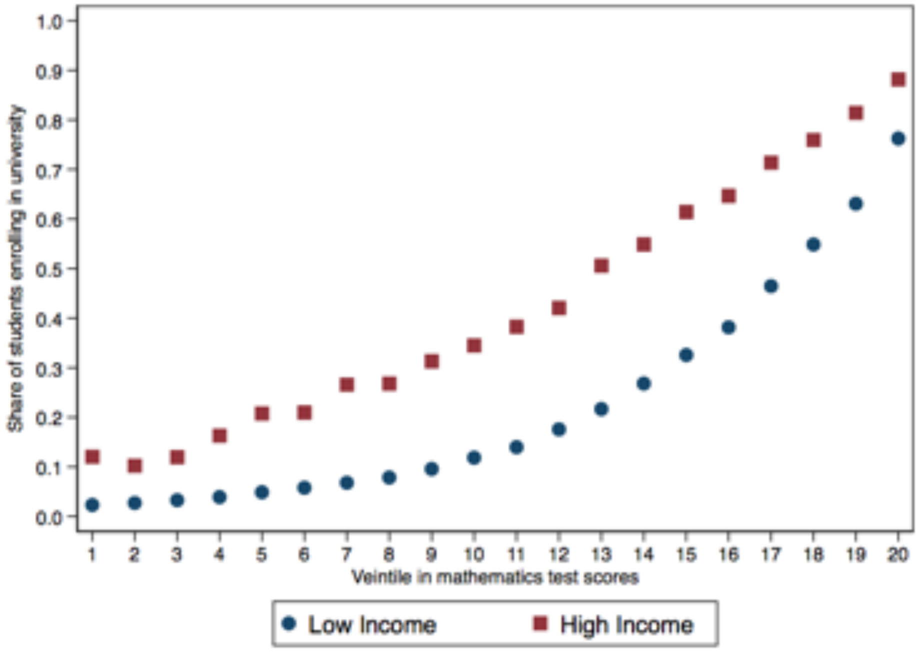
Table H.I: Effect of older siblings' eligibility for funding on older siblings' own enrollment and education expenditure

	Enrolls in higher ed.	Enrolls in vocational higher ed.	Enrolls in university	Takes up a scholarship	Annual expenditure in tuition fees (000 CLP)	Annual expenditure in tuition and enrollment fees (000 CLP)
	(1)	(2)	(3)	(4)	(5)	(6)
Older sibling is eligible for a loan	0.077	-0.066	0.143	-0.031	15.569	25.014
	(0.010)	(0.010)	(0.010)	(0.008)	(20.533)	(21.898)
Observations	37504	37504	37504	37504	37504	37504
Outcome mean	0.69	0.27	0.42	0.17	714.835	815.897

Notes: The table presents estimates of the effect of older siblings' eligibility for university student loans on their own enrollment and on the implied expenditure in tuition and enrollment fees. All specifications control for a linear polynomial of the running variable which slope is allowed to change at the cutoff. Bandwidths are the same used in table VII. In parenthesis, standard errors clustered at family level.

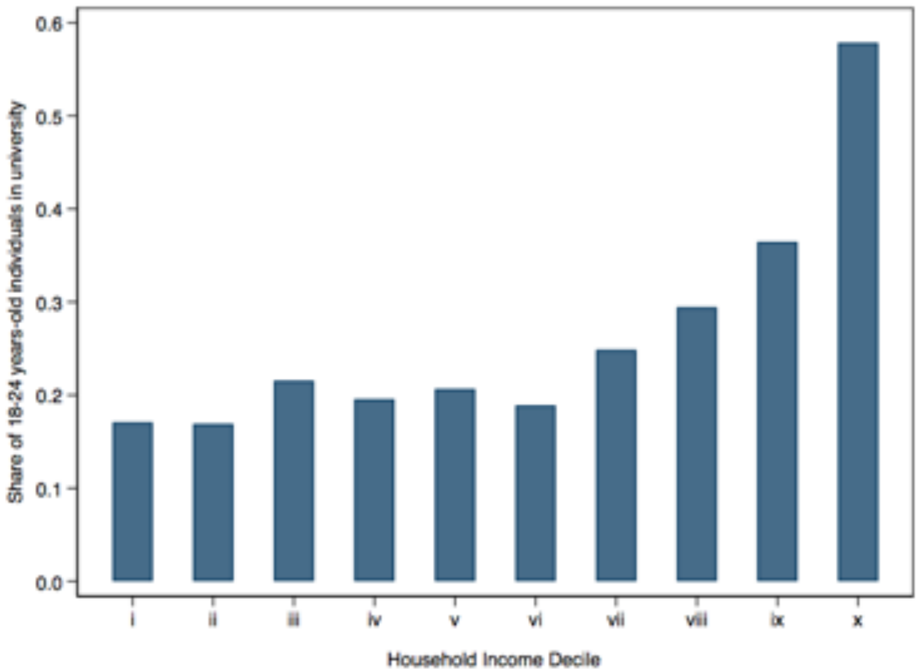
I Inequality in Access to Higher Education in Chile

Figure I.I: Share of students going to university vs performance in mathematics standardized test



Notes: This figure illustrates how the gap in university enrollment observed across income groups evolves with ability. 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 blue dots correspond to low-income students, while the red squares correspond to high-income students. Low-income students come roughly from households in the bottom 20% of the income distribution, while high-income students from households in the top 20%. The statistics in this table are based on the sample of students in grade 10 in 2006, 2008, 2010 and 2012.

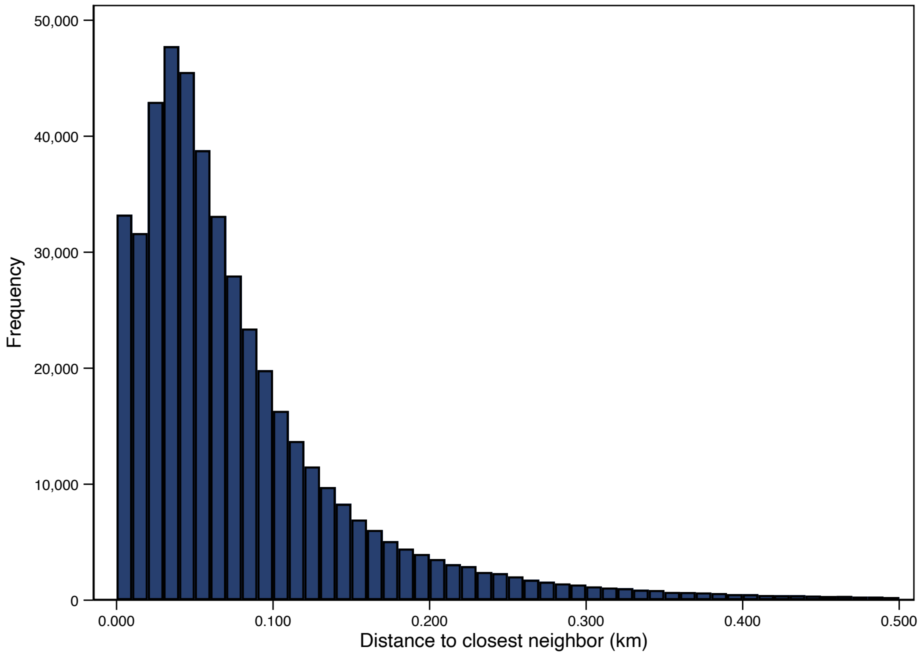
Figure I.II: Share of students going to university by household income (2015)



Notes: This figure illustrates the relationship between the share of 18 to 24 years old individuals going to university in 2015 and their household income. It was build using data from the Chilean national household survey, CASEN (http://observatorio.ministeriodesarrollosocial.gob.cl/casen-multidimensional/casen/basedatos.php).

J Distance to closest Neighbor

Figure J.I: Distribution of distance between potential applicants and their closest neighbor



Notes: This figure illustrates the distribution of distance between potential applicants' household and their closest neighbor. Potential applicants are individuals that appear in the PSU registers between 2007 and 2012. Their neighbors are individuals that appear in the PSU registers one year before them.