Household Reallocation and Sibling Spillovers from College Financial Aid*

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Declaration

I, Pedro Cubillos, hereby declare that the work presented in this dissertation is my own original work. Where information has been derived from other sources, I confirm that this has been clearly and fully identified and acknowledged. No part of this dissertation contains material previously submitted to the examiners of this or any other University, or any material previously submitted for any other assessment.

Signature: Pedro Cubillos

Date: 07/09/2025

Clasification

✓ an empirical/econometric study

□ the examination of a theoretical problem

□ a critical analysis of a policy issue

□ an analytical survey of empirical and/or theoretical literature

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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, educational attainment, and parental investment. On the contrary, students from low income households benefits more when older siblings receive scholarships rather than loans. 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, with relevant differences across the income distribution and financial constraints.

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Contents

1 Introduction

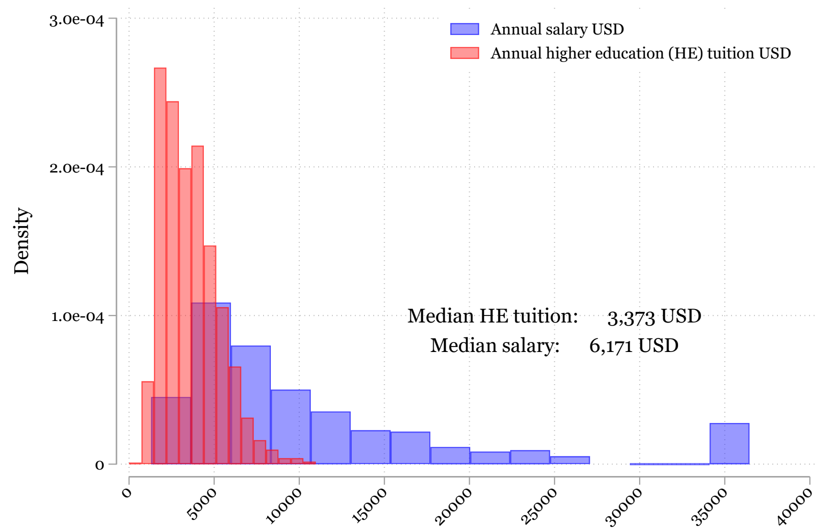
Expanding access to higher education remains one of the most powerful tools for reducing inequality and promoting upward mobility. College financial aid has therefore become a cornerstone of education policy in countries with high tuition costs, liquidity constraints, and low enrollment rates (Black 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 one half of the median annual earnings—making financial aid central to access (see Figure 1), and it is one of the most expensive countries in Latin America to study in (Ortiz et al., 2025). 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 interest 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, while 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. This is also true if when analyzing academic performance in the college entry exam and parental investment 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. ***Disclaimer:*** *There are many reasons why I do not fin anything, but is mainly because I don't have sufficient observation and the gap between a 18 years old and 10 years old sibling is quite a lot. This part is in progress and I can complement the data using more SIMCE years and also using not only 4th grade but also 8th grade.*

Finally, by exploiting the SGL loan reform of 2012, I find some preliminary evidence of an increase in the university enrollment, particularly for low 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 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. 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; 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), with the relaxation of education costs through scholarships or loans being a form that is opposite but complementary to what is known as an income shock.

The paper is organized as follow. Section 2 summarize the institutional backgraound 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.

Admission to higher education in Chile is centralized and highly standardized. Until recently, students seeking entry into universities 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 we focus separately on university programs and vocational programs, as the financial aid rules and labor market outcomes differ substantially across these tracks.

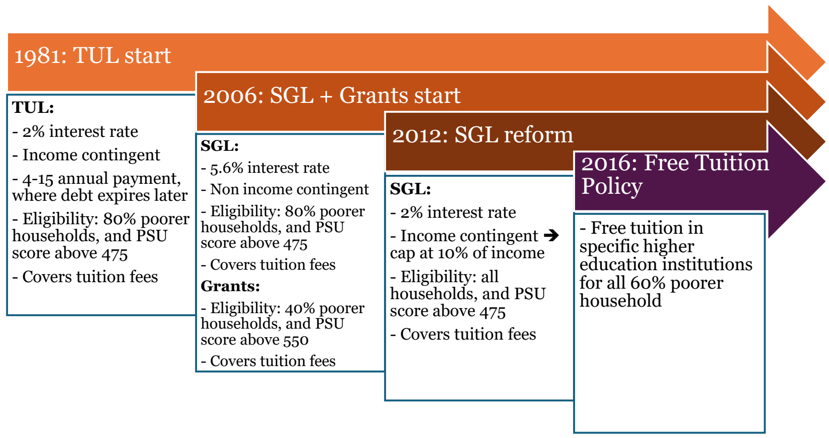
Financial aid was similarly structured through centralized application and allocation processes. Students applied for aid simultaneously with university admission, and eligibility was determined by sharp cutoffs on observables such as PSU scores, household income percentile, and type of institution attended. 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

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 (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.

households.

Eligibility for both loan programs depends on a combination of academic and socioeconomic criteria. Academically, applicants must score above institution- and program-specific thresholds on the national admission exam, the PSU, or meet a minimum high school GPA. 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 Bicentennial 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 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.[1]

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

This centralized structure—characterized by transparent admission rules, sharp aid eligibility thresholds, and detailed administrative records—provides a unique setting to study how financial aid shapes educational choices, intra-household investment decisions, and long-term outcomes.

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.

[1] The Bicentennial 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.

The Department of Assessment, Evaluation and Academic Registers (DEMRE) provides individual-level data on test scores, demographic characteristics, and school background for each test taker in each year from 2007 and 2019. This data include also the information of the program's[2] 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.[3] These datasets include information on whether the applicant enroll to college during this year, and the information of the program enrolled. To this data, we 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, we 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, we are 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.

Since my aim in this paper is to study sibling spillover from college financial aid, I focus on pairs of successive siblings, in which the older sibling applied to a higher education program between 2008 and 2016, and the younger sibling completed high school after (i.e. at 12th grade) or took the nation-wide standardized test SIMCE at 4th or 8th grade described below. I identify siblings using surnames and schools following Aguirre and Matta (2021)'s credible assumptions.

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 administrative 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

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

[3] 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.

others, the type of school (public, voucher or private), tuition fees (copay), and quality.[4] 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.

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 A1 and A2.

2.3 Outcomes

This section summarizes the main outcomes studied in this paper, also presented in Tables A1 and A2. 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.

First, we 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, we examine outcomes related to college enrollment, distinguishing between university and vocational programs. Third, we 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, we 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 4 illustrates how some of these outcomes correlate with PSU performance. Panel A

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

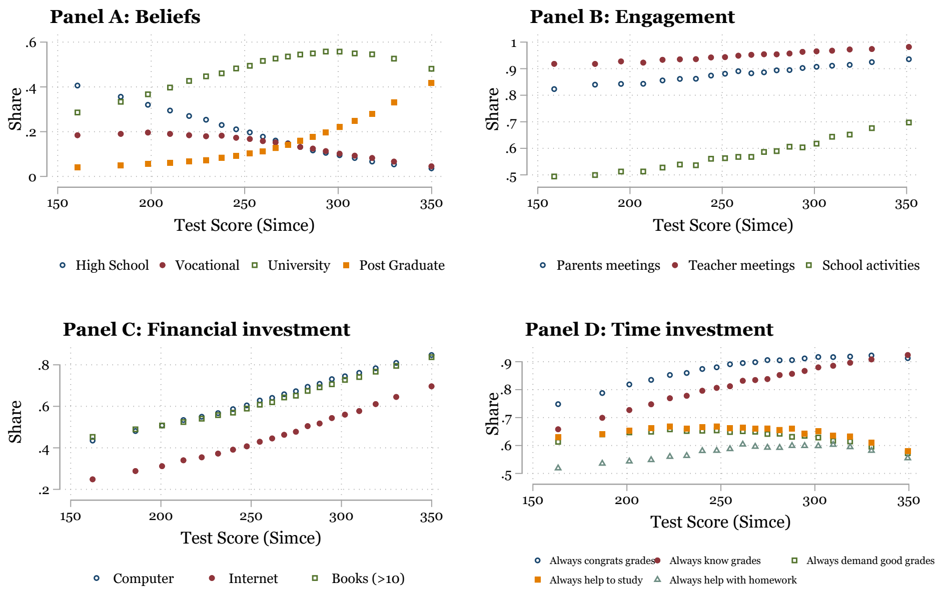
shows that students with higher PSU scores are more likely to enroll in university programs rather than vocational tracks. Panel B shows a positive correlation between PSU scores and the cost, quality, and private status of the student's secondary school. These variables, which proxy parental investment,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

For the sample of fourth- and eighth-grade students, we divide outcomes into two groups. First, educational attainment is measured by performance on nationwide standardized tests in math and reading. Second, we 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 3 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.

3 Economic Framework

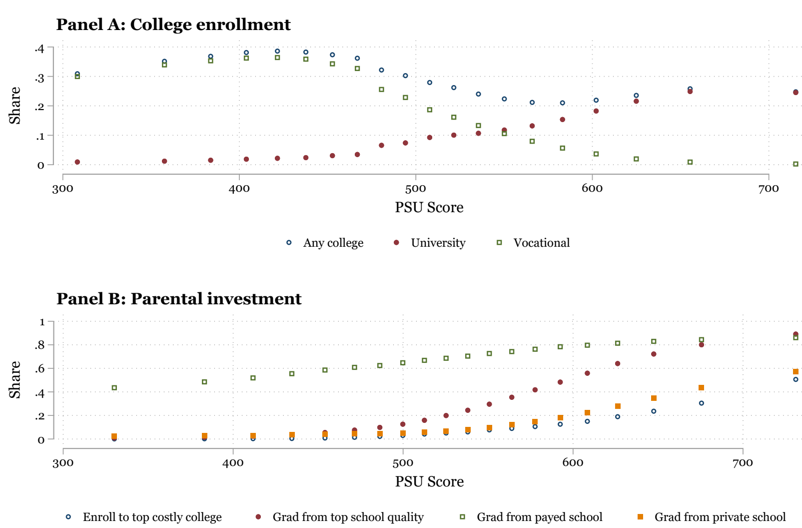
I construct a simple theoretical model to understand the intertemporal allocation of resources across different children withing the household. It borrow some aspects from existing literature in siblings resources allocation and inequality aversion (Bharadwaj et al., 2018; Behrman et al., 1982; Boneva and Rauh, 2018; Giannola, 2024), and intertemporal decisions on parental investment in education considering financial constraints and credit access (Lochner and Monge-Naranjo, 2011; Cunha et al., 2010). Combining both I bring new insights into the literature, which also help to understand the underlying empirical findings.

Figure 3: 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)

Figure 4: 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.

3.1 Preferences, Payment Rules, 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.[5] 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

[5] See proof in Appendix B.

is 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.[6] Lastly, household are allowed to save money 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 we asume that both budget constraints are binding, and that $I^A = I_1^A$; $I^B = I_1^B + \delta I_2^B$; $Y = Y_1 + Y_2$.[7] Different repayment rules (e.g., fixed vs. income-contingent) 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 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.

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

[6] 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 $t = 2$.

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

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_{A1} and the composite $Z \equiv I_{B1} + \delta I_{B2}$ according to CES shares.

At $\tau = 1$ the closed-form share rule gives

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

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 $I^*_{A1} = s(\kappa)M$). For any parameter x that enters only via M (for example R, π, L_A), the total derivative is

$$\frac{\partial I^*_{A1}}{\partial x} = s(\kappa)\,\frac{\partial M}{\partial x}.$$

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

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

$$\begin{aligned}
\frac{\partial I^*_{A1}}{\partial R} \;&=\; s(\kappa)\cdot\frac{\partial M}{\partial R} \;=\; s(\kappa)\cdot\big(-\delta L_A\big) \;<\; 0,\\
\frac{\partial I^*_{A1}}{\partial \pi} \;&=\; s(\kappa)\cdot\frac{\partial M}{\partial \pi} \;=\; s(\kappa)\cdot\big(\delta Y^B\big) \;>\; 0,\\
\frac{\partial I^*_{A1}}{\partial L_A} &= s(\kappa)\cdot\frac{\partial M}{\partial L_A} = s(\kappa)\cdot\big(1-(1+R)\delta\big).
\end{aligned}$$

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.

At $\tau = 1$ a higher repayment R reduces the effective budget M (because it tightens expected period-2 resources) and both I_{A1} 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 $\partial I_{A1}^*/\partial L_A$ 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).

Finally we turn attention on the role of inequality aversion. Because $\kappa = \kappa(\rho)$, changes in ρ affect the CES shares themselves. Differentiate $I_{A1}^* = s(\kappa(\rho))M$ with respect to ρ; since M is independent of ρ, we obtain

$$\frac{\partial I_{A1}^*}{\partial \rho} = M \cdot \frac{d}{d\rho}\left(\frac{\kappa(\rho)}{1+\kappa(\rho)}\right) = M \cdot \frac{\kappa'(\rho)}{(1+\kappa)^2},$$

where

$$\frac{\kappa'(\rho)}{\kappa} = \frac{\gamma \Delta \ln\theta \cdot \alpha - N \cdot (1-\gamma)}{\alpha^2},$$

with $\Delta \ln\theta \equiv \ln\theta_A - \ln\theta_B$ and $N \equiv \ln(c_A/c_B) + \gamma\rho\Delta\ln\theta$ (see derivation in the appendix). Equivalently,

$$\boxed{\frac{\partial I_{A1}^*}{\partial \rho} = M \cdot \frac{\kappa}{(1+\kappa)^2} \cdot \frac{\gamma \Delta \ln\theta \cdot \alpha - N \cdot (1-\gamma)}{\alpha^2}}.$$

Proposition 3 (Comparative static w.r.t. inequality aversion ρ)**.** *The sign of $\partial I_{A1}^*/\partial\rho$ is in general ambiguous and depends on the technology parameters (γ), the relative baseline abilities θ_A, θ_B and the weight ratio c_A/c_B. Intuitively:*

- *If parents place symmetric weights and $\theta_A < \theta_B$ (younger is lower-ability), then increasing inequality aversion (moving ρ in the direction that reduces inequality tolerance) tends to* raise I_{A1} *(compensatory transfers) — i.e. $\partial I_{A1}^*/\partial\rho < 0$ if we parametrize ρ so that lower values mean more aversion.*

- *If instead the efficiency motive dominates (high ρ in the utilitarian region), an increase in ρ shifts investment toward the child with higher marginal return and $\partial I_{A1}^*/\partial\rho$ may be positive.*

A precise sign condition is given by the numerator in the boxed expression above; the formal derivation is in the appendix.

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 $\tau = 1$ (policy changes that shift the economy across the threshold will produce non-differentiable changes in the allocation). In applied work it is therefore useful to report both the local (knife-edge) derivatives and the directional effects in each corner regime (see Appendix A for the full expressions). The expressions above assume interiority in the allocation between children (the CES share rule). If feasibility or nonnegativity bind, evaluate the signs via the corner formulas provided previously.

This framework provides a tractable way to analyze how households allocate educational investments across children under intertemporal budget constraints and borrowing opportunities. By incorporating differences in loan eligibility, repayment schemes, and child characteristics, the model highlights the underlying trade-offs parents face between efficiency and equality. In particular, it generates empirical 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, we implement a regression discontinuity design (RDD) that exploits sharp eligibility thresholds in Chile's student aid system. In particular, we leverage the fact that access to key financial aid programs—such as the SGL (state-guaranteed loan), TUL (traditional university loan), and Bicentennial 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 we 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.[8] We define an indicator $D_{s(i),t-1} = \mathbb{1}(Score_{s(i),t-1} \geq c)$

[8]For simplicity, we denote here the PSU score of the older sibling taken one year before $(t-1)$, but in all regressions we consider any time gap between older and younger sibling measures. For example, we 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 we include also additional results checking whether this effects change depending on this gap.

for eligibility. Our 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. We 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.[9] The coefficient τ identifies the causal effect of aid eligibility under standard RDD assumptions of continuity in potential outcomes around the threshold.

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. 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,[10] we use a fuzzy RDD framework. We 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.

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

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

4.3 Strategy validation

We 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 manipulation checks.[11] 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.[12] 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 we 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 we 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 better 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.

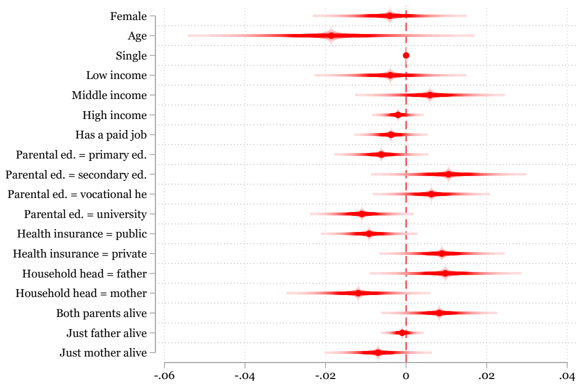
4.4 Estimating differential impact of repayment scheme using a Difference-in-discontinuity design

To examine how changes in loan repayment schemes affect the impact of financial aid eligibility, we extend the RDD framework using a difference-in-discontinuities (DiDC) design (Grembi et al., 2016; Tramontin Shinoki et al., 2024). Specifically, we 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

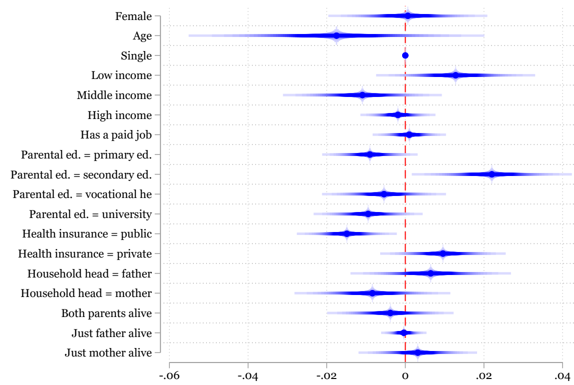
[11] This Figure is a reproduction of the one shown in the Appendix in Barrios-Fernández (2022).

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

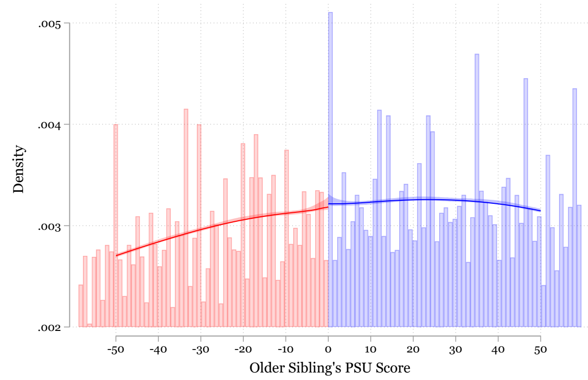
Figure 5: Regression discontinuity design validation



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.

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). We 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, we expect $\beta_0 > 0$, meaning on positive spillover effects of sibling s financial aid eligibility on student i (younger sibling) outcomes.

This approach allows us 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.

5 Results

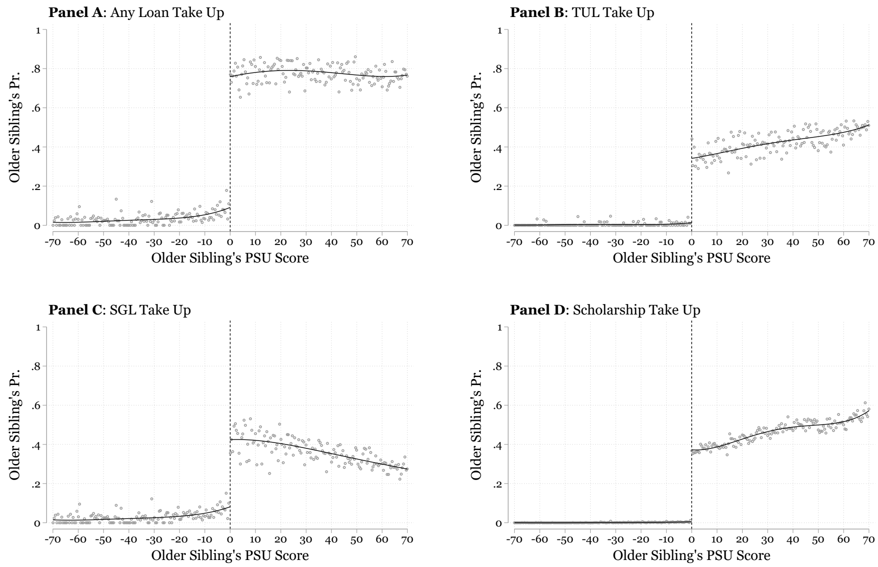
5.1 Older sibling's own effects of financial aid eligibility

5.1.1 Financial aid take up and college enrollment

Figure 6

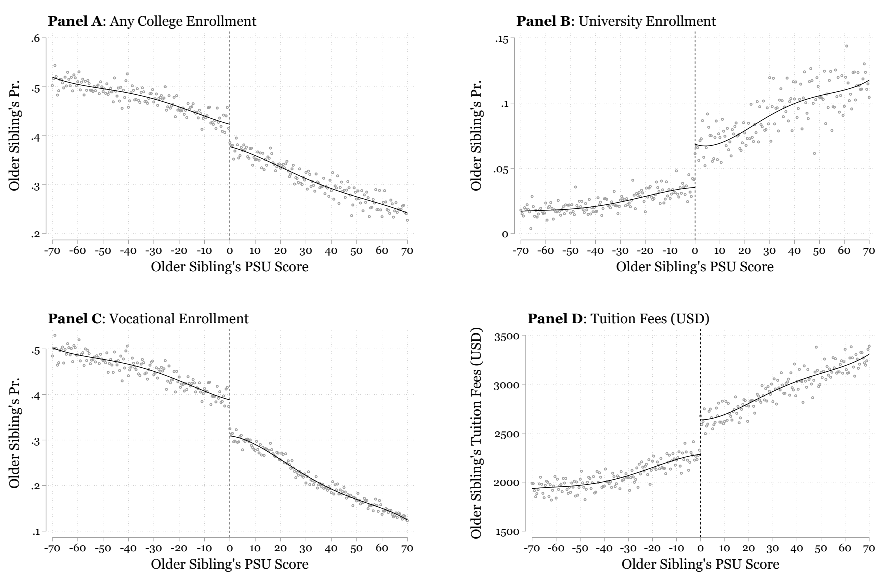
Figure 7

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. 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). Same figures including all students are presented in the Appendix. Panel D 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

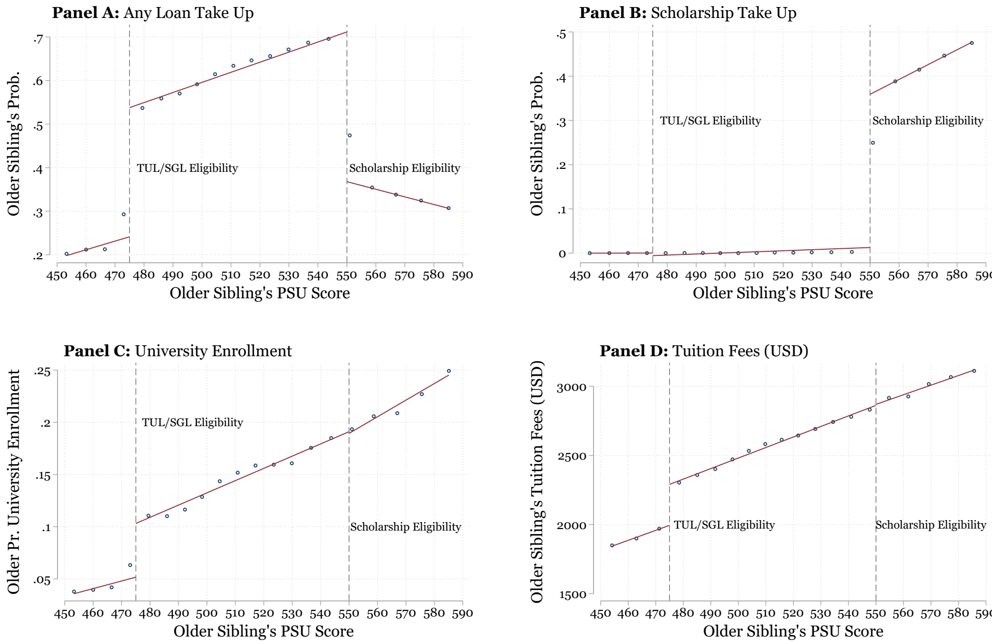
Figure 7: Older's siblings own effect of being eligible for college loans on college enrollment



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).

5.1.2 Effects of scholarship eligibility relative to loan

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

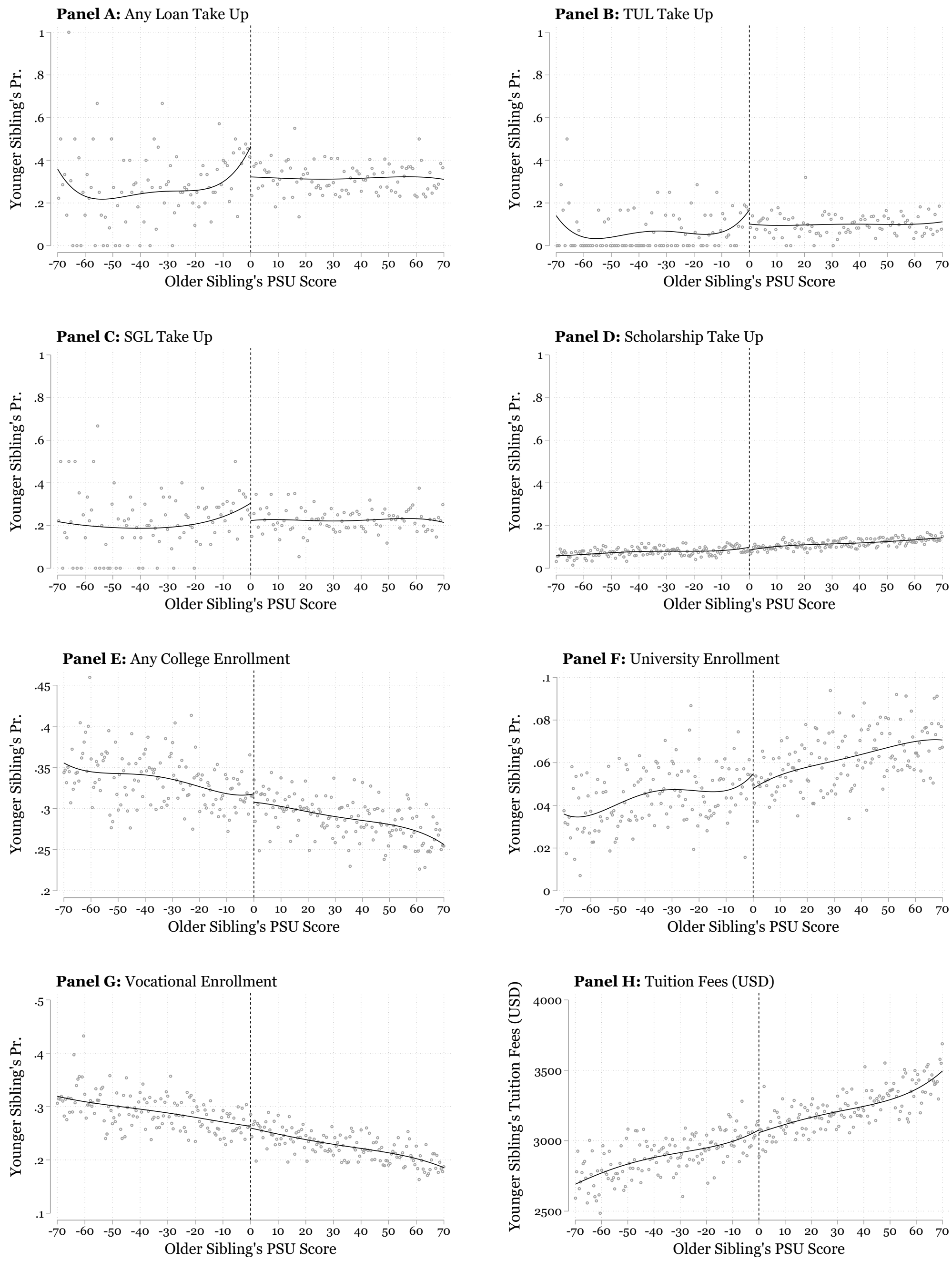


Note: All figures consider only income quntiles 1 and 2, which are the eligibles for the scholarship. Also, they only consider cohorts 2008-2012, which are the years where the scholarship had the explicit rule of PSU score above 550.

5.2 Sibling spillover effects of financial aid eligibility at college entrance

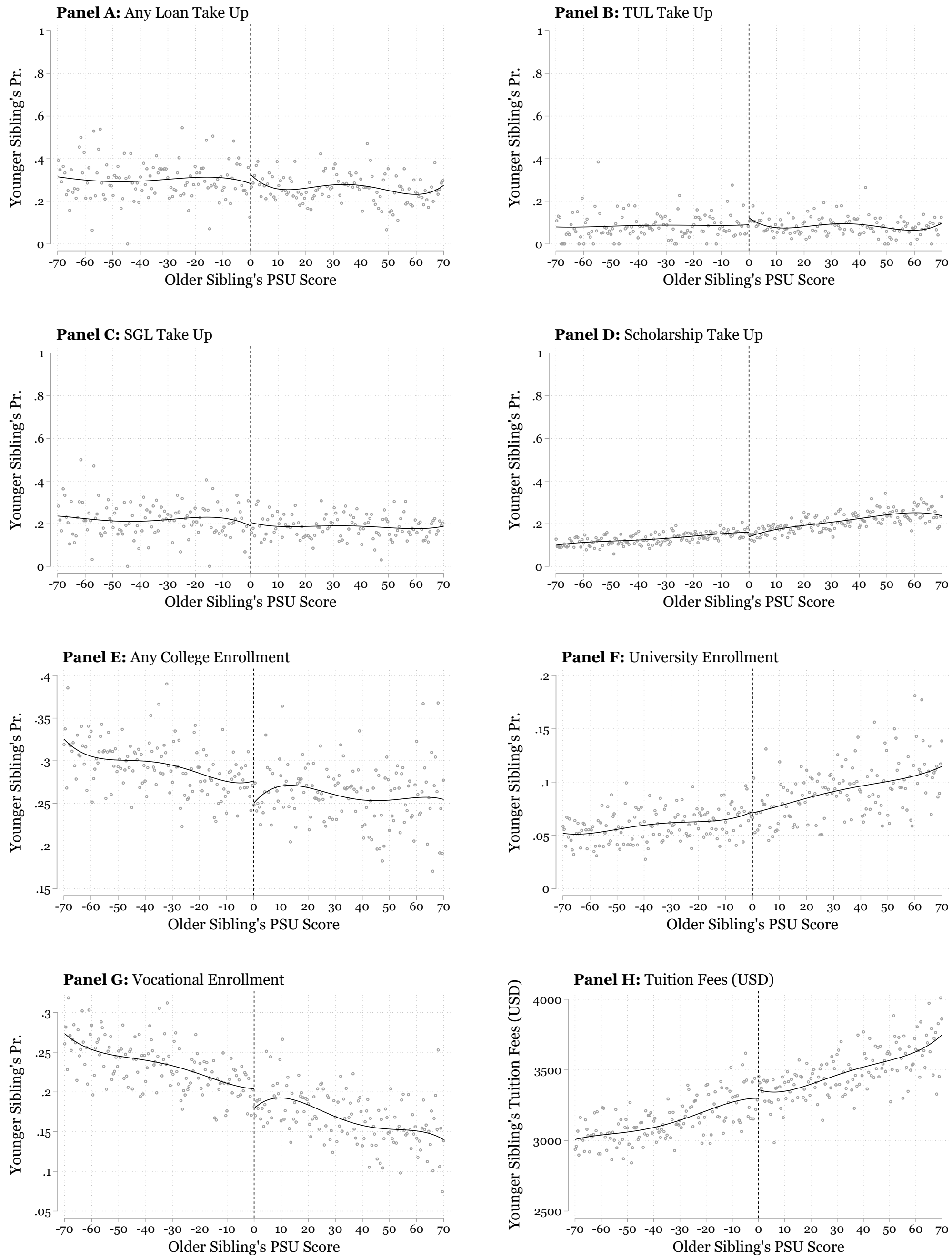
5.2.1 Financial aid take up and college enrollment

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.

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 1: 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

Table 2: 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		0.296***		0.296***		0.296***		0.296***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−0.078*	−0.820	−0.054	−0.609	−0.006	−0.070	0.032	0.353
	(0.04)	(0.55)	(0.04)	(0.48)	(0.03)	(0.28)	(0.02)	(0.27)
Mean Dep. Var.	0.271	0.271	0.216	0.216	0.060	0.060	0.160	0.160
Bandwidth	±82.4	±75.1	±73.6	±76.5	±69.7	±75.1	±77.0	±75.6
Observations	2,239	2,043	2,019	2,086	1,928	2,043	2,122	2,065
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

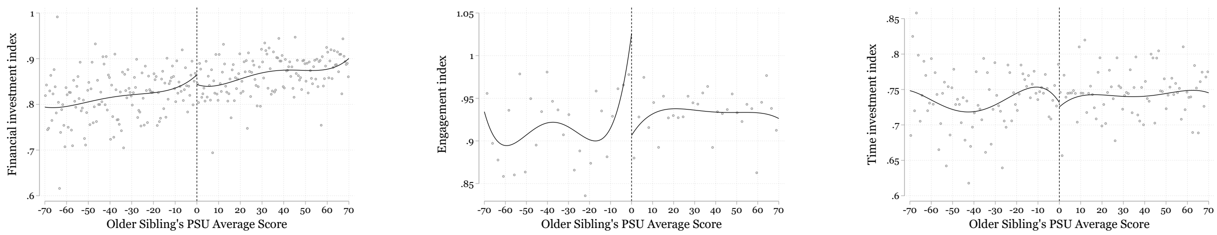
Table D.1 and D.1 and D1 A1

5.2.3 Student's educational attainment

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

5.3.1 Parental behavior

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



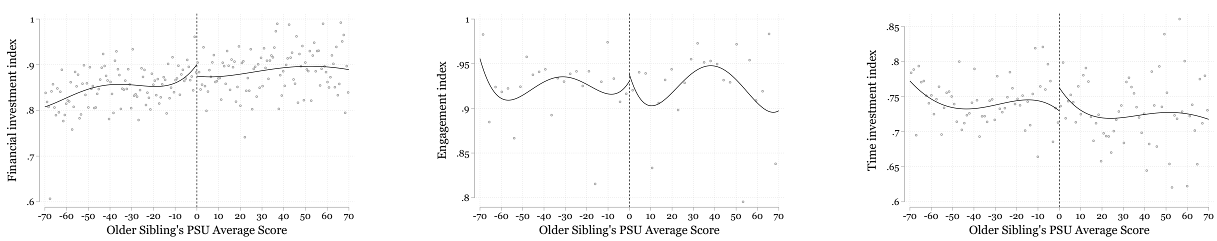
Panel A: Financial investment

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.

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

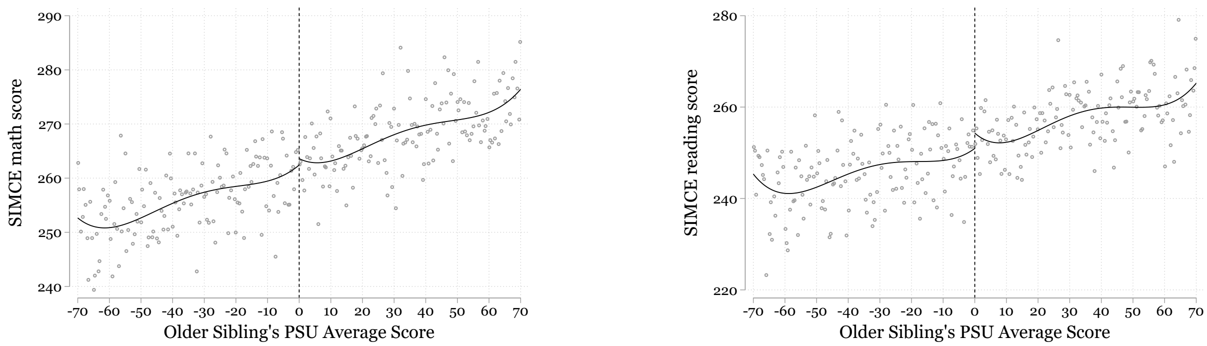
Panel B: Parental engagement

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.

5.3.2 Student's educational attainment

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

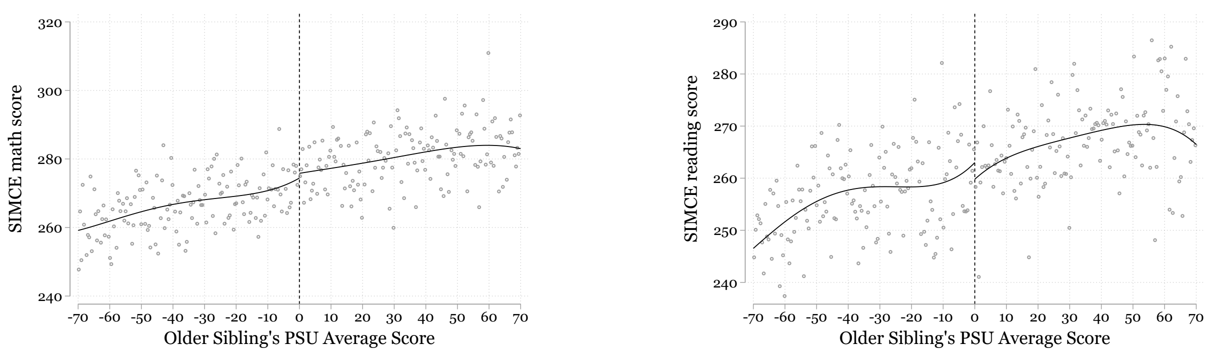


Panel A: Financial investment

Panel B: Parental engagement

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: Financial investment

Panel B: Parental engagement

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 we estimate equation 9 in order to estimate the differential effects of older siblings loan take up across different payment rules. Particularly we focus on the SGL loan which is the one that was reformed in the year 2012.

Table 3 show the results, and we focus particularly in the estimator β_0

Table 3: 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. 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

6 Conclusion

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Appendix A: Descriptive statistics

Table A1: 12th Grade College Applicants' (PSU) Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
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

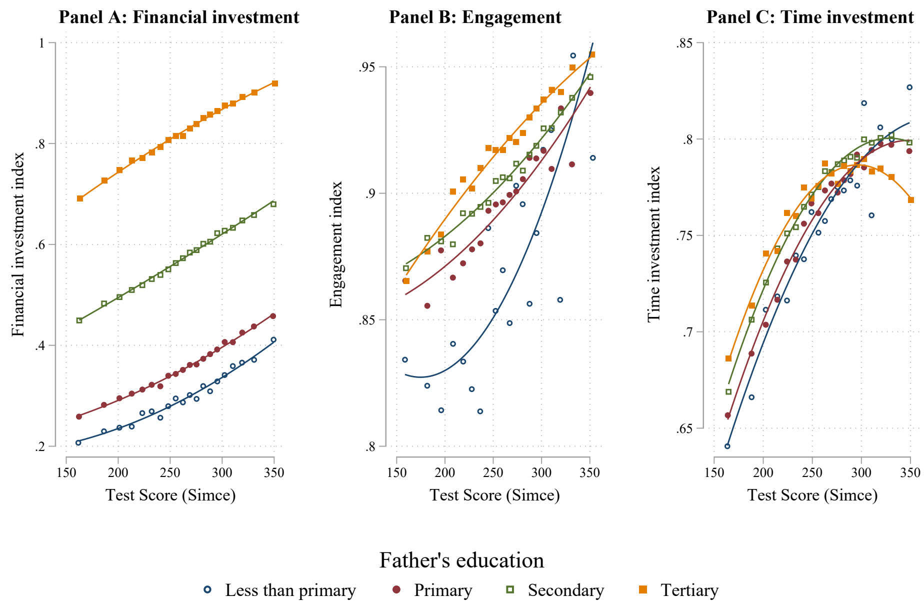
Notes: Observations cover each student taking the college entrance examination test (PSU) between the years 2009 and 2016, at the ages 17 to 22.

Table A2: 4th and 8th Grade SIMCE Students' Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Demographics					
Female	167,327	0.49	0.50	0	1
Academic					
SIMCE math score	150,873	273.11	48.82	92	405
SIMCE reading score	114,596	254.68	50.85	99	383
Socioeconomic					
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

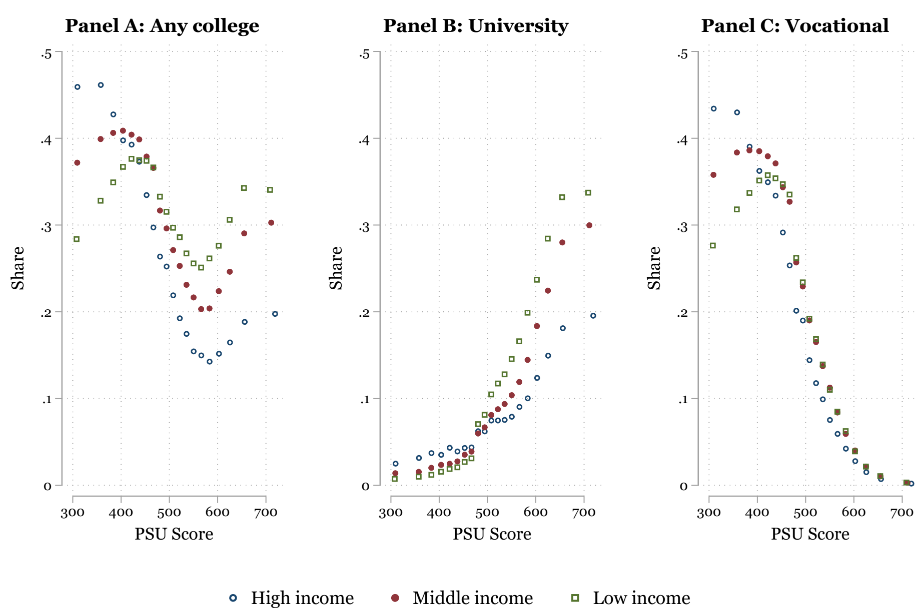
Notes: Observations cover all school student at 4th and 8th grade that took the standardized test SIMCE in math and reading and whose parents answered the corresponding family survey. Differences in the number of observations are because not all questions were asked every year.

Figure A1: Measures of parental involvement index by father's education



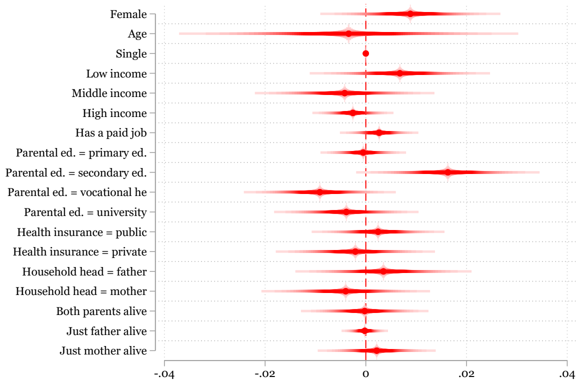
Note: The measures presented in these figures follow the ones from Figure 3, but I construct an summary indexes based on Kling et al. (2007). I also differentiate the variables relationship by father's highest education level.

Figure A2: Measures of college enrollment by parents income level

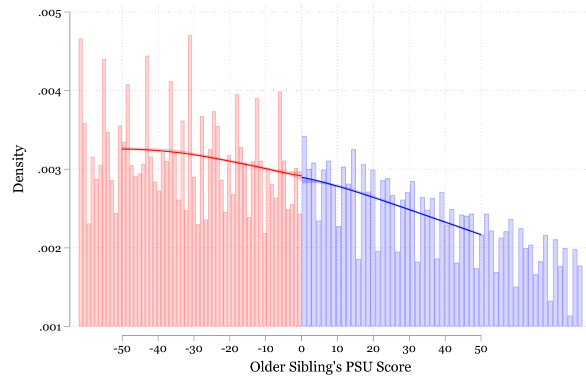


Note: The measures presented in these figures follow the ones from Figure 4, but I construct an summary indexes based on Kling et al. (2007). I also differentiate the variables relationship by household income level.

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, socioecononomic, 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: The theoretical model

B.1 Solving the model and comparative statics predictions

First order conditions. With multipliers λ_1 (period-1 budget) and λ_2 (period-2 budget) the interior FOCs are

$$\lambda_1 = U^{1-\rho}\, c_A H_A^{\rho-1}(1-\gamma)\theta_A^{\gamma} I_{A1}^{-\gamma},$$
$$\lambda_1 = U^{1-\rho}\, c_B H_B^{\rho-1}(1-\gamma)\theta_B^{\gamma}(I_{B1}+\delta I_{B2})^{-\gamma},$$
$$\lambda_2 = U^{1-\rho}\, c_B H_B^{\rho-1}(1-\gamma)\theta_B^{\gamma}\delta(I_{B1}+\delta I_{B2})^{-\gamma},$$
$$\lambda_1 = (1+r)\lambda_2.$$

Combining the second and third FOCs gives $\lambda_2 = \delta\lambda_1$, and with the S-FOC we obtain the Euler/price condition $(1+r)\delta = 1$ as the knife edge for interiority in savings vs. early investment. I also define auxiliary parameters such as $\alpha \equiv (1-\gamma)\rho - 1$ [13], $\kappa \equiv \left(\frac{c_A\theta_A^{\gamma\rho}}{c_B\theta_B^{\gamma\rho}}\right)^{1/\alpha}$, and $\tau \equiv (1+r)\delta$. It is convenient to work with the composite $Z \equiv I_{B1} + \delta I_{B2}$. The timing regime is determined by τ as follows.

We collect the main comparative static results across the three timing regimes. Two mechanical derivatives hold in all regimes:

$$\frac{\partial I_{B2}}{\partial R} = -L_A, \qquad \frac{\partial I_{B2}}{\partial \pi} = Y^B.$$

These follow directly from the period-2 feasibility condition $I_{B2} = Y_2 + \pi Y^B + (1+r)S - (1+R)L_A$. The timing choice for investment in B is governed by the Euler/price condition $\tau \equiv (1+r)\delta \lesseqgtr 1$. If $\tau < 1$ households prefer early investment in B; if $\tau > 1$ households prefer to save and invest late; $\tau = 1$ is the knife edge.

Case II: early investment dominates ($\tau < 1$).

$$S^* = 0, \qquad I_{A1}^* = \frac{\kappa}{1+\kappa}(Y_1 + L_A), \qquad I_{B1}^* = \frac{1}{1+\kappa}(Y_1 + L_A),$$

$$I_{B2}^* = Y_2 + \pi Y^B - (1+R)L_A.$$

Comparative statics (signs):

$$\frac{\partial I_{B2}}{\partial R} = -L_A < 0, \qquad \frac{\partial I_{B1}^*}{\partial R} = 0, \qquad \frac{\partial I_{A1}^*}{\partial R} = 0.$$

[13] $\alpha \neq 0$

Interpretation: when saving is unattractive, higher repayment hits I_{B2} mechanically and parents do not (optimally) shift period-1 resources to protect period-2 investment.

Case I: knife edge ($\tau = 1$). Define the effective budget

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

The household is indifferent at the margin between early and late investment. The CES share rule applies to I_{A1} versus the composite $Z \equiv I_{B1} + \delta I_{B2}$:

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

Comparative statics follow continuously as limits of Cases II and III.

Case III: save & invest late ($\tau > 1$). In the interior late-investment regime (corner $I_{B1}^* = 0$ often arises), the effective priced budget is

$$M_\tau = \delta(1+r)(Y_1 + L_A) + \delta\big(Y_2 + \pi Y^B - (1+R)L_A\big), \qquad \kappa_\tau = \kappa \cdot \tau^{-1/\alpha}.$$

The optimal composite and A-investment are

$$Z^* = \frac{1}{1+\kappa_\tau}M_\tau, \qquad I_{A1}^* = \frac{\kappa_\tau}{1+\kappa_\tau}\cdot\frac{M_\tau}{\tau}, \qquad Z^* = \delta I_{B2}^*.$$

Comparative statics (exact expressions and signs):

$$\frac{\partial M_\tau}{\partial R} = -\delta L_A \quad\Rightarrow\quad \frac{\partial I_{A1}^*}{\partial R} = -\frac{\kappa_\tau}{1+\kappa_\tau}\cdot\frac{\delta L_A}{\tau} \;<\; 0,$$

$$\frac{\partial I_{B2}^*}{\partial R} = -\frac{L_A}{1+\kappa_\tau} \;<\; 0, \qquad \frac{\partial S^*}{\partial R} = -\frac{\partial I_{A1}^*}{\partial R} \;>\; 0.$$

Thus raising R reduces period-2 resources and (in this regime) induces more saving S, lowers I_{B2} and typically lowers I_{A1} (households shift resources towards building period-2 funds).

For the success probability π:

$$\frac{\partial M_\tau}{\partial \pi} = \delta Y^B \quad\Rightarrow\quad \frac{\partial I_{B2}^*}{\partial \pi} = \frac{Y^B}{1+\kappa_\tau} > 0, \qquad \frac{\partial I_{A1}^*}{\partial \pi} = \frac{\kappa_\tau}{1+\kappa_\tau}\cdot\frac{\delta Y^B}{\tau} > 0.$$

that means that higher π (greater chance the older sibling earns) raises expected period-2 resources and allows higher investments (both I_{B2} and I_{A1} following the share rule).

B.2 Inequality aversion

From equation 1, we want to show how changes in the parameter ρ affect the inequality aversion of the household using three different scenarios. Particularly, we want to show that $\rho \to -\infty \implies \min(H_A, H_B)$.

Proof. **Limit as $\rho \to -\infty$.** To do so, consider the CES utility function

$$U(H_A, H_B) = \left(c_A H_A^p + c_B H_B^p\right)^{1/p}, \qquad \text{with } a + b = 1.$$

Taking logarithms, we obtain

$$\log U(H_A, H_B) = \frac{\log\left(c_A H_A^p + c_B H_B^p\right)}{p}.$$

To analyze the limit as $p \to -\infty$, apply L'Hôpital's rule:

$$\lim_{p \to -\infty} \frac{\log\left(c_A H_A^p + c_B H_B^p\right)}{p} = \lim_{p \to -\infty} \frac{c_A H_A^p \log H_A + c_B H_B^p \log H_B}{c_A H_A^p + c_B H_B^p}.$$

Let $M := \min(H_A, H_B)$. Divide numerator and denominator by M^p:

$$\lim_{p \to -\infty} \frac{c_A (H_A/M)^p \log H_A + c_B (H_B/M)^p \log H_B}{c_A (H_A/M)^p + c_B (H_B/M)^p}.$$

Now observe:

$$\begin{cases} (H_A/M)^p \to 0 & \text{if } H_A > M, \\ (H_B/M)^p \to 0 & \text{if } H_B > M, \\ (H_A/M)^p = 1 & \text{if } H_A = M, \\ (H_B/M)^p = 1 & \text{if } H_B = M. \end{cases}$$

Hence the fraction tends to $\log M$. Therefore,

$$\lim_{p \to -\infty} \log U(H_A, H_B) = \log M.$$

Exponentiating both sides, we obtain the Leontief utility function:

$$\lim_{p \to -\infty} U(H_A, H_B) \; = \; \min(H_A, H_B).$$

Limit as $\rho \to 1$ (linear case). At $\rho = 1$ the CES expression is well-defined and equals

$$U(H_A, H_B; 1) = c_A H_A + c_B H_B.$$

Since the map $\rho \mapsto (c_A H_A^\rho + c_B H_B^\rho)^{1/\rho}$ is continuous at $\rho = 1$ (for $H_A, H_B > 0$), we have

$$\lim_{\rho \to 1} U(H_A, H_B; \rho) = U(H_A, H_B; 1) = c_A H_A + c_B H_B.$$

Limit as $\rho \to 0$ (Cobb–Douglas). Write

$$\log U(H_A, H_B; \rho) = \frac{1}{\rho} \, \log\bigl(c_A \, H_A^\rho + c_B \, H_B^\rho\bigr).$$

Use $x^\rho = e^{\rho \log x} = 1 + \rho \log x + o(\rho)$ as $\rho \to 0$. Then

$$c_A \, H_A^\rho + c_B \, H_B^\rho = c_A\bigl(1 + \rho \log H_A + o(\rho)\bigr) + c_B\bigl(1 + \rho \log H_B + o(\rho)\bigr) = 1 + \rho\bigl(c_A \log H_A + c_B \log H_B\bigr) + o(\rho),$$

where we used $a + b = 1$. Hence

$$\log\bigl(c_A \, H_A^\rho + c_B \, H_B^\rho\bigr) = \log\Bigl(1 + \rho m + o(\rho)\Bigr) = \rho m + o(\rho), \qquad m := c_A \log H_A + c_B \log H_B.$$

Therefore

$$\lim_{\rho \to 0} \log U(H_A, H_B; \rho) = \lim_{\rho \to 0} \frac{\rho m + o(\rho)}{\rho} = m = a \log H_A + b \log H_B.$$

Exponentiating gives

$$\lim_{\rho \to 0} U(H_A, H_B; \rho) = \exp\bigl(c_A \log H_A + c_B \log H_B\bigr) = H_A^{c_A} \, H_B^{c_B}.$$

$\square$

Appendix C: Model

Choose nonnegative $I_1^A, I_1^B, I_2^B, S, L^A$ to maximize

$$U = \left[c_A H_A^\rho + c_B H_B^\rho\right]^{1/\rho}, \qquad H_A = \theta_A^\gamma (I_1^A)^{1-\gamma}, \quad H_B = \theta_B^\gamma (I_1^B + \delta I_2^B)^{1-\gamma},$$

subject to the period budgets

$$I_1^A + I_1^B + S = Y_1 + L^A, \tag{10}$$

$$I_2^B = Y_2 + \pi Y^A + (1+r)S - (1+R)L^A, \tag{11}$$

with $R > r$, $c_A, c_B > 0$, $\theta_A, \theta_B > 0$, and $\gamma \in (0,1)$. Throughout assume $U > 0$.

Useful derivatives. For $j \in \{A, B\}$,

$$\frac{\partial U}{\partial H_j} = U^{1-\rho} c_j H_j^{\rho-1}.$$

Hence

$$\begin{aligned}
\frac{\partial U}{\partial I_1^A} &= U^{1-\rho} c_A H_A^{\rho-1}\, \theta_A^\gamma (1-\gamma)(I_1^A)^{-\gamma}, \\
\frac{\partial U}{\partial I_1^B} &= U^{1-\rho} c_B H_B^{\rho-1}\, \theta_B^\gamma (1-\gamma)(I_1^B + \delta I_2^B)^{-\gamma}, \\
\frac{\partial U}{\partial I_2^B} &= \delta\, U^{1-\rho} c_B H_B^{\rho-1}\, \theta_B^\gamma (1-\gamma)(I_1^B + \delta I_2^B)^{-\gamma} = \delta\, \frac{\partial U}{\partial I_1^B}.
\end{aligned}$$

Lagrangian and KKT system

Let λ_1 and λ_2 be multipliers on (10)–(11), and $\mu_{A1}, \mu_{B1}, \mu_{B2}, \mu_S, \mu_L \geq 0$ on nonnegativity. The Lagrangian is

$$\mathcal{L} = U + \lambda_1\big(Y_1 + L^A - I_1^A - I_1^B - S\big) + \lambda_2\big(Y_2 + \pi Y^A + (1+r)S - (1+R)L^A - I_2^B\big) + \sum_x \mu_x x$$

where the sum runs over $x \in \{I_1^A, I_1^B, I_2^B, S, L^A\}$ with the corresponding μ_x.

FOCs (KKT).

$$\begin{aligned}
\partial_{I_1^A}\mathcal{L}: &\quad \frac{\partial U}{\partial I_1^A} - \lambda_1 + \mu_{A1} = 0,\\
\partial_{I_1^B}\mathcal{L}: &\quad \frac{\partial U}{\partial I_1^B} - \lambda_1 + \mu_{B1} = 0,\\
\partial_{I_2^B}\mathcal{L}: &\quad \frac{\partial U}{\partial I_2^B} - \lambda_2 + \mu_{B2} = 0,\\
\partial_{S}\mathcal{L}: &\quad -\lambda_1 + (1+r)\lambda_2 + \mu_S = 0,\\
\partial_{L^A}\mathcal{L}: &\quad \lambda_1 - (1+R)\lambda_2 + \mu_L = 0,
\end{aligned}$$

together with primal feasibility (10)–(11) plus nonnegativity and complementary slackness:

$$\mu_{A1} I_1^A = \mu_{B1} I_1^B = \mu_{B2} I_2^B = \mu_S S = \mu_L L^A = 0, \qquad \mu_{\cdot} \geq 0.$$

Interior equalities and *within-period* allocation

If $I_1^A, I_1^B, I_2^B > 0$ then $\mu_{A1} = \mu_{B1} = \mu_{B2} = 0$ and

$$\frac{\partial U}{\partial I_1^A} = \lambda_1, \qquad \frac{\partial U}{\partial I_1^B} = \lambda_1, \qquad \frac{\partial U}{\partial I_2^B} = \lambda_2.$$

Equalizing $\partial U/\partial I_1^A$ and $\partial U/\partial I_1^B$ yields

$$c_A H_A^{\rho-1} \theta_A^{\gamma} (I_1^A)^{-\gamma} = c_B H_B^{\rho-1} \theta_B^{\gamma} (I_B^{\text{eff}})^{-\gamma}, \qquad I_B^{\text{eff}} \equiv I_1^B + \delta I_2^B. \tag{12}$$

Using $H_A = \theta_A^{\gamma}(I_1^A)^{1-\gamma}$ and $H_B = \theta_B^{\gamma}(I_B^{\text{eff}})^{1-\gamma}$, (12) simplifies to

$$c_A \theta_A^{\gamma\rho} \, (I_1^A)^{\rho(1-\gamma)-1} = c_B \theta_B^{\gamma\rho} \, (I_B^{\text{eff}})^{\rho(1-\gamma)-1}. \tag{13}$$

Let

$$\kappa \equiv \rho(1-\gamma) - 1, \qquad \phi \equiv \frac{c_B \theta_B^{\gamma\rho}}{c_A \theta_A^{\gamma\rho}}.$$

If $\kappa \neq 0$, (13) gives the *within-period* share rule

$$\left(\frac{I_1^A}{I_B^{\text{eff}}}\right)^{\kappa} = \phi \quad \Longrightarrow \quad I_1^A = \Phi \, I_B^{\text{eff}}, \qquad \Phi \equiv \phi^{1/\kappa}. \tag{14}$$

(When $\kappa = 0$, the MRS is constant and (13) becomes a linear trade-off with the usual possibility of corners across children.)

Timing of B's investment

From the FOCs,

$$\frac{\partial U}{\partial I_2^B} = \delta\,\frac{\partial U}{\partial I_1^B} \quad\Longrightarrow\quad \lambda_2 = \delta\,\lambda_1 \quad \text{whenever } I_1^B, I_2^B > 0. \tag{$\ast$}$$

The financial FOCs imply

$$\lambda_1 = (1+r)\lambda_2 + \mu_S, \qquad \lambda_1 = (1+R)\lambda_2 - \mu_L. \tag{15}$$

Because $R > r$, one cannot have $S > 0$ and $L^A > 0$ simultaneously.

We now characterize the three mutually exclusive regimes.

Regime S (Saver): $S > 0,\ L^A = 0$

Then $\mu_S = \mu_L = 0$ and $\lambda_1 = (1+r)\lambda_2$. If $I_1^B, I_2^B > 0$, combining with ($\ast$) gives

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

If instead $\delta(1+r) \neq 1$, timing is a corner: late-only if $\delta(1+r) > 1$ and early-only if $\delta(1+r) < 1$.

When the timing condition $\delta(1+r) = 1$ holds, rewrite the constraints by eliminating S to obtain the present-value (PV) budget at rate r:

$$I_1^A + I_1^B + \frac{I_2^B}{1+r} = Y_1 + \frac{Y_2 + \pi Y^A}{1+r}. \tag{16}$$

Since $\delta = 1/(1+r)$, we have $I_B^{\text{eff}} = I_1^B + \delta I_2^B = I_1^B + \frac{I_2^B}{1+r}$, hence

$$I_1^A + I_B^{\text{eff}} = \underbrace{Y_1 + \frac{Y_2 + \pi Y^A}{1+r}}_{=:M_r}. \tag{17}$$

Together with the share rule (14),

$$I_1^{A*} = \frac{\Phi}{1+\Phi}\,M_r, \qquad (I_B^{\text{eff}})^* = \frac{1}{1+\Phi}\,M_r, \tag{18}$$

while any split (I_1^{B*}, I_2^{B*}) satisfying $I_1^{B*} + \frac{I_2^{B*}}{1+r} = (I_B^{\text{eff}})^*$ is optimal.

Regime L (Borrower): $L^A > 0,\ S = 0$

Then $\mu_S = \mu_L = 0$ and $\lambda_1 = (1+R)\lambda_2$. If $I_1^B, I_2^B > 0$, ($*$) gives

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

Otherwise, timing is a corner: late-only if $\delta(1+R) > 1$, early-only if $\delta(1+R) < 1$.

When $\delta(1+R) = 1$, eliminating L^A yields the PV budget at rate R:

$$I_1^A + I_1^B + \frac{I_2^B}{1+R} = Y_1 + \frac{Y_2 + \pi Y^A}{1+R}. \tag{19}$$

Because $\delta = 1/(1+R)$, $I_B^{\text{eff}} = I_1^B + \frac{I_2^B}{1+R}$, so

$$I_1^A + I_B^{\text{eff}} = \underbrace{Y_1 + \frac{Y_2 + \pi Y^A}{1+R}}_{=:M_R}. \tag{20}$$

Hence the levels are

$$I_1^{A*} = \frac{\Phi}{1+\Phi} M_R, \qquad (I_B^{\text{eff}})^* = \frac{1}{1+\Phi} M_R, \tag{21}$$

with any split satisfying $I_1^{B*} + \frac{I_2^{B*}}{1+R} = (I_B^{\text{eff}})^*$ optimal.

Regime A (No intertemporal trade): $S = L^A = 0$

Now (10)–(11) reduce to

$$I_1^A + I_1^B = Y_1, \qquad I_2^B = Y_2 + \pi Y^A,$$

and the financial FOCs (15) imply

$$(1+r)\lambda_2 \le \lambda_1 \le (1+R)\lambda_2. \tag{22}$$

If $I_1^B, I_2^B > 0$ then ($*$) holds; combining with (22) yields the *timing band*

$$\frac{1}{1+R} \le \delta \le \frac{1}{1+r}. \tag{23}$$

When (23) is strict, both I_1^B and I_2^B are interior; otherwise B's timing is a corner (early-only if $\delta < 1/(1+R)$, late-only if $\delta > 1/(1+r)$). Allocation within period 1 between I_1^A and I_1^B follows the share rule (14) with the period-1 resource Y_1, accounting for the given (nontradeable) δI_2^B

contribution to I_B^{eff}.

Propositions and Proofs

Proposition 4 (Saver regime $S > 0, L^A = 0$)**.** *Suppose $S > 0$ and $L^A = 0$. Then $\lambda_1 = (1+r)\lambda_2$. An interior timing split for B ($I_1^B > 0,\ I_2^B > 0$) occurs if and only if $\delta(1+r) = 1$. If $\delta(1+r) > 1$ (resp. < 1), the optimal timing is a corner with $I_1^B = 0$ and $I_2^B > 0$ (resp. $I_2^B = 0$ and $I_1^B > 0$). When $\delta(1+r) = 1$, the PV budget reduces to $I_1^A + I_B^{\text{eff}} = M_r$ and the optimal levels are given by (18).*

Proof. With $S > 0$ and $L^A = 0$, complementary slackness gives $\mu_S = \mu_L = 0$ and thus $\lambda_1 = (1+r)\lambda_2$. If B's timing is interior, ($*$) implies $\lambda_2 = \delta\lambda_1$, hence $\delta(1+r) = 1$. Conversely, if $\delta(1+r) = 1$, $\lambda_2 = \delta\lambda_1$ and both I_1^B, I_2^B can be positive. If $\delta(1+r) > 1$, the PV bang-per-buck of investing one unit at $t = 2$ in B, which equals $\delta(1+r)$, exceeds that at $t = 1$ (which equals 1), so $I_1^B = 0$. If $\delta(1+r) < 1$ the reverse corner holds. When $\delta = 1/(1+r)$, eliminate S from the constraints to obtain (17); combine with (14) to get (18). □

Proposition 5 (Borrower regime $L^A > 0, S = 0$)**.** *Suppose $L^A > 0$ and $S = 0$. Then $\lambda_1 = (1+R)\lambda_2$. An interior timing split for B occurs if and only if $\delta(1+R) = 1$. If $\delta(1+R) > 1$ (resp. < 1), the optimal timing is late-only (resp. early-only). When $\delta(1+R) = 1$, the PV budget reduces to $I_1^A + I_B^{\text{eff}} = M_R$ and the optimal levels are given by (21).*

Proof. With $L^A > 0$ and $S = 0$, complementary slackness gives $\mu_S = \mu_L = 0$ and hence $\lambda_1 = (1+R)\lambda_2$. Interior timing plus ($*$) yields $\delta(1+R) = 1$. Corner logic follows from comparing the PV effectiveness of one unit invested at $t = 2$, namely $\delta(1+R)$, to that of $t = 1$, which is 1. Under $\delta = 1/(1+R)$, eliminate L^A to obtain (20), then combine with (14) to get (21). □

Proposition 6 (No intertemporal trade $S = L^A = 0$)**.** *Suppose $S = L^A = 0$. Then an interior timing split for B occurs if and only if*

$$\frac{1}{1+R} \le \delta \le \frac{1}{1+r}.$$

If $\delta < 1/(1+R)$ (resp. $\delta > 1/(1+r)$) the optimal timing is early-only (resp. late-only). In all cases, the period-1 allocation between I_1^A and I_1^B follows the share rule (14) given the period-1 resource Y_1.

Proof. With $S = L^A = 0$, the financial FOCs imply the band (22). If $I_1^B, I_2^B > 0$, ($*$) gives $\delta = \lambda_2/\lambda_1$, which combined with (22) yields (23). If $\delta < 1/(1+R)$, then $\delta < \lambda_2/\lambda_1$ is infeasible, implying $I_2^B = 0$ (early-only). If $\delta > 1/(1+r)$, then $\delta > \lambda_2/\lambda_1$ is infeasible, implying $I_1^B = 0$ (late-only). The within-period share rule is (14), applied to the period-1 resource constraint $I_1^A + I_1^B = Y_1$. □

Remark. When $\kappa = 0$ (i.e. $\rho = 1/(1-\gamma)$), (13) yields a constant MRS across children; the allocation across I_1^A and I_B^{eff} may then be interior or corner depending on (c_j, θ_j). The regime and timing characterizations above remain valid.

Appendix D: Additional results and robustness checks

D.1 Additional results from Section 5.2

Table D1: 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 D2: 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		0.297***		0.299***		0.296***
		(0.01)		(0.01)		(0.01)
RD Estimate	−0.021	−0.569	−0.041*	−0.451*	0.004	−0.111
	(0.04)	(0.45)	(0.02)	(0.27)	(0.04)	(0.38)
Mean Dep. Var.	0.278	0.282	0.072	0.071	0.206	0.210
Bandwidth	±58.1	±77.8	±74.4	±79.5	±59.3	±76.5
Observations	1,663	2,133	2,029	2,163	1,688	2,108
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 D3: 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 D4: 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^{***}		0.299^{***}		0.297^{***}
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−282.8	−2,545	−0.016	−0.195	0.006	0.126	-0.112^{**}	-0.934^{*}
	(201.0)	(2,304)	(0.04)	(0.41)	(0.03)	(0.33)	(0.05)	(0.51)
Mean Dep. Var.	3288.494	3283.496	0.614	0.610	0.021	0.021	0.164	0.163
Bandwidth	±54.2	±63.9	±50.9	±70.1	±86.0	±78.6	±54.8	±77.4
Observations	1,081	1,244	1,475	1,922	2,289	2,135	1,582	2,122
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 D5: 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 D6: 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		0.298***		0.298***		0.299***		0.299***
		(0.01)		(0.01)		(0.01)		(0.01)
RD Estimate	−0.175**	−1.850*	−0.214**	−2.570**	−0.172**	−1.773**	−0.101	−1.517
	(0.08)	(0.98)	(0.09)	(1.24)	(0.08)	(0.87)	(0.09)	(0.94)
Mean Dep. Var.	0.111	0.111	0.091	0.089	0.065	0.044	0.038	0.017
Bandwidth	±86.2	±84.2	±86.7	±91.5	±68.9	±89.8	±53.8	±80.3
Observations	2,328	2,272	1,927	2,000	1,914	2,383	1,559	2,205
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

D.2 Additional results from Section 5.3

Table D7: RD Estimates of older sibling eligible for college loan 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	0.260***	0.260***	0.260***	0.260***
	(0.01)	(0.01)	(0.01)	(0.01)
RD Estimate (2SLS)	−0.051	−0.025	−0.028	−0.007
	(0.05)	(0.06)	(0.08)	(0.06)
Mean Dep. Var.	0.845	0.880	0.695	0.777
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	12,351	13,353	12,559	20,708
Panel B: High income students				
First Stage	0.299***	0.299***	0.299***	0.299***
	(0.06)	(0.06)	(0.06)	(0.06)
RD Estimate (2SLS)	−0.158	−0.053	0.143	−0.181
	(0.13)	(0.10)	(0.29)	(0.24)
Mean Dep. Var.	0.845	0.880	0.695	0.777
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	596	615	604	1,072
Panel C: Low income students				
First Stage	0.280***	0.280***	0.280***	0.280***
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	−0.087	−0.065	−0.037	−0.069
	(0.06)	(0.07)	(0.10)	(0.07)
Mean Dep. Var.	0.845	0.880	0.695	0.777
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	6,712	7,438	6,825	11,040

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. Given policy restrictions bandwidths are set at 70 points. Results does not change importantly if we compute optimal bandwidths as in previous tables. Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table D8: RD Estimates of older sibling eligible for college loan on younger sibling's parental financial 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	0.266***	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 D9: 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 D10: 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 D11: 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	0.186***	0.186***	0.186***	0.186***
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	−0.013	−0.039	0.018	−0.102
	(0.05)	(0.05)	(0.09)	(0.07)
Mean Dep. Var.	0.863	0.896	0.699	0.810
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	8,219	8,828	8,339	12,990
Panel B: High income students				
First Stage	−0.018	−0.018	−0.018	−0.018
	(0.08)	(0.08)	(0.08)	(0.08)
RD Estimate (2SLS)	0.303	−1.342	1.077	4.308
	(0.99)	(1.67)	(2.25)	(14.21)
Mean Dep. Var.	0.863	0.896	0.699	0.810
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	240	252	242	386
Panel C: Low income students				
First Stage	0.252***	0.252***	0.252***	0.252***
	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.053	−0.087	−0.026	−0.063
	(0.05)	(0.05)	(0.08)	(0.07)
Mean Dep. Var.	0.863	0.896	0.699	0.810
Bandwidth	±70.0	±70.0	±70.0	±70.0
Observations	4,844	5,273	4,911	7,566

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. Given policy restrictions bandwidths are set at 70 points. Results does not change importantly if we compute optimal bandwidths as in previous tables. Standard errors are clustered at family level. * p<0.10, ** p<0.05, *** p<0.01

Table D12: RD Estimates of older sibling eligible for college scholarship on younger sibling's parental financial 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	0.184^{***}	0.185^{***}	0.184^{***}	0.186^{***}	0.184^{***}	0.184^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	0.027	−0.057	0.050	−0.122	−0.030	−0.098
	(0.10)	(0.06)	(0.09)	(0.08)	(0.10)	(0.20)
Mean Dep. Var.	0.734	0.847	0.726	0.755	0.592	0.440
Bandwidth	±48.0	±71.4	±57.7	±67.3	±55.4	±45.7
Observations	2,855	13,628	9,170	8,197	8,912	3,320
Panel B: High income students						
First Stage	0.038	−0.034	−0.020	0.009	−0.025	0.038
	(0.12)	(0.06)	(0.13)	(0.12)	(0.07)	(0.12)
RD Estimate (2SLS)	−3.301	7.695	0.354	−16.69	−0.999	−4.735
	(4.60)	(24.55)	(0.92)	(96.94)	(13.82)	(6.90)
Mean Dep. Var.	0.736	0.848	0.723	0.758	0.595	0.442
Bandwidth	±37.1	±82.8	±42.2	±49.3	±77.5	±56.5
Observations	63	446	187	167	322	115
Panel C: Low income students						
First Stage	0.251^{***}	0.252^{***}	0.252^{***}	0.251^{***}	0.253^{***}	0.251^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	−0.018	−0.052	0.052	0.028	−0.040	-0.272^{*}
	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)	(0.14)
Mean Dep. Var.	0.735	0.847	0.725	0.758	0.591	0.437
Bandwidth	±58.7	±61.9	±50.4	±47.6	±50.6	±63.7
Observations	2,056	7,104	4,788	3,561	4,954	2,658

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 D13: 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	0.186^{***}	0.186^{***}	0.184^{***}	
	(0.02)	(0.02)	(0.02)	
RD Estimate (2SLS)	0.051	−0.140	−0.159	
	(0.04)	(0.21)	(0.10)	
Mean Dep. Var.	0.933	0.955	0.669	
Bandwidth	±81.5	±79.3	±48.6	
Observations	10,217	1,297	14,630	
Panel B: High income students				
First Stage	0.003	−0.009	−0.034	
	(0.12)	(0.05)	(0.06)	
RD Estimate (2SLS)	−1.736	3.590	0.437	
	(2.18)	(7.45)	(1.78)	
Mean Dep. Var.	0.932	0.954	0.668	
Bandwidth	±48.4	±167.8	±79.5	
Observations	183	69	679	
Panel C: Low income students				
First Stage	0.251^{***}	0.252^{***}	0.251^{***}	
	(0.03)	(0.03)	(0.03)	
RD Estimate (2SLS)	0.050	0.012	−0.128	
	(0.05)	(0.17)	(0.10)	
Mean Dep. Var.	0.932	0.956	0.670	
Bandwidth	±47.8	±61.3	±47.7	
Observations	3,724	606	8,125	

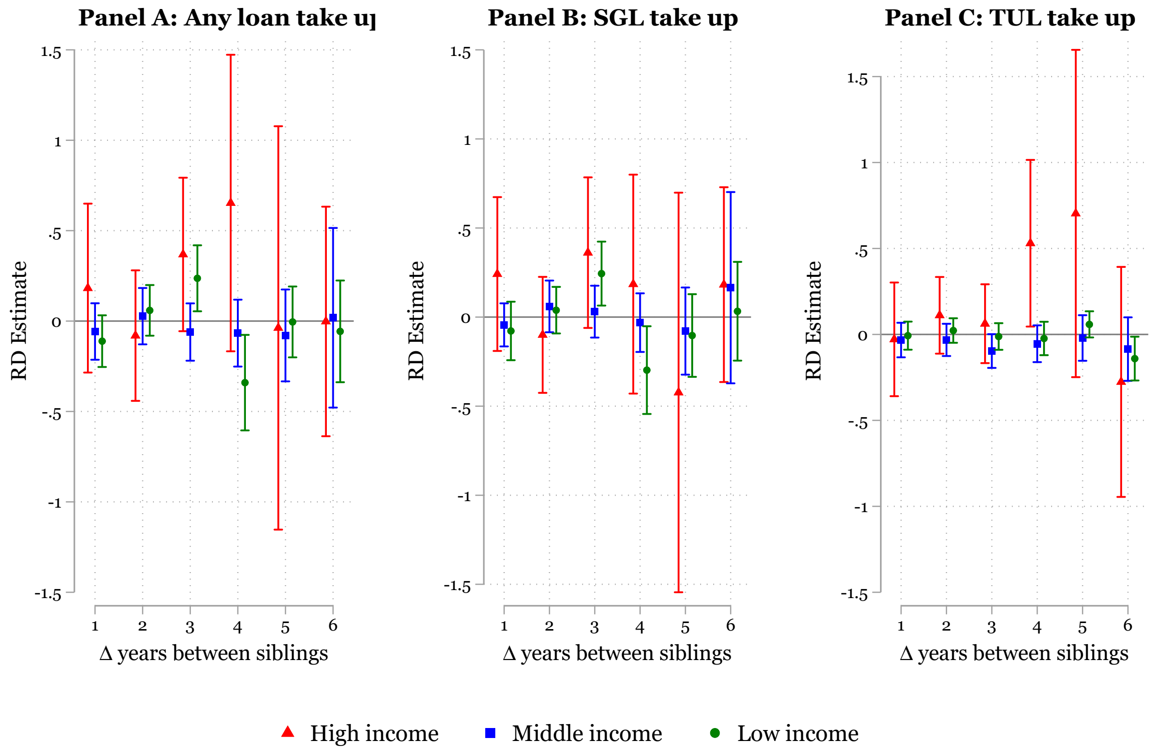
Note: Each observation is a single student taking the standarized SIMCE test in math and reading at 4th and 8th grade, during the years 2009-2017, whose older sibling applied for entering to a higher education institution between years 2008-2016. All regressions control for demographic variables, age 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 D14: RD Estimates of older sibling eligible for college scholarship 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	0.183^{***}	0.184^{***}	0.183^{***}	0.184^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
RD Estimate (2SLS)	0.082	−0.036	−0.152	0.133
	(0.05)	(0.08)	(0.11)	(0.09)
Mean Dep. Var.	0.048	0.130	0.613	0.175
Bandwidth	±53.9	±52.1	±58.2	±56.6
Observations	14,675	14,264	15,805	15,438
Panel B: High income students				
First Stage	0.041	−0.002	0.042	−0.017
	(0.11)	(0.09)	(0.11)	(0.08)
RD Estimate (2SLS)	−0.946	0.417	−1.748	2.417
	(1.39)	(1.13)	(3.10)	(3.92)
Mean Dep. Var.	0.049	0.134	0.612	0.169
Bandwidth	±59.0	±66.5	±61.1	±70.3
Observations	476	541	501	562
Panel C: Low income students				
First Stage	0.251^{***}	0.251^{***}	0.251^{***}	0.251^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
RD Estimate (2SLS)	0.054	−0.123	−0.038	0.130
	(0.05)	(0.08)	(0.11)	(0.08)
Mean Dep. Var.	0.049	0.131	0.614	0.174
Bandwidth	±58.7	±54.7	±57.7	±57.4
Observations	8,944	8,367	8,800	8,723

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

Figure D1: Heterogeneous effects estimations from Table **??**, column X



Notes: Beliefs represent

Appendix E: Further analysis for differential effects on repayment scheme

E.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, 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.

The following sequence of tables shows how the assignment changes for an applicant with $p_i = 699$, applying to four programs in the following order: (1) Engineering at UCh, (2) Engineering at UAI, (3) Sociology at UCh, and (4) Sociology at UAI. The cutoffs (c_j) and the running variable $s_i = p_i - c_j$ for each program are shown in the columns. Here UCh (University of Chile) is a traditional university, therefore applicants may apply for the TUL loan, while UAI is a non-traditional and the only possible loan that may get is the SGL.

Since $s_i = -1$ for Engineering at UAI, the applicant just misses that cutoff and is assigned to the fallback program (Sociology at UCh):

	Program	p_i	c_j	s_i	Assignment
1.	Engineering at UCh	699	740	-41	
2.	Engineering at UAI	699	700	-1	
3.	Sociology at UCh	699	660	39	← fallback
4.	Sociology at UAI	699	650	49	

If the applicant's score were 700 instead of 699, they would just meet the Engineering at UAI cutoff and be assigned to that target program:

	Program	p_i	c_j	s_i	Assignment
1.	Engineering at UCh	700	740	-40	
2.	Engineering at UAI	700	700	0	← target
3.	Sociology at UCh	700	660	40	
4.	Sociology at UAI	700	650	50	

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*.