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Should I Stay of Should I Go?
Neighbors' Effects on University Enrollment

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Abstract
This paper investigates whether the decision to attend university depends on university enrollment of close neighbors. I create a unique dataset combining detailed geographic information and educational records from different public agencies in Chile, and exploit the quasi-random variation generated by the rules that determine eligibility for student loans. I find that close neighbors have a large and significant impact on university enrollment of younger applicants. Potential applicants are around 11 percentage points more likely to attend university if a close neighbor enrolled the year before. This effect is particularly strong in areas with low exposure to university and among individuals who are more likely to interact; the effect decreases both with geographic and social distance and is weaker for individuals who have spent less time in the neighborhood. I also show that the increase in university attendance translates into retention and university completion. These effects are mediated by an increase in applications rather than by an improvement on applicants' academic performance. This set of results suggests that policies that expand access to university generate positive spillovers on close peers of the direct beneficiaries.

Key words: Neighbors' effects, university access, spatial spillovers
JEL Codes: I21; I24; R23; R28

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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 in both developing and developed countries. While not all of these individuals would benefit from a university education, enrollment is low even among those with high academic potential.[1] 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].[2] This evidence also shows that the barriers preventing students to take full advantage of their education opportunities are higher in areas where university attendance is low, suggesting that the neighborhoods where individuals live matter.[3]

This paper builds on these findings and investigates whether potential applicants' decision to attend university is affected by university enrollment of close neighbors. Although the role of peers in education has been widely studied, this paper is among the first looking at how they influence enrollment in higher education.[4] This question is relevant from a pol-

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[1]   Figure A12 in the appendix shows that in the case of Chile —the setting studied in this paper— the gap in university enrollment persists along the ability distribution.

[2]   Hoxby and Avery [2013] show 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. This, despite the fact that better schools would admit and provide them 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 Dominican Republic respectively. Bettinger et al. [2012] and Hoxby and Turner [2015] look at them in the United States, and Oreopoulos and Dunn [2013] in Canada. Carrell and Sacerdote [2017] on the other hand, argues that interventions that increase university enrollment work not because of the information they provide, but instead because they compensate for 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.

[3]   This is also consistent with recent studies on neighborhood effects like Chetty et al. [2016] and Chetty and Hendren [2018a] that show that exposure to better neighborhoods increases the probability of college enrollment. Burdick-Will and Ludwig [2010] discusses the literature on neighborhood effects and education attainment.

[4]   Bifulco et al. [2014] studies how having classmates with a college-educated mother affects college enrollment. Mendolia et al. [2018] investigates how peers' ability affect performance on high stake exams and on university attendance. Carrell et al. [2018] looks at the effect of having disruptive peers at the elementary school on long-term outcomes, including college enrollment.

icy perspective because these neighbors' effects would imply that programs that expand access to university generate externalities that should be incorporated into their design and evaluation. In addition, by addressing this question I contribute to understanding if neighborhood effects are driven at least in part by exposure to better peers. This in contrast to only being driven by exposure to better institutions (i.e. schools, health services, public infrastructure, security).

I study these neighbors' effects in Chile, taking advantage of the fact that eligibility for student loans depends on students scoring above a cutoff on the university admission exam and that eligibility for this type of funding increases university enrollment [Solis, 2017]. Exploiting the discontinuity generated by this cutoff rule, I implement a fuzzy RD using potential applicants' enrollment as outcome and instrumenting their neighbors' enrollment with an indicator of their eligibility for student loans.

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

A key challenge for the identification of neighbors' effects is to distinguish 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 shocks. Since potential applicants who have a close neighbor near the student loans eligibility cutoff are very similar, the fuzzy RD used in this paper allows me to rule out the estimated effects to be driven by differences in individual or neighborhood characteristics, eliminating in this way concerns about correlated effects.

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, neighbors' decision should not be affected by what potential applicants do one year later.

This lagged structure and the fact that the variation on neighbors' enrollment only comes from eligibility for funding allows me to abstract from the "reflection problem".

Based on this empirical analysis, I provide three sets of results. Firstly, I find that having a close neighbor going to university has a large and significant impact on potential applicants' university enrollment, increasing it by around 11 percentage points. This effect is stronger when individuals are more likely to interact. Only the closest neighbors seem to matter and the effect quickly decays with distance, completely disappearing after 250 meters. The effects also seem to be stronger among neighbors who are closer in gender and socioeconomic status, and for individuals who have lived in the neighborhood for longer. I also show that this increase in university attendance translates into second year retention and university completion, what suggests that at least a fraction of the applicants who decided to enroll following their neighbors, are benefited by their decision.

Secondly, my findings show that student-loans generate spatial spillovers on the close neighbors of the direct beneficiaries. I study how this indirect effects evolve depending on the level of exposure to university in the neighborhood, and find that they are stronger in areas with low or mid levels of exposure; indeed, the effect virtually disappears in areas where on average 57% of the potential applicants have a close neighbor enrolling in university. Neighbors are not the only group of peers that may affect potential applicants' enrollment decision. I also investigate what happens in the case of siblings and find that a similar indirect effect arises in this context. Potential applicants with an older sibling marginally eligible for student loans are also more likely to enroll in university.

Finally, I show that the increase in university enrollment documented for both neighbors and siblings, is mediated by an increase in the number of potential applicants taking the university admission exam and applying to university and to financial aid. I find no effects on their attendance or on their academic performance during high school.

These results are consistent with two broad classes of mechanisms. First, neighbors may increase university enrollment of potential applicants by providing them with relevant information about applications, returns and the overall university experience. Second,

they could also affect the expected returns of going to university. Although with the data that I have available I cannot perfectly distinguish between them, I present suggestive evidence that information is the mechanism behind the documented responses.

This paper contributes to existing research in several ways. Firstly, it contributes to the literature on peers' effects. Since the publication of the Coleman Report [Coleman, 1966], peers' effects in education have been widely studied.[5] Although the majority of these studies have focused in the classroom, others have looked at neighborhoods [Goux and Maurin, 2007, Gibbons et al., 2013, 2017], and at the family [Goodman et al., 2015, Dustan, 2018, Joensen and Nielsen, 2018].[6] Others have studied peer effects in higher education [Sacerdote, 2001, Zimmerman, 2003, Stinebrickner and Stinebrickner, 2006, Foster, 2006, Lyle, 2007, Carrell et al., 2009, Feld and Zölitz, 2017]. Few of them find sizeable effects when looking at academic performance. However, as pointed out by Hoxby and Weingarth [2005] and further discussed by Lavy et al. [2012], Burke and Sass [2013] and Imberman et al. [2012] this could be a consequence of assuming linear-in-means average effects; indeed, when relaxing this assumption, they find large peers' effects for some groups of individuals. On the other hand, studies looking at "social" outcomes like program participation, group membership, church attendance, alcohol consumption, drug use, teenage pregnancy and criminal behavior find much bigger effects [Case and Katz, 1991, Gaviria and Raphael, 2001, Sacerdote, 2001, Duflo and Saez, 2003, Boisjoly et al., 2006, Maurin and Moschion, 2009, Mora and Oreopoulos, 2011, Dahl et al., 2014].

This paper is novel not only because of the outcome and type of peers analyzed, but also because in the Chilean setting I can overcome a challenge commonly faced by previous studies, which is how to define the relevant peer group. Using, for instance, the whole class or looking at neighbors' effects using a too large definition of neighborhood may di-

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[5]   See for instance Hoxby [2000], Boozer and Cacciola [2001], Hoxby [2002], Hanushek et al. [2003], Angrist and Lang [2004], Burke and Sass [2013], Ammermueller and Pischke [2009], Lavy and Schlosser [2011], Mora and Oreopoulos [2011], Imberman et al. [2012], Lavy et al. [2012], Sojourner [2013], Bursztyn and Jensen [2015]

[6]   These papers study the relation between education investment decisions of siblings. Goodman et al. [2015] look at correlations between siblings' college-major choices, Dustan [2018] at the choice of high school and Joensen and Nielsen [2018] at the subjects taken during high school. Although related to my work, the focus of these studies is on different margins.

lute the effects of the actual peers. The detailed information I have on neighbors, allows me to study how the effects evolve with physical and social distance.

Secondly, this paper contributes to the literature on underinvestment in higher education. This literature has shown that especially in disadvantaged contexts, individuals face constraints that prevent them from taking full advantage of the education opportunities that they have available. The hypotheses most commonly studied for explaining this phenomenon are liquidity and information constraints, but there is also evidence that other behavioral constraints play a role.[7] In this paper, I add a new element to the analysis by investigating the role of neighbors and siblings on the university enrollment decision. These peers could contribute to reduce some of the frictions previously discussed. In addition, by exploiting variation that comes from a funding program, I also discuss indirect effects of programs designed to relax liquidity constraints (i.e. spillovers of funding on the peers of the direct beneficiaries).

Finally, it adds 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].[8] However, from these results we cannot tell to what extent the observed effects are driven by exposure to better peers or to better institutions (i.e. schools, health services, infrastructure, security).[9] This paper focuses on the role of peers by exploiting a source of variation that allows the identification of neighbors'

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[7]   Examples of papers studying liquidity constraints include Dynarski [2000], Seftor and Turner [2002], Dynarski [2003], Long [2004], van der Klaauw [2002], Solis [2017]; on the other hand examples of papers investigating information frictions include 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 [2008], Castleman and Page [2015]. Carrell and Sacerdote [2017] on the other hand, argues that differences in support and encouragement are key to explain this. Lavecchia et al. [2016] discusses the literature on behavioral constraints that may explain why some individuals do not take full advantage of their education opportunities.

[8]   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, wellbeing, criminal behavior, among others.

[9]   The policy implications of these two alternative explanations are very different. As Burdick-Will and Ludwig [2010] point out, if neighborhood effects are mainly driven by the quality of local institutions, then educational attainment could be improved by investing in these institutions without having to move disadvantaged individuals to different areas.

effects keeping the neighborhood where individuals live fixed.

The rest of the paper is organized in seven sections. The second section describes the Chilean higher education system, while the third describes the data. The fourth section discusses the identification strategy, and the fifth 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 relate the main results of the paper to previous findings. Finally, section eight concludes.

2   Higher Education in Chile

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

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. Only universities can grant academic degrees, and in 2017 they attracted 48.1% of the students entering higher education.

Despite the expansion experienced by the higher education system in the last decades, inequality in access to university remains high.[10] 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.[11]

Although part of this inequality can be explained by differences in academic potential measured by students' performance in standardized tests in grade 10, Figure 1 shows that

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[10]   According to figures of the Ministry of Education, the number of students going to university was five times bigger in 2017 than in 1990. The number of students going to professional institutes increased by 10 times over the same period. In the case of vocational centers, it doubled.

[11]   Figure A13 in the appendix illustrates university attendance rates for the whole income distribution. According to the same survey, the main reasons for not attending higher education among individuals between 18 and 24 years old are personal (49.7%) and economic (47.5%). Academic performance is mentioned in less than 1.5% of the cases as a reason for not going to higher education.

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 out of 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 other eight private universities select their students using a centralized deferred acceptance admission system that only considers students' performance in high school and in a national level university admission exam (PSU).[12] The PSU is taken in December, at the end of the Chilean academic year, but students typically need to register before mid-August.[13] Since 2006 all the students graduating from public and voucher schools are eligible for a fee waiver that in practice makes the PSU free for them.[14]

The universities that do not participate in the centralized system have their own admission processes.[15] Although they could use their own entrance exams, the PSU still

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[12] The PSU has four sections: Language, mathematics, social sciences and natural sciences. The raw scores obtained by students in each of these sections are adjusted to obtain a normal distribution of scores with mean 500 and standard deviation 110. The extremes of the distribution are truncated to obtain a minimum score of 150 and a maximum score of 850 in each section. In order to apply, students need to take language, mathematics and at least one of the other sections. Universities are free to set the weights allocated to these instruments 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. Once a student is admitted in one of her preferences, all the others are dropped.

[13] In 2017, the registration fee for the PSU was CLP 30,960 (USD 47).

[14] Around 93% of the high school students in Chile attend public or voucher schools. The entire registration process operates through an online platform that automatically detects the students' eligibility for the scholarship.

[15] I observe enrollment in all the universities of the country, independently of the admission system they use.

plays an important role in the selection of their students, mostly due to strong financial incentives for both the students and the institutions.[16] For instance, the largest financial aid programs available for university studies require students to score above a cutoff in the PSU.

2.3 Financial Aid

In Chile, the majority of the financial aid comes from the government. There are two student loans and multiple scholarship programs designed to fund studies in different types of higher education institutions. The allocation of these benefits is in charge of the Ministry of Education. This section, briefly describes the programs that fund university degrees, emphasizing the rules that generate the discontinuities which are later exploited in this paper.

Students that need financial aid have to apply for it between October and November using an online platform (this is before taking the PSU). After verifying if the information provided by applicants is correct, the Ministry of Education informs them to which benefits they are eligible. 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 them to consider the funding they have available before applying and enrolling in higher education.

There are two student loans 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 higher education institution.[17] In order to be eligible for these loans, students need to obtain an average PSU score (language and mathematics) above

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[16]   Firstly creating a new test generate 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 attracted the best students of each cohort. It was eliminated in 2016, but it was in place during the period analyzed in this study.

[17]   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%, in the case of the CAE it varied between 5% and 6%. On top of that, while the repayment of the FSCU has always been income contingent, the CAE used to have fixed installments.

475 and come from households in the bottom 90% of the income distribution.[18]

Solis [2017] documents that eligibility for student loan creates a discrete jump in the probability of university enrollment amongst financial aid applicants. This is the discontinuity that I exploit in this paper, but this time to study the indirect effects generated by university attendance on the neighbors and siblings of the beneficiaries.

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 above 550) and that they are focused on students from more disadvantaged backgrounds. I do not use this discontinuity because it does not affect enrollment; once students have access to subsidized credits such as CAE and FSCU, offering them a scholarship does not make a difference in their decision to attend university. 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 in terms of the support they offer.

Given that in Chile universities have complete freedom to define 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 in a specific program.[19] At the university level, the reference tuition fee is around 80% of the actual fee. This means that students need to cover the additional 20% using their own resources, taking a private loan or if available, applying to scholarships offered by their institutions.

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[18] In the case of the FSCU, they need to come from households in the bottom 80% of the income distribution; the CAE, on the other hand, used to be focused on students in the bottom 90% of the income distribution, but since 2014 the loan is available to anyone that satisfies the academic requirements.

[19] 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 real tuition fee.

3   Data

This section describes the sources of the data 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 administrative data of different government 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, from the Education Quality Agency and from the Census.

This data makes it possible to follow students throughout high school. It contains information on demographic characteristics, attendance and academic performance (GPA) for each individual in every grade. In addition, it registers the educational track chosen by students and also schools characteristics such as their administrative dependence (i.e. public, voucher, private) and the municipality where they are located. All this information is available from 2002 onwards, meaning that the first cohort that I can follow between grades 9 and 12 is the one completing high school in 2005.

I also observe all the students who register for taking the PSU. As discussed in Section 2, the PSU is free for students graduating from public and voucher high schools, so the majority signs up for the test even if they do not plan to apply to university.[20] Apart from observing the scores that students obtain in each one of the sections of this exam, the data contains information on applications to the universities that participate 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.

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[20]   In the period that I study, more than 85% of the high school graduates appear in the registers of the PSU.

These variables are later used to study if the identifying assumptions of the 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.[21]

The Ministry of Education keeps records of all the applications and allocation of financial aid. The type and amount of benefits are only observed for individuals who enroll in higher education, what 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 graduation from higher education. These records contain individual-level data of students attending any higher education institution in the country, and report the programs and institutions in which students are enrolled.[22] This data, as the data on financial aid, is available from 2006 onwards.

The neighbors' and siblings' samples combines information from all these datasets.[23] The former includes students that appear in the PSU registers between 2006 and 2012, while the latter students that appear in the PSU registers between 2006 and 2015. The difference in the years included in each sample is just driven by data availability.

3.2   Sample Definition

This section describes the steps and restrictions imposed on the data to build the estimation sample. The first step in this process is to match potential applicants observed in time t with their neighbors observed in $t-1$.

To make this possible, I geocoded students' addresses. Since these addresses do not in-

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[21]   The information on demographic and socioeconomic variables, addresses and parents is not available for all the students in the registers. Some of it can be recovered from the 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.

[22]   This dataset includes students enrolled in university, professional institutes and vocational centers.

[23]   Although the focus of this paper is on neighbors, I also investigate what happens with potential applicants when an older sibling goes to university T years before her. The sample used for this purpose is described in Section A.1 in the appendix.

clude postcodes, the geocoding process was very challenging, especially in regions with high levels of rural population where the street names are not well defined. Thus, this study focuses on three regions where the identification of neighbors was easier and that together represent more than 60% of the total population of the country: *Metropolitana of Santiago*, *Bio-bío* and *Valparaíso*.[24]

After geocoding the addresses, potential applicants of year t were matched to their 60 closest neighbors registered for taking the PSU in $t-1$. Then, the demographic, socioeconomic and academic variables from other datasets were added to potential applicants and their neighbors. Finally, each individual was linked to their respective neighborhood unit. Neighborhood units correspond to subareas within a municipality and are defined by the Ministry of Social Development to decentralize certain local matters and to foster citizen participation and community-based management.[25] After this process, I end with a sample of more than 550,000 potential applicants and their respective neighbors.

To build the estimation sample, I apply some additional restrictions. I only keep individuals graduating from regular education programs no more than 3 years before registering for the PSU (i.e. no remedial programs), and individuals who were between 17 and 22 years old when taking the test. In addition, I drop applicant-neighbor pairs in which the applicant completes high school before the neighbor. Finally, I also drop the pairs in which applicants and neighbors are siblings. These restrictions make me lose around one third of the observations.[26]

The main analyses focus on potential applicants and their closest neighbor, but I also study how they are affected by other individuals that live close to them (i.e. n-th closest neighbor, best neighbor among n and best neighbor within d meters). In all these cases, I work only with potential applicants whose neighbors apply to financial aid; these are the only neighbors that could change their university enrollment decision based on eligibility

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[24] Even in these regions, it was not possible to geocode 100% of applicants' addresses. I identified addresses for near 85% of the sample. This implies that for some applicants, only a subset of close neighbor was identified. Unless the missing neighbors are selected in a very particular way, this should work against finding effects.

[25] Standard errors are clustered at this level.

[26] Note that these restrictions do not affect the internal validity of the identification strategy.

for student-loans. As a consequence of this last restriction, another third of the original sample is lost. Note that this restriction is only imposed on neighbors, and does not affect potential applicants.[27]

The first two columns of table 1 present summary statistics for the sample of potential applicants and their closest neighbors. The third column characterizes all the students in the PSU registers between 2007 and 2012.

Potential applicants and their closest neighbors are very similar. The only relevant differences are in academic variables. Neighbors, who by definition apply to 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 in part driven by the fact that more of them actually take the test. Despite the restrictions imposed to build this sample, potential applicants look very similar to the rest of the individuals that appear in the PSU registers.

4   Identification Strategy

The identification of neighbors' effects is challenging. Families are not randomly allocated to neighborhoods and once in the neighborhoods they face similar circumstances, which makes it difficult to distinguish between social interactions and correlated effects. 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 studies how close neighbors going to university in year $t-1$ affect individuals that could apply to university in year t. Since neighbors decide whether to enroll or not into university before potential applicants, their decision should not be affected by what potential applicants do one year later. If the decision of the younger applicant does not affect the decision of the older neighbor the "reflection problem" disappears.

To identify these neighbors' effects I exploit the fact that eligibility for student loans depends on the score obtained in the PSU. This allows me to implement a fuzzy RD

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[27]   Once more this restriction does not affect the internal validity of the identification strategy. The restriction is only imposed on the neighbors. Potential applicants are in my sample even if they do not apply for funding.

instrumenting neighbors' university enrollment (U_n) with an indicator variable that takes value 1 if the student's PSU score is above the student loans eligibility cutoff (L_n). This means that the variation on neighbors' university enrollment comes only from eligibility for funding. Thus, even if the decision of the younger applicant would affect the decision of the older neighbor, by using this instrument I am able to abstract from the "reflection problem".

In addition, since neighbors around the student loans eligibility threshold are very similar, this approach also eliminates concerns related to correlated effects. [28]

Using this strategy, I estimate the following specification:

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

Where U_{at} is the university enrollment status of potential applicant a on year t and U_{nt-1} is the university enrollment status of neighbor n on year $t-1$.

Note, this specification only includes neighbor n. In order to interpret β_n as 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 university enrollment of contemporaneous peers does not affects applicants' own university enrollment (Section A.2 in the appendix discuss this in detail).[29]

If this assumption is not satisfied, β_n can be interpreted as a reduced form parameter capturing not only the effect of neighbor n on potential applicant a, but also the effects that other neighbors affected by n generate on a. This is still a relevant parameter from a policy perspective.

For the RD estimation, I use optimal bandwidths computed according to Calonico et al. [2014b] and provide parametric and non-parametric estimates. 2SLS estimates come from specifications that assume a flexible functional form for the running variable and instru-

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[28]   Apart from neighbors, also the neighborhoods and other individuals who live near them are similar.
[29]   Considering the timing of the application and enrollment process, individuals have limited scope to respond to university enrollment of their contemporaneous peers. Figure A15 shows that this is the case and that contemporaneous peers do not seem to affect potential applicants' enrollment

ment U_{nt-1} with a dummy variable that indicates if neighbor n was eligible for student loans on $t-1$, L_{nt-1}. Non-parametric estimates come from local polynomials regressions that use a triangular kernel to give more weight to observations closer to the cutoff. The implementation of this last approach follows Calonico et al. [2014a] and Calonico et al. [2017].

Section A.4 in the appendix presents a series of analyses that investigates if the assumptions required for the validity of the RD estimates are satisfied. First, it shows that there are no discontinuities at the cutoff in a rich set of demographic, socioeconomic and academic characteristics of potential applicants and their neighbors.

Second, it provides evidence that there is no manipulation of the running variable around the cutoff. In order to study this, I implement the density discontinuity test suggested by Cattaneo et al. [2018].[30]

In addition to the robustness checks just mentioned, I also study if potential applicants' decision of going to university has an effect on their older neighbors. As discussed earlier, there should be no effect in this case, something that is corroborated by the results of this exercise.

Finally, section A.4 also shows that the results are robust to different bandwidths choices and that there are no jumps like the ones observed at the student loans eligibility cutoff in other points where there should not be.

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 that could apply to university on year t, while the neighbors are individuals that applied to university on

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[30] In this setting, it is not easy to think of a way in which applicants could manipulate the running variable. All the PSU process, from the creation to the correction of the tests, is carried out under strict measures of security. In addition, final scores are the result of a transformation that adjusts 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. Considering this, it seems very unlikely that potential applicants could manipulate their neighbors' scores.

year $t - 1$. This section begins by looking at what happens with potential applicants' enrollment probability when their closest neighbor is eligible for student loans and goes to university.[31] Then, it incorporates other close neighbors to the analysis and studies how the effect evolves with physical distance. It concludes by investigating heterogeneous effects by social distance and by the university enrollment rates observed in potential applicants' municipalities.

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 a specification like the one presented in equation 1, instrumenting neighbors' university enrollment with their eligibility for student loans.

Panel (a) of Figure 2 illustrates the first stage of this exercise. It shows that neighbors' probabilities of going to university increase by around 18 percentage points when they become eligible for a loan. This figure, significantly different from zero, captures the direct effect of student loans on university enrollment. According to it, this type of funding roughly doubles the probability of going to university for students with PSU scores near the eligibility threshold.

Panel (b), on the other hand, illustrates the reduced form. It shows that potential applicants whose closest neighbor is eligible for a student loan in year $t - 1$ are around 2 percentage points more likely to enroll in university on 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 the close neighbors of these beneficiaries. This indirect effect represents more than a 10% of the direct effect of student loans on university enrollment.

If this reduced form effect only works through neighbors taking-up the student loans and

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[31]   Section A.3 in the appendix studies how potential applicants respond to what happens to other neighbors, including the best among n and the best within d meters.

going to university, the first stage and reduced form estimates can be combined to estimate the effect of exposure to a close neighbor going to university on potential applicant's university enrollment. Table 2 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 11 percentage points when their closest neighbor enrolls in university. This figure is statistically different from zero, and represents around one third of the enrollment probability of individuals at the cutoff.

This estimate would be an upper bound of the effect of neighbors' enrollment on applicants' enrollment if having a close neighbor eligible for funding makes potential applicants more aware of funding opportunities, independently if the neighbor goes or not to university.[32] However, the information intervention implemented by Busso et al. [2017] among grade 12 students in Chile, shows that in this setting learning about funding opportuni-ties alone does not generate responses like the ones I find,[33] alleviating concerns related to this type of violations to the exclusion restriction.

Note however that enrolling in university is not necessarily something good. If the applicants who respond to their neighbors' enrollment do not have the skills required to succeed in university, then this neighbors' effects could be something negative. Table 3 explores this in more detail by investigating if the difference in enrollment persist one year after the shock and if there is a difference on higher education and university completion rates.

Columns 1 and 2 look at retention in the university system and at retention in the same institution where applicants originally enrolled respectively.[34] The estimates reported on these columns are very similar to the effects on enrollment, suggesting that the compliers

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[32] If the applicant becomes aware of the funding opportunities only when the neighbor uses it and goes to university, then this would be a mechanism through which exposure works and not a violation to the exclusion restriction.

[33] This intervention provided students with tailored information about funding opportunities and labor market outcomes of graduates from different programs. They find no extensive margin responses. They find no increase in enrollment to non-selective or selective institutions.

[34] In both cases, 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.

of the IV do not drop out at higher rate than always takers. In addition, columns 3 and 4 look at the probability of completing higher education or university before 2018. These results show that potential applicants with a close neighbor going to university one year before them, are around 7 percentage points more likely to complete a university degree. Although these coefficients are only marginally significant, they represent an important fraction of the effect on enrollment, what suggests that the neighbor shock experienced by some applicants is beneficial for at least an important fraction of the compliers.

5.2 How do neighbors' effects evolve with distance?

This section investigates how neighbors' effects evolve with physical and social distance. Both types of distance could be relevant if they affect the likelihood of interactions between individuals.

All the results discussed so far have focused on the closest neighbor. However, there could be other neighbors that are relevant for potential applicants. In order to study this, I estimate the same baseline specification presented in Section 4, but replacing university enrollment of the closest neighbor by university enrollment of the n-th closest neighbor.

Thus, I estimate independent specifications to study how each one of the eight closest neighbors affect potential applicants' university enrollment. As discussed in Section 4 to interpret the results of this specification as the effect of neighbor n on potential applicant a, we need to assume that university enrollment of contemporaneous peers does not affects individuals' university enrollment.[35] If this assumption is not satisfied, then the estimated coefficient can be interpreted as a reduced form parameter that captures not only the effect of neighbor n on applicant a, but also the effect that other individuals affected by n have on a.[36]

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[35] I show that this indeed seems to be the case in Figure A15.

[36] A more detailed discussion on this is presented in Section A.2. An alternative approach to study this would be to include the enrollment status of multiple neighbors simultaneously in the same specification. In case of counting with instruments for the enrollment of each neighbor it would be possible to proceed in a similar way as I do now. In my setting, this is not possible. The instrument I have is valid only locally. In addition, it is relevant only for neighbors that apply for financial aid. To estimate a specification like this one, I would need to find applicants with many neighbors applying for funding and with PSU scores close enough to the eligibility threshold. Unfortunately, this type of potential applicants are scarce in my sample.

Panel A on Figure 3 reports OLS and RD estimates for this analysis. Each dot corresponds to the estimates obtained from the eight independent regressions mentioned in the previous paragraph. The horizontal axis, apart from reporting the relative distance to the applicant, presents in parenthesis the average distance between the n-th closest neighbor and applicant a. According to the figure, on average potential applicants live at 34 meters from their closest neighbor registered for the PSU the previous year, and at about 57 meters from the second closest one. The RD estimates, represented by blue circles, quickly decay. The coefficient associated to the second closest neighbor is around 4 percentage points, and in the case of the third closest neighbor it is below 2 percentage points. In addition, only the coefficient associated to the closest neighbor is significantly different from zero. The pattern observed in the case of OLS is substantially different. Although there is a small drop on the size of the coefficient, they are very persistent.

In order to study how the effects evolve with geographic distance, I estimate an additional specification in which potential applicants and their eight closest neighbors are pooled together. I present two set of results. The first one comes from splitting the sample in three equal parts depending on the distance between potential applicants and their neighbors. The second one comes from a specification that uses the whole sample and adds an interaction between neighbors' university enrollment and distance.

As illustrated in Panel B of Figure 3 the pattern of the RD estimates presented in blue are consistent with the results on Panel A. The effect of neighbors on potential applicants decays with distance, becoming non-significant at 125 meters and reaching 0 at 250 meters. As before, the OLS estimates are persistent, and in this case they even seem to increase a little bit.

The difference between OLS and RD estimates illustrate the relevance of correlated effects in this context. As discussed earlier, the composition of neighborhoods is not random, which means that individuals who live relatively close to each other are similar in many dimensions (i.e. household income, parental education). In addition, these individuals live under similar circumstances, and are exposed to similar institutions and shocks.

Thus, it is not surprising to find a persistent correlation in outcomes of neighbors, even if they do not interact with each other.

In the context of peers' effects, these results also highlight the importance of using an appropriate reference group. The results discussed in this section suggest that interactions between neighbors occur at a very local level. Therefore, using a too broad definition of neighborhood could dilute the effect of the relevant peers (i.e. what happens with individuals living 200 meters apart does not seem to be relevant for potential applicants).

The extent to which individuals interact with each other is not only determined by physical distance. In the rest of this section I study how the effects evolve depending on social distance and depending on time spent at the neighborhood. Given the results just discussed, I focus my attention only on the closest neighbor and to study heterogeneity I split the sample in different sub-groups.

The results in Table 4 suggest that the effects are bigger when potential applicants are closer to their neighbors in socioeconomic status, gender and age.[37] Although the precision of these estimates does not allow me to rule out that they are equal, finding that the coefficients are larger when individuals are closer in social terms is consistent with the idea that interactions between neighbors are important for these effects to arise.

In line with these results, Table 5 shows that the effect seems to be stronger for potential applicants who have lived for longer in the neighborhood and for the cases in which neighbors plan to continue living with their parents when going to university (i.e. plan to remain in the neighborhood). The effect is also stronger for potential applicants

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[37] Socioeconomic status is measured by an index that combines information on household income, parental education, health insurance and high school administrative dependence. This index is build by extracting the first component from a principal component analysis that included household income, parental education, health insurance and high school administrative dependence. Using this index, potential applicants and neighbors are classified in two socioeconomic groups (below or above the median); they are defined as similar if they belong to the same broad group. Similar results are obtained using instead of two, for groups. Results available upon request. Table A5 in the appendix present additional heterogeneity analyses. According to these results, students coming from very disadvantaged backgrounds or who follow the vocational track during high school are less responsive. This suggest that the effects are driven by potential applicants who are better prepared for the PSU and for whom it is easier to score above the student loans eligibility threshold and to be admitted in some university if they decide to apply. The estimated effect is also bigger for females, although the difference with the effect estimated for males is not statistically significant.

whose mothers do not work outside the household. The time spent by the applicants and other members of their families at the neighborhood may strengthen the relations between neighbors, increasing in this way the likelihood of exposure and interactions.

5.3 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 that exist in the country, this also translates into spatial inequality. The map in Figure 4 illustrates this for Santiago, Chile's capital city.[38] The red areas in the map correspond to neighborhoods where on average 24.6% of potential potential applicants are exposed to a close neighbor who goes to university, while the green areas represent neighborhoods where this figure is above 56%. Since I do not have a formal definition of neighborhoods, in order to create these areas I used a k-cluster algorithm that classified individuals according to their geographic coordinates in 1150 clusters (i.e. 10 per municipality in my sample).

According to the results discussed in previous section, 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 bit more than 10% of their direct effect. In order to estimate the full extent of these indirect effects, we would need to investigate if they also emerge between other peers.[39] 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.

So far, the analyses have assumed that direct and indirect effects are constant across different areas. However, they may change depending on how exposed to university are individuals from different areas. I study this by estimating the direct and indirect effect of student loans independently for low, mid and high exposure neighborhoods.

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[38] Figures A16 and A17 in the appendix present similar maps for Valparaíso and Concepción, two of the other cities analyzed in this paper.

[39] According to the results discussed in Section 5.2, in the context of neighbors these spillover seem to be very local. Section 6.1 studies indirects effects between siblings.

Figure 5 presents the results of this exercise. The top panel shows the first stage estimates, the panel in the middle the reduced form estimates, and the panel at the bottom the results obtained when combining them by 2SLS. These last estimates capture the effects of neighbors' enrollment 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) is bigger in areas where university attendance rates are higher. The reduced form results and the exposure effects on the other hand seem stronger in low and mid attendance areas. Indeed, in high attendance areas these coefficient are non-significant and almost negligible.

Although the standard errors of these estimates do not allow me to conclude that they are statistically different, these results shows that indirect effects are relevant in low and mid attendance areas. There, they represent roughly a 15% of the direct effects, indicating that exposure to neighbors who are eligible for funding and go to university affects the enrollment of potential applicants. This suggests that policies that increase exposure to these type of neighbors would also increase enrollment in areas where university attendance is relatively low.

6 Siblings and Other Educational Outcomes

This section starts by investigating if indirect effects as the ones discussed in previous sections also arise among siblings. Then it studies how university enrollment of neighbors and siblings affect other educational outcomes of potential applicants, to understand what are the margins that they adjust that result on the documented increase in university enrollment.

6.1 Siblings Effects

Neighbors are not the only peers that could affect university enrollment of potential applicants. If indirect effects as the ones described in previous sections also arise among other peers, this is something that we would like to incorporate in the evaluation and

design of policies that seek to expand access to university.

As discussed in Section 3, apart from identifying neighbors, my data allows me to identify siblings. I use this data to study how having an older sibling receiving a student-loan and going to university affects potential applicants' university enrollment. To do this, I estimate the same specification used in the case of neighbors, but replacing neighbors by older siblings.

Although the siblings' sample is similar to the neighbors' sample, it is worth mentioning that it covers a longer period of time —2006 to 2015— and that the potential applicants in this sample (i.e. the younger siblings) obtain higher PSU scores than potential applicants in the neighbors sample.

The top panel of Figure 6 shows that siblings who are eligible for student loans are around 16 percentage points more likely to enroll in university than to those who are not eligible. This figure, statistically different from zero, represents the direct effect of student loans in this group.

The second panel presents the reduced form. It shows that potential applicants with an older sibling eligible for student loans are more than 2 percentage points more likely to go to university than those whose older sibling are not eligible. This indirect effect is slightly bigger than in the case of neighbors. This result is consistent with the idea that exposure is relevant. If interactions between siblings are more intense than among neighbors, this could explain the difference in the coefficient.[40]

As in the case of neighbors, if these effects are purely going through older siblings taking up the loans and going to university, the first stage and reduced form results can be combined to obtain an estimate of the effect of exposure to siblings going to university. Table 6 presents these results. The first two columns show 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 increases potential applicants' probability of going by between 13 and 16

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[40] The samples used to estimate neighbors and siblings are different. This could also be behind the differences in the effects documented for both samples.

percentage points. As in the case of the reduced form, this coefficient is also bigger than in the case of neighbors.[41]

In this setting however, satisfying the exclusion restriction is more challenging. Apart from the transmission of information about funding opportunities, having an older sibling going to university with a student loans could affect the household budget constraint. This could explain at least some part of the response observed in younger siblings.

However, it is important to consider that student loans only cover a share of the tuition fees.[42] This means that students and their families still need to pay part of them, in addition to other costs involved in going to university, including the foregone earnings of labor. If families have limited resources, then sending one child to university, even with a student-loan, should reduce the chances of going for the younger ones.[43]

There could also be scenarios where the student loans could relax the household budget constraint in a more significant way.[44] Thus, it cannot be ruled out that at least some part of the effects found for siblings are driven by changes in household resources.

6.2 Other Educational Outcomes

This section looks at changes on the academic performance and on the application decisions of potential applicants. This allows me to identify the margins that potential applicants adjust and that mediate the increase in enrollment documented in previous sections. To study this, I employ once more the fuzzy RD used in previous sections, but this time to investigate how these other outcomes change when a close neighbor or an older sibling goes to university.

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[41]   Table A6 in the appendix investigates if the documented difference in enrollment persists when looking at second year retention. As in the case of neighbors, the estimates reported on this table are very similar to the effects on enrollment, suggesting that the compliers of the IV do not drop out at higher rate than always takers.

[42]   student loans cover up to the reference tuition fee set by the government. See Section 2 for more details.

[43]   An exception to this could be given by siblings whose age difference is big enough to allow the older one to graduate before the younger one applies to university. In this case, the older sibling could help to fund the younger sibling studies. However, I do not find differences depending on the age gap between siblings. These results are not presented in the paper, but are available upon request.

[44]   This would be the case if for instance parents were able to save or borrow to pay for exactly one university degree; or if having one child in university would change their willingness to borrow.

According to the results presented in table 7, potential applicants with a close peer (i.e. closest neighbor or sibling) going to university are more likely to take the PSU, to apply for financial aid and to have an active application to university; [45] they are also more likely to be eligible for student loans and to take them up. I find no effects on attendance or on academic performance during high school, [46] and the apparent improvement on PSU scores is driven by the extensive margin response mentioned earlier.[47]

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

7   Discussion

The results presented in this paper show that exposure to close peers that enroll in university increases the probability of potential applicants' enrollment and that the effects are stronger when potential applicants and their peers are more likely to interact.

These results are consistent with two broad classes of mechanisms. Firstly, neighbors and siblings could affect potential applicants' university enrollment by expanding their access to relevant information. Alternatively, they could directly affect the returns of going to university.

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[45]   I only observe applications to universities that use the centralized admission system described in section 2. These are the applications I use as outcome.

[46]   In Chile, the GPA scale goes from 1.0 to 7.0. The minimum GPA to pass to the next grade or to finish high school is 4.0.

[47]   I replaced missing scores in the PSU by 0 (or -475 after centering the PSU scores around the student loans eligibility threshold). Thus, if potential applicants with neighbors or siblings going to university are more likely to take the admission test, this automatically creates an increase on average performance (i.e. they are less likely to have -475 points in the PSU). Although a formal analysis of performance in the PSU would need a selection model, this result suggests that the main drivers of the observed results are generated by the decision to take the PSU and apply to university.

There is vast evidence that information frictions affect individual schooling decisions in both developing and developed countries. Jensen [2010] for instance shows that providing information on returns to education to grade 8 students in Dominican Republic increased the years of high school completed.

Students seem to face similar information frictions in the case of higher education. Hoxby and Turner [2015] study this in the US and shows that in low-income areas, even high achieving students know little about costs, quality and the overall college experience. The situation in Chile is similar. Hastings et al. [2016] document that students from disadvantaged groups have limited and imprecise information on returns to education. These results suggest that university enrollment could be increased by tackling these information constraints.[48]

An alternative way in which neighbors and siblings could affect potential applicants' enrollment is by directly affecting the returns of going to university. This would be the case for instance if they face a social sanction for going to university. Austen-Smith and Fryer [2005] formalizes this idea and shows that individuals may choose to underinvest in education to gain acceptance in their social group. Along this line, Bursztyn and Jensen [2015] finds that students respond to peers pressure and that when effort is observable they adjust it according to the prevalent social norm (i.e. reduce effort when peers view it as something bad, increase effort when peers value it). This is not the only way in which peers could affect the expected returns of going to university. They could also be affected if for instance individuals enjoy spending time with their peers or if they are competitive and want to surpass their peers achievements.[49]

Although, I cannot perfectly distinguish between these two classes of mechanisms, not finding responses on high school attendance or an improvement on academic performance, suggests that individuals are not experiencing relevant changes on their expected returns

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[48] Providing relevant information on returns to higher education though is challenging. As shown by Hastings et al. [2015] these returns can be very different depending on the institution and program attended. In addition, if higher education institutions charge fees, then information about funding opportunities may also be relevant.

[49] Returns nest multiple ways in which these peers' effects may arise. Changes in aspirations, models of competition, the existence of social norms or models of interdependent preferences can be accommodated to this framework.

of going to university. If this were the case, we would expect them to increase the effort that they make to be admitted in college, something that does not seem to be occurring. The results seem more consistent with the transmission of information.

However, interventions providing Chilean students with tailored information about funding opportunities and returns to higher education —like Busso et al. [2017] and Hastings et al. [2015] — do not find extensive margin responses and even when looking at the type of institution and program that students choose to attend, they do not seem to generate large effects. Similarly, Bettinger et al. [2012] finds no relevant responses in college enrollment to a pure information intervention in the United States. However, when complementing the information with personalized support to fill the application for financial aid, they find that college enrollment increases by a similar magnitude to the one documented in this paper. Also in the United States, Carrell and Sacerdote [2017] designed an intervention to investigate what makes programs that foster college attendance effective. They argue that what makes these programs effective is not the information that they provide, but rather their ability to compensate for the lack of encouragement and support that students receive at home or at the school.

According to these results, expanding information on funding and returns to education has not been very effective in increasing university enrollment. This suggest that the information transmitted by peers is different to the one traditionally provided in information interventions. It may be different on its content,[50], but it might also be more relevant because it comes from someone closer.[51] However, if information on returns to education increases the expected returns to university, we would expect it to translate into an increase in the effort exerted by students. As discussed earlier in this section, this does not seem to be happening.

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[50] Potential applicants may learn about the application process, their likelihood of being successful and other elements related to the whole university experience. Hoxby and Turner [2013] shows that providing high achieving applicants from disadvantaged backgrounds with this type of information and an application fee waiver changes the set of colleges to which they apply. This reduces the gap on the type of college to which high achieving students from different backgrounds attend by 5 percentage points.

[51] Nguyen [2008] finds that individuals are able to process information on returns to education in a sophisticated way, and that they respond differently depending on who provides the information.

With the data that I have available, I cannot tell exactly what potential applicants learn from their peers. The results are consistent with receiving information that makes them to realize that university is a possibility for individuals like them, and to incorporate it as an option in their choice set. Investigating what individuals exactly learn from their peers seems an interesting avenue for future research that would also contribute to gain a better understanding of the mechanisms behind my results.

8   Conclusions

Recent studies have shown that especially in disadvantaged contexts individuals face constraints that prevent them from taking full advantage of the education opportunities that they have available. In the context of university enrollment, financial constraints are relevant, but there is growing evidence that the lack of information, support, and encouragement also plays an important role in this context. In both developing and developed countries, these constraints seem to be more relevant in areas where exposure to university is lower.

This paper investigates whether potential applicants' decision to attend university is affected by university enrollment of close neighbors. To address this question, I use rich administrative data from Chile and take advantage of the variation generated by the rules that define eligibility for student loans. Exploiting this quasi-random variation, I implement a fuzzy RD that allows me to eliminate concerns about correlated effects and to abstract from the 'reflection problem'.

I find that neighbors have a large and significant impact on the university enrollment of potential applicants. Having a close neighbor going to university increases their enrollment probability by around 11 percentage points. I also show that this effect is stronger when the interactions between neighbors are more likely to occur. Indeed, only the closest neighbors seems to matter, and the effects decline quickly with distance, disappearing after 250 meters. The effect also seems to be stronger when potential applicants and their neighbors are closer in terms of age, gender and socioeconomic status and when

they have spent more time in the neighborhood. The fact that neighbors' effects are very local highlights the relevance of using an appropriate reference group when studying peers' effects.

The increase in university attendance is not necessarily something good. If the applicants responding to their neighbors enrollment do not have the skills required to complete university, the decision of going could end damaging them. However, I find that the difference in enrollment persists when looking at retention at the second year and that it also translates into higher rates of university completion.

I also show that student loans generate indirect effects on close peers of their direct beneficiaries. In the case of neighbors, this indirect effect seems to be stronger in areas with low and mid levels of exposure to university, where it represents a 15% of the direct effect of student loans on enrollment. I find that a similar indirect effect arises in the context of siblings. These spillovers should be incorporated to the evaluation and design of funding programs, and could also be relevant in the context of other policies that seek to expand access to university.

My main results are consistent with two broad classes of mechanisms, both related to some of the constraints that may affect individuals' schooling decisions. First, neighbors may increase university enrollment of potential applicants by providing them with relevant information about returns, their likelihood of a successful application, or about the overall university experience. Second, they could also directly affect the returns of going to university. Although with the data that I have available I cannot perfectly distinguish between them, finding no increase on potential applicants' effort or academic performance suggests that information is the mechanism behind my results.

No finding effects on effort or on academic performance, also suggest that the type of information that drives the documented effects is not related to returns to education. This is consistent with the results of information interventions providing students with information on funding opportunities and returns to higher education, which have been shown not to be very effective at increasing college enrollment. It seems that potential

applicants receive information that makes them to realize that university is a possibility for them, and to incorporate it as an option in their choice set. Investigating what potential applicants exactly learn from their university-going neighbors and siblings seems a promising avenue for future research. Addressing this question would also contribute to gaining a better understanding of the mechanisms behind peers effects in this and other settings.

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Figure 1: 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 2: First Stage and Reduced Form of Neighbors' RD

(a) First Stage: Neighbors' 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].

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Figure 3: Effect of Neighbors on Potential Applicants by Distance

(a) Evolution of Effects by Distance Rank

(b) Evolution of Effects by Physical Distance

Notes: This figure illustrates how the effects of different neighbors on potential applicants evolve with distance. These coefficients come from specifications that include a potentially different linear function of the running variable on each side of the cutoff. The estimation uses optimal bandwidths computed following Calonico et al. [2014b] for the main specification.

Figure 4: University Attendance across Neighborhoods in Santiago

Exposure to University

- Low exposure
- Mid exposure
- High exposure

Notes: The figure illustrates the share of potential applicants exposed to a close neighbor going to university before they complete highschool in different areas of Santiago between 2006 and 2012. In red areas the average exposure is 24.6%, in yellow areas 36.4% and in green areas 56.1%. 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 5: Neighbors' Effects by Municipality Level of Attendance

(a) First Stage

(b) Reduced Form

(c) 2SLS Estimates

Notes: The figure illustrates how neighbors' effects evolve depending on the level of attendance of the municipality of potential applicants. The dots represent coefficients from three different samples: low, mid and high attendance municipalities. The specification used controls by a linear polynomial of the running variable. The bandwidth used correspond to the optimal bandwidths computed for the whole sample. The lines represent 95% confidence intervals. Standard errors are clustered at the neighborhood unit level.

Figure 6: First Stage and Reduced Form of Siblings' RD

(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 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].

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Table 1: Summary Statistics

	Neighbors (1)	Potential Applicants (2)	Whole country (3)
1. Demographic characteristics			
Female	0.56	0.53	0.54
Age when taking the PSU	18.30	17.72	18.08
2. Socioeconomic characteristics			
Low Income ($\leq$ 288K CLP)	0.57	0.54	0.57
Mid Income ($\leq$ 864K CLP)	0.36	0.36	0.30
High Income ($>$ 864K CLP)	0.07	0.10	0.13
Parental ed. = primary ed.	0.07	0.08	0.13
Parental ed. = secondary ed.	0.55	0.55	0.52
Parental ed. = other	0.01	0.01	0.01
Parental ed. = vocational he	0.09	0.07	0.06
Parental ed. = professional he	0.09	0.08	0.05
Parental ed. = university	0.20	0.21	0.23
3. Academic characteristics			
Public high school	0.37	0.36	0.41
Charter high school	0.58	0.57	0.49
Private high school	0.05	0.07	0.10
Education track = academic	0.74	0.65	0.66
Education track = vocational	0.26	0.35	0.34
High school GPA (Grade 12)	5.72	5.57	5.48
Avg. score in the PSU (centered at the cutoff)	47.76	-9.90	-20.40
4. Family structure			
Family size	4.46	4.62	4.48
Household head = father	0.61	0.61	0.59
Household head = mother	0.31	0.31	0.28
Household head = other	0.08	0.08	0.13
Distance to closest neighbor (km)	0.05	0.05	
Age difference	1.58	1.58	
Observations	193,101	193,101	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 2: 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)	0.119***	0.146***	0.130**	0.117*
	(0.039)	(0.049)	(0.055)	(0.065)
First stage	0.175***	0.166***	0.171***	0.172***
	(0.009)	(0.010)	(0.011)	(0.013)
Reduced form	0.021***	0.024***		
	(0.007)	(0.008)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	78,441	127,478	83,894	133,911
PSU Polynomial	1	2	1	2
Bandwidth	(56.08-70.60)	(75.22-132.05)	(56.08-70.60)	(75.22-132.05)
Kleibergen-Paap F statistic	399.17	260.64		
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. $*p-value < 0.1$ $**p-value < 0.05 ***p-value < 0.01$.

Table 3: Persistence of the Effect of Neighbors on Potential Applicants' University Enrollment

	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)	0.117***	0.093**	0.068*	0.068*
	(0.038)	(0.037)	(0.041)	(0.036)
First stage	0.175***	0.175***	0.175***	0.175***
	(0.009)	(0.009)	(0.009)	(0.009)
Reduced form	0.020***	0.016**	0.012*	0.012*
	(0.007)	(0.007)	(0.007)	(0.007)
Years fixed effects	Yes	Yes	Yes	Yes
N. of students	78,441	78,441	78,441	78,441
Kleibergen-Paap F statistic	399.17	399.17	399.17	399.17
Outcome mean	0.31	0.28	0.48	0.25

Notes: The table presents estimated effects of neighbors on potential applicants' permanence in the system and in the university where they start 1 year after enrollment. It also present estimated effects on their probability of completing higher education and university. 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 to 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. 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 2. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

Table 4: Effect of Neighbors on Potential Applicants by Social Distance

| | Socioeconomic Status | | Gender | | Age | |
	Same (1)	Different (2)	Same (3)	Different (4)	1 year (5)	> 1 year (6)
Neighbor goes to university (t-1)	0.174*** (0.046)	0.018 (0.072)	0.146*** (0.053)	0.090 (0.058)	0.160*** (0.055)	0.076 (0.060)
First stage	0.185*** (0.011)	0.160*** (0.012)	0.182*** (0.011)	0.168*** (0.011)	0.167*** (0.010)	0.184*** (0.018)
Reduced form	0.032*** (0.009)	0.003 (0.012)	0.027** (0.010)	0.015 (0.010)	0.027*** (0.009)	0.014 (0.011)
Difference	0.156* (0.088)		0.056 (0.078)		0.084 (0.082)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N. of potential applicants	48,118	30,323	39,997	38,444	43,200	32,337
Kleibergen-Paap Wald F Statistic	298.54	190.46	289.90	237.08	247.87	193.28
Outcome mean	0.30	0.33	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 2. In parenthesis, standard errors clustered at neighborhood unit level.
*p-value<0.1 **p-value<0.05 ***p-value<0.01

Table 5: Effect of Neighbors on Potential Applicants by Time at the Neighborhood

	Time at the neighborhood		Neighbors remain-leave		Mother works outside the hh.	
	≥ 4 years	< 4 years	Remain	Leave	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor goes to university (t-1)	0.145***	0.049	0.132***	0.065	0.184***	0.081
	(0.053)	(0.108)	(0.046)	(0.084)	(0.058)	(0.057)
First stage	0.191***	0.210***	0.174***	0.197***	0.172***	0.176***
	(0.012)	(0.025)	(0.010)	(0.019)	(0.012)	(0.011)
Reduced form	0.028***	0.010	0.023***	0.013	0.032***	0.014
	(0.010)	(0.023)	(0.008)	(0.017)	(0.010)	(0.010)
Difference	0.096		0.067		0.103	
	(0.119)		(0.098)		(0.081)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N. of potential applicants	39,160	7,508	56,727	15263	35,690	38,031
Kleibergen-Paap F statistic	250.67	80.98	290.65	105.67	222.69	269.52
Outcome mean	0.32	0.32	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 2. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

Table 6: Effect of 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)	0.160** (0.068)	0.140** (0.064)	0.165** (0.079)
First stage	0.159*** (0.009)	0.156*** (0.010)	0.158*** (0.011)	0.161*** (0.013)
Reduced form	0.021*** (0.009)	0.025** (0.011)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	57,713	95,652	57,713	95,652
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	223.21		
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. $*p-value < 0.1 **p-value < 0.05 ***p-value < 0.01$

Table 7: Effect of Neighbors and Siblings on Potential Applicants' Academic Performance and Application Behavior

	Neighbors (1)	Siblings (2)
Panel A - Academic Performance		
High school GPA at grade 12 (1-7)	0.000 (0.001)	0.095* (0.058)
High school attendance	0.007 (0.009)	0.013 (0.010)
PSU Performance	33.832** (13.840)	25.550* (15.299)
PSU Performance | Taking the PSU	6.865 (9.279)	5.820 (9.677)
Panel B - Application Behavior		
Take PSU	0.057** (0.022)	0.048* (0.029)
Apply to financial aid	0.048 (0.042)	0.139*** (0.046)
Eligible for financial aid	0.079* (0.042)	0.117* (0.049)
Take up financial aid	0.088** (0.038)	0.117* (0.049)
Active application to CRUCH universities	0.068* (0.039)	0.084* (0.053)

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 ($n = 78,441$) 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. Optimal bandwidths are used in all the specifications and were computed following Calonico et al. [2014b]. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

A   Appendix

A.1   Siblings Sample

Although the focus of this paper is on neighbors, I also investigate what happens with potential applicants when an older sibling goes to university T years before her. The sample that I use 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 managed to identify 273,806 pairs of siblings. Proceeding in the same way as with neighbors, 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. 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 students-loan 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 observations. Table A1 presents the summary statistics for this sample.

Table A1: Summary Statistics - Siblings' Sample

	Siblings (1)	Potential Applicants (2)
1. Demographic characteristics		
Female	0.55	0.54
Age	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. Family structure		
Family 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 siblings.

A.2 Identification Strategy: Further Discussion

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

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

Where, N_a is the set of relevant neighbors for potential applicant a and U_{nt} is a dummy variable indicating if 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 applicants. Thus, their decision should not be affected by what potential 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).[52]

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

$$U_{at} = \alpha + \beta_{mt-1} U_{mt-1} + \sum_{n \in N_a \backslash U_{mt-T}} \beta_{n\tau} U_{n\tau} + \varepsilon_{it} \qquad (3)$$

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 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 using all the information available.

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[52]   If younger applicants' decision enter equation 2, instrumenting enrollment of the older neighbor with student-loan eligibility would be enough to solve the reflection problem.

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.[53] To satisfy the assumption in the third case we would need to assume that neighbors applying two or more years before potential 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 generate on a. This is still a relevant parameter from a policy perspective.

A fuzzy RD can be thought as a particular case of IV. 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 applicant and her neighbor. In my setting, this will only be true around the student

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[53]   We are already assuming that younger applicants' decision are not part of equation 2.

loans eligibility treshold 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.[54]

A3. Exclusion:

The instrument only affects potential 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 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 in any reasons that would make individuals to decide not to enroll in university because they are eligible for financial aid.[55]

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 RD 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 loans 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 of university because of their eligibility for funding.

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[54] 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.

[55] Note that 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.

A.3 Other Neighbors Definitions

The results discussed on section 5 focus on the closest neighbor. However, there could be other neighbors that are relevant for potential applicants. To investigate this, I identify the best neighbor among the closest 3 and 5, and the best living within 75 and 100 meters from potential applicants.

When implementing these exercises, the sample size decreases with the radius being analyzed. The student-loans cutoff is relatively low (percentile 40 in the PSU distribution); this makes it more difficult to find individuals that being the best of a group are at the same time 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 in 100 meters is close enough to the cutoff may be very different to those where the best in 200 meters is close. Thus, these results do not tell us much about how neighbors effect evolve with distance. Each estimate comes from a different sample, what means that apart from distance to the relevant neighbor many other things may be changing.

Table A2 presents the results of these analysis. When looking at the effect of the best neighbor among 3 or the best neighbor within 75 meters the coefficient obtained is in the same range as the one discussed in the main section. In this case they are only significant at a 90% level what in part reflects the fact that sample sizes are smaller in this case. When looking at the best neighbor among the closest 5, the coefficient is bigger and significant at a 95% level. This result is consistent with the idea that the effects of exposure are stronger when there are fewer people going to university. Finally, when looking at the effect of the best neighbor within 100 meters, the coefficient drops and becomes not statistically different from 0.

Table A2: Effects of other Close Neighbors on Potential Applicants' University Enrollment

	Best among 5 closest			Best within 75 meters	
	(1)	(2)		(3)	(4)
Neighbor goes to university (t-1)	0.142***	0.161**		0.094**	0.0105*
	(0.053)	(0.069)		(0.047)	(0.056)
First Stage	0.174***	0.169***		0.198***	0.190***
	(0.013)	(0.016)		(0.047)	(0.013)
Reduced form	0.025***	0.027**		0.019**	0.020*
	(0.009)	(0.011)		(0.009)	(0.011)
Year fixed effects	Yes	Yes		Yes	Yes
N. of students	63,876	169,482		62,129	219,495
PSU Polynomial	1	2	1	2	
Bandwidth	(46.80-69.50)	(56.10-163.30)	(51.50-74.30)	(75.70-187.76)	
Kleibergen-Paap F statistic	179.56	112.36		253.00	205.07
Outcome mean	0.220	0.220		0.247	0.247

Notes: The table presents results for specifications that study the effect of other close neighbors on potential applicants' university enrollment. Columns 1 and 2 look at the effect of the best neighbor among the closest 3 and 5, while columns 3 and 4 look at the effect of the best neighbor within 75 and 50 meters. All specifications include a linear polynomial of PSU which slope is allowed to differ at both sides of the cutoff. All specifications use optimal bandwidths computed according to Calonico et al. [2014b]. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

A.4 Robustness Checks

In this section, I study if the identification assumptions of my empirical strategy are satisfied. I start by investigating if there is evidence of manipulation in the running variable, and then I check if other variables that could be related to the decision of going to university present jumps around the student loans eligibility threshold. I continue showing the results of placebo exercises and the robustness of my estimates to different bandwidths choices. I finish this section discussing some issues that could emerge due to missing observations.

A.5 Manipulation of the running variable

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

In this case, it would mean that potential applicants have the ability of affecting the average PSU score of their older neighbors and siblings. As discussed in section 2, the PSU is a national level test which application and marking processes are completely centralized. 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 need to be above the eligibility cutoff.

All this makes it very difficult, even for the students taking the test to manipulate their score around the threshold. Considering this, it seems very unlikely that potential applicants can strategically affect it.

In the context of neighbors, a way in which potential applicants could change the score they obtain in the PSU 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 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 select them.

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 A1 and A7 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 0.7791, whereas in the case of siblings it is 0.5968. Therefore, the results I find do not seem to be driven by manipulation of the running variable.

A.6 Discontinuities in potential confounders

A second concern in the context of an RD is the existence of other discontinuities around the cutoff that may explain the differences we observe in the outcome of interest.

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

Figure A2 summarizes these results for neighbors, and figure A8 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 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 applicants characteristics around the threshold. In the case of neighbors, there is one significant coefficient. Neighbors to the right of the cutoff seem to come from households where parents are more likely to have attended vocational higher education; note however, that in the case of potential applicants, this difference is clearly not significant. In addition, the magnitudes of these coefficients are quite small and the differences in university enrollment documented in section 5 are robust to the inclusion of neighbors' parental education as control. Indeed, they are robust to the inclusion of all the variables in these figures. [56]

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[56] These specification are not presented here, but they are available upon request.

A.7 Placebo exercises

This setting allows me to perform placebo exercise to study if the potential applicants' enrollment decision has any effect on the decision of their older neighbors or siblings. Given the timing of both decisions, we should not find any effect; what happens with potential applicants in t, should not change the probabilities of going to university of their older peers in t-T.

Figures A3 and A9 illustrate the results when performing this exercise in the same sample I use in when estimating the main results. Table A3 presents the estimated coefficients of this exercise. It is reassuring not finding discontinuities around the eligibility threshold; both, the levels and slopes seem to be continuous around it. As in section 5, table A3 present the estimated coefficient using two stages least squares and local polynomials. The coefficients are small and never significant.

In addition to this robustness check, I also study if there are significant discontinuities in points different to the student loans eligibility threshold. Since in these points there is no first stage, we should not find jumps like the ones we observe around the threshold. Figure A4 presents these results for neighbors and siblings. As can be appreciated, none of these jumps is significant.

A.8 Different bandwidths

In this section, I study how sensible are my results to the bandwidth choice. 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 too far from the relevant cutoff.

Figures A5 and A10 presents the estimated coefficients when using bandwidths that go from 0.4 to 1 times the optimal bandwidth. These results correspond to specifications that use polynomial of degree 1 on both sides of the eligibility threshold. Changing the bandwidths does not make an important difference on the estimated coefficients.

A.9   Missing students

In this section, I discuss how missing information about applicants and their older peers could affect my results. As mentioned in Section 3, to identify neighbors I rely on the geocoding process of addresses; since the addresses I use do not include postcode, finding them was not always possible. This is especially the case in rural areas, where there is no precise information on the names of all the roads and locations. In this geocoding process, I loss around 15% of my sample.

To analyze how serious this threat could be, I present an additional exercise just focusing in the Metropolitan Region of Santiago; in this area the geocoding rate of success was higher. Table A4 presents the results to this exercise.

The coefficients obtained in both cases are slightly bigger than the ones I discuss in the rest of the paper. However, they are not significantly different from them. In part, this can reflect differences between students from this region and the ones that are being excluded from this exercise.

Figure A1: 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 A2: Discontinuities in other Covariates at the Cutoff

(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 A3: 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 A4: Neighbors and Siblings 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 A5: Neighbors' Effects with 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 A6: First Stage and Reduced Form of Neighbors' RD (P2)

(a) First Stage: Neighbors' 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 A7: Density of 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 A8: Discontinuities in other Covariates 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].

Table A3: Effect of Potential Applicants on Neighbors and Siblings University Enrollment

	2SLS-1 (1)	2SLS-2 (2)	CCT-1 (3)	CCT-2 (4)
Panel A - Neighbors				
Potential applicant goes to university (t+1)	0.040	0.003	-0.009	-0.005
	(0.073)	(0.092)	(0.101)	(0.119)
First stage coefficient	0.098***	0.100***	0.098***	0.104***
	(0.006)	(0.008)	(0.008)	(0.009)
Reduced form coefficient	0.004	0.000		
	(0.007)	(0.009)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	75,102	95,632	75,102	95,632
PSU Polynomial	1	2	1	2
Bandwidth	(61.30-62.90)	(71.70-89.90)	(61.30-62.90)	(71.70-89.90)
Kleibergen-Paap F statistic	265.11	167.09		
Panel B - Siblings				
Potential applicant goes to university (t+1)	-0.000	-0.036	-0.014	-0.010
	(0.073)	(0.078)	(0.084)	(0.092)
First stage coefficient	0.133***	0.129***	0.098***	0.104***
	(0.008)	(0.008)	(0.008)	(0.009)
Reduced form coefficient	-0.000	-0.005	0.098***	0.104***
	(0.010)	(0.010)	(0.008)	(0.009)
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	42,486	88,158	42,486	88,158
PSU Polynomial	1	2	1	2
Bandwidth	(37.18-46.03)	(79.70-104.11)	(37.18-46.03)	(79.70-104.11)
Kleibergen-Paap F statistic	289.17	265.49		

Notes: The table presents the results of a placebo exercise in which I estimate the effects of potential applicants (t) on neighbors' university enrollment (t-1) and on older sibling's university enrollment (t-T). 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 or family level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

Figure A9: Placebo Exercise: Effect of Potential Applicants (t) on 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 A10: Siblings' Effects with 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 A11: First Stage and Reduced Form of Siblings RD (P2)

(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].

Table A4: Effect of Neighbors on Potential Applicants University Enrollment (Metropolitan Region of Santiago)

	2SLS-1	2SLS-2	CCT-1	CCT-2
	(1)	(2)	(3)	(4)
Neighbor goes to university (t-1)	0.156**	0.192**	0.175**	0.151*
	(0.061)	(0.075)	(0.087)	(0.091)
First stage coefficient	0.128***	0.128***	0.133***	0.136***
	(0.010)	(0.013)	(0.013)	(0.017)
Reduced form coefficient	0.020***	0.025***		
	(0.008)	(0.009)		
Year fixed effects	Yes	Yes	Yes	Yes
N. of students	58,717	77,735	58,717	77,735
PSU Polynomial	1	2	1	2
Bandwidth	(58.22-88.56)	(78.45-121.26)	(58.22-88.56)	(78.45-121.26)
Kleibergen-Paap F statistic	157.97	95.95		
Outcome mean	0.28	0.29	0.28	0.29

Notes: The table presents the results of analysis similar to those presented in table 2 for focusing in RM. 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. *p-value<0.1 **p-value<0.05 ***p-value<0.01

A.10   Additional Figures and Tables

Figure A12: 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 A13: Share of Students going to University vs 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).

Figure A14: 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.

Figure A15: Reduced Form of Neighbors' RD: Neighbors applying the Same year and Two years before Applicants

(a) Neighbors apply on the same year

(b) Neighbors apply two years before

Notes: This figure illustrates reduced forms similar to the one presented in Figure 2, but this time focusing on the closest neighbor applying to university the same year as the applicant (panel (a)) and two years before the applicant (panel (b)). Both panels show how potential applicants' probability of going to university evolves with the PSU score of their neighbors. The PSU score is centered around the student-loans eligibility threshold. Each dot represents the share of potential applicants 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 A16: University Attendance across Neighborhoods in Valparaiso and Vina del Mar

Exposure to University

- Low exposure
- Mid exposure
- High exposure

Notes: The figure illustrates the share of potential applicants exposed to a close neighbor going to university before they complete highschool in different areas of Santiago between 2006 and 2012. In red areas the average exposure is 24.6%, in yellow areas 36.4% and in green areas 56.1%. 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 A17: University Attendance across Neighborhoods in Concepción and Talcahuano

Notes: The figure illustrates the share of potential applicants exposed to a close neighbor going to university before they complete highschool in different areas of Santiago between 2006 and 2012. In red areas the average exposure is 24.6%, in yellow areas 36.4% and in green areas 56.1%. 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)

Table A5: Heterogeneity in the Effects of Closest Neighbor on Potential Applicants' Enrollment

| | Household Income | | | High School Track | | Gender | |
	Low (≤ CLP 270K) (1)	Mid (CLP 270K - CLP 834K) (2)	High (> CLP 834K) (3)	Academic track (4)	Vocational track (5)	Male (6)	Female (7)
Neighbor goes to university (t-1)	0.081*	0.208**	0.056	0.136**	0.057	0.081	0.155***
	(0.041)	(0.079)	(0.201)	(0.056)	(0.038)	(0.053)	(0.056)
First stage	0.191***	0.153***	0.152***	0.171***	0.180***	0.185***	0.167***
	(0.010)	(0.012)	(0.032)	(0.011)	(0.012)	(0.011)	(0.010)
Reduced form	0.015**	0.032***	0.008	0.023**	0.010	0.015	0.026***
	(0.008)	(0.012)	(0.030)	(0.010)	(0.007)	(0.010)	(0.009)
Difference		0.127;-0.025		0.080		0.074	
		(0.089);(0.206)		(0.069)		(0.077)	
N. of potential applicants	45,019	27,760	5,653	48,600	29,841	36,609	41,832
Kleibergen-Paap F statistic	349.70	150.29	22.07	261.32	214.65	277.42	260.24

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. Finally, columns 6 and 7 look at heterogeneous effects by gender. 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 2. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

Table A6: Persistence of the Effect of Siblings on Potential Applicants' University Enrollment

| | Pr. of remaining in the: | |
| | University System | Same Institution |
	(1)	(2)
Neighbor goes to university (t-1)	0.097**	0.083*
	(0.046)	(0.045)
First stage	0.170***	0.170***
	(0.009)	(0.009)
Reduced form	0.016**	0.014*
	(0.008)	(0.008)
Years fixed effects	Yes	Yes
N. of students	57,713	57,713
Kleibergen-Paap F statistic	362.60	362.60
Outcome mean	0.25	0.23

Notes: The table presents the estimated effects of siblings on potential applicants' permanence in the system and in the same institution where they started 1 year after enrollment. Column 1 looks at permanence in any university, while column 2 to permanence in the same university in which potential applicants enrolled in their first year. In both cases, 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. 2SLS estimates come from specifications that control for a linear polynomial of the PSU which slopes are allowed to change at the cutoff. Bandwidths are the same used in the specifications presented in Table 6. In parenthesis, standard errors clustered at neighborhood unit level. *p-value<0.1 **p-value<0.05 ***p-value<0.01

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