HOUSEHOLD REALLOCATION AND SIBLING SPILLOVERS FROM COLLEGE FINANCIAL AID*

Pedro Cubillos†

First draft: September 8, 2025
This draft: September 8, 2025

Preliminary version. Please do not circulate or cite.

Abstract

This paper studies the short-term spillover effects of college financial aid on younger siblings in Chile, leveraging a regression discontinuity design (RDD) based on eligibility thresholds for college loans and scholarships over the years 2008-2016. Results show that, when applying to college, only younger sibling from high income families benefits from older sibling receiving a college loan, by increasing financial aid take up, university enrollment, and educational attainment. On the contrary, students from low income households benefits more when older siblings receive scholarships rather than loans, from which high-income applicants do not benefit. There are no discernible effects on younger siblings in 4th and 8th grade in terms of standardized test scores, parental investment, and parental beliefs. Moreover, by exploiting a reform on college loan repayment scheme in 2012 and using an Difference in Discontinuity (DiDC) approach, I document that more flexible repayment helps poorer families to reallocate resources to younger siblings applying to college. These results shed light on how household reallocate resources and younger sibling benefits depending on the type of aid and repayment scheme received by the older sibling, with relevant differences across the income distribution and financial constraints.

*I am grateful to Marcos Vera-Hernández for his guidance, time, and support in this process. I also thank the Chilean Ministry of Education, the Comision Ingresa, and the Department of Assessment, Evaluation and Academic Registers for sharing the data used in this project. All errors are my own.

†Department of Economics. University College London. E-mail: pedro.cubillos.24@ucl.ac.uk

1 Introduction

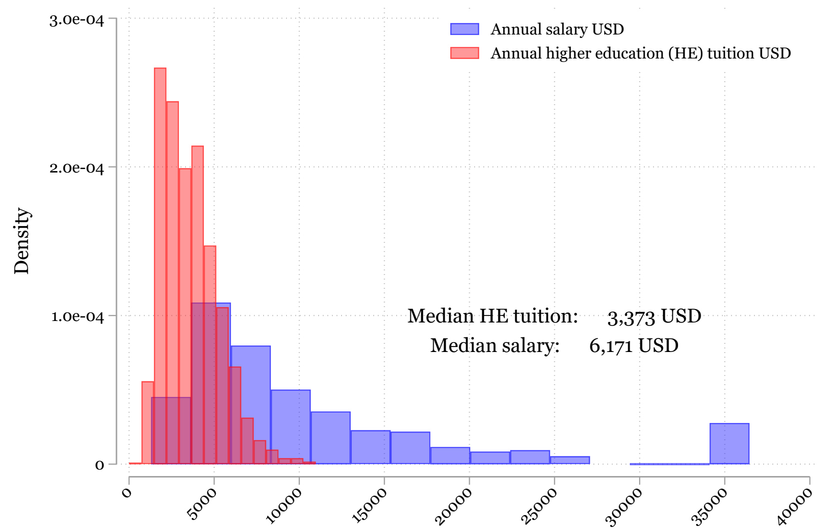
Expanding access to higher education remains one of the most powerful tools for reducing inequality and promoting upward mobility. College financial aid has therefore become a cornerstone of education policy in countries with high tuition costs, liquidity constraints, and low enrollment rates (Black et al., 2023; Carneiro and Heckman, 2002; Denning et al., 2019; Dynarski, 2003; Dynarski et al., 2021; Fack and Grenet, 2015; Londoño-Vélez et al., 2020; Solis, 2017; Solís, 2024). A large body of research shows that financial aid improves access to higher education and shapes recipients' labor market outcomes. Yet far less is known about how these programs reshape the allocation of resources within the household, and in particular, how they affect younger siblings.

Household responses to financial aid are not trivial. Parents often face trade-offs when allocating time and resources across children. If parents are motivated by efficiency alone, they may concentrate resources on the child with the greatest immediate opportunities. But if they are also driven by inequality aversion—a preference for balancing outcomes across children—they may redistribute resources toward younger siblings once one child secures financial aid. Siblings themselves may also adjust their aspirations and effort in response to the opportunities created by an older sibling's aid. Understanding these dynamics is crucial for assessing the broader welfare effects of financial aid and its role in shaping intergenerational mobility.

While some recent studies have begun to document spillover effects of college financial aid on siblings' enrollment and borrowing (Altmejd et al., 2021; Barrios-Fernández, 2022) and on family financial behavior (Bhargava et al., 2025), the evidence remains scarce. In particular, we lack systematic evidence on (i) whether younger siblings benefit educationally when older siblings receive aid, (ii) how these effects vary across family backgrounds, and (iii) whether repayment schemes alter parental resource allocation by changing the perceived burden of debt. This paper addresses these questions by explicitly linking financial aid to sibling spillovers in education.

I study these dynamics in the Chilean higher education system between 2008 and 2016, a period marked by high tuition fees and rapid expansion of financial aid. I analyze the effects of eligibility and take-up of two college loans—each with distinct repayment schemes—and a major scholarship program on younger siblings' outcomes at two critical stages: when applying to college at the end of 12th grade, and at 4th and 8th grade, when students take the nation-wide standardized test (SIMCE). This setting allows me to capture both immediate spillovers effects and longer-run shifts in educational investment within the household.

Figure 1: Students' annual tuition fees and income distribution



Note: The data corresponds to each student who entered higher education between 2008 and 2016. The annual tuition fee corresponds to the program the student entered in a given year, and the information on annual household income comes from survey data associated with the student's application, which is matched one-to-one at the student level. The values in USD are adjusted by the corresponding year inflation rate.

Chile provides an ideal setting for this analysis for three reasons. First, tuition costs are exceptionally high relative to household income—more than half of the median annual earnings—making financial aid central to access (see Figure 1).[1] Second, the admissions process is centralized, based on a standardized national exam and transparent criteria (GPA, test scores, and program-specific weights). These institutional features ensure clear eligibility rules and generate detailed administrative data covering every student's complete schooling history, socioeconomic background, college application, and aid receipt. Third, Chile's aid programs are diverse, including the state guaranteed loan (SGL), the traditional universities loan (TUL), and the *Bicentenario* Scholarship (BS), each with sharp eligibility thresholds and distinct repayment rules.

My empirical strategy exploits these institutional features. First, I implement a regression discontinuity design (RDD) based on sharp eligibility cutoffs: for instance, the SGL requires a minimum score of 475 on the entrance exam and belonging to the bottom 80% of the income distribution, while the *Bicentenario* Scholarship requires a score of 550 and being in the bottom 40%. The SGL and TUL loans differ markedly in repayment: the SGL carried a higher interest rate and was non–income-contingent, while the TUL offered more flexible repayment conditions and partial forgiveness. Second, I exploit a major 2012 reform of the SGL that reduced the in-

[1]See (Ortiz et al., 2025) for a discussion and summary on the costs and financial aids in higher education in Latin America, including Chile.

terest rate from 5.6% to 2% and introduced income-contingent repayments capped at 10% of income. Using a Difference-in-Discontinuity (DiDC) design (Grembi et al., 2016), I estimate how this reform altered parental reallocation of resources and sibling outcomes, complementing the comparative analysis across loans and scholarships.

The results for students applying to a higher education program (12th grade) show that younger sibling from high income household benefits from older siblings loan take up, particularly on outcomes such as financial aid take up, university enrollment and educational attainment. However, the effects for low income household is null and even negative for some specific outcomes. However, when we replicate the estimations but for older siblings' eligibility and take up of scholarship rather than loans, the effects for low income families become in general positive and larger in magnitude, but somewhat noisy. This is also true if when analyzing academic performance at late school years. This present initial evidence that burden imposed for loans in contrast to scholarship can be harmful for younger siblings in low income households, probably by reallocating more resources on the older siblings going to college.

In the other hand, I do not find clear effects on students outcomes at 4th-8th grade, either for academic attainment or for parental investments and beliefs. Although there are some indications that the effects of scholarships is more positive than loans for low income students, the results are inconsistent and indicate that the effects are negligible.

Finally, by exploiting the SGL loan reform of 2012, I find some preliminary evidence of an increase in the university enrollment, particularly for low and middle income households, evidencing again that the repayment scheme can be an important factor on how households allocate resources across the income distribution. Particularly, this result suggest that the relaxation of repayment of the loan is a beneficial scheme for low-middle income household and their younger siblings, which goes in line with the findings for scholarship eligibility.

This paper connects to four strands of the literature at the intersection of human capital investment and household financial behavior. First, it builds on the large literature studying the effects of college financial aid on access, persistence, and long-run outcomes (Aguirre, 2021; Black et al., 2023; Bucarey et al., 2020; Carneiro and Heckman, 2002; Denning et al., 2019; Dynarski, 2003; Dynarski et al., 2021; Fack and Grenet, 2015; Londoño-Vélez et al., 2020; Solis, 2017; Solís, 2024). This work has shown that aid increases enrollment and graduation, improves labor market returns, and reduces inequality in access, but has largely focused on the direct beneficiaries of aid. My paper instead highlights intra-household spillovers, showing that the benefits of financial aid may extend to younger siblings who are not direct recipients.

Second, I relate to the growing evidence on sibling spillovers in education (Aguirre and Matta, 2021; Altmejd et al., 2021; Barrios-Fernández, 2022; Goodman et al., 2015; Karbownik and Özek, 2023; Qureshi, 2018) and beyond (Altonji et al., 2017; Landersø et al., 2020; Persson et al., 2025). This literature emphasizes the role of social and familial networks in shaping educational decisions and aspirations. While prior studies have shown that older siblings' college enrollment can affect younger siblings' choices, little is known about how the design of financial aid programs (loans versus scholarships, repayment schemes) mediates these spillovers. Furthermore, Barrios-Fernández (2022) studies sibling spillovers and the same policy as me, by he focuses on the effect of older brother (or closest neighbour) enrolling in college, instrumented by the loan eligibility. But not the effect of accessing the financial aid per se. My contribution is to show that not only does aid affect siblings, but that the form of aid and repayment rules shape the magnitude and direction of these intra-household effects. Moreover, I study students outcomes at different educational stages (4th, 8th, and 12th grade), and a broader set of outcomes, including various measures of parental time and financial investment, beliefs about educational achievement, and school engagement.

Third, my paper relates to work on borrowing constraints, loan limits, and repayment schemes (Albagli and Garcia-Echalar, 2025; Bhargava et al., 2025; Black et al., 2023; Carneiro and Heckman, 2002; Denning and Jones, 2019; Hanushek et al., 2014; Lochner and Monge-Naranjo, 2011, 2012; Solís, 2024). This literature shows that relaxing borrowing constraints influences borrowing behavior but often has limited effects on educational attainment—for example, Denning and Jones (2019) find that higher loan limits increase borrowing without improving degree completion. Additionally, there is evidence that the type of repayment affects household decisions and risk behaviour (Battaglia et al., 2024). By studying Chile's reform that reduced interest rates and introduced income-contingent repayments, I extend this line of work by showing how repayment design affects not only borrowers' financial behavior but also the allocation of resources across siblings.

Finally, this study contributes to the literature on parental investment and intra-household allocation (Attanasio et al., 2020a,b; Becker and Tomes, 1976; Behrman et al., 1982; Bharadwaj et al., 2018; Boneva and Rauh, 2018; Breining et al., 2020; Celhay and Gallegos, 2025; Dahl and Lochner, 2012; Dizon-Ross, 2019; Guryan et al., 2008; Yi et al., 2015). A central theme in this work is whether parents invest in children according to efficiency motives (favoring the child with higher returns) or inequality aversion (smoothing outcomes across children). While most empirical evidence has focused on early childhood health and education, my paper provides new evidence from the context of higher education finance. By analyzing how younger siblings benefit from older siblings' financial aid, I document that household responses reflect not only constraints and opportunities but also parental preferences over inequality among their children, bringing the concept of inequality aversion to the study of financial aid. Moreover, this study complements the literature related to income shocks and parental investment (e.g. Borra et al., 2024).

This work presents novel results that help to understand the within-household consequences of financial aid, and more specifically, how younger siblings may benefit from it. The design of financial aid, in terms of repayment scheme and socioeconomic targeting, provides important insights for policymakers, particularly in a context where college enrollment is low and costly. This paper shows some preliminary evidence that the amplifying effect -i.e., by considering siblings or peers spillovers- of student benefits found by the literature appears to be advantageous for select population groups, even if moderate. That rise concerns on understanding this phenomenon in other highly studied contexts, such as the United States, Colombia, and beyond.

The paper is organized as follow. Section 2 summarize the institutional background and how the different sources of data are combined. Section 3 shows a simple economic model that helps to understand the dynamics on household resources allocation across children and time. Section 4 describe the two main empirical strategies, namely RDD and DiDC methods. Section 5 shows the main results of the paper. And finally, Section 6 concludes.

2 Background and Data

2.1 Higher Education and Financial Aid in Chile

This study takes place in Chile, a country that has experienced profound changes in the financing of higher education over the past two decades. The Chilean higher education system is composed of universities and vocational institutions, with universities offering longer and typically more costly degree programs. Access to these programs depends heavily on financial aid, particularly for students from low- and middle-income households, as tuition fees are among the highest relative to income in the OECD—amounting to roughly one-half of median household income. Public financial aid thus plays a central role in expanding educational opportunities and in shaping household decisions around higher education (Solis, 2017).

Admission to higher education in Chile is centralized and highly standardized. Until recently, students seeking entry into college were required to take the national college entrance exam, the *Prueba de Selección Universitaria* (PSU), which was administered once a year and covered mathematics, reading, and other subject-specific modules. Admission decisions were based on a weighted combination of high school GPA, PSU scores, and program-specific weights that varied by field of study and institution (for example, engineering programs placed more weight on mathematics, while humanities programs emphasized reading). Each university and program set transparent and publicly available admission rules based on these observable criteria, meaning that student placement was determined in a clear and centralized manner.

The Chilean higher education system is composed of three main types of institutions: (i) traditional universities (*universidades tradicionales*), which include the older, publicly funded universities that belong to the Council of Rectors of Chilean Universities (CRUCH); (ii) newer private universities, which have proliferated since the 1980s and rely almost entirely on tuition revenues; and (iii) vocational institutions, which encompass professional institutes and technical training centers offering shorter and less costly programs. In this paper I focus separately on university programs and vocational programs, as the financial aid rules and labor market outcomes differ substantially across these tracks.

Financial aid was similarly structured through centralized application and allocation processes. Students applied for aid simultaneously with university admission, and eligibility was determined by sharp cutoffs on observables such as PSU scores, household income percentile, and type of institution attended. Chile's aid portfolio included two major student loan programs—the *Crédito con Aval del Estado* (state-guaranteed loan, SGL) and the *Fondo Solidario de Crédito Universitario* (TUL) offered by traditional universities—as well as a range of scholarships, most prominently the *Bicentenario* Scholarship. These instruments differed not only in generosity but also in repayment design and eligibility criteria. Over time, significant reforms were introduced, including reductions in loan interest rates, the introduction of income-contingent repayment, expansions in scholarship coverage, and eventually the introduction of a free-tuition policy in 2016. The combination of sharp eligibility rules, centralized admissions, and rich administrative data linking school histories, test scores, socioeconomic background, and higher education outcomes provides a unique setting for studying how financial aid shapes household investment decisions and intra-family resource allocation.

2.1.1 Student Loan Programs: TUL and SGL

Chile operates two main student loan programs: the TUL and the SGL. The TUL program, created in 1981, is restricted to students attending traditional universities. These loans are subsidized by the state, administered directly by universities, and feature income-contingent repayment with a 2% real interest rate. Repayment obligations begin two years after graduation, and annual payments are capped as a share of income, with remaining balances forgiven after a fixed horizon.

The SGL program was introduced in 2006 with the explicit goal of broadening access beyond the traditional university system to accredited private universities and vocational institutions. SGL loans were initially provided by private banks at market-level interest rates (around 5.6% real) with standard repayment schedules. Mounting concerns over debt burdens and defaults led to a major 2012 reform, which reduced the interest rate to 2%, introduced income-contingent repayment capped at 10% of annual income, and allowed repayment suspensions during unemployment. These changes significantly altered borrowing incentives and repayment risks for households.

Eligibility for both loan programs depends on a combination of academic and socioeconomic criteria. Academically, applicants must score above 475 points in average between math and reading tests on the national admission exam, the PSU, or meet a minimum high school GPA.[2] Socioeconomic eligibility is determined through the FUAS form (*Formulario Único de Acreditación Socioeconómica*), which collects detailed family information cross-checked with tax and social security records to assign students to income quintiles. Figure 2 summarize the eligibility rules and main characteristics of each college financial aid studied in this paper.

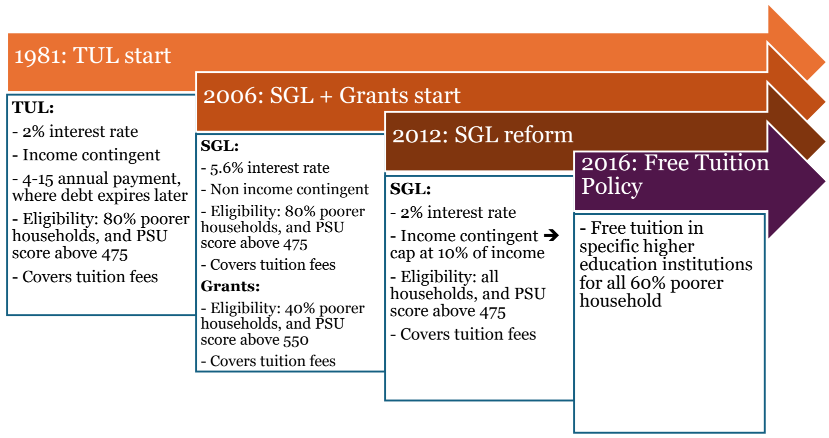
2.1.2 Scholarship Programs

Alongside loans, the Chilean government provides a wide set of targeted scholarships designed to reduce inequality in access to higher education. These programs include not only tuition support but also subsidies for living expenses. For example, students from vulnerable households may qualify for food scholarships (BAES) and transportation assistance (TNE). Additional need-based grants cover textbooks, dormitory housing, or relocation costs for students moving from their hometowns to university centers.

The most prominent tuition-based program is the *Bicentenario* Scholarship (*Beca Bicentenario*), introduced in 2006 to expand access for academically qualified students from the bottom income quintiles. Eligibility is determined through the centralized aid application system (FUAS), which collects socioeconomic information, and through academic merit criteria. To qualify, students

[2]The analysis of eligibility using GPA is not addressed in this paper.

Figure 2: College financial aid timeline in Chile



Note: Own elaboration using historical records. It is important to note that there is a wide variety of scholarships, of different types (covering tuition or living costs), and that the year in which each one begins varies. The diagram here is simplified, and for more information, I recommend following this link.

must typically belong to the lowest 40% of the income distribution, as verified by the Ministry of Social Development, and must obtain a minimum score on the national admission exam (PSU) of 550 points, as well as maintain satisfactory academic performance throughout their studies. The scholarship applies exclusively to students enrolled in accredited programs at traditional universities (CRUCH) or other eligible institutions.[3]

Over time, the *Bicentenario* Scholarship has become one of the largest scholarship programs in Chile, both in terms of beneficiaries and budgetary allocation, reflecting its central role in widening higher education opportunities for disadvantaged but high-achieving students.

2.1.3 Centralized Admissions and Aid Application Process

Admissions and financial aid in Chile are highly centralized and tightly coordinated. Students in their final year of high school register for the PSU and simultaneously submit the FUAS form to apply for financial aid. The Ministry of Education then processes test scores and socioeconomic information to determine eligibility, and communicates both admission results and aid awards in advance of enrollment deadlines. Once students confirm enrollment, tuition payments from

[3]The *Bicentenario* Scholarship covers up to the "reference tuition" (*arancel de referencia*) established annually by the Ministry of Education. Since this amount is frequently below the posted tuition fee charged by universities, students often need to combine the scholarship with loans (such as CAE or TUL) or household resources to fully finance their studies. Importantly, recipients are required to remain in good academic standing, with institutions monitoring GPA and progression standards; failure to do so results in suspension or termination of benefits.

loans or scholarships are transferred directly to institutions, ensuring full integration between the admissions and financing systems.

2.2 Data and Sample

This study combines multiple administrative datasets covering the universe of high school graduates, PSU test takers (i.e. college applicants), financial aid applicants, and primary and secondary school students in Chile.

The Department of Assessment, Evaluation and Academic Registers (DEMRE) provides individual-level data on test scores, demographic characteristics, and school background for each college entry exam (PSU) taker in each year from 2007 and 2019. This data include also the information of the program's[4] application after taking the exam, in which students have to set their preferences and eligibility depends on vacancies in each program and the weighted score.[5] These datasets include information on whether the applicant enroll to college during this year, and the information of the program enrolled. To this data, I also match program specific characteristics, such as type of institution (e.g., traditional or not, private or public, vocational or university program, etc.), tuition fees, among others. Finally, I complement this information with yearly data on students' program choice, enrollment status, institutional characteristics, and graduation outcomes.

To be able to apply for a college financial aid, the students have to fill a survey related to socioeconomic background (called FUAS), which is used to define the eligibility for financial aids. This socioeconomic data including family income quintile, parental education, and labor force status. Combining this information and PSU test scores, I am allow to define financial aid eligibility. Moreover, I access to information of yearly financial aid assignment through the data provided by the Minstry of Education (for the case of *Bicentenario* scholarship and TUL loan) and *Comision Ingresa*, which provided information of SGL loan take up. The last, particularly, provides information on the specific amount taken by the students.

In order to understand more deep dynamics on household resources allocation, I also focus on a variety of outcomes at 4th and 8th grade. To this end, I add two additional key sources to measure students attainment and parental investment. First, I use school students administra-

[4]Defined as a combination on college institution and major.

[5]Each program select the weights in a discretionary form, which is know before application. Is a combination between GPA (also called NEM), GPA ranking within school, math score, reading score, and either history or science score, depending on the program.

tive records provided by the Ministry of Education, that offer detailed information on students' academic trajectories. Using this source, I construct a comprehensive panel dataset at individual level spanning the years 2007 to 2019, which includes annual data on attendance, enrollment, GPA, grade retention, and school characteristics. These school characteristics include, among others, the type of school (public, voucher or private), tuition fees (copay), and quality.[6] Secondly, I use the data provided by the *Sistema de Medición de la Calidad de la Educación* (SIMCE), spanning 2007 to 2019. SIMCE is a nationwide assessment that evaluates Chile's national curriculum through standardized tests administered in selected grades (2, 4, 6, 8, and 10). Additional to having student's test scores, this dataset includes a survey given to parents and students, which include a rich amount of parents and household information. This survey will be used to measure parental investment and beliefs following Celhay and Gallegos (2025), which is described in the next subsection.

Since my aim in this paper is to study sibling spillover from college financial aid, I focus on sibling pairs in which the firstborn applied to a higher education program between 2008 and 2015, and the younger sibling subsequently took either the college entry exam (PSU, at the end of 12th grade) or the national standardized SIMCE test in 4th or 8th grade. I identify siblings using surnames and schools following Aguirre and Matta (2021)'s credible assumptions.

Linking all these datasets, I construct two main samples. The first one consist in all younger siblings taking the college entry exam (PSU) for the first time from years 2007 and 2016, from which we are able to match with a successive older sibling who took the PSU test before him, between 2008 and 2015. The second sample consist in all students at 4th and 8th grade taking the SIMCE test after the older took the PSU, where I measure educational attainment (math and reading test scores) and a variety of parental outcomes described below. This sample is also matched with a older sibling who took the PSU exam before the younger took the SIMCE. These two samples and the main variables are shown in Tables 1.

2.3 Outcomes

This section summarizes the main outcomes studied in this paper, also presented in the Table 1. For the sample of students (younger siblings) applying to higher education—i.e., those who took the national college entry exam (PSU) between 2009 and 2016—we divide the outcomes into four groups.

[6]Quality is commonly measured as the average score of students in Math and Reading in the standardized SIMCE and PSU tests.

Table 1: Students' summary statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Panel A: 12th Grade College Applicants (PSU)					
Age	176,235	19.10	0.93	17	22
Female	176,235	0.54	0.50	0	1
Public school	174,592	0.34	0.47	0	1
Voucher school	174,592	0.59	0.49	0	1
Private school	174,592	0.04	0.20	0	1
PSU NEM score	176,235	545.62	97.43	213	826
PSU math score	176,235	508.34	102.23	150	850
PSU reading score	176,235	502.48	100.52	150	850
PSU weighted score	176,235	505.41	93.43	168	850
Any loan take up	176,235	0.28	0.45	0	1
SGL take up	176,235	0.22	0.42	0	1
TUL take up	176,235	0.07	0.26	0	1
Scholarship take up	176,235	0.13	0.34	0	1
University enrollment	176,235	0.07	0.26	0	1
Vocational enrollment	176,235	0.22	0.41	0	1
Any college enrollment	176,235	0.29	0.45	0	1
Parents education:					
Primary education or less	167,449	0.09	0.28	0	1
Secondary education	167,449	0.53	0.50	0	1
Higher education	167,449	0.38	0.49	0	1
Low income household	176,234	0.43	0.49	0	1
Middle income household	176,234	0.48	0.50	0	1
High income household	176,234	0.09	0.29	0	1
Panel B: 4th and 8th Grade Students (SIMCE)					
Female	167,327	0.49	0.50	0	1
SIMCE math score	150,873	273.11	48.82	92	405
SIMCE reading score	114,596	254.68	50.85	99	383
Father's education level:					
Primary education or less	128,788	0.15	0.36	0	1
Secondary education	128,788	0.45	0.50	0	1
Higher education	128,788	0.40	0.49	0	1
Mother's education level:					
Primary education or less	131,642	0.14	0.35	0	1
Secondary education	131,642	0.47	0.50	0	1
Higher education	131,642	0.39	0.49	0	1
Household income (USD)	131,272	1197.41	1123.84	83	3833
Parental beliefs: Highest educational level reached by child					
High School	117,849	0.06	0.24	0	1
Vocational	117,849	0.14	0.35	0	1
College	117,849	0.54	0.50	0	1
Postgraduate	117,849	0.22	0.42	0	1
Parental financial investment					
Has computer	46,594	0.90	0.30	0	1
Has internet	44,457	0.76	0.43	0	1
Has > than 10 books	68,803	0.81	0.39	0	1
Parental engagement					
Parents assist to parents' meetings	47,125	0.93	0.25	0	1
Parents assist to teacher meetings'	7,261	0.97	0.18	0	1
Parents assist to school activities	116,554	0.68	0.46	0	1
Parental time investment					
Parents congrats grades	71,762	0.86	0.35	0	1
Parents know grades	58,406	0.73	0.45	0	1
Parents demand good grades	45,514	0.73	0.44	0	1
Parents help to study	58,468	0.59	0.49	0	1
Parents help with homework	27,129	0.42	0.49	0	1

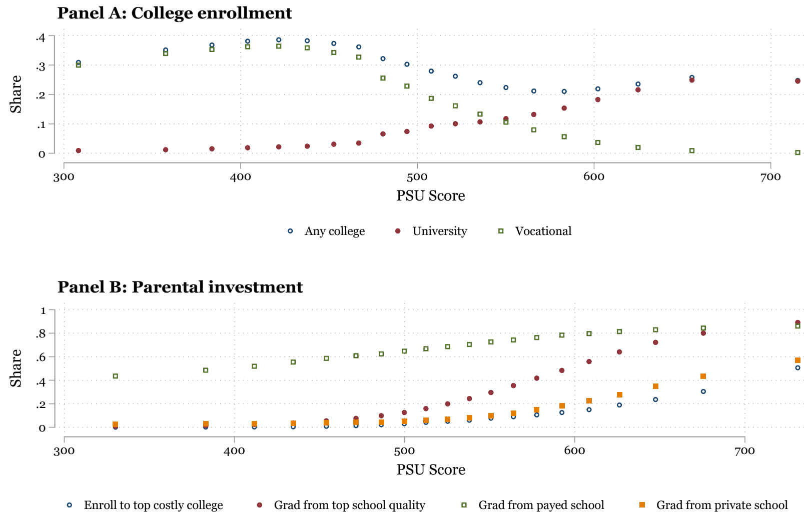
Notes: Panel A: Observations cover each student taking the college entrance examination test (PSU) between the years 2009 and 2016, at the ages 17 to 22. Panel B: Observations cover all school student at 4th and 8th grade that took the standardized test SIMCE in math and reading and whose parents answered the corresponding family survey. Differences in the number of observations are because not all questions were asked every year

First, I consider outcomes related to financial aid take-up, capturing whether students obtained one of the main benefits such as the SGL, the TUL, or the *Bicentenario* scholarship. Second, I examine outcomes related to college enrollment, distinguishing between university and vocational programs. Third, I analyze outcomes associated with educational attainment, measured through PSU test scores in math and reading, as well as high school GPA (averaged over grades 9–12) and the student's within-school cohort ranking (here called PSU NEM). Finally, I consider outcomes related to parental investment, including the tuition cost of the program attended and characteristics of the secondary school of graduation, such as cost and quality.

Figure 3 illustrates how some of these outcomes correlate with PSU performance. Panel A shows that students with higher PSU scores are more likely to enroll in university programs rather than vocational tracks. Panel B shows a positive correlation between PSU scores and the cost, quality, and private status of the student's secondary school. These variables, which proxy parental investment, suggest that family resources may play a critical role in shaping educational attainment.

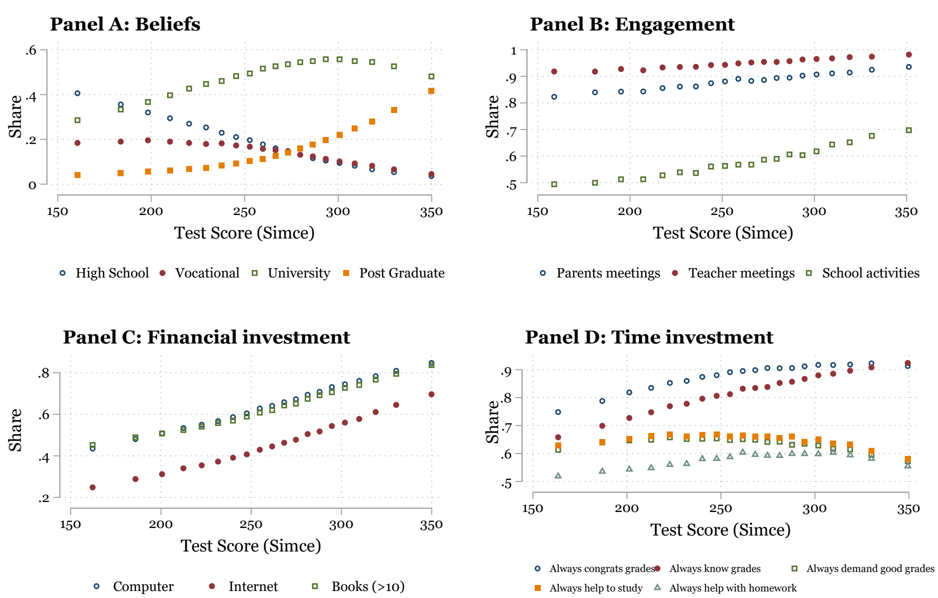
For the sample of fourth- and eighth-grade students, I divide outcomes into two groups. First, educational attainment is measured by performance on nationwide standardized tests in math and reading. Second, I analyze four measures that approximate parental behavior and the allocation of resources to younger siblings, following approaches used in Bharadwaj et al. (2018) and Celhay and Gallegos (2025). Figure 4 illustrates how these measures correlate with average student performance in math and reading. Panel A shows that parents of higher-performing students are more likely to expect their children to reach university or postgraduate education, rather than only high school or vocational studies. Panel B shows that while parental engagement in school-related activities is generally high (at least 50%), it still increases with student performance. Panel C documents a positive correlation between parental financial investment and student outcomes, measured as having at home computer, internet, and more than 10 books. Finally, Panel D shows that higher-achieving students are more likely to be congratulated by their parents and to have parents aware of their grades, but time-intensive support such as help with homework follows an inverted-U pattern, appearing more relevant when students are at the lower end of the performance distribution.

Figure 3: Measures of parental investment and students choices at 12th grade (college entry)



Note: The measures presented in these figures are constructed using the PSU, Chile's standardized college entry exam. Panel A shows the type of college program (university versus vocational) in which the student enrolls in a given year. Panel B describes the characteristics of the secondary school from which the student graduated at the end of 12th grade, prior to entering higher education. Additional figure by father's education in Figure A1.

Figure 4: Measures of parental involvement in children's education at 4th grade



Note: The measures presented in these figures are constructed using the SIMCE standardized test, which is administered nationally in Chile. Each student taking the test is linked to a rich set of variables collected through parent and student surveys, from which I construct the indicators shown. Panel A captures parental beliefs about the highest educational level their child is expected to attain. Panel B reports dichotomous measures of whether parents participate in school activities or meetings. Panel C reflects parental financial investment, specifically whether the household owns the items listed in the figure. Panel D measures the time parents invest in their child's studies; unlike the previous panels, this information is self-reported by students rather than parents. This Figure is a close replication of the one in Celhay and Gallegos (2025). Additional figure by father's education in Figure A2.

3 Economic Framework

I construct a simple theoretical model to understand the intertemporal allocation of resources across different children withing the household. It borrow some aspects from existing literature in siblings resources allocation and inequality aversion (Bharadwaj et al., 2018; Behrman et al., 1982; Boneva and Rauh, 2018; Giannola, 2024), and intertemporal decisions on parental investment in education considering financial constraints and credit access (Lochner and Monge-Naranjo, 2011). Combining both I bring new insights into the literature, which also help to understand the underlying empirical findings.

3.1 Preferences, Financial Aid, and Human Capital Production Technology

Consider a representative household with two child $i = \{A, B\}$, where the first is older than the second. I consider two periods, where Child A is in college at $t = 1$ and in the labor market at $t = 2$, and Child B is in school at $t = 1$ and in college at $t = 2$. The household needs to allocate resources (investment in education) in each period to each child, and may care about investment inequality across children (i.e. inequality aversion). By assuming separability assumption between parents' consumption and child outcomes and an standard functional form (Behrman et al., 1982; Bharadwaj et al., 2018; Giannola, 2024), the parental preferences on children outcomes can be modeled as a simple CES utility function:

$$U(H_A, H_B) = (c_A H_A^{\rho} + c_B H_B^{\rho})^{\frac{1}{\rho}} \tag{1}$$

where H_i represents the final outcome (in this case educational attainment) of each child i, and c_i is a child-specific preference (Giannola, 2024). The inequality aversion in child outcomes is governed by the parameter $\rho \in (-\infty, 1]$. If $\rho \to -\infty$, then the utility function simplifies to $U = \min(H_A, H_B)$, and parents aim to produce same final outcomes between children (perfect complements). If $\rho \to 0$, the utility function approximate to a Cobb-Douglas, and if $\rho \to 1$, it approximate to a linear utility function, in where parents are indifferent regarding inequality among children. Hence, here parents face the trade-off between efficiency and inequality, as might be the case that the maximisation problem doesn't give an equal distribution of resources towards children, given, for example, to different perceptions of children ability and complementarity between investment's timing and ability (Boneva and Rauh, 2018).

Parents choose how much to invest I_t^i in each child $i = \{A, B\}$, in each period $t = \{1, 2\}$, in order to maximise utility $U(H_A, H_B)$ subject to two constraints. This follows for example Giannola (2024), but consider a two-period maximisation problem including savings and borrowings, given the empirical question is focus particularly in this intertemporal decision. Specifically, the first constraint is a budget constraint as follows:

$$t = 1: \quad I_1^A + I_1^B + S \leq Y_1 + L^A \cdot \mathbb{1}\{\text{AidEligible}\} \tag{2}$$

$$t = 2: \quad I_2^B \leq Y_2 + \pi \cdot Y_2^A + (1 + r)S - (1 + R)L^A \tag{3}$$

where L^A is the amount of loan offered to Child A (e.g., SGL or TUL), $\mathbb{1}(\text{AidEligible})$ is an indicator of financial aid eligibility, and R is interest rate for the loan L^A, which may be zero (if it's a scholarship) or income-contingent. Y_t is the income of the household in each period, and Y_2^A is the income of the older brother in period $t = 2$ after graduating from college, which is multiplied by the probability π of finding a job.[7] Lastly, household are allowed to save earning with an interest rate r.

The second constraint is the human capital production function H_i achieved by each child i, which depends on child baseline ability (θ_i) and total educational investment (I_i), and follows a Cobb-Douglas functional form:

$$H_i(\theta_i, I_i) = \theta_i^{\gamma} \cdot I_i^{1-\gamma} \qquad i = \{A, B\} \tag{4}$$

Therefore, the maximisation problem becomes as follow:

$$\max_{I_1^A, I_1^B, I_2^B, S} U = \left[c_A(\theta_A^{\gamma}(I_1^A)^{1-\gamma})^{\rho} + c_B(\theta_B^{\gamma}(I_1^B + \delta I_2^B)^{1-\gamma})^{\rho} \right]^{1/\rho} \tag{5}$$

subject to

$$I_1^A + I_1^B + S = Y_1 + L^A, \qquad I_2^B = Y_2 + \pi \cdot Y^A + (1 + r)S - (1 + R)L^A,$$

and nonnegativity of choice variables. Here I asume that both budget constraints are binding, and that $I^A = I_1^A;\ I^B = I_1^B + \delta I_2^B;\ Y = Y_1 + Y_2$.[8] Different repayment rules (e.g., fixed vs. income-contingent, or interest rate) affect future available income for educational investment and therefore intertemporal choices. If repayment is delayed or forgiven under income-contingent rules, the household may invest more in B (a spillover effect), or reduce savings for A. Moreover, there is some evidence that parents are inequality averse and tend to invest more on the ones with

[7] The reason of this is that older sibling's employment status has an impact on whether the household has to pay or not the loan, which affect also how much the household can invest on the younger sibling in period $t = 2$.

[8] Here δ captures diminishing returns to late investment (e.g., education is more productive earlier) (Boneva and Rauh, 2018)

less ability to equalize final outcomes (Behrman et al., 1982). This might depend on the income distribution, because household face intertemporal restrictions. For example, could be the case that, given the eligibility for a financial aid, parents could be more willing to invest more in the older children than in the younger. However, in this simple model I do not consider different repayment rules more than varying the interest rate, and do not allow some key variables to change across the income distribution, such as π.

Solving the household's maximization problem yields closed-form share rules for investment in the two children, with the timing of investment in the younger sibling determined by the Euler condition

$$(1+r)\delta \lesseqgtr 1.$$

The timing threshold $\tau \equiv (1+r)\delta$ governs whether the solution is interior in the timing margin or whether a corner arises. If $\tau < 1$ households strictly prefer early investment for child B and the optimal savings choice is $S^* = 0$ (a corner). If $\tau > 1$ households strictly prefer to shift resources to period 2 and typically set $I^*_{B1} = 0$ (another corner). The knife edge $\tau = 1$ is the only case where the two timing margins can be interior simultaneously; it therefore provides a convenient point to compute comparative statics that coincide with the continuous limit of the corner regimes.

Proposition 1 (Knife-edge case)**.** *At $\tau = 1$, households are marginally indifferent between early and late investment in the younger sibling. Optimal allocations follow CES shares out of the effective budget*

$$M \equiv (Y_1 + L^A) + \delta\big(Y_2 + \pi Y^B - (1+R)L^A\big).$$

Comparative statics at this knife-edge case are continuous limits of the two polar regimes. It is split between I_1^A and the composite $Z \equiv I_1^B + \delta I_2^B$ according to CES shares.

Proof of Proposition 1 in Appendix C. At $\tau = 1$ the closed-form share rule gives

$$I_1^{A*} = \frac{\kappa}{1+\kappa} M, \qquad Z^* = \frac{1}{1+\kappa} M,$$

with

$$\kappa \equiv \left(\frac{c_A \theta_A^{\gamma\rho}}{c_B \theta_B^{\gamma\rho}}\right)^{1/\alpha}, \qquad \alpha \equiv (1-\gamma)\rho - 1 \ (\alpha \neq 0).$$

Write $s(\kappa) \equiv \kappa/(1+\kappa)$ (so $I_1^{A*} = s(\kappa)M$). For any parameter x that enters only via M (for example R, π, L_A), the total derivative is

$$\frac{\partial I_1^{A*}}{\partial x} = s(\kappa)\,\frac{\partial M}{\partial x}.$$

Because $\partial M/\partial x$ is simple, we obtain immediately:

Proposition 2 (Comparative statics at $\tau = 1$)**.** *At $\tau = 1$ the following hold:*

$$\frac{\partial I_1^{A*}}{\partial R} = s(\kappa) \cdot \frac{\partial M}{\partial R} = s(\kappa) \cdot \big(-\delta L_A \big) < 0,$$
$$\frac{\partial I_1^{A*}}{\partial \pi} = s(\kappa) \cdot \frac{\partial M}{\partial \pi} = s(\kappa) \cdot \big(\delta Y^B \big) > 0,$$
$$\frac{\partial I_1^{A*}}{\partial L_A} = s(\kappa) \cdot \frac{\partial M}{\partial L_A} = s(\kappa) \cdot \big(1 - (1+R)\delta \big).$$

Analogous expressions hold for the composite $Z^* = M/(1+\kappa)$ (with the complement $1 - s(\kappa)$ multiplying $\partial M/\partial x$). Thus at the knife edge changes in R, π, L_A operate purely through the effective budget M and are split between A and B according to CES shares.

Proof of Proposition 2 in Appendix C. At $\tau = 1$ a higher repayment R reduces the effective budget M (because it tightens expected period-2 resources) and both I_1^A and the composite Z fall proportionally to their CES shares; a higher success probability π increases M and so increases both investments. The loan L_A has an ambiguous effect through M because it raises first-period resources but increases future repayment: the sign of $\partial I_1^{A*}/\partial L_A$ depends on whether $1 - (1+R)\delta$ is positive or negative (i.e., whether the net effect of one extra dollar of loan on the effective budget is positive).

In sum, computing comparative statics at $\tau = 1$ is both feasible and informative: the knife edge yields closed-form derivatives that are the continuous limits of the corner regimes $\tau < 1$ and $\tau > 1$. For $\tau \neq 1$ one must handle corner solutions. Comparative statics still exist, but derivatives can be discontinuous at $\tau = 1$. Even with some weaknesses and some aspect still in construction, this framework provides a simple tractable way to analyze how households allocate educational investments across children under intertemporal budget constraints and borrowing opportunities. By incorporating differences in loan amount, repayment, and child characteristics, the model highlights the underlying trade-offs parents face between efficiency and equality. In particular, it generates theoretical predictions about whether aid eligibility for one child crowds in or crowds out investment in the sibling, how the nature of financial support (scholarships versus loans) influences household savings behavior, and whether softer repayment rules affect the intra-household allocation of educational resources.

4 Empirical Strategy

4.1 Regression discontinuity design

To estimate the causal effects of financial aid eligibility on household behavior and educational outcomes, I implement a regression discontinuity design (RDD) that exploits sharp eligibility thresholds in Chile's student aid system. In particular, I leverage the fact that access to key financial aid programs—such as the SGL (state-guaranteed loan), TUL (traditional university loan), and *Bicentenario* Scholarship—is determined by a discrete cutoff in standardized test scores (PSU).

Eligibility for financial aid is a deterministic function of a student's average score in the mathematics and reading sections of the PSU. For example, SGL and TUL requires a minimum score of 475, while the scholarship require a higher threshold of 550 points. This creates a natural discontinuity that I exploit to compare students just above and just below the cutoff.

Let $Score_{s(i),t-1}$ denote the standardized test score for student's i older sibling $s(i)$ at the year $t-1$, and let c be the cutoff for aid eligibility.[9] This lagged structure allows me to avoid the reflection problem suggested by Manski (1993) and Barrios-Fernández (2022). I define an indicator $D_{s(i),t-1} = \mathbb{1}(Score_{s(i),t-1} \geq c)$ for eligibility. The main parameter of interest is the effect of crossing this threshold on outcomes Y_{it}, which include financial aid take up, university enrollment, educational attainment, household educational investment in younger siblings, among others described in Section 2. I estimate the following local linear specification:

$$Y_{it} = \alpha + \tau D_{s(i),t-1} + f(Score_{s(i),t-1} - c) + \varepsilon_{it} \tag{6}$$

where $f(\cdot)$ is a local polynomial function (typically linear or quadratic) estimated on either side of the cutoff.[10] The coefficient τ identifies the causal effect of aid eligibility under standard RDD assumptions of continuity in potential outcomes around the threshold.

[9] For simplicity, I denote here the PSU score of the older sibling taken one year before $(t-1)$, but in all regressions I consider any time gap between older and younger sibling measures. For example, I may analyze educational attainment of student i five years after a sibling s receive the financial aid. All regressions control for this time gap, and I include also additional results checking whether this effects change depending on this gap.

[10] Specifically, its defined as: $f(Score_{s(i),t-1}) = \beta_0 \cdot (Score_{s(i),t-1}) + \beta_1 \cdot (Score_{s(i),t-1}) \cdot \mathbb{1}(Score_{s(i),t-1} \geq c)$

4.2 Fuzzy RDD: Eligibility vs. Take-up

A key challenge in estimating the effect of credit or scholarship access on college enrollment (and other outcomes) is the possibility of self-selection: students who initially score below the loan eligibility cutoff on the PSU may choose to retake the test in later years and eventually reach the required score, thereby becoming eligible for student loans. Also, not all of the eligible students take the loan or scholarship. To address this issue, I employ a fuzzy regression discontinuity design, using the PSU score from a student's first attempt as an instrument for eventual loan/scholarship eligibility. This approach takes advantage of the fact that all students who score above the cutoff on their first try immediately qualify for the financial aid, while only a subset of those who fall short may later qualify by retaking the test and meeting the 475-point (or 550 for scholarship) threshold. Since not all students just below the cutoff will retake the PSU or succeed in surpassing the threshold, there remains a discontinuous jump in the probability of financial aid access at the initial cutoff, which supports identification.

In sum, because not all eligible students take up the aid, and some ineligible students may be granted exceptions,[11] I use this fuzzy RDD framework. I treat actual receipt of aid ($Z_{s,t-1}$) as an endogenous variable and use eligibility D_i as an instrument:

$$Z_{s,t-1} = \pi_0 + \pi_1 D_{st} + f(Score_{s(i),t-1} - c) + \eta_i \tag{7}$$

$$Y_{it} = \beta_0 + \beta_1 \widehat{Z}_{s,t-1} + f(Score_{s(i),t-1} - c) + \nu_{it} \tag{8}$$

Here, β_1 represents the local average treatment effect (LATE) of actually receiving aid, identified for compliers—those whose aid take-up is induced by the eligibility rule. The 2SLS estimates would need to be interpreted with caution, as they might be measures of an upped bound effects. That is the case if the actual eligibility for loan/scholarship of the older sibling affect directly the outcomes of the younger, and not merely through the actual take up of these financial aids.

4.3 Strategy validation

I estimate both sharp and fuzzy versions of the RDD using local linear regressions and triangular kernel weights, following the procedure of Calonico et al. (2014) for bias-corrected confidence intervals and optimal bandwidth selection. Standard errors are clustered at family level.

I perform standard robustness checks in Figure 5, including continuity of variables and ma-

[11] Not addressed here, but may be possible and this forms part of further analyisis.

nipulation checks.[12] Panel A and Panel B check whether there are demographic, socioeconomic, or family variables that could affect the allocation of student benefits, in this case, college loans.[13] The older sibling's score, which is our variable of interest, is used to construct the treatment and running variable. Panel A shows the variables for the older sibling, where I consider it most important that there be no statistically significant effect. I include Panel B as a complement, which show the variables for the younger sibling and the same running and treatment variable as Panel A, but it is plausible to find an effect on variables associated with the allocation of household resources, such as investment in health. Even though the effects are not close to zero, Panel A rejects the null hypothesis of an effect different from zero at 95% confidence in all variables except one (at 90%), validating the identification strategy of the empirical methodology. Panel B shows similar results, especially in variables where I would expect no effect. However, some statistically significant effects are seen in variables such as parents' secondary education or a reduction in the use of public health services (and an increase in private health services, showing a potential positive impact on investment in the health of the child).

Panel C also shows that the manipulation check condition is met, where the running variable corresponding to the older sibling's PSU score is continuous across the threshold (475 points) normalized to zero.

Further validation checks are needed. First, a placebo test is necessary to verify that the observed effect stems directly from the older sibling's benefit—either through their interaction with the younger sibling or changes in parental behavior—rather than some other factor. For this, the placebo test should evaluate the same outcomes under the same specification, but, for example, examining how the younger sibling's eligibility and take-up of financial aid in a later period might affect the older sibling, where I would logically expect null effects. Second, it is worth studying how the results vary with the choice of bandwidth. This check was performed for one of the main results and is presented in Figures B1 and B2, based on the results in Tables 2 and B1.

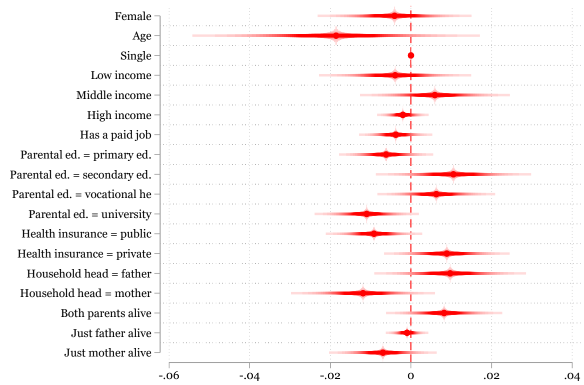
4.4 Estimating differential impact of repayment scheme using a Difference-in-discontinuity design

To examine how changes in loan repayment schemes affect the impact of financial aid eligibility, I extend the RDD framework using a difference-in-discontinuities (DiDC) design (Grembi et al.,

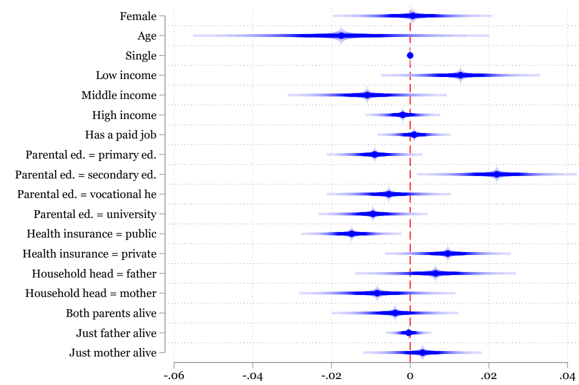
[12]This Figure is a reproduction of the one shown in the Appendix in Barrios-Fernández (2022).

[13]For college scholarship similar analysis see Figure A3.

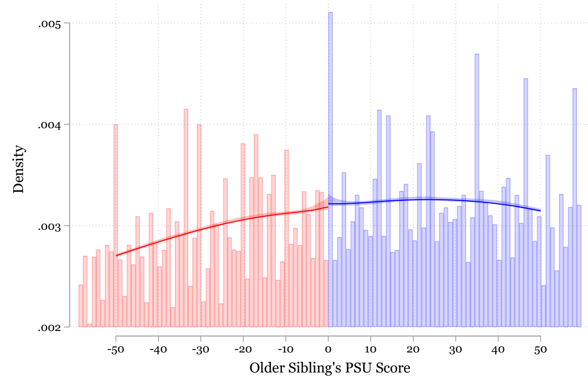
Figure 5: Regression discontinuity design validation



Panel A: Continuity of variables older sibling



Panel B: Continuity of variables younger sibling



Panel C: Manipulation check (McCrary Test)

Note: Panel A and B illustrate the coefficients obtained by estimating the discontinuity effect (loan eligibility) on a set of demographic, socioecononomic, and family variables that could affect the estimation of the main outcomes of interest. Panel A specifically refers to the variables of older sibling, and Panel B to the younger. In both the discontinuity is with respect to older sibling PSU score (normalized to zero using the cutoff for loan eligibility) and confident intervals are at 95% level. In the other hand, Panel C shows the estimated density of the PSU score at both sides of the loan eligibility cutoff (normalized to zero), with 95% confident intervals level.

2016; Tramontin Shinoki et al., 2024). Specifically, I exploit temporal variation in the terms of the SGL loan program—most notably, the 2012 reform that reduced interest rates and introduced income-contingent repayment caps. This approach also follows very closely what Albagli and Garcia-Echalar (2025) does.

Let T_t index cohorts, where $T_t = 0$ denotes cohorts applying before the reform (e.g., 2008–2011), and $T_t = 1$ indicates cohorts exposed to the reformed loan regime (e.g., 2012–2016). I estimate the DiDC treatment effect β_0 following Grembi et al. (2016):

$$Y_{it} = \delta_0 + \delta_1 \cdot S_{s,t-1} + D_{s,t-1} \cdot (\gamma_0 + \gamma_1 \cdot S_{s,t-1}) + T_t \cdot [\alpha_0 + \alpha_1 \cdot S_{s,t-1} + D_{s,t-1} \cdot (\beta_0 + \beta_1 \cdot S_{s,t-1})] + \varepsilon_{i,t} \quad (9)$$

where $S_{s,t-1} = Score_{s,t-1} - c$ is the normalized PSU score relative to the cutoff c for student's i sibling s, and $D_{s,t-1}$ denotes a dummy for scores above the cutoff ($S_{s,t-1} \geq 0$). This difference-in-discontinuities estimate captures how the causal impact of aid eligibility changes when the repayment conditions become more favorable (e.g., interest rate drops from 5.6% to 2%, or introduction of a 10% income cap on repayments). The coefficient β_0 recovers the treatment effect of aid eligibility under the reformed loan regime. If softer repayment schemes relax household liquidity constraints or reduce perceived debt burden, I expect $\beta_0 > 0$, meaning on positive spillover effects of sibling s financial aid eligibility on student i (younger sibling) outcomes. I also apply a 2SLS estimation consistent with the fuzzy RDD discussed in the previous section, using eligibility as an instrument for actual take-up of financial aid, focusing here specifically on loans.

This approach allow me to explore whether financial aid is more effective when repayment is more forgiving, and whether household responses—particularly inter-sibling investments—are sensitive to the policy environment.[14]

5 Results

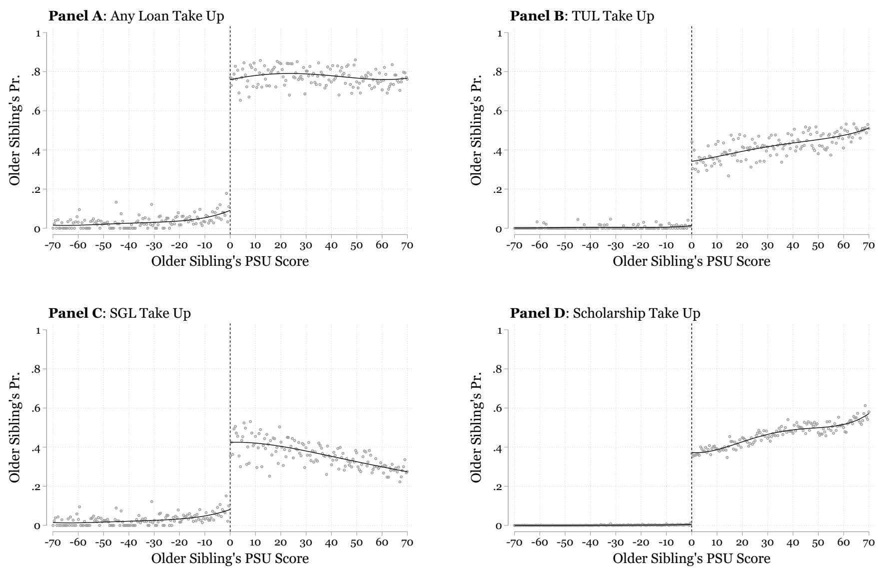
5.1 Older sibling's own effects of financial aid eligibility

I begin the analysis by validating the impact of being eligible for financial aid (loans and scholarships) at the individual level (older sibling). Specifically, I examine whether eligibility increases the likelihood of actual take-up and whether it has discernible effects on key outcomes such as college enrollment, as shown in Barrios-Fernández (2022) and Solis (2017). The first, serves as a validation of the first stage in our 2SLS estimations presented in the next section.

[14]Further analysis to exploit differential effect of repayment scheme is included in the Appendix D

Figure 6 illustrates take-up rates for these programs. As expected, there is a notably discontinuity at the eligibility thresholds for both loans (475 points, Panel A, B, and C) and scholarships (550 points, Panel D), with large jumps in take-up probabilities. For instance, Panel A shows an increase of nearly 70 percentage points in the probability of taking up any loan, with similar effects observed for both the SGL and TUL programs. In the case of scholarships (Panel D), the increase is around 40 percentage points. These results highlight that eligibility rules are not perfectly sharp: being above or below the cutoff does not guarantee eligibility with certainty. For this reason, throughout the paper I adopt a 2SLS (Fuzzy RDD) approach to estimate the LATE for compliers at the threshold.

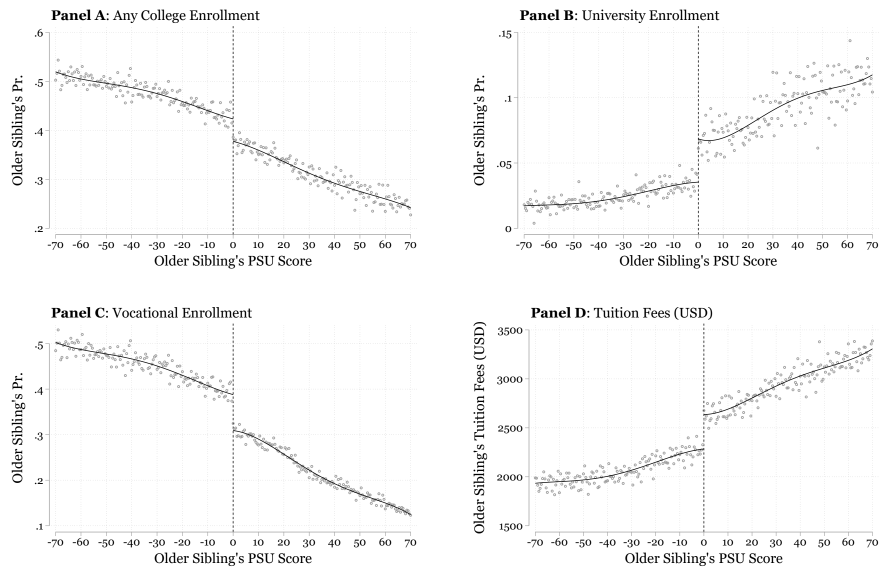
Figure 6: Older's siblings own probability of financial aid take up based on eligibility for college loans and scholarship



Note: Here the score is relative to 475 points in Panel A, B and C, and to 550 points in Panel D. Panel A, B, and C consider only students who enrolled in a university program, and not vocational. The reason is that there are some students below the eligibility rule od 475 PSU points that are eligible for the SGL loan if they had an overall GPA in high school above 5.3 (in a scale of 1.0-7.0). Panel D consider only income quntiles 1 and 2, which are the eligibles for the scholarship. Also, it only considers cohorts 2008-2012, which are the years where the scholarship had the explicit rule of PSU score above 550

Additionally, Figure 7 shows how eligibility for any type of loan affects the probability of college enrollment among applicants. Panel A indicates an overall negative effect on the probability of enrolling in any type of college program. This result, however, is driven largely by a substantial reduction in the likelihood of enrolling in vocational programs (Panel C). In contrast, Panel B shows a positive and sizable increase in enrollment in university programs, which generally offer higher returns but also involve higher costs. Consistent with this shift, Panel D demonstrates that loan eligibility leads students to enroll in more expensive programs.

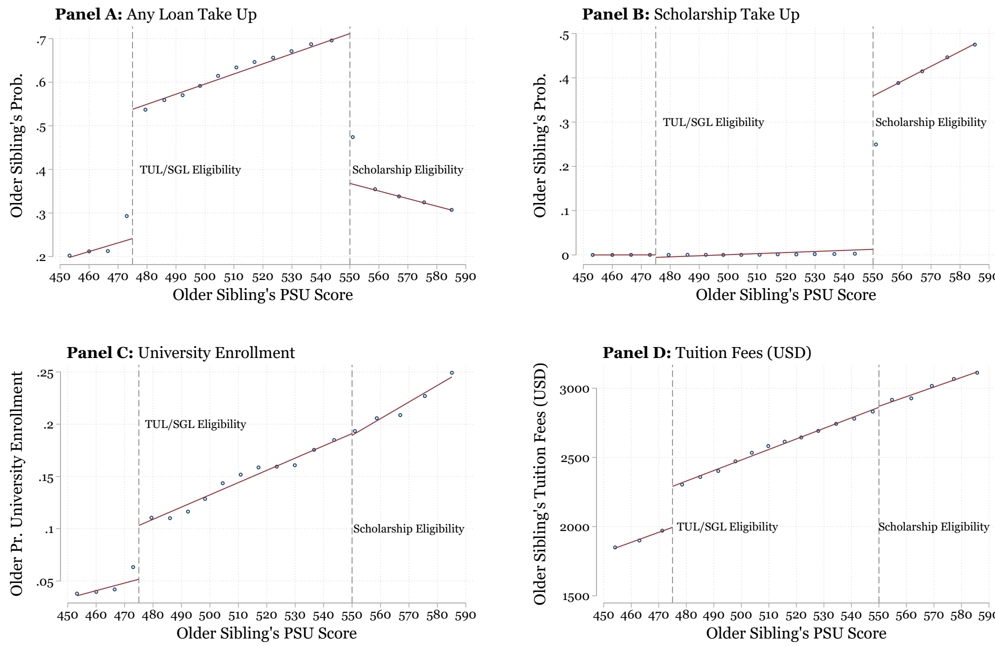
Figure 7: Older's siblings own effect of being eligible for college loans on college enrollment



Note: Here the score is relative to the college loan eligibility rule, which is a score of 475. Panel A, B, C, and D consider all students (older siblings) who apply -i.e. took the PSU test- for a college program for the first time from 2008 to 2016, and are eligible for a loan (80% poorer households).

Finally, Figure 8 summarizes the main results from the previous figures, but now comparing three groups of students: those not eligible for any benefit (PSU score < 475), those eligible for loans (SGL and TUL, PSU score > 475), and those eligible for the *Bicentenario* Scholarship (PSU score > 550). This comparison focuses exclusively on students from households in the bottom 40% of the income distribution, who are eligible for the scholarship. The findings are particularly striking. Panel A shows that loan eligibility substantially increases the probability of loan take-up, but this probability drops considerably once students also qualify for the scholarship. Importantly, loan take-up does not fall to zero, suggesting that some students may use loans as a complement to the scholarship. Panel B confirms the substitution pattern: the reduction in loan take-up is offset by a significant rise in scholarship take-up among those with PSU scores above 550. Panels C and D provide further validation of our empirical strategy and comparison framework between loan and scholarship eligibility. Despite the sharp change in financial aid take-up around the 550-point cutoff, there is no clear discontinuity in key outcomes such as university enrollment or program tuition fees. This implies that, at the margin and on average, eligibility for different benefits does not directly alter program quality or cost, but rather shifts the way higher education is financed. According to the hypotheses of this paper, such shifts in financing mechanisms may have heterogeneous effects on siblings, particularly through changes in parental investment and related outcomes, which are going to be analyzed in the next section.

Figure 8: Older's siblings own effect of being eligible for scholarship relative to loan



Note: All figures consider only income quntiles 1 and 2, which are the eligibles for the scholarship. Also, they only consider cohorts 2008-2012, which are the years where the scholarship had the explicit rule of PSU score above 550.

5.2 Sibling spillover effects of financial aid at college entrance

This section presents one of the main results of the paper: the sibling spillover effects of having an older sibling who received financial aid—either through loans or scholarships—on younger siblings who are themselves applying to college. Understanding these spillovers is crucial, as they shed light on how household educational decisions extend beyond the direct recipient of aid, influencing broader patterns of access, investment, and achievement within the family. I focus on younger siblings who sat for the PSU (college entrance exam) in a year following their older sibling's application.

The analysis proceeds in three steps. First, I estimate the effects on financial aid take-up and college enrollment decisions of younger siblings. Second, I study outcomes related to parental investment, measured through the quality of the high school attended and the tuition cost of the postsecondary program chosen. Finally, I examine effects on educational attainment, as reflected in PSU test scores. Together, these results provide a comprehensive picture of how financial aid targeted to one child can shape the educational trajectories of others in the household.

5.2.1 Financial aid take up and college enrollment

First, Figures 9 graphically illustrate the reduced-form effect of older sibling eligibility for loans on similar outcomes for younger siblings, such as financial aid take-up and college enrollment. Across all panels, I find no discernible effects: there are no clear discontinuities around the respective eligibility thresholds for either type of financial aid.

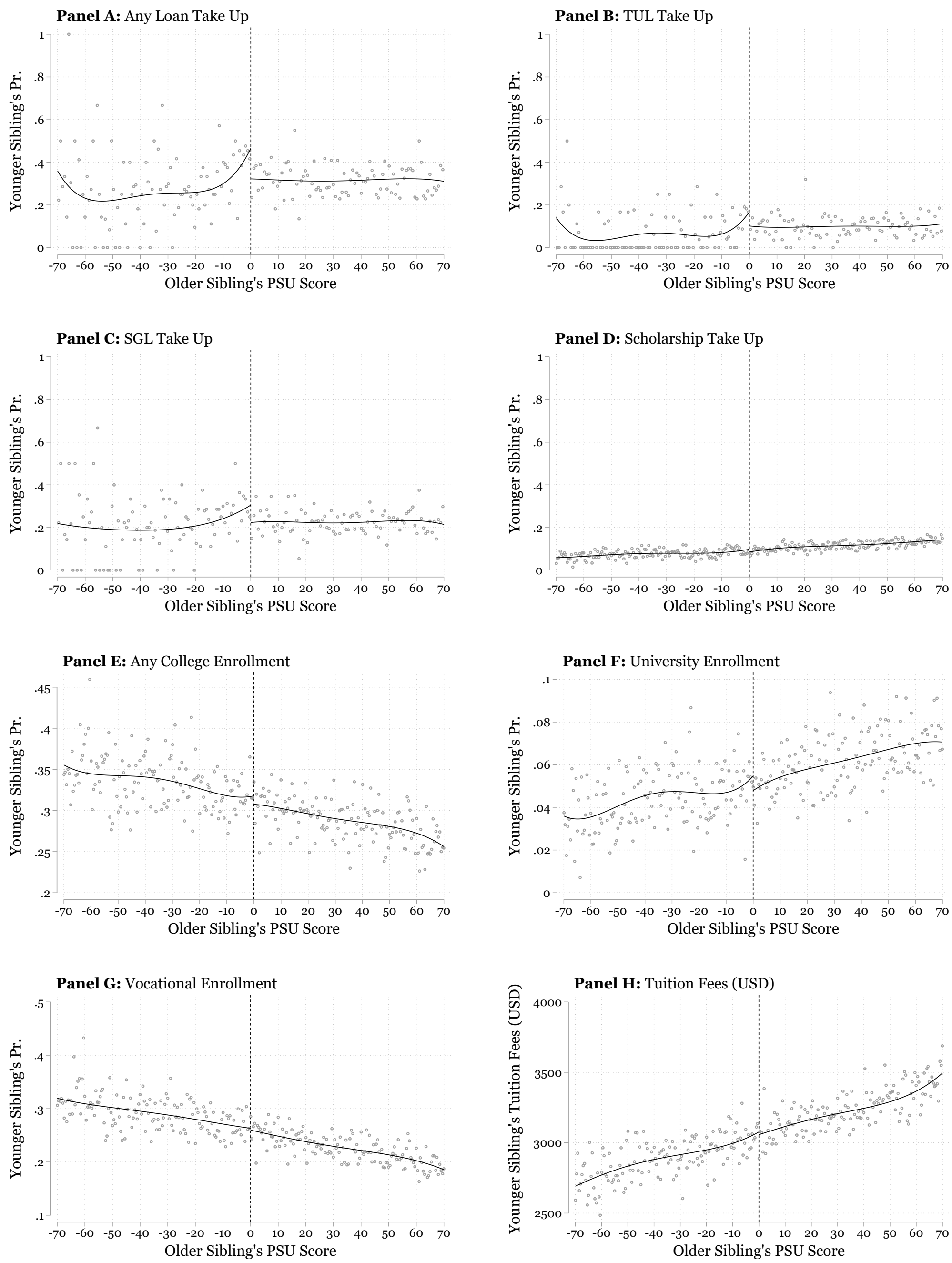
However, when I examine heterogeneous effects by household income, the results reveal important insights. Table 2, Panel B, reports the estimates for younger siblings from higher-income households, defined as those with monthly income above USD $1,000. In this group, I find a positive effect on financial aid take-up. For instance, the effect of having an older sibling eligible for aid increases the probability of taking up any loan by 6 percentage points in the reduced form, and by 23 percentage points among compliers (column 2), significant at the 5% level. Reduced-form effects range between 3 and 5 percentage points across different types of loans and scholarships, while the corresponding 2SLS estimates lie between 12 and 17 percentage points. By contrast, Panel C, which focuses on siblings from low-income households (monthly income below USD $400), shows effects that are essentially zero and statistically imprecise. In all specifications, the first stage of the 2SLS is strong and satisfies the conditions for a valid instrument, consistent with the patterns shown in Figure 6.[15]

In Table B1, I repeat the analysis but focus on college enrollment outcomes. Here, the results are less precise. For high-income households, the effect on overall college enrollment—and especially on university enrollment—is positive, reaching about 8 percentage points among compliers in the latter case (column 4). However, these effects are not statistically significant. Interestingly, the pattern is reversed for low-income households. Having an older sibling who accesses a college loan reduces the probability of enrolling in any type of higher education program, with negative effects of 2 percentage points in the reduced form (column 1) and 8 percentage points in the 2SLS specification (column 2). The results are noisier when distinguishing between university and vocational enrollment, but the overall evidence points to a discouraging effect among low-income families.

For the case of the effect of older siblings accessing scholarships, I first observe that the reduced form shown in Figure 10 does not display any notable jump, similar to the analysis of loan effects. However, these effects change considerably when looking at heterogeneous results. Table 3 no longer shows positive or statistically significant effects for students from high-income households in terms of loan and scholarship take-up. Conversely, the effects for low-income

[15] Further analysis was included by analyzing heterogeneous effects by age gap and household income in Figure B3

Figure 9: Sibling spillover effects of older sibling being eligible for college loan on financial aid take up and college enrollment



Note: Here the score is relative to loan eligibility (475-points). That is, it shows the reduce form of older sibling being eligible for a loan on younger sibling outcomes. All figures consider younger siblings applying to college between 2009 and 2016, whose older sibling applied to before, and between 2008 and 2015.

households now appear larger and positive, at least for the take-up of any loan (columns 1 and 2). In particular, the 2SLS estimation indicates an increase of six percentage points in any loan take-up if the older sibling accessed a scholarship. Nevertheless, these effects are not observed for other types of loans or even for scholarships.

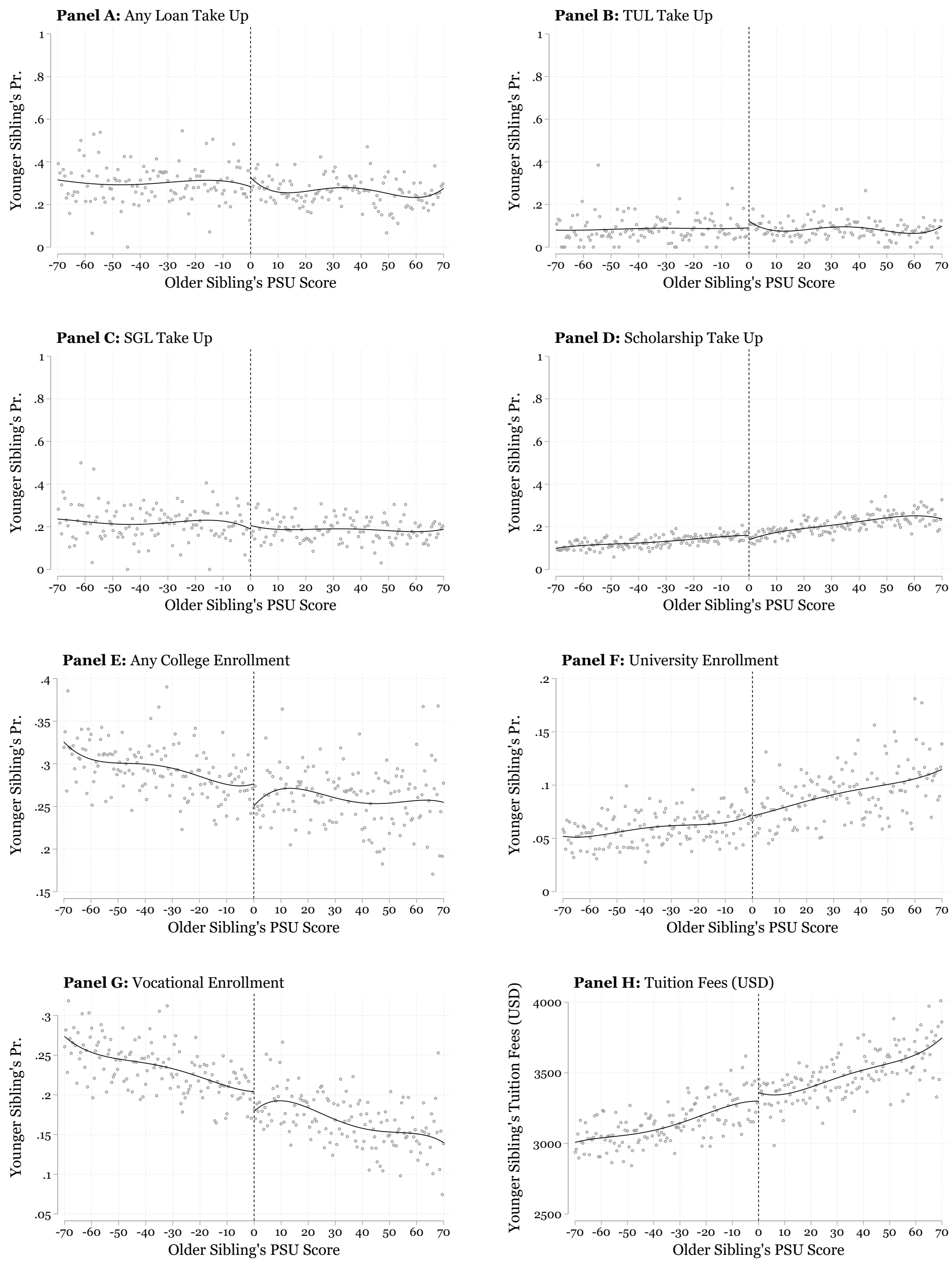
Table 2: RD Estimates of older sibling eligible for college loan on younger sibling's financial aid take up

	Any loan take up		SGL Loan		TUL Loan		Scholarship	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.259***		0.263***		0.259***		0.270***
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	0.001	−0.004	0.004	0.014	−0.005	−0.022	0.005	−0.015
	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)	(0.00)	(0.02)
Mean Dep. Var.	0.275	0.274	0.223	0.223	0.057	0.056	0.099	0.094
Bandwidth	±59.7	±33.5	±67.6	±31.0	±50.0	±33.1	±65.1	±27.2
Observations	75,762	42,920	84,668	39,900	63,540	42,920	81,822	35,445
Panel B: High-income applicants								
First Stage		0.264***		0.264***		0.259***		0.259***
		(0.01)		(0.01)		(0.02)		(0.02)
RD Estimate	0.060**	0.228**	0.051*	0.173*	0.035**	0.134*	0.030*	0.118**
	(0.03)	(0.11)	(0.03)	(0.10)	(0.02)	(0.07)	(0.02)	(0.06)
Mean Dep. Var.	0.274	0.275	0.223	0.223	0.058	0.057	0.097	0.097
Bandwidth	±69.0	±59.8	±53.8	±60.9	±69.2	±51.2	±49.5	±45.2
Observations	5,264	4,542	4,055	4,603	5,313	3,862	3,745	3,408
Panel C: Low-income applicants								
First Stage		0.260***		0.260***		0.259***		0.259***
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	0.005	0.018	0.002	0.010	0.002	0.008	0.003	−0.016
	(0.01)	(0.04)	(0.01)	(0.04)	(0.00)	(0.02)	(0.01)	(0.03)
Mean Dep. Var.	0.275	0.274	0.223	0.223	0.058	0.056	0.099	0.095
Bandwidth	±63.9	±37.4	±67.1	±40.6	±66.1	±32.3	±62.0	±35.2
Observations	38,198	23,136	39,907	25,270	39,443	20,173	37,404	21,958

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

On the other hand, Table B2 again presents the results for college enrollment, but now also considering whether the older sibling accessed a scholarship (instead of a loan, as before). First, it is important to note that the effect on low-income applicants is no longer negative and statistically significant, but rather closer to zero. This could suggest that, even if younger siblings do not directly benefit from their older siblings' scholarships, these scholarships do not act as a backfire for their higher education. Second, I now observe that the effects for high-income applicants are not positive, but rather negative (although somewhat noisy). It is difficult to provide a theoretical justification for these results, and a detailed understanding of why this may occur is left for future analysis.

Figure 10: Sibling spillover effects of older sibling being eligible for college scholarship on financial aid take up and college enrollment



Note: Here the score is relative to scholarship eligibility (550-points). That is, it shows the reduce form of older sibling being eligible for a loan on younger sibling outcomes. All figures consider younger siblings applying to college between 2009 and 2016, whose older sibling applied to before, and between 2008 and 2015.

Table 3: RD Estimates of older sibling eligible for college scholarship on younger sibling's financial aid take up

	Any loan take up		SGL Loan		TUL Loan		Scholarship	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.288***		0.288***		0.288***		0.289***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	0.002	0.007	−0.001	−0.006	0.005	0.019	−0.013	−0.034
	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)	(0.01)	(0.02)
Mean Dep. Var.	0.274	0.274	0.217	0.217	0.060	0.061	0.161	0.162
Bandwidth	±53.8	±57.5	±54.7	±57.1	±66.3	±57.0	±41.5	±58.1
Observations	47,220	50,292	47,927	49,928	56,782	49,571	37,417	50,764
Panel B: High-income applicants								
First Stage		0.295***		0.295***		0.295***		0.295***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−0.073	−0.829	−0.053	−0.604	−0.006	−0.064	0.033	0.379
	(0.05)	(0.59)	(0.04)	(0.52)	(0.03)	(0.30)	(0.02)	(0.29)
Mean Dep. Var.	0.273	0.273	0.217	0.217	0.060	0.060	0.161	0.161
Bandwidth	±70.0	±70.0	±70.0	±70.0	±69.7	±70.0	±70.0	±70.0
Observations	1,928	1,928	1,928	1,928	1,928	1,928	1,928	1,928
Panel C: Low-income applicants								
First Stage		0.289***		0.290***		0.288***		0.288***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	0.023*	0.059*	0.013	0.029	0.010	0.027	−0.014	−0.038
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
Mean Dep. Var.	0.274	0.274	0.217	0.217	0.061	0.061	0.162	0.162
Bandwidth	±53.8	±58.2	±56.3	±61.7	±57.5	±55.2	±58.7	±57.7
Observations	24,328	26,209	25,346	27,619	25,968	24,873	26,436	25,968

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

5.2.2 Parental investment

Regarding parental investment, I use as measures the characteristics of the high school from which the student graduates when applying to college, as well as the cost of the college program they enroll in. Table B3 summarizes the effect of the older sibling receiving a loan. For both high-income (Panel B) and low-income (Panel C) applicants, no statistically significant effects are observed, either in the reduced form or in the 2SLS estimations. The only discernible pattern is that high-income applicants might pay more and are slightly more likely to graduate from private colleges, but these results cannot be reliably interpreted due to low statistical precision.

A similar exercise analyzing the effects of scholarships is presented in Table B.1. Here, again, no statistically significant or interpretable results are found. As in the case of the outcomes in the previous section, the only noteworthy observation is that the effects appear somewhat less negative for low-income applicants in some cases, suggesting that scholarships could be more beneficial for low-income applicants than for high-income ones, especially compared to the effect of loans. In summary, the evidence indicates no discernible effects in terms of parental investment, likely because these school-related decisions may be more static, and long-term effects might be more informative to analyze.

5.2.3 Student's educational attainment

Finally, in this section,I analyze the results on college entry exam scores of younger siblings after the older sibling has obtained a loan or scholarship. Starting with the effect of loans, Table B5, Panel A, shows negative effects across all outcomes: PSU NEM (average GPA during the last four years of high school), PSU Rank (GPA ranking within school and cohort), and math and reading PSU scores. When separating the effects by applicant income, I observe that those who benefit from the older sibling's loan are applicants from high-income households, at least in terms of NEM, ranking, and reading scores. The opposite pattern is observed in Panel C, where applicants from low-income households—although not statistically significant for all outcomes except math scores—experience negative effects.

Furthermore, following the trend observed in previous results, Table B.1 shows that the effect of scholarships again generates negative—and now statistically significant—effects for high-income applicants, while the effects for low-income applicants are no longer negative and remain close to zero.

These findings contribute to the evidence that loans tend to benefit only high-income applicants and may even have negative consequences for low-income applicants. However, this pattern is reversed when analyzing the effect of scholarships: although the effects for low-income applicants cease to be negative and may even be positive, this does not occur for high-income applicants, who appear to be negatively affected. This analysis is complemented by the following section, which analyses sibling spillover effects for younger siblings in 4th and 8th grade.

5.3 Sibling spillover effects of financial aid at 4th and 8th grade

In this section, I examine the effects on students in 4th and 8th grade, focusing on parental behavior as captured by nationwide surveys and educational attainment using test scores from the SIMCE assessments in math and reading, administered to all students. I cover the period from 2009 to 2019 when these tests were administered. This approach allow me to investigate how parental factors may be associated with student performance across different grade levels and income groups, providing a broader perspective on early and middle school educational outcomes.

5.3.1 Parental behavior

I begin by graphically analyzing the reduced form effects of loans (Figure 11) and scholarships (Figure 12) on three indices constructed from the variables described in Section 2, related to parental financial investment, time investment, and engagement. These variables are derived from the surveys associated with the SIMCE tests that all students take in 4th and 8th grade. Similar to the evidence presented in Section 5.2, no discernible discontinuity is observed around the eligibility cutoff for the older sibling's loan or scholarship. Although Panel B in both figures contains fewer observations due to some survey questions not being asked in certain years, the reduced form clearly indicates a null effect of these financial aids.

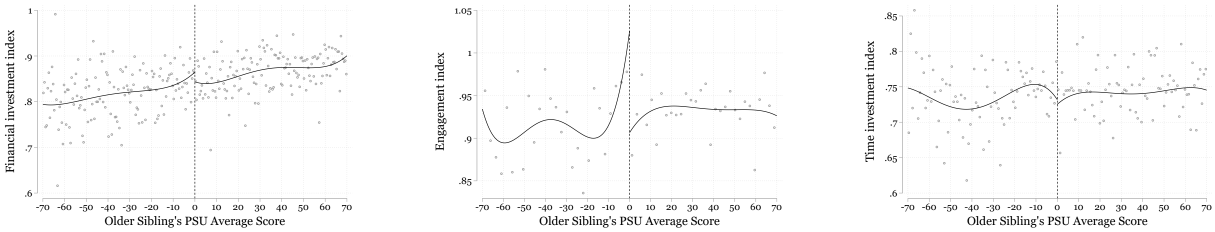
The 2SLS estimates by household income of the effects on parental financial investment are presented in Tables B7 and B8.[16] For the loan effects (Table B7), even though the first stage of the 2SLS estimates is strong, no statistically significant effects are found in any case. While generally negative effects are observed for both groups, no concrete conclusions can be drawn. The same holds for the estimation of scholarship effects (Table B8), where no effects significantly differ from zero. It is worth noting that the sample size for high-income students is substantially reduced, which weakens the first stage of the 2SLS and further limits the ability to draw conclusions for this group.[17]

Tables B9 and B10 repeat the exercise, but analyzing parental investment. For loans (Table B9), Panel A shows no statistically significant effects for all students, and the estimates are negative. However, when examining results by income (Panels B and C), no clear pattern emerges between positive and negative effects, and the low precision of the estimates makes it difficult to draw definitive conclusions. The same applies to the scholarship effects (Table B10), where the low precision and lack of consistent results prevent any strong conclusions. The most plausible interpretation is that sibling spillover effects through parental time investment are likely negligible, both for scholarships and loans.

[16] Since my analysis has generally focused on the effects from the fuzzy RDD, for space considerations I report only the 2SLS estimations in this section.

[17] This issue also arises in some of the later estimations for other outcomes.

Figure 11: Effects of older sibling eligibility for college loan on younger sibling parent's outcomes at 4th and 8th grade



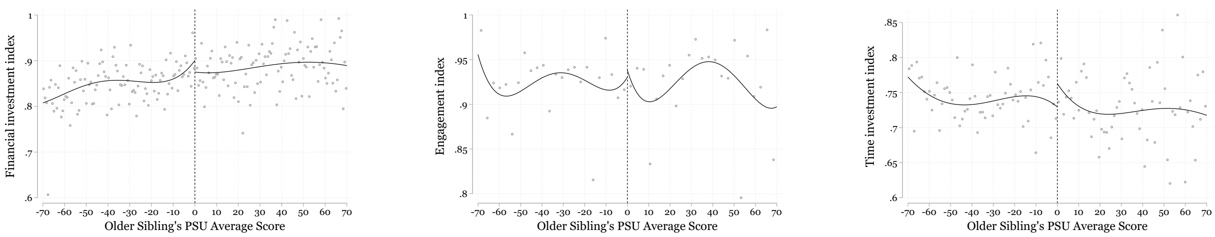
Panel A: Financial investment

Panel B: Parental engagement

Panel C: Time investment

Note: In all figures zero represent the standarized cutoff for college loan at 475-points for the older sibling. Outcomes are measures for younger siblings and come from SIMCE datasets as described in Section 2. Panel A captures parental beliefs about the highest educational level their child is expected to attain. Panel B reports dichotomous measures of whether parents participate in school activities or meetings. Panel C reflects parental financial investment, specifically whether the household owns the items listed in the figure. I constructed the summary indexes based on Kling et al. (2007)

Figure 12: Effects of older sibling eligibility for college scholarship on younger sibling parent's outcomes at 4th and 8th grade



Panel A: Financial investment

Panel B: Parental engagement

Panel C: Time investment

Note: In all figures zero represent the standarized cutoff for college scholarship at 550-points for the older sibling. Outcomes are measures for younger siblings and come from SIMCE datasets as described in Section 2. Panel A captures parental beliefs about the highest educational level their child is expected to attain. Panel B reports dichotomous measures of whether parents participate in school activities or meetings. Panel C reflects parental financial investment, specifically whether the household owns the items listed in the figure. I constructed the summary indexes based on Kling et al. (2007)

Third, I analyze the effects on parental engagement at the school. Table B11 presents the effect of older siblings' college loans on parental engagement, measured by whether parents attend parent-teacher meetings (column 2), meetings with teachers (column 3), school activities (column 4), and an overall index combining these three measures (column 1). Observations are very limited in the first three columns for high-income students (Panel B), but for low-income students (Panel C), a consistent—albeit noisy—negative effect on parental engagement is observed, particularly in attendance at school activities. When repeating the analysis for the effect of scholarships (Table B12), the limited number of observations remains an issue, but it is now less clear that there is a negative effect for students from low-income households.

Finally, I estimate the effects of the same benefits on parents' beliefs regarding the highest educational level they expect their children to achieve. Table B13 shows the effects of loans. Here, the observation issue does not persist, as these variables are available for all SIMCE years. However, the effects are quite noisy and statistically insignificant. While Panels A–C show a negative effect on the expectation of completing only high school (column 1) and vocational programs (column 2), a positive effect on graduation from a university program (column 3), and a negative but closer-to-zero effect on postgraduate attainment (column 4), these estimates do not allow for concrete conclusions regarding sibling spillovers in parental beliefs. The same applies to the analysis of scholarship effects (Table B14), although the direction of the effects is not exactly the same.

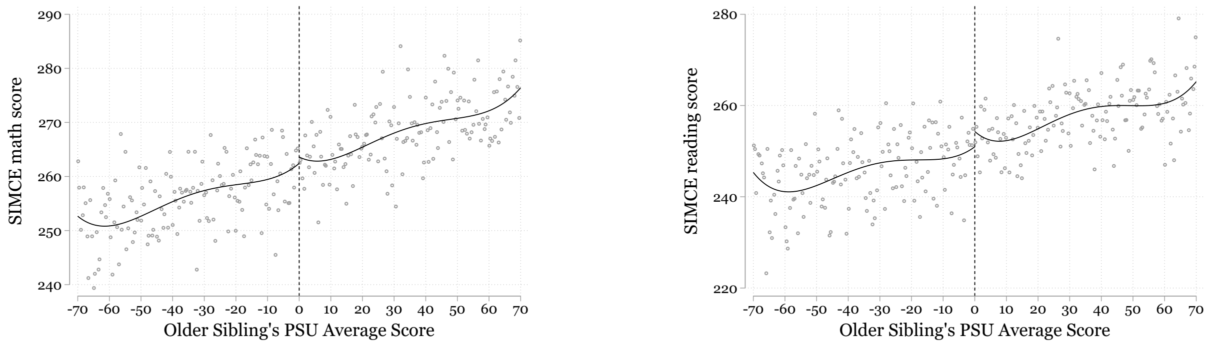
5.3.2 Student's educational attainment

In this subsection, I also use the SIMCE test results, but now focusing specifically on student performance on these exams. First, consistent with the previous results, the reduced form shown in Figures 13 and 14, for loans and scholarships respectively, does not display any clear effect around the eligibility cutoff for each benefit.

Turning to the 2SLS analyses by income level, Table B15 presents the effect of the older sibling's loan and scholarship on younger siblings' test scores in math and reading. Comparing the RD estimates of college loans in math and reading (columns 1 and 2) with those of college scholarships (columns 3 and 4), I observe that scholarships appear to have a larger positive effect than loans for the full sample (Panel A). However, these effects are not statistically significant. Similarly, no clear or consistent effects are found for high-income students (Panel B), likely due to the small number of observations. For low-income students (Panel C), positive effects are observed across both subjects and types of financial aid, but these are not statistically significant, and no meaningful conclusions can be drawn when comparing loans and scholarships.

Overall, these findings are consistent with the earlier results on parental outcomes, in that no consistent sibling spillover effects are found for any outcome at the 4th and 8th grade levels.

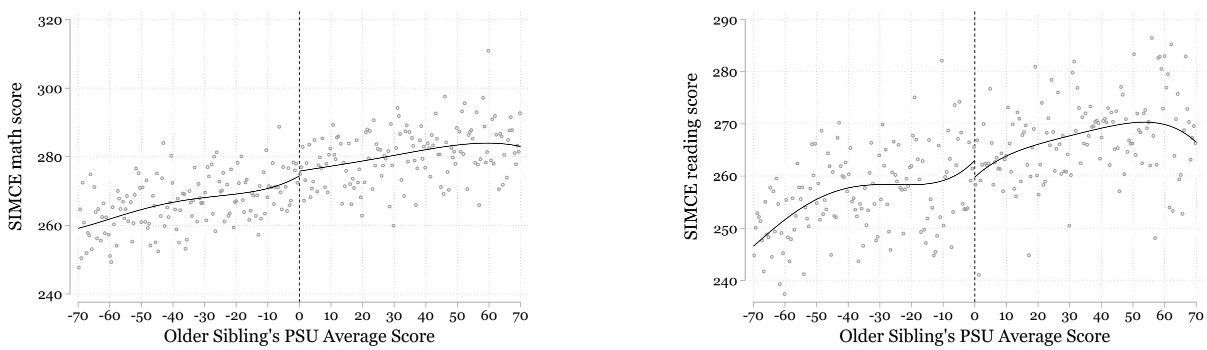
Figure 13: Effects of older sibling eligibility for college loan on younger sibling school attainment at 4th and 8th grade



Panel A: Math test score **Panel B:** Reading test score

Note: In all figures zero represent the standarized cutoff for college loan at 475-points for the older sibling. Outcomes are measures for younger siblings and come from SIMCE datasets as described in Section 2. Panel A represent Math SIMCE test scores, and Panel B is for Reading SIMCE test score.

Figure 14: Effects of older sibling eligibility for college scholarship on younger sibling school attainment 4th and 8th grade



Panel A: Math test score **Panel B:** Reading test score

Note: In all figures zero represent the standarized cutoff for college scholarship at 550-points for the older sibling. Outcomes are measures for younger siblings and come from SIMCE datasets as described in Section 2. Panel A represent Math SIMCE test scores, and Panel B is for Reading SIMCE test score.

5.4 Differential effects of financial aid across payment rules

In this section, I estimate equation 9 to disentangle the differential effects of older siblings' loan take-up under different repayment rules. I focus in particular on the SGL loan, which was reformed in 2012 to reduce the interest rate from 5.6% to 2% and to change the repayment scheme from non–income-contingent to income-contingent, with a 10% cap on monthly formal labor market earnings.

Table 4 presents the results for four of our main outcomes, with particular attention to the estimator β_0, which captures the treatment effect of aid eligibility under the reformed loan regime. All regressions account for take-up and enrollment trends by including the variables of eligibility and exposure separately. Panel A, which represents all college applicants, shows a positive effect of being eligible for (or actually taking up) the college loan and being exposed to the reform, both on loan and scholarship take-up as well as on university enrollment. However, these results are statistically insignificant, except for university enrollment when applying a fuzzy DiDC estimated by 2SLS (column 6), where we observe a 3.6 percentage point increase, significant at the 10% level. Even though no statistically significant effects are found for applicants from high- and low-income households (Panels B and C), it is noteworthy that the effect for high-income applicants is virtually zero, while for low-income applicants it is 2.5%. This suggests that the effect observed in Panel A may be driven by middle-income households, providing weak but suggestive evidence in support of the hypothesis that the repayment scheme can be a relevant factor when estimating sibling spillovers from college financial aid.

Table 4: DiDC estimates of older sibling eligible for college loan on younger sibling's outcomes

	Any loan take up		Scholarship take up		University enrollment		Vocational enrollment	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
DiDC = β_0	0.002	0.004	0.004	0.011	0.011	0.036*	−0.015	−0.042
	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.04)
Mean Dep. Var.	0.275	0.275	0.099	0.099	0.054	0.054	0.254	0.254
Bandwidth	±60	±60	±60	±60	±60	±60	±60	±60
Observations	75,762	75,762	75,762	75,762	75,762	75,762	75,762	75,762
Panel B: High-income applicants								
DiDC = β_0	−0.060	−0.183	−0.013	−0.031	0.001	−0.003	0.005	0.019
	(0.08)	(0.23)	(0.04)	(0.13)	(0.04)	(0.10)	(0.06)	(0.19)
Mean Dep. Var.	0.275	0.275	0.099	0.099	0.054	0.054	0.254	0.254
Bandwidth	±60	±60	±60	±60	±60	±60	±60	±60
Observations	2,452	2,452	2,452	2,452	2,452	2,452	2,452	2,452
Panel C: Low-income applicants								
DiDC = β_0	−0.011	−0.034	−0.008	−0.027	0.007	0.025	−0.016	−0.035
	(0.02)	(0.06)	(0.01)	(0.04)	(0.01)	(0.02)	(0.02)	(0.06)
Mean Dep. Var.	0.275	0.275	0.099	0.099	0.054	0.054	0.254	0.254
Bandwidth	±60	±60	±60	±60	±60	±60	±60	±60
Observations	44,841	44,841	44,841	44,841	44,841	44,841	44,841	44,841

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Bandwidths were set at 60 points for reason of simplification, given that a bandwidth above 75 points overlap with scholarship eligibility. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

6 Conclusion and discussion

This paper investigates the extent to which college financial aid received by older siblings generates spillover effects on younger siblings. Using rich administrative data from Chile and exploiting both discontinuities in eligibility rules and the 2012 reform of the SGL loan, I provide new evidence on how the design of financial aid programs may shape intra-household dynamics. The analysis shows some suggestive effects on financial aid take-up, university enrollment, and performance on the college entry exam, but no clear impacts on earlier educational outcomes such as parental investment or student performance in 4th and 8th grade. Taken together, these results highlight that the intergenerational transmission of educational opportunities within families is shaped by financial aid policies, though the effects are modest and context-dependent.

Beyond its empirical findings, this paper contributes to the literature in several important ways. First, it broadens our understanding of sibling spillovers by shifting the focus from direct educational inputs or school environments to the role of financial aid, a channel that has received little attention despite its growing policy relevance. Second, by exploiting Chile's unique higher education context—with its combination of high tuition costs, expansive aid programs, and rich administrative records—this study provides evidence from a setting that is both distinctive and informative for other countries in the region and beyond, such as the USA. Finally, the paper highlights how the design of financial aid—particularly the distinction between loans and scholarships and the structure of repayment rules—can shape intra-household dynamics depending on the income distribution, offering novel insights for policymakers concerned with equity, access, and the unintended consequences of financial aid programs.

In terms of mechanism, sibling spillovers can generally operate through a variety of channels. In this research, while not derived empirically, I find some evidence consistent with a role model effect, whereby younger siblings are motivated by their older siblings, gaining information about college applications and financial aid (Barrios-Fernández, 2022). This mechanism could encourage greater academic effort, particularly at the transition to higher education. By contrast, my initial hypothesis that parental investment might be a complementary channel finds little support: the null results at younger ages (4th and 8th grade) suggest that parental responses are not the dominant pathway. Instead, the evidence points toward stronger direct sibling effects than parental investment responses (Qureshi, 2018). One interpretation is that once parents become familiar with financial aid and perceive access to higher education as more feasible, they may reduce their own effort toward younger children. Moreover, the heterogeneous results by income level indicate that spillovers may even be negative, particularly in the case of loans rather than scholarships, which suggests that financial burden could itself be a harmful factor. This interpretation gains support when examining the 2012 SGL loan reform, which altered repayment rules and appears to have shifted outcomes for certain groups.

There remains, however, considerable scope for future research to clarify the mechanisms behind these findings. A first step would be to explore heterogeneity by gender and sibling matching, since role-model effects may differ when siblings are of the same gender or close in age. Accounting for family size and birth order could also prove important, as sibling dynamics may operate differently in larger households where parental resources are more thinly distributed. Another promising avenue is to study the long-term consequences of aid exposure, not only for educational trajectories but also for labor market outcomes and social mobility, to assess whether the modest short-run effects accumulate over time. It would also be valuable to test alternative definitions of household income—incorporating wealth, indebtedness, or multidimensional poverty—in order to refine the heterogeneity analysis. Finally, developing a new theoretical framework combining different types of benefits and complementarity between them, and also allow key variables to depend on income distribution, could help reconcile the mixed evidence across income groups and shed light on the different roles of scholarships versus loans.

References

Aguirre, J. (2021). Long-term effects of grants and loans for vocational education. *Journal of Public Economics*, 204:104539.

Aguirre, J. and Matta, J. (2021). Walking in your footsteps: Sibling spillovers in higher education choices. *Economics of Education Review*, 80:102062.

Albagli, P. and Garcia-Echalar, A. (2025). Rethinking Student Loan Design: Evidence from a Price-Based Reform in Chilean Higher Education. *Unpublished manuscript*.

Altmejd, A., Barrios-Fernández, A., Drlje, M., Goodman, J., Hurwitz, M., Kovac, D., Mulhern, C., Neilson, C., and Smith, J. (2021). O Brother, Where Start Thou? Sibling Spillovers on College and Major Choice in Four Countries*. *The Quarterly Journal of Economics*, 136(3):1831–1886.

Altonji, J. G., Cattan, S., and Ware, I. (2017). Identifying Sibling Influence on Teenage Substance Use. *Journal of Human Resources*, 52(1):1–47. Publisher: University of Wisconsin Press Section: Article.

Attanasio, O., Boneva, T., and Rauh, C. (2020a). Parental Beliefs about Returns to Different Types of Investments in School Children. *Journal of Human Resources*. Publisher: University of Wisconsin Press Section: Article.

Attanasio, O., Meghir, C., and Nix, E. (2020b). Human Capital Development and Parental Investment in India. *The Review of Economic Studies*, 87(6):2511–2541.

Barrios-Fernández, A. (2022). Neighbors' Effects on University Enrollment. *American Economic Journal: Applied Economics*, 14(3):30–60.

Battaglia, M., Gulesci, S., and Madestam, A. (2024). Repayment Flexibility and Risk Taking: Experimental Evidence from Credit Contracts. *The Review of Economic Studies*, 91(5):2635–2675.

Becker, G. S. and Tomes, N. (1976). Child Endowments and the Quantity and Quality of Children. *Journal of Political Economy*, 84(4, Part 2):S143–S162. Publisher: The University of Chicago Press.

Behrman, J. R., Pollak, R. A., and Taubman, P. (1982). Parental Preferences and Provision for Progeny. *Journal of Political Economy*, 90(1):52–73. Publisher: The University of Chicago Press.

Bharadwaj, P., Eberhard, J. P., and Neilson, C. A. (2018). Health at Birth, Parental Investments, and Academic Outcomes. *Journal of Labor Economics*, 36(2):349–394. Publisher: The University of Chicago Press.

Bhargava, P., Black, S. E., Denning, J. T., Fairlie, R. W., and Gurantz, O. (2025). A Family Affair: The Effects of College on Parent and Student Finances.

Black, S. E., Turner, L. J., and Denning, J. T. (2023). PLUS or Minus? The Effect of Graduate School Loans on Access, Attainment, and Prices.

Boneva, T. and Rauh, C. (2018). Parental Beliefs about Returns to Educational Investments—The

Later the Better? *Journal of the European Economic Association*, 16(6):1669–1711.

Borra, C., Costa-Ramón, A., Gonzalez, L., and Sevilla, A. (2024). The Causal Effect of an Income Shock on Children's Human Capital. *Journal of Labor Economics*. Publisher: The University of Chicago Press.

Breining, S., Doyle, J., Figlio, D. N., Karbownik, K., and Roth, J. (2020). Birth Order and Delinquency: Evidence from Denmark and Florida. *Journal of Labor Economics*, 38(1):95–142. Publisher: The University of Chicago Press.

Bucarey, A., Contreras, D., and Muñoz, P. (2020). Labor Market Returns to Student Loans for University: Evidence from Chile. *Journal of Labor Economics*, 38(4):959–1007. Publisher: The University of Chicago Press.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, 82(6):2295–2326. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA11757.

Carneiro, P. and Heckman, J. J. (2002). The Evidence on Credit Constraints in Post-Secondary Schooling. *The Economic Journal*, 112(482):705–734. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1468-0297.00075.

Celhay, P. and Gallegos, S. (2025). Early Skill Effects on Parental Beliefs, Investments and Children Long-Run Outcomes1. *Journal of Human Resources*. Publisher: University of Wisconsin Press Section: Articles.

Dahl, G. B. and Lochner, L. (2012). The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit. *American Economic Review*, 102(5):1927–1956.

Denning, J. T. and Jones, T. R. (2019). Maxed Out? The Effect of Larger Student Loan Limits on Borrowing and Education Outcomes. *Journal of Human Resources*. Publisher: University of Wisconsin Press Section: Article.

Denning, J. T., Marx, B. M., and Turner, L. J. (2019). ProPelled: The Effects of Grants on Graduation, Earnings, and Welfare. *American Economic Journal: Applied Economics*, 11(3):193–224.

Dizon-Ross, R. (2019). Parents' Beliefs about Their Children's Academic Ability: Implications for Educational Investments. *American Economic Review*, 109(8):2728–2765.

Dynarski, S., Libassi, C. J., Michelmore, K., and Owen, S. (2021). Closing the Gap: The Effect of Reducing Complexity and Uncertainty in College Pricing on the Choices of Low-Income Students. *American Economic Review*, 111(6):1721–1756.

Dynarski, S. M. (2003). Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion. *American Economic Review*, 93(1):279–288.

Fack, G. and Grenet, J. (2015). Improving College Access and Success for Low-Income Students: Evidence from a Large Need-Based Grant Program. *American Economic Journal: Applied Eco-*

nomics, 7(2):1–34.

Giannola, M. (2024). Parental Investments and Intra-household Inequality in Child Human Capital: Evidence from a Survey Experiment. *The Economic Journal*, 134(658):671–727.

Goodman, J., Hurwitz, M., Smith, J., and Fox, J. (2015). The relationship between siblings' college choices: Evidence from one million SAT-taking families. *Economics of Education Review*, 48:75–85.

Grembi, V., Nannicini, T., and Troiano, U. (2016). Do Fiscal Rules Matter? *American Economic Journal: Applied Economics*, 8(3):1–30.

Guryan, J., Hurst, E., and Kearney, M. (2008). Parental Education and Parental Time with Children. *Journal of Economic Perspectives*, 22(3):23–46.

Hanushek, E. A., Leung, C. K. Y., and Yilmaz, K. (2014). Borrowing Constraints, College Aid, and Intergenerational Mobility. *Journal of Human Capital*, 8(1):1–41. Publisher: The University of Chicago Press.

Karbownik, K. and Özek, U. (2023). Setting a Good Example?: Examining Sibling Spillovers in Educational Achievement Using a Regression Discontinuity Design. *Journal of Human Resources*, 58(5):1567–1607. Publisher: University of Wisconsin Press Section: Articles.

Kling, J. R., Liebman, J. B., and Katz, L. F. (2007). Experimental Analysis of Neighborhood Effects. *Econometrica*, 75(1):83–119. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0262.2007.00733.x.

Landersø, R. K., Nielsen, H. S., and Simonsen, M. (2020). Effects of School Starting Age on the Family. *Journal of Human Resources*, 55(4):1258–1286. Publisher: University of Wisconsin Press Section: Article.

Lochner, L. and Monge-Naranjo, A. (2012). Credit Constraints in Education. *Annual Review of Economics*, 4(Volume 4, 2012):225–256. Publisher: Annual Reviews.

Lochner, L. J. and Monge-Naranjo, A. (2011). The Nature of Credit Constraints and Human Capital. *American Economic Review*, 101(6):2487–2529.

Londoño-Vélez, J., Rodríguez, C., and Sánchez, F. (2020). Upstream and Downstream Impacts of College Merit-Based Financial Aid for Low-Income Students: Ser Pilo Paga in Colombia. *American Economic Journal: Economic Policy*, 12(2):193–227.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3):531–542.

Ortiz, E. A., Salcedo, O. V. D., Calvo, S., Morales, K., and Mori, J. (2025). El gasto real de estudiar educación superior en América Latina ¿cuánto invierten las familias y qué apoyo financiero reciben los estudiantes? *IDB Publications*. Publisher: Inter-American Development Bank.

Persson, P., Qiu, X., and Rossin-Slater, M. (2025). Family Spillover Effects of Marginal Diagnoses:

The Case of ADHD. *American Economic Journal: Applied Economics*, 17(2):225–256.

Qureshi, J. A. (2018). Siblings, Teachers, and Spillovers on Academic Achievement. *Journal of Human Resources*, 53(1):272–297. Publisher: University of Wisconsin Press Section: Article.

Solis, A. (2017). Credit Access and College Enrollment. *Journal of Political Economy*, 125(2):562–622. Publisher: The University of Chicago Press.

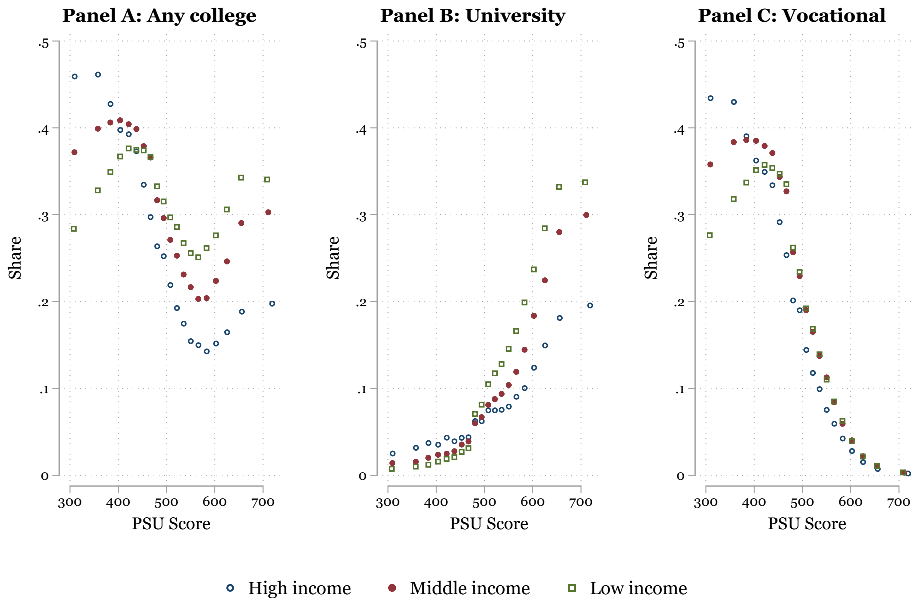
Solís, A. (2024). University Loans and Grants: Effects on Educational and Labor Market Outcomes. *Journal of Labor Economics*. Publisher: The University of Chicago Press.

Tramontin Shinoki, S., Picchetti, P., and Campos de Xavier Pinto, C. (2024). Difference-in-Discontinuities: Estimation, Inference and Validity Tests.

Yi, J., Heckman, J. J., Zhang, J., and Conti, G. (2015). Early Health Shocks, Intra-household Resource Allocation and Child Outcomes. *The Economic Journal*, 125(588):F347–F371. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecoj.12291.

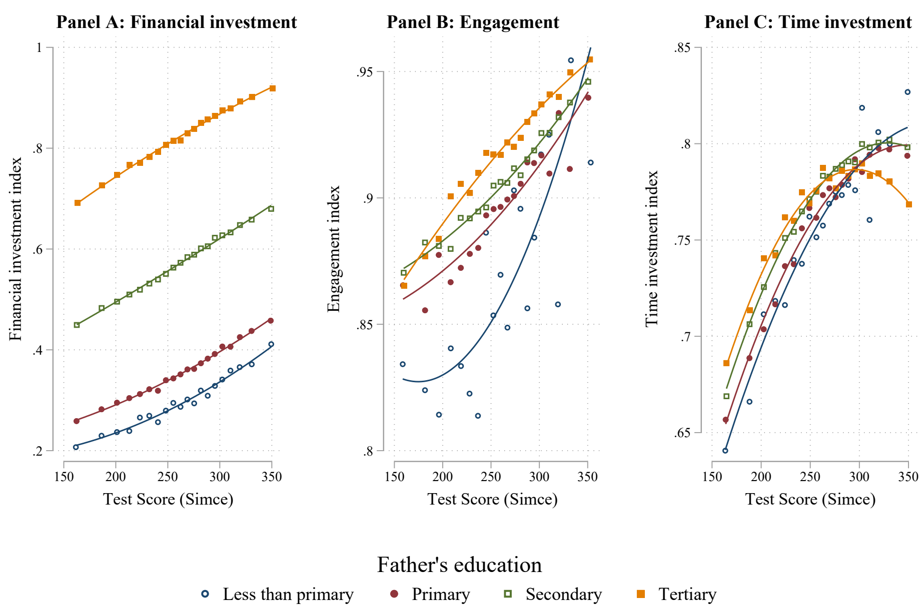
Appendix A: Descriptive statistics

Figure A1: Measures of college enrollment by parents income level



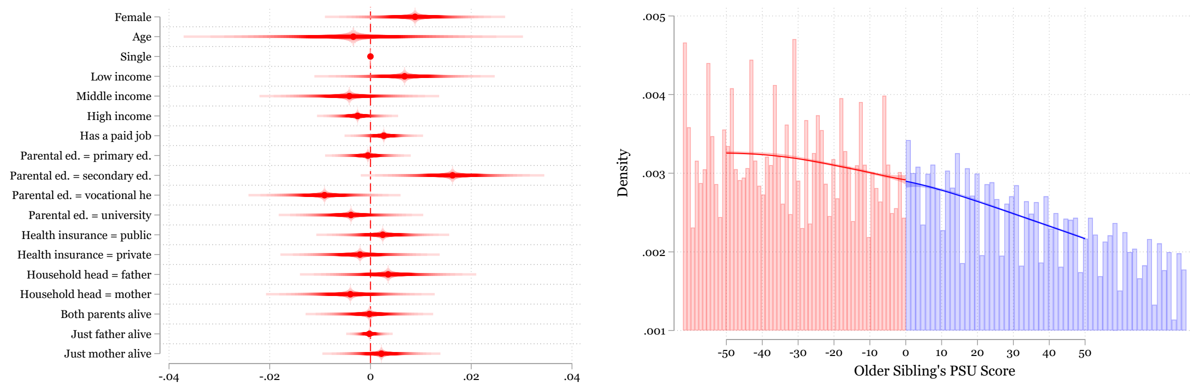
Note: The measures presented in these figures follow the ones from Figure 3, but I construct an summary indexes based on Kling et al. (2007). I also differentiate the variables relationship by household income level.

Figure A2: Measures of parental involvement index by father's education



Note: The measures presented in these figures follow the ones from Figure 4, but I construct an summary indexes based on Kling et al. (2007). I also differentiate the variables relationship by father's highest education level.

Figure A3: Regression discontinuity design validation



Panel A: Continuity of variables older sibling

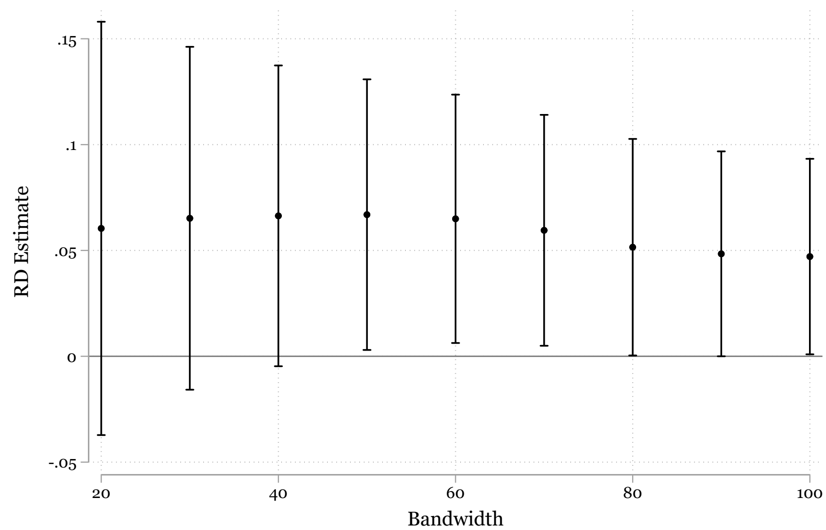
Panel B: Manipulation check (McCrary Test)

Note: Panel A illustrate the coefficients obtained by estimating the discontinuity effect (scholarship eligibility) on a set of demographic, sociecononomic, and family variables that could affect the estimation of the main outcomes of interest. In both the discontinuity is with respect to older sibling PSU score (normalized to zero using the cutoff for scholarship eligibility) and confident intervals are at 95% level. In the other hand, Panel B shows the estimated density of the PSU score at both sides of the scholarship eligibility cutoff (normalized to zero), with 95% confident intervals level.

Appendix B: Additional results and robustness checks

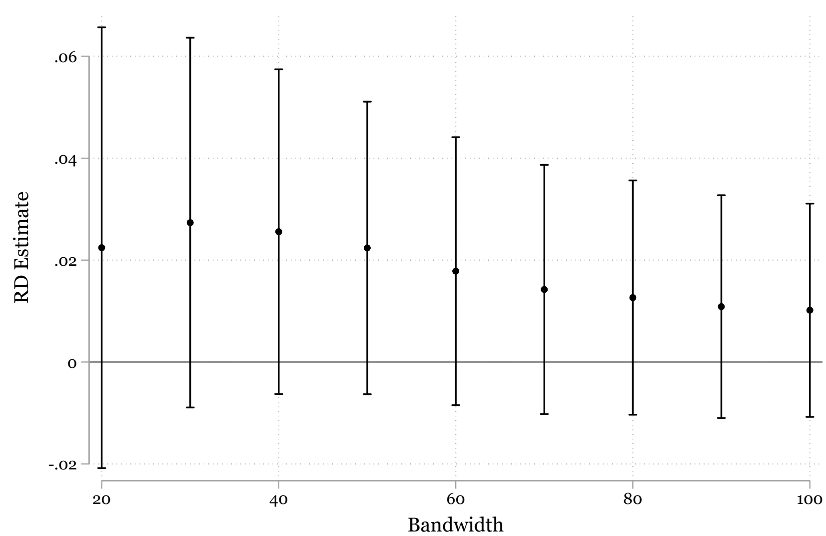
B.1 Additional results from Section 5.2

Figure B1: Results replication by different bandwidth choices



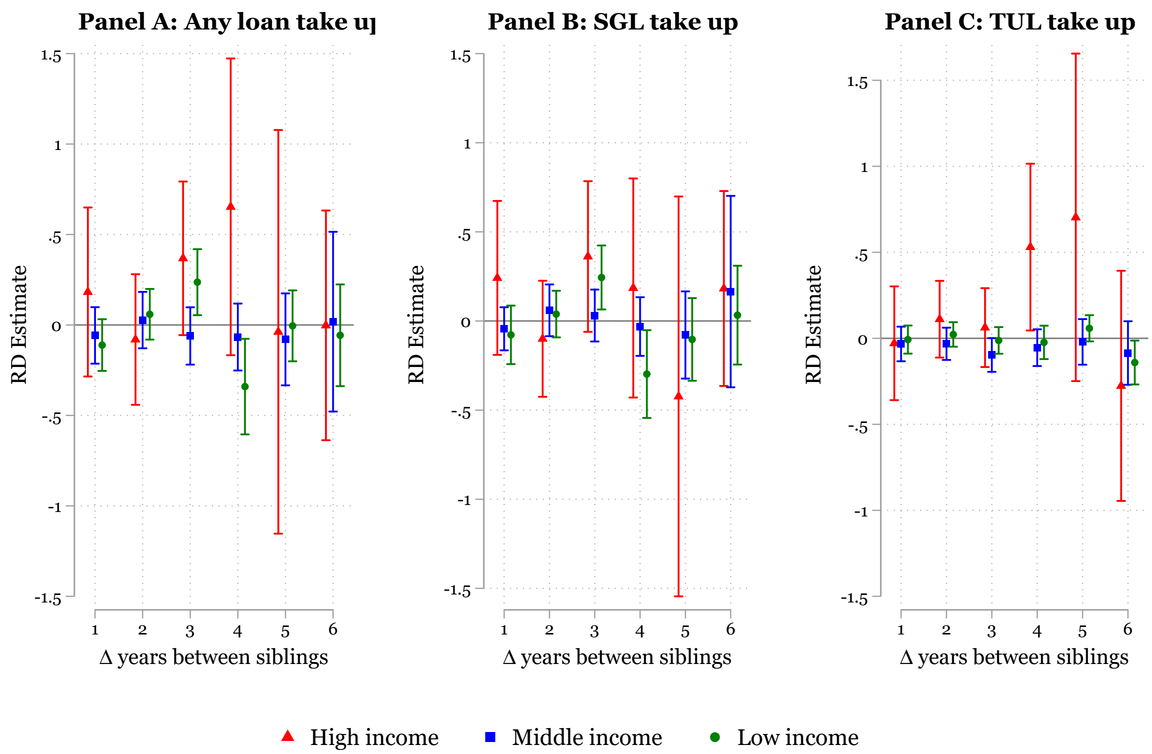
Note: Replication of the results from Table 2, Panel B, Column 2. Bandwidths were chosen manually. Confident intervals at 95% level.

Figure B2: Results replication by different bandwidth choices



Note: Replication of the results from Table B1, Panel B, Column 4. Bandwidths were chosen manually. Confident intervals at 95% level.

Figure B3: Heterogeneous effects by household income and age gap between siblings



Note: Replication of the results from Table 2. High income is defined as household with monthly income above 1,000 USD. Middle income between 400 and 1,000 USD. And low income below 400 USD. Confident intervals at 95% level.

Table B1: RD Estimates of older sibling eligible for college loan on younger sibling's college enrollment

	Any College Enrollment		University Enrollment		Vocational Enrollment	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All applicants						
First Stage		0.259***		0.269***		0.259***
		(0.02)		(0.02)		(0.02)
RD Estimate	−0.005	−0.012	−0.000	−0.012	−0.005	−0.008
	(0.01)	(0.03)	(0.00)	(0.02)	(0.01)	(0.03)
Mean Dep. Var.	0.308	0.310	0.054	0.051	0.251	0.257
Bandwidth	±58.7	±33.3	±54.0	±27.9	±71.5	±44.1
Observations	74,486	42,920	68,393	36,089	89,017	56,824
Panel B: High-income applicants						
First Stage		0.259***		0.259***		0.259***
		(0.02)		(0.02)		(0.02)
RD Estimate	0.017	0.021	0.020	0.080	−0.011	−0.071
	(0.03)	(0.11)	(0.01)	(0.05)	(0.03)	(0.10)
Mean Dep. Var.	0.309	0.310	0.054	0.054	0.257	0.255
Bandwidth	±36.4	±47.4	±55.6	±49.4	±38.1	±50.6
Observations	2,681	3,570	4,219	3,710	2,832	3,823
Panel C: Low-income applicants						
First Stage		0.260***		0.260***		0.260***
		(0.02)		(0.02)		(0.02)
RD Estimate	−0.024**	−0.082*	−0.009*	−0.031	−0.013	−0.051
	(0.01)	(0.05)	(0.00)	(0.02)	(0.01)	(0.04)
Mean Dep. Var.	0.307	0.310	0.054	0.053	0.248	0.257
Bandwidth	±67.9	±39.9	±60.7	±39.6	±84.0	±38.8
Observations	40,171	24,680	36,499	24,680	47,684	24,123

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B2: RD Estimates of older sibling eligible for college scholarship on younger sibling's college enrollment

	Any College Enrollment		University Enrollment		Vocational Enrollment	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All applicants						
First Stage		0.289***		0.288***		0.289***
		(0.01)		(0.01)		(0.01)
RD Estimate	−0.006	−0.021	0.003	0.009	−0.009	−0.030
	(0.01)	(0.03)	(0.00)	(0.02)	(0.01)	(0.03)
Mean Dep. Var.	0.281	0.278	0.072	0.072	0.206	0.206
Bandwidth	±69.6	±59.0	±65.4	±57.9	±60.6	±59.0
Observations	59,431	51,190	56,105	50,292	52,642	51,190
Panel B: High-income applicants						
First Stage		0.295***		0.295***		0.295***
		(0.01)		(0.01)		(0.01)
RD Estimate	−0.021	−0.499	−0.039*	−0.445	0.004	−0.054
	(0.04)	(0.48)	(0.02)	(0.30)	(0.04)	(0.41)
Mean Dep. Var.	0.278	0.281	0.072	0.072	0.206	0.209
Bandwidth	±58.1	±70.0	±70.0	±70.0	±59.3	±70.0
Observations	1,663	1,928	1,928	1,928	1,688	1,928
Panel C: Low-income applicants						
First Stage		0.291***		0.291***		0.289***
		(0.01)		(0.01)		(0.01)
RD Estimate	−0.007	−0.019	0.002	0.004	−0.007	−0.014
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
Mean Dep. Var.	0.281	0.280	0.072	0.072	0.206	0.205
Bandwidth	±68.1	±65.2	±60.1	±64.9	±57.9	±52.2
Observations	30,211	29,054	26,994	28,840	25,968	23,621

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B3: RD Estimates of older sibling eligible for college loan on younger sibling's parental investment at 12th grade

	Tuition Fees (USD)		Grad. payed school		Grad. private school		Grad. top tier school	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.259^{***}		0.260^{***}		0.259^{***}		0.266^{***}
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	27.68	54.57	0.003	0.009	−0.002	−0.007	-0.011^{**}	-0.045^{*}
	(24.47)	(112.3)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)	(0.02)
Mean Dep. Var.	3096.833	3069.038	0.591	0.586	0.018	0.016	0.109	0.104
Bandwidth	±65.9	±35.6	±57.7	±41.2	±58.0	±34.7	±51.6	±29.4
Observations	53,495	29,706	72,633	52,547	73,253	44,439	65,941	37,999
Panel B: High-income applicants								
First Stage		0.260^{***}		0.277^{***}		0.264^{***}		0.265^{***}
		(0.02)		(0.01)		(0.01)		(0.01)
RD Estimate	125.2	475.2	−0.017	−0.063	0.014	0.030	−0.041	−0.145
	(149.6)	(456.9)	(0.03)	(0.09)	(0.02)	(0.06)	(0.03)	(0.10)
Mean Dep. Var.	3068.158	3071.973	0.591	0.594	0.017	0.018	0.110	0.111
Bandwidth	±34.0	±41.8	±57.6	±72.2	±47.4	±58.7	±54.7	±58.0
Observations	1,728	2,192	4,339	5,504	3,543	4,410	4,144	4,372
Panel C: Low-income applicants								
First Stage		0.259^{***}		0.272^{***}		0.259^{***}		0.260^{***}
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	35.71	123.4	0.010	−0.014	0.001	0.007	−0.006	−0.023
	(35.07)	(136.7)	(0.01)	(0.06)	(0.00)	(0.01)	(0.01)	(0.02)
Mean Dep. Var.	3090.340	3075.386	0.592	0.583	0.018	0.017	0.112	0.104
Bandwidth	±58.9	±45.5	±63.0	±25.7	±60.7	±35.4	±59.2	±39.0
Observations	22,222	17,491	37,306	16,026	36,140	21,754	35,923	24,356

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B4: RD Estimates of older sibling eligible for college scholarship on younger sibling's parental investment at 12th grade

	Tuition Fees (USD)		Grad. payed school		Grad. private school		Grad. top tier school	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.289***		0.288***		0.288***		0.288***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	2.965	12.60	0.010	0.024	0.003	0.010	−0.009	−0.032
	(30.66)	(103.8)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)	(0.02)
Mean Dep. Var.	3284.081	3288.895	0.615	0.614	0.021	0.021	0.162	0.163
Bandwidth	±59.4	±52.9	±45.0	±57.3	±59.6	±56.2	±58.9	±57.7
Observations	34,647	31,192	39,940	49,478	51,416	48,705	51,190	50,292
Panel B: High-income applicants								
First Stage		0.290***		0.295***		0.295***		0.295***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−282.8	−2,545	−0.016	−0.195	0.020	0.230	−0.112**	−1.087*
	(201.0)	(2,304)	(0.04)	(0.41)	(0.03)	(0.37)	(0.05)	(0.58)
Mean Dep. Var.	3288.494	3283.496	0.614	0.610	0.021	0.021	0.164	0.162
Bandwidth	±54.2	±63.9	±50.9	±70.0	±70.0	±70.0	±54.8	±70.0
Observations	1,081	1,244	1,475	1,911	1,911	1,911	1,582	1,928
Panel C: Low-income applicants								
First Stage		0.288***		0.290***		0.297***		0.289***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	19.22	43.83	0.005	0.011	0.002	0.004	0.001	0.013
	(40.47)	(111.5)	(0.01)	(0.04)	(0.00)	(0.01)	(0.01)	(0.02)
Mean Dep. Var.	3283.816	3287.904	0.611	0.614	0.021	0.021	0.164	0.162
Bandwidth	±61.4	±55.6	±65.6	±50.7	±45.2	±77.4	±48.3	±59.2
Observations	18,090	16,618	28,980	22,861	20,482	33,312	21,998	26,632

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B5: RD Estimates of older sibling eligible for college loan on younger sibling's educational attainment at 12th grade

	PSU NEM		PSU Rank		PSU Math		PSU Reading	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.273^{***}		0.259^{***}		0.259^{***}		0.259^{***}
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	-0.013	-0.215^{***}	-0.029	-0.188^{**}	-0.024^{*}	-0.125^{**}	-0.032^{**}	-0.154^{**}
	(0.01)	(0.08)	(0.02)	(0.08)	(0.01)	(0.06)	(0.01)	(0.06)
Mean Dep. Var.	-0.005	-0.017	-0.007	-0.016	-0.156	-0.171	-0.194	-0.204
Bandwidth	±66.5	±23.6	±53.4	±34.0	±52.4	±32.3	±49.3	±33.4
Observations	83,076	30,801	48,862	31,803	66,662	41,784	62,967	42,920
Panel B: High-income applicants								
First Stage		0.263^{***}		0.265^{***}		0.259^{***}		0.264^{***}
		(0.02)		(0.01)		(0.02)		(0.01)
RD Estimate	0.129^{*}	0.457^{**}	0.149^{**}	0.532^{**}	0.015	0.044	0.118^{**}	0.350^{*}
	(0.07)	(0.23)	(0.06)	(0.23)	(0.07)	(0.23)	(0.06)	(0.19)
Mean Dep. Var.	-0.012	-0.010	-0.000	-0.006	-0.164	-0.163	-0.192	-0.183
Bandwidth	±51.0	±54.8	±71.8	±57.4	±43.9	±45.3	±50.7	±61.5
Observations	3,823	4,144	4,610	3,635	3,307	3,408	3,823	4,702
Panel C: Low-income applicants								
First Stage		0.259^{***}		0.261^{***}		0.271^{***}		0.260^{***}
		(0.02)		(0.02)		(0.02)		(0.02)
RD Estimate	-0.021	-0.150	-0.033	-0.145	-0.028	-0.187^{*}	-0.020	-0.097
	(0.02)	(0.09)	(0.03)	(0.10)	(0.02)	(0.10)	(0.02)	(0.08)
Mean Dep. Var.	0.002	-0.016	-0.001	-0.007	-0.149	-0.171	-0.181	-0.201
Bandwidth	±79.4	±36.3	±73.6	±53.6	±60.2	±26.9	±64.2	±41.2
Observations	45,640	22,569	27,708	21,137	36,303	16,719	38,422	25,578

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B6: RD Estimates of older sibling eligible for scholarship on younger sibling's educational attainment at 12th grade

	PSU NEM		PSU Rank		PSU Math		PSU Reading	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All applicants								
First Stage		0.288***		0.288***		0.288***		0.288***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−0.013	−0.049	−0.018	−0.072	−0.009	−0.033	−0.012	−0.037
	(0.02)	(0.06)	(0.02)	(0.08)	(0.02)	(0.05)	(0.01)	(0.05)
Mean Dep. Var.	0.117	0.118	0.095	0.094	0.073	0.075	0.026	0.036
Bandwidth	±65.9	±57.0	±62.2	±55.3	±60.0	±55.8	±69.0	±57.0
Observations	56,466	49,928	37,823	33,879	51,886	48,833	59,014	49,571
Panel B: High-income applicants								
First Stage		0.295***		0.295***		0.295***		0.295***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−0.150*	−1.712	−0.177*	−2.208	−0.172**	−1.952*	−0.101	−1.441
	(0.09)	(1.12)	(0.10)	(1.42)	(0.08)	(1.07)	(0.09)	(1.05)
Mean Dep. Var.	0.113	0.113	0.094	0.094	0.065	0.062	0.038	0.024
Bandwidth	±70.0	±70.0	±70.0	±70.0	±68.9	±70.0	±53.8	±70.0
Observations	1,928	1,928	1,586	1,586	1,914	1,928	1,559	1,928
Panel C: Low-income applicants								
First Stage		0.290***		0.290***		0.290***		0.290***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	0.002	0.019	0.005	0.024	0.021	0.058	0.014	0.035
	(0.03)	(0.07)	(0.03)	(0.10)	(0.02)	(0.06)	(0.02)	(0.06)
Mean Dep. Var.	0.116	0.116	0.092	0.095	0.075	0.073	0.033	0.029
Bandwidth	±52.1	±62.4	±51.1	±62.4	±57.1	±60.3	±60.4	±64.5
Observations	23,621	27,868	14,724	17,625	25,781	26,994	26,994	28,840

Note: Each observation is a single student applying for entering to a higher education institution at the ages between 17 and 22, during the years 2009-2016, whose older sibling applied for entering to a higher education institution between years 2008-2015. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Panel A represent the full sample within the bandwidth, Panel B is a selection for students from families with high income (> 1,000 USD monthly), and Panel C for low income families (< 400 USD monthly). Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

B.2 Additional results from Section 5.3

Table B7: RD Estimates of older sibling eligible for college loan on younger sibling's parental financial investment

	Index (1)	Has computer (2)	Has internet (3)	Has > 10 books (4)
Panel A: All students				
First Stage	0.226***	0.231***	0.216***	0.247***
	(0.03)	(0.04)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.078	−0.053	−0.022	−0.001
	(0.06)	(0.07)	(0.09)	(0.07)
Mean Dep. Var.	0.846	0.880	0.695	0.777
Bandwidth	±49.6	±50.7	±63.2	±51.0
Observations	8,992	9,914	11,452	15,607
Panel B: High income students				
First Stage	0.363*	0.524**	0.240	0.327*
	(0.21)	(0.21)	(0.18)	(0.17)
RD Estimate (2SLS)	−0.153	−0.016	0.204	−0.196
	(0.14)	(0.08)	(0.33)	(0.27)
Mean Dep. Var.	0.844	0.878	0.693	0.776
Bandwidth	±38.7	±39.5	±46.5	±42.3
Observations	323	347	403	652
Panel C: Low income students				
First Stage	0.343***	0.315***	0.347***	0.309***
	(0.05)	(0.04)	(0.05)	(0.04)
RD Estimate (2SLS)	−0.109	−0.073	−0.054	−0.082
	(0.08)	(0.09)	(0.12)	(0.08)
Mean Dep. Var.	0.845	0.880	0.694	0.778
Bandwidth	±48.7	±55.3	±53.6	±50.3
Observations	4,870	6,038	5,415	8,214

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B8: RD Estimates of older sibling eligible for college scholarship on younger sibling's parental financial investment

	Index	Has computer	Has internet	Has > 10 books
	(1)	(2)	(3)	(4)
Panel A: All students				
First Stage	0.256^{***}	0.254^{***}	0.249^{***}	0.212^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.014	−0.051	0.009	−0.098
	(0.05)	(0.06)	(0.09)	(0.08)
Mean Dep. Var.	0.867	0.899	0.700	0.816
Bandwidth	±59.6	±60.0	±67.8	±56.8
Observations	7,119	7,721	8,113	10,751
Panel B: High income students				
First Stage	0.006	0.000	0.000	−0.149
	(0.02)	(0.02)	(0.02)	(0.11)
RD Estimate (2SLS)	−0.093	−1.155	−0.267	3.498
	(0.65)	(1.02)	(1.29)	(9.71)
Mean Dep. Var.	0.868	0.904	0.698	0.810
Bandwidth	±36.4	±37.6	±36.0	±70.0
Observations	120	132	121	387
Panel C: Low income students				
First Stage	0.367^{***}	0.356^{***}	0.382^{***}	0.277^{***}
	(0.05)	(0.05)	(0.05)	(0.03)
RD Estimate (2SLS)	−0.081	-0.125^{**}	−0.075	−0.060
	(0.05)	(0.06)	(0.10)	(0.08)
Mean Dep. Var.	0.870	0.902	0.701	0.817
Bandwidth	±48.9	±49.3	±47.1	±56.2
Observations	3,453	3,797	3,374	6,156

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel. Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B9: RD Estimates of older sibling eligible for college loan on younger sibling's parental financial investment

	Index (1)	Congrats grades (2)	Know grades (3)	Demand good grade (4)	Help to study (5)	Help with homework (6)
Panel A: All students						
First Stage	0.266***	0.265***	0.269***	0.264***	0.270***	0.270***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	−0.083	−0.057	−0.015	−0.080	−0.027	−0.109
	(0.08)	(0.05)	(0.08)	(0.09)	(0.09)	(0.18)
Mean Dep. Var.	0.738	0.852	0.735	0.747	0.612	0.454
Bandwidth	±50.4	±53.2	±43.8	±55.0	±42.2	±42.6
Observations	4,330	16,774	11,014	10,453	10,805	4,538
Panel B: High income students						
First Stage	0.320***	0.317***	0.468***	0.328***	0.303***	0.444***
	(0.07)	(0.07)	(0.11)	(0.07)	(0.06)	(0.10)
RD Estimate (2SLS)	0.101	0.127	−0.022	−0.033	0.417	−0.263
	(0.58)	(0.21)	(0.47)	(0.54)	(0.46)	(0.70)
Mean Dep. Var.	0.739	0.851	0.736	0.750	0.613	0.454
Bandwidth	±62.5	±73.1	±38.7	±81.3	±67.6	±41.2
Observations	273	1,168	430	667	777	222
Panel C: Low income students						
First Stage	0.282***	0.294***	0.284***	0.283***	0.282***	0.288***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.121	−0.064	−0.098	−0.253**	0.034	−0.047
	(0.09)	(0.08)	(0.09)	(0.10)	(0.10)	(0.18)
Mean Dep. Var.	0.739	0.851	0.736	0.747	0.611	0.454
Bandwidth	±54.9	±37.7	±50.9	±53.0	±53.2	±41.3
Observations	2,635	6,595	6,978	5,771	7,474	2,423

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B10: RD Estimates of older sibling eligible for college scholarship on younger sibling's parental time investment

	Index	Congrats grades	Know grades	Demand good grade	Help to study	Help with homework
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All students						
First Stage	0.147^{***}	0.223^{***}	0.224^{***}	0.242^{***}	0.246^{***}	0.152^{***}
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
RD Estimate (2SLS)	0.060	−0.046	0.055	−0.135	−0.011	−0.030
	(0.09)	(0.06)	(0.08)	(0.09)	(0.09)	(0.19)
Mean Dep. Var.	0.735	0.846	0.724	0.757	0.593	0.442
Bandwidth	±50.1	±70.0	±64.2	±59.0	±59.1	±47.2
Observations	2,970	13,379	10,046	7,290	9,504	3,417
Panel B: High income students						
First Stage	0.000	−0.017	−0.146	0.147	0.147	0.000
	(0.00)	(0.13)	(0.10)	(0.16)	(0.14)	(0.10)
RD Estimate (2SLS)	−9.182	22.56	0.364	−14.51	0.200	−10.34
	(31.54)	(149.2)	(0.87)	(59.37)	(4.09)	(29.79)
Mean Dep. Var.	0.735	0.846	0.723	0.757	0.594	0.442
Bandwidth	±39.9	±70.0	±42.3	±52.8	±64.4	±53.4
Observations	70	386	190	177	279	114
Panel C: Low income students						
First Stage	0.238^{***}	0.312^{***}	0.339^{***}	0.331^{***}	0.341^{***}	0.252^{***}
	(0.06)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
RD Estimate (2SLS)	0.012	−0.045	0.065	0.010	−0.018	−0.210
	(0.07)	(0.06)	(0.09)	(0.09)	(0.09)	(0.14)
Mean Dep. Var.	0.735	0.846	0.726	0.758	0.591	0.440
Bandwidth	±58.1	±69.4	±51.3	±47.4	±51.1	±61.6
Observations	2,032	7,854	4,866	3,510	4,979	2,580

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B11: RD Estimates of older sibling eligible for college loan on younger sibling's parental financial investment

	Index	Assist to meetings	Assist to citations	Assist to activities
	(1)	(2)	(3)	(4)
Panel A: All students				
First Stage	0.260^{***}	0.265^{***}	0.260^{***}	0.267^{***}
	(0.01)	(0.02)	(0.01)	(0.02)
RD Estimate (2SLS)	−0.113	−0.031	−0.109	-0.108^{**}
	(0.11)	(0.05)	(0.14)	(0.05)
Mean Dep. Var.	0.926	0.936	0.958	0.671
Bandwidth	±77.0	±53.1	±66.9	±47.6
Observations	1,719	10,576	1,541	23,659
Panel B: High income students				
First Stage	0.487^{***}	0.468^{***}	0.367^{***}	0.299^{***}
	(0.12)	(0.11)	(0.08)	(0.06)
RD Estimate (2SLS)	−0.035	0.425	0.017	0.271
	(0.09)	(0.50)	(0.03)	(0.21)
Mean Dep. Var.	0.927	0.935	0.962	0.672
Bandwidth	±31.5	±39.0	±49.7	±70.3
Observations	30	330	58	1,939
Panel C: Low income students				
First Stage	0.281^{***}	0.284^{***}	0.280^{***}	0.284^{***}
	(0.02)	(0.03)	(0.02)	(0.03)
RD Estimate (2SLS)	−0.120	−0.060	−0.092	-0.117^{*}
	(0.11)	(0.05)	(0.14)	(0.07)
Mean Dep. Var.	0.927	0.936	0.958	0.673
Bandwidth	±67.9	±48.4	±69.0	±44.8
Observations	778	5,403	812	11,430

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B12: RD Estimates of older sibling eligible for college scholarship on younger sibling's parental engagement with school

	Index	Assist to meetings	Assist to citations	Assist to activities
	(1)	(2)	(3)	(4)
Panel A: All students				
First Stage		0.245***		0.164***
		(0.02)		(0.01)
RD Estimate (2SLS)		0.050		−0.154
		(0.05)		(0.10)
Mean Dep. Var.		0.931		0.669
Bandwidth		±70.0		±48.2
Observations		8,915		14,523
Panel B: High income students				
First Stage		−0.059		−0.044
		(0.05)		(0.05)
RD Estimate (2SLS)		−1.683		0.084
		(1.85)		(1.61)
Mean Dep. Var.		0.931		0.668
Bandwidth		±38.9		±70.0
Observations		137		595
Panel C: Low income students				
First Stage		0.357***		0.229***
		(0.03)		(0.02)
RD Estimate (2SLS)		0.052		−0.121
		(0.05)		(0.10)
Mean Dep. Var.		0.932		0.670
Bandwidth		±48.2		±47.6
Observations		3,766		8,125

Note: Blank columns are due small sample, given one of the variables is only available a few years. Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B13: RD Estimates of older sibling eligible for college loan on younger sibling's parents expectation about highest educational level

	High shcool	Vocational	University	Postgraduate
	(1)	(2)	(3)	(4)
Panel A: All students				
First Stage	0.270***	0.268***	0.269***	0.269***
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	−0.019	−0.033	0.046	−0.011
	(0.03)	(0.04)	(0.06)	(0.04)
Mean Dep. Var.	0.065	0.175	0.592	0.134
Bandwidth	±43.0	±47.2	±45.9	±45.4
Observations	20,247	22,000	21,385	21,204
Panel B: High income students				
First Stage	0.355***	0.306***	0.347***	0.310***
	(0.08)	(0.06)	(0.08)	(0.07)
RD Estimate (2SLS)	−0.062	−0.122	0.274	−0.118
	(0.07)	(0.13)	(0.23)	(0.18)
Mean Dep. Var.	0.066	0.172	0.591	0.138
Bandwidth	±46.3	±66.4	±53.9	±64.6
Observations	1,253	1,820	1,470	1,766
Panel C: Low income students				
First Stage	0.284***	0.283***	0.287***	0.284***
	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.007	−0.075	0.073	−0.008
	(0.05)	(0.07)	(0.08)	(0.05)
Mean Dep. Var.	0.066	0.175	0.593	0.133
Bandwidth	±44.6	±46.2	±42.5	±45.0
Observations	10,462	10,778	9,953	10,606

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B14: RD Estimates of older sibling eligible for college scholarship on younger sibling's parents expectation about highest educational level

	High shcool (1)	Vocational (2)	University (3)	Postgraduate (4)
Panel A: All students				
First Stage	0.149^{***}	0.149^{***}	0.148^{***}	0.149^{***}
	(0.01)	(0.02)	(0.01)	(0.01)
RD Estimate (2SLS)	0.082	−0.035	−0.154	0.135
	(0.05)	(0.08)	(0.11)	(0.09)
Mean Dep. Var.	0.048	0.130	0.614	0.175
Bandwidth	±55.5	±53.4	±57.9	±56.3
Observations	15,201	14,523	15,663	15,283
Panel B: High income students				
First Stage	−0.041	−0.038	−0.035	−0.034
	(0.05)	(0.05)	(0.05)	(0.05)
RD Estimate (2SLS)	−0.962	0.403	−2.068	2.728
	(1.49)	(1.21)	(3.95)	(4.66)
Mean Dep. Var.	0.049	0.134	0.612	0.169
Bandwidth	±59.7	±65.6	±68.8	±70.0
Observations	484	536	555	559
Panel C: Low income students				
First Stage	0.205^{***}	0.205^{***}	0.205^{***}	0.205^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	0.056	−0.128	−0.043	0.136
	(0.06)	(0.08)	(0.11)	(0.09)
Mean Dep. Var.	0.048	0.130	0.613	0.175
Bandwidth	±50.1	±52.1	±55.2	±56.0
Observations	7,714	7,976	8,455	8,529

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table B15: RD Estimates of older sibling eligible for college loan and scholarship on younger sibling's SIMCE test scores at 4th and 8th grade

	Loans effects		Scholarship effects	
	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)
Panel A: All students				
First Stage	0.274^{***}	0.268^{***}	0.184^{***}	0.183^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	2.179	7.068	−0.754	1.783
	(4.77)	(5.57)	(9.22)	(10.34)
Mean Dep. Var.	262.660	248.782	273.582	258.870
Bandwidth	±41.2	±46.6	±48.0	±54.0
Observations	24,420	21,414	17,202	14,589
Panel B: High income students				
First Stage	0.427^{***}	0.354^{***}	0.033	0.034
	(0.09)	(0.08)	(0.12)	(0.12)
RD Estimate (2SLS)	−10.53	28.70	318.3	−137.0
	(19.19)	(23.01)	(1, 117)	(901.7)
Mean Dep. Var.	262.702	248.741	273.459	258.899
Bandwidth	±44.2	±48.6	±53.7	±53.2
Observations	1,470	1,127	597	403
Panel C: Low income students				
First Stage	0.284^{***}	0.284^{***}	0.252^{***}	0.250^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	1.221	7.093	6.542	3.863
	(6.15)	(7.14)	(7.68)	(10.11)
Mean Dep. Var.	262.832	248.775	273.072	258.780
Bandwidth	±48.4	±49.7	±61.4	±56.9
Observations	14,339	11,746	12,108	8,865

Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for grade, demographic variables, age difference between siblings, and test year fixed effects. Optimal bandwidths are calculated using a MSE-optimal bandwidth selector and a triangular kernel.Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Appendix C: The theoretical model

C.1 Proof of Proposition 1 (and model derivation)

Proof. We prove the proposition in four steps: (i) state regularity and interiority assumptions, (ii) derive the knife-edge Euler condition from the FOCs, (iii) show that at the knife edge the dynamic problem is equivalent to a static CES allocation on an effective budget M and solve it, and (iv) establish continuity with the corner regimes.

Assumptions. Assume primitives satisfy $c_A, c_B, \theta_A, \theta_B > 0$, $0 < \gamma < 1$, $\rho \neq 0$ and $\alpha \equiv (1-\gamma)\rho - 1 \neq 0$. Assume feasible incomes are such that an interior solution for $I_{A1}, I_{B1}, I_{B2}, S$ is possible (strictly positive choices exist that satisfy period budgets). These assumptions guarantee the differentiability and interiority used below.

(i) FOCs and the Euler/price condition. Write the Lagrangian with multipliers $\lambda_1 \geq 0$ (period-1 budget) and $\lambda_2 \geq 0$ (period-2 budget). The interior first-order conditions (FOCs) are, using $U = (c_A H_A^\rho + c_B H_B^\rho)^{1/\rho}$:

$$\lambda_1 = U^{1-\rho}\, c_A H_A^{\rho-1}(1-\gamma)\theta_A^\gamma I_{A1}^{-\gamma},$$

$$\lambda_1 = U^{1-\rho}\, c_B H_B^{\rho-1}(1-\gamma)\theta_B^\gamma (I_{B1} + \delta I_{B2})^{-\gamma},$$

$$\lambda_2 = U^{1-\rho}\, c_B H_B^{\rho-1}(1-\gamma)\theta_B^\gamma \delta (I_{B1} + \delta I_{B2})^{-\gamma},$$

together with the S-FOC (period-1 vs period-2 resource price)

$$-\lambda_1 + (1+r)\lambda_2 = 0.$$

Dividing the second FOC by the third yields $\lambda_2 = \delta\lambda_1$. Substituting into the S-FOC gives the Euler/price condition

$$(1+r)\delta = 1.$$

Thus $\tau \equiv (1+r)\delta = 1$ is the unique knife-edge at which the period-1 and period-2 marginal values are jointly consistent with interiority in both timing margins.

(ii) Reduction to an effective one-period budget at $\tau = 1$. Define the composite variable $Z \equiv I_{B1} + \delta I_{B2}$. The two period constraints are

$$I_{A1} + I_{B1} + S = Y_1 + L_A, \qquad I_{B2} \leq Y_2 + \pi Y^B + (1+r)S - (1+R)L_A.$$

Multiply the second constraint by δ and, using $\tau = (1+r)\delta = 1$, rewrite δI_{B2} feasibility as

$$\delta I_{B2} \le \delta\big(Y_2 + \pi Y^B - (1+R)L_A\big) + \delta(1+r)S = \delta\big(Y_2 + \pi Y^B - (1+R)L_A\big) + S.$$

Add the period-1 equation $I_{A1} + I_{B1} + S = Y_1 + L_A$ to this inequality for δI_{B2}. The left-hand side sums to $I_{A1} + I_{B1} + \delta I_{B2} = I_{A1} + Z$, while the right-hand side equals

$$(Y_1 + L_A) + \delta\big(Y_2 + \pi Y^B - (1+R)L_A\big) \equiv M.$$

Thus any feasible allocation must satisfy

$$I_{A1} + Z \le M.$$

Conversely, given any pair (I_{A1}, Z) with $I_{A1}+Z \le M$, one can construct feasible period-by-period choices (I_{B1}, I_{B2}, S) that satisfy the original constraints (for instance choose S so the period-1 budget binds and split Z into I_{B1} and δI_{B2} consistent with the second constraint). Hence, at $\tau = 1$ the dynamic feasibility set projects exactly onto the static budget constraint $I_{A1} + Z \le M$. With interiority we work on the equality $I_{A1} + Z = M$.

(iii) Static CES problem and closed-form solution. At $\tau = 1$ the household's problem is therefore equivalent to

$$\max_{I_{A1}, Z \ge 0} \widetilde{U}(I_{A1}, Z) = \Big[c_A(\theta_A^{\gamma} I_{A1}^{1-\gamma})^{\rho} + c_B(\theta_B^{\gamma} Z^{1-\gamma})^{\rho}\Big]^{1/\rho} \quad \text{s.t.} \quad I_{A1} + Z = M.$$

Maximizing the interior objective inside the $\frac{1}{\rho}$ power yields

$$\Phi(I_{A1}, Z) = c_A \theta_A^{\gamma\rho} I_{A1}^{(1-\gamma)\rho} + c_B \theta_B^{\gamma\rho} Z^{(1-\gamma)\rho}.$$

The FOC for I_{A1} (combined with the budget equality) gives the standard CES ratio condition

$$\frac{c_A \theta_A^{\gamma\rho} I_{A1}^{(1-\gamma)\rho-1}}{c_B \theta_B^{\gamma\rho} Z^{(1-\gamma)\rho-1}} = 1.$$

Let $\alpha = (1-\gamma)\rho - 1 \neq 0$ and define

$$\kappa \equiv \left(\frac{c_A \theta_A^{\gamma\rho}}{c_B \theta_B^{\gamma\rho}}\right)^{1/\alpha}.$$

The ratio condition implies $I_{A1}/Z = \kappa$. Solving with $I_{A1} + Z = M$ yields the interior closed forms

$$I_{A1}^* = \frac{\kappa}{1+\kappa} M, \qquad Z^* = \frac{1}{1+\kappa} M,$$

which are the claimed CES shares out of the effective budget M.

(iv) Continuity with the corner regimes. The effective budget M depends linearly on the primitives (in particular on R, π, L_A). For $\tau \neq 1$ the timing margin becomes non-interior and the solution typically lies on a corner (either $S^* = 0$ when $\tau < 1$ or $I^*_{B1} = 0$ when $\tau > 1$). Standard arguments (e.g. by examining the sign of the Euler condition or via the implicit function theorem applied on each regime) show that as $\tau \to 1^-$ or $\tau \to 1^+$ the corner solutions and their Lagrange multipliers approach the interior knife-edge solution. Therefore the comparative statics computed at $\tau = 1$ coincide with the continuous limits of directional comparative statics from the two polar regimes. This establishes that the knife-edge derivatives are the appropriate local derivatives and that they summarize the limiting behavior of the model across timing regimes.

Collecting the steps above proves the proposition. $\square$

C.2 Proof of Proposition 2

Proof. At the knife edge $\tau = 1$ the interior solution yields the closed form

$$I_{A1}^{*} = \frac{\kappa}{1+\kappa} M = s(\kappa)\, M, \qquad s(\kappa) \equiv \frac{\kappa}{1+\kappa},$$

where

$$M = (Y_1 + L_A) + \delta\big(Y_2 + \pi Y^B - (1+R)L_A\big).$$

Note that κ depends only on $(c_A, c_B, \theta_A, \theta_B, \gamma, \rho)$ and therefore is constant with respect to the parameters R, π, L_A that enter M.

The claimed derivatives follow immediately by the chain rule. Since $s(\kappa)$ is constant in R, π, L_A,

$$\frac{\partial I_{A1}^{*}}{\partial x} = s(\kappa)\,\frac{\partial M}{\partial x} \quad \text{for } x \in \{R, \pi, L_A\}.$$

Computing the partials of M gives

$$\frac{\partial M}{\partial R} = -\delta L_A, \qquad \frac{\partial M}{\partial \pi} = \delta Y^B, \qquad \frac{\partial M}{\partial L_A} = 1 - (1+R)\delta,$$

and substituting these expressions yields the formulas in the proposition. The sign statements are immediate: $\partial I_{A1}^{*}/\partial R = s(\kappa)(-\delta L_A) < 0$, $\partial I_{A1}^{*}/\partial \pi = s(\kappa)(\delta Y^B) > 0$, while the sign of $\partial I_{A1}^{*}/\partial L_A$ depends on whether $1 - (1+R)\delta$ is positive or negative.

The same argument applied to $Z^* = M/(1+\kappa) = (1 - s(\kappa))M$ yields the analogous expressions for the composite Z^*, completing the proof. □

Appendix D: Further analysis for differential effects on repayment scheme

D.1 2-Dimensional RDD using program eligibility rules

Another way to analize how the repayment scheme can generate differential spillover effects across younger siblings, is to compare eligible students for TUL loan (available to students who enroll in traditional universities) versus the SGL loan (available to students who enroll in non-traditional institutions). These two credit programs differ in interest rates, repayment conditions, and coverage, and may therefore influence enrollment choices, persistence, and later outcomes. However, eligibility is not chosen: it is mechanically determined by the type of institution in which the student ultimately enrolls. By exploiting the discontinuous admission rules that dictate whether a student crosses the cutoff for a target (often traditional) program or falls back to a (non-traditional) alternative (Aguirre and Matta, 2021), we create a research design that allows for a credible comparison of students who are just above or below these cutoffs and are thus quasi-randomly exposed to TUL or SGL eligibility.

The centralized higher education admission system in Chile generates a sharp decision rule that we exploit to identify causal effects of program enrollment and associated loan schemes. Applicants submit a ranked list of preferred programs. For each applicant, we focus on the *admission margin* between a **target program** (their first available choice at that point in the ranking) and a **fallback program** (the next available option). Admission depends on whether the applicant's score is above or below the cutoff for the target program.

Formally, let p_i denote the admission score of applicant i, and c_j the admission cutoff for program j. We define the running variable:

$$r_i = \sum_j (p_i - c_j) \cdot t_{ij},$$

where t_{ij} is an indicator equal to one if program j is the applicant's target program. The key discontinuity is at $r_i = 0$. If $r_i \geq 0$, the applicant is assigned to the target program; otherwise, they are assigned to the fallback program:

$$a_{ij} = t_{ij} \cdot \mathbb{1}(r_i \geq 0) + f_{ij} \cdot \big(1 - \mathbb{1}(r_i \geq 0)\big).$$

This rule generates quasi-random assignment near the cutoff: conditional on the margin, applicants just above and just below c_j are similar in all observable and unobservable characteristics.

This assignment rule is particularly relevant in the Chilean context because of the financing structure of higher education. Students with an admission score of at least 475 points who enroll in a *traditional university* are eligible for the TUL loan. Those who enroll in a *non-traditional institution* (private universities outside CRUCH or technical/professional institutes) are eligible for the SGL loan. Therefore, the discontinuity in program assignment simultaneously induces: (1) a discontinuous change in the type of institution a student attends, and (2) a discontinuous change in the type of loan program they can access. We refer to this empirical strategy as a two-dimensional regression discontinuity design (2D-RDD), since it exploits a discontinuity in both enrollment and financing conditions.

Conditional on the margin and on being close to the cutoff, this discontinuity in assignment acts as an instrument for enrollment. Moreover, because enrollment at traditional vs. non-traditional institutions determines loan eligibility, the same discontinuity also identifies the effect of accessing TUL versus SGL. This is why we refer to our empirical approach as a *two-dimensional RDD*.