The Returns to College Choice: Loans, Scholarships and Labor Outcomes*

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Abstract

To estimate causal effects of college choice, we exploit eligibility rules for student loans in a regression discontinuity design. Loan programs induce students to pursue college degrees that are more expensive and prolonged relative to technical education. Although higher education is profitable, the marginal return of college is identical to that of technical education when students are about 30 years old. The college premium seems to increase over time, possibly offsetting the initial experience gap and covering cost differences under moderate discount rates. We study the effects of debt burden on college choice using a similar cutoff rule for scholarships.

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1 Introduction

Decisions about human capital investment need to consider the returns of different types of education. The optimality of this choice relies on the accuracy of the estimated benefits and costs of various types of educational options. Typically, the possibilities for a high school graduate are to enter directly into the labor market, to pursue a technical degree (e.g., a two-year program at a community college), or to enroll in a bachelor's degree program (e.g., four-year degree at a university). Despite their importance, the estimated returns on earnings vary significantly across studies and are the cause of a heated debate (Kane and Rouse [1995] and Dale and Krueger [2002]).

The primary challenge in the estimation of these returns lies in the existence of a non-random selection into the different types of education. In particular, students choosing colleges or vocational institutions may differ in unobservable aspects (to the econometrician) that are correlated with education and also affect the labor market outcomes biasing the OLS estimates of the return. Few papers have been able to address this issue with complete enrollment information. This paper tries to provide new evidence on the causal estimation of the returns to college choice.

This paper estimates the causal effect of college choice on labor market outcomes. We identify the returns to college and technical/vocational education using a natural experiment in admissions to higher education in Chile.[1] Students scoring at or above a cutoff on the national college admission test grants them eligibility for the state-sponsored loan programs, generating an exogenous increase in college enrollment. Students below the cutoff can obtain loans to enroll only in programs that award certificates and associates degrees (vocational programs hereafter), whereas similar students but above the cutoff can also borrow to enroll in colleges that grant bachelor's degrees (college programs hereafter), enabling a regression discontinuity design.[2] We find that loan eligibility generates a ten-percentage-point increase in the probability of college enrollment, which is explained by a lower rate of admissions to vocational programs. On average, students just above the cutoff accumulate 0.18 more years of education, which translates into 1.8 additional years of college for the complier.[3]

[1] In the US, the typical choice of high school graduates is between two-year and four-year colleges, which are similar to the college and vocational institutions in the Chilean context.

[2] We refer to all types of programs that award diplomas, certificates and associates degrees of four years' duration or less as community colleges or vocational institutions. Also, we refer to institutions that grant four-year (or longer) degrees in colleges and universities as "colleges." We use the terms community, vocational, and technical college interchangeably.

[3] In this case, a complier is a student who enrolls in college if she scores above the eligibility cutoff but joins a

We combine rich administrative records of educational and labor outcomes at the individual level to exploit our natural experiment. The educational records cover the universe of the high school graduates who took the admissions test for higher education between 2006 and 2016. The data include the information on the eligibility status and take-up for loans and scholarships and detailed enrollment information from all the institutions in the educational system. The administrative records on labor outcomes cover all workers in the formal sector and include monthly earnings and employment status from 2002 to 2018. The final panel data allow us to track individuals for 11 years after their high school graduation and their labor market records when they are about 30 years old. The high-quality administrative data we use have three significant advantages relative to the data used in previous work. First, the data present no attrition or missing information about students' educational choices, especially those who move across institutions.[4] Second, the considered aid programs are at the national level, thus ensuring large sample sizes that yield more-precise estimates. Third, given other aid programs based on similar cutoff rules, we can use other natural experiments to study alternative mechanisms, such as debt aversion.

First, we find that college loan eligibility has significant positive impacts on college enrollment and graduation, as well as an adverse effect on labor experience. In fact, student loan eligibility diverts students to college programs that have lower graduation rates and longer time to graduation. Hence, college loan eligibility increases the probability of college graduation by 44 percentage points. However, the graduation rate in vocational programs for the complier at the cutoff is 66 percentage points. Also, college programs display longer periods until graduation, which translate into a significant decrease in labor experience. These results are consistent with Cohodes and Goodman [2014] and Angrist et al. [2016] who show that grants divert students from 2-year colleges in the US.[5].

Second, we find no significant differences in the labor market outcomes between college and technical graduates for 30-year-old workers. We explore potential differences in four outcomes: annual earnings, labor participation, the labor-intensive margin (measured as the number of months employed

vocational program when scoring just below the cutoff (Angrist et al. [1996]).

[4] Goodman et al. [2016] argue that most of the US-based literature documents potentially idiosyncratic effects of a single college.

[5] Cohodes and Goodman [2014] study a merit aid program in Massachusetts that incentivize students to enroll at in-state public colleges with lower graduation rates and lower quality. Angrist et al. [2016] study a grant in Nebraska that diverts students from 2-year colleges into public colleges and universities, affecting the graduation rates negatively.

in the formal sector in a given year), and job stability (as measured by the frequency of missing earnings in a given year). For all these labor outcomes, our estimates are precise and reject statistical differences between the two types of education. Therefore, the returns to a vocational degree plus the additional work experience are similar to the returns to a college bachelor's degree when workers are in their late twenties. These findings are in line with the previous literature (Kane and Rouse [1995], Dale and Krueger [2002, 2014]).

Third, we also study the evolution of labor outcomes over time, observing three main stylized facts. First, students below the eligibility cutoff entered the labor force earlier, thus obtaining more labor experience and displaying significantly higher earnings during their first years in the labor market. Second, the accumulated additional experience is persistent 11 years after high school graduation, corresponding to 14 extra months in the labor force for those choosing vocational programs. Third, in spite of the negative income effects of college in earlier periods, we observe an incipient favorable trend for college graduates that becomes positive 11 years after high school graduation and could eventually offset the initial negative wage gap of students above the cutoff.

Fourth, we study one mechanism that could explain the lack of positive effects on wages of the college-educated—the existence of so-called debt aversion (Thaler [1990]). If students are affected by holding debt after graduation, they may be discouraged to invest in human capital or may be prone to making sub-optimal labor market choices. In effect, the absence of credit constraints allows people to smooth consumption across periods, and the debt associated with college investments has a minor income effect. In contrast, if students are debt-averse, individuals may resist smoothing consumption because they are reluctant to hold debt, even under no liquidity constraints (see Field [2009] and Rothstein and Rouse [2011]).

We explore a second natural experiment to test the presence of debt aversion. The Bicentenario Scholarship (BC) awards the same proportion of tuition as the loan programs to eligible students who score at a different cutoff on the admissions test (i.e., higher than the cutoff used for loan eligibility). Using the random variation of scholarship allocations around the cutoff, we can identify the effects of holding debt on educational and labor decisions. Hence, students who are just below the BC threshold should finance their educational investment with debt (through the loan programs), while students just above the cutoff receive a scholarship that reduces outstanding debt drastically.

We reject the presence of debt aversion, as we find no effects of the BC scholarship on college choices or labor outcomes. Regarding educational decisions, we show that all students around the cutoff enroll either in college or in vocational education for at least one year, and the proportion of students choosing each type is the same across the cutoff, consistent with Solis [2017].[6] Also, we see no effects of the BC scholarship on labor outcomes 11 years after high school. In fact, we find that holding debt produces a small and significant positive impact on wages in the short run, consistent with Field [2009] and Rothstein and Rouse [2011]. However, those positive effects become zero in the longer horizon.

Fifth, we assess the optimality of each educational alternative, calculating the net present value of a college degree for graduates when they are about 30 years old. The discounted values account for the time value of money, tuition costs, the differences in graduation rates, accumulated experience, the dynamics of salaries, and the intensity of participation in the labor force of the two types of education. We find that both college and vocational education have a positive net present discounted value of the investment (NPV) several years after high school graduation. We see that students just above the loan eligibility cutoff accumulate significantly higher tuition costs, which is equivalent to doubling the monetary investment for the complier.

We explore the minimum wage gap that could make college education optimal. Using the estimates of Mincer equations, we forecast the earnings for each type of higher education and explore the parameter configurations that yield a higher NPV for college graduates than for vocational graduates. We find that a college premium growth of two percent ensures the optimality of the college education if the discount rate is below three percent.

Our paper contributes to the vast literature on the labor market returns to different college choices. To address the endogeneity problem, some authors have used proxies for unobserved ability (Dale and Krueger [2002, 2014], Jepsen et al. [2014]), matching procedures (Black and Smith [2004], Reynolds [2012]), and instrumental variables (Mountjoy [2017]). Other papers use, as we do, regression discontinuity designs to arguably identify causal estimates of college choice on education and labor market outcomes accounting for selection on unobservables. Saavedra [2008] and Hoekstra [2009] study en-

[6] We also investigate the quality and prestige of the institutions around the cutoff. We find no statistically significant differences between the choices of students financed by loans and students funded by the scholarship.

rollment at two (single) highly-selective flagship universities, suggesting that their marginal applicant should be at the top of the ability distribution. However, public policies typically target marginal students in the middle and lower parts of the ability distribution to expand enrollment in higher education. Zimmerman [2014] considers only a single university in which the marginal applicants are close to the mean, as in our case.[7] Similarly, Öckert [2010] studies the labor market returns for marginal admitted students in Sweden. He finds no significant differences between barely accepted and barely rejected students.

Among the Chilean literature on college returns, Rau et al. [2013] estimate a factor model to measure returns to college accounting for sorting in unobserved heterogeneity. They find significant negative returns to the marginal university student and suggest that the poor design of loan programs induces low-quality colleges. After the initial version of our paper, Bucarey et al. [2018] also investigated the impact of the loan programs in Chile using the same RD design as we do. Their paper does not identify debt effects and, through a static analysis, focuses on the quality of the educational institutions and finds similar conclusions as Rau et al. [2013].[8]

Our paper is also related to the extensive literature determining the effects of student aid on college enrollment (e.g., Van der Klaauw [2002], Dynarski [2003], Bettinger [2004], Kane [2006], Nielsen et al. [2010], among Deming and Dynarski [2010] among others) and the discussion about the prevalence of credit constraints (e.g., Carneiro and Heckman [2002], Gurgand et al. [2011], Stinebrickner and Stinebrickner [2008] and Lochner and Monge-Naranjo [2011]). In this paper, we study how two aid configurations affect enrollment and graduation—first, when only loans are available to fund the different levels of education, and second, when a generous grant is given in a context with less-binding credit constraints. We document that loans affect enrollment and graduation but that a generous scholarship does not affect either outcome when loans are available. Interestingly, this finding is

[7]The PSU test in Chile shares some similarities with the SAT (Scholastic Assessment Test) in the US. Both tests display scores in about the same range (SAT: [200, 800] and PSU:[150,850]) and use a distribution centered in 500 and standard deviation 100 (PSU is 110). The loan cutoff is equivalent to 950 SAT points, and the BC scholarship to 1100 points (SAT 50th percentile is 1050). The loan eligibility cutoff is 0.25 standard deviation below the average ability level, which corresponds to 950 in the SAT distribution, and the scholarship is at 0.5 standard deviation above the average (1100 SAT points).

[8]Other papers study the Chilean context using similar data. Hastings et al. [2013] study the returns to the field of study using program admission cutoffs in college. Using the same identification strategy Kaufmann et al. [2013] and Kaufmann et al. [2015] study the returns to college quality in the marriage market and the inter-generational effects. Solis [2013] study the effects of college enrollment on political participation.

consistent with the lifetime permanent income hypothesis, which, in the absence credit constraints, implies that individuals can smooth consumption and make optimal decisions (in our case, optimal investment decisions. See Friedman [1957] and Eisner [1967]).

Our results also contribute to the scarce research on debt aversion and educational choices. Field [2009] shows, through a field experiment of assigning aid packages by lottery at NYU Law School, that educational debt has the potential to influence career choices when entering school and when choosing a job after graduation. Rothstein and Rouse [2011] compare students at an elite university in the US after a policy change that replaced credit-based aid packages with full scholarships. Using students with no aid as a counterfactual, they found that students with loans are more likely to choose high-paying jobs. Both articles use data from highly selective universities. In our paper, the focus is on students with average ability and all the institutions available to them. We find that accessing grants to replace student loans have no effect on enrollment and the quality of the chosen institutions.

The paper proceeds as follows: Section 2 describes the institutional background. Section 3 presents our data. Section 4 introduces the estimation strategy, while Section 5 validates the approach. Regarding our results, Section 6 introduces the main findings, and Section 7 shows results on debt aversion. Section 8 uses our data to present a dynamic analysis based on net present values. Section 9 concludes.

2 Institutional background

College tuition fees in Chile are relatively high and similar across institutions. As in the US, the Chilean university system has both public and privately-owned universities with considerable heterogeneity in their quality and prestige.[9] The average annual tuition is about 2.1 million 2017 pesos (4,200 US dollars), equivalent to 47 percent of the median household's earnings.[10] Even at the cheapest public university, a family in the poorest quintile would pay about 84 percent of their available

[9] The universities in Chile are categorized as "traditional" or "private" universities. The traditional universities are 25 institutions founded before 1981, some of which are public (e.g., University of Chile) and some of which are private (e.g., Catholic University of Chile). All of these traditional universities receive substantial direct funding from the government. The so-called "private" universities are 33 institutions founded after 1981. These universities do not receive direct aid from the government and are financed mainly by student tuition.

[10] Median household earnings are calculated using the 2009 household survey National Socioeconomic Characterization Survey (CASEN).

earnings to cover one year of tuition.[11] Since the average student at the loan cutoff takes 4.5 years to graduate, students need to finance their higher education with aid and loans.

Moreover, lending institutions offer college loans to a very restricted portion of the population. Households seeking student loans would be subject to strict earnings eligibility criteria required by banks. In 2007, the most generous bank (a partly state-owned bank, BancoEstado) had a minimum earnings requirement that was above the average earnings of the 40th percentile of the earnings distribution. Furthermore, banks required families to show earnings from the more stable formal sector to process a loan, which is a very restrictive condition, as the 36 percent of the labor force belongs to the informal sector. Paying tuition fees with students' labor earnings is also not a plausible strategy: the average labor earnings for high school graduates (between 18 and 20 years old) is about the minimum wage (about 420 USD per month), implying that one year of college tuition fees requires the yearly earnings from a full-time job.

Given the tight credit constraints, students from households below the median earnings rely strongly on government scholarships and publicly sponsored loans to finance their higher education. The Ministry of Education provides, by far, the most relevant source of funding. Although universities offer loans and scholarships to attract outstanding students at the top of the admission test score distribution, that select group is not relevant to our analysis, which focuses on students near the average admission test score. The assignment of public funding is highly centralized and linked to the student's performance on the national college admission test, *Prueba de Selección Universitaria* (PSU hereafter).

The *PSU score* is the average score on the two mandatory tests in mathematics and language. The scores are normalized to have a mean of 500 and a standard deviation of 110, which are similar to the SAT scores in the US.[12] The PSU outcome and high school GPA are the only variables that factor into college admission decisions.[13] The Ministry of Education determines eligibility for scholarships and loans based strictly on the PSU scores of all the students who take the test at the same time and

[11]For households in the second and third quintiles, the amounts are 50 and 32 percent, respectively.

[12]The SAT has the same mean and standard deviation as the PSU. PSU scores range from 150 to 850 points, while SAT scores range from 200 to 800. The registration fees for the PSU and SAT are in the same range of 50 dollars. The PSU registration fee is waived for all students graduating from public and voucher schools who apply for a waiver.

[13]The PSU also contains optional tests in History and Science used by universities to rank applicants but not considered by the Ministry of Education for financial aid eligibility.

only once per yearly admissions process.

Next, we briefly describe the application and selection process timeline for college admission in Chile. Before graduating from high school in November, students register for the PSU test.[14] Students wanting to receive financial aid (or loans) from the Ministry of Education have to submit a declaration of socioeconomic status (Formulario Ú nico de Acreditación Socioeconómica, FUAS hereafter), which the tax authority uses to determine the earnings percentile of the student's household.[15] Students take the PSU test in the second week of December and receive their scores and the income quintile classification in the first week of January. Based on this information, students know whether or not they are eligible for financial aid or government-sponsored loans. Starting in the second week of January, students apply to different college programs and eventually enroll if an educational institution admits them. Universities and other educational institutions report to the Ministry of Education the enrollment of all their students so that those eligible can receive potential payments of loans and scholarships. All educational institutions have access only to information on students' earnings once the enrollment period is over. Teaching usually begins in March.

The data ensure top-quality information to the universe of students who participated in the PSU test regarding their scores and subsequent enrollment activities in higher education.

2.1 The Loan Programs and the Bicentenario Scholarship

The most relevant higher education financing programs offered by the government are the Traditional University Loan (TUL) and the State-Guaranteed Loan (SGL). Both programs cover tuition fees up to an upper-limit amount, referred to as the reference tuition, which was close to 90% of the tuition costs for the years considered here.[16] These loans do not cover any other expenses associated with attending college (room and board, books, transportation, etc.), and, therefore, there is still scope for liquidity constraints.

[14] The typical instruction period runs from March to November.

[15] This declaration is similar to the financial information reported on the Free Application for Federal Student Aid (FAFSA) to determine the student's expected family contribution (EFC) by the U.S. Department of Education. However, the amount and the level of complexity of the required information are entirely different, to prevent misallocation or discouragement, as documented by Dynarski and Scott-Clayton [2013].

[16] The Ministry of Education determines the maximum amount that can be financed by loans and grants for each program. The amount depends on the quality of institutional assets and the labor market prospects of graduates of each program.

To be eligible for loans for college, students need to satisfy two requirements. First, they must be classified among the first four income quintiles. The income quintiles are calculated using the households survey CASEN, and each household classification is determined by the tax authority using official records. Second, students need to score at least 475 points on the PSU test. Note that students who score below 475 can obtain the SGL loan only if they enroll in accredited vocational programs, conditional on having high school grades above a certain threshold. Consequently, most students substitute college for a vocational program when they score below the cutoff.

The TUL program allows traditional universities to use public funds to make loans to their students.[17] Each university is in charge of assigning the loans to their students and collecting the loan repayments after graduation.[18]

The SGL program shares some similarities with the US Federal Guaranteed Student Loan programs (unsubsidized Stafford loans) regarding the financial need condition for applicants and the repayment scheme after graduation. However, two substantial differences are: i) the requirement of a minimum score on the PSU admission test in Chile; and ii) the fact that the SGL program is managed through the private banks in Chile, whereas federal student loans in the US are made to eligible students directly by the government.

A key feature of the SGL program is that, for the period analyzed in this paper, it resembles available loans in the conventional credit market in terms of interest rates, installment calculations and the enforceability of the repayments. Initially, the real interest rates were about six percent per year, slightly higher than the yearly average mortgage rate observed in the same period. Repayment is scheduled in fixed monthly installments for 20 years (regardless of the borrower's earnings), with a grace period of 18 months after graduation. If a bank cannot collect loan repayments from the students, the guarantors (the state and the educational institution) must pay the bank and become responsible for enforcing collection from the student. [19]

[17] There are 25 traditional universities and about 35 so-called "private." The universities founded after the 1981 reform do not receive direct funding from the State.

[18] The TUL loan was introduced in 1981 and was the primary source of financial aid for students until the introduction of the SGL in 2006. Previous to 2006, each university determined eligibility independently, based on the public budget granted to each institution by the government.

[19] The educational institution is responsible for repaying the bank with 90% (70%) [60%] of the capital and interest accumulated if the student drops out in her first year (second year) [third year or later], and the state covers the difference up to 90 percent. After the student graduates, the state guarantees 90 percent of the total debt.

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The third most important mechanism of aid is the Bicentenario (BC) scholarship that covers the reference tuition. Students from the poorest 40 percent of households must score at or just above 550 PSU-points to be eligible for the award and to enroll in traditional universities. This program reaches about 5% of the population of students and more than 50% of all qualified individuals. Students scoring below the 550-point cutoff still have access to the loan programs, whereas students scoring above the 550-point cutoff are eligible for the BC award, which would imply a sizable decrease in the amount of debt that the student holds.

The BC scholarship shares some features of the Pell Grants in the US, as they are both publicly funded grants that need not be repaid and are limited to high school graduates with some financial need (income quintile in Chile and the student's expected family contribution in the US). A fundamental difference is that the BC requires a specific score on the admission test before enrolling in higher education, whereas the Pell Grant requires only satisfactory academic progress after enrolling in higher education.

3 Data and Sample

3.1 Data Sources

We combined five sources of administrative records covering from the high school graduation until labor market participation.

3.1.1 Education Data

We observe a student from the moment she registers for the PSU test (just before high school graduation) until she leaves the educational system. To do that, we combine administrative individual-level data from four different sources. The first data source consists of the records of students who take the PSU test. We have data on PSU test takers for the high school cohort from 2006 to 2016. Each student's records contain PSU score, high school GPA, age when taking the PSU, school of graduation, as well as a rich set of demographics, socioeconomic and family backgrounds, such as household size, self-reported household earnings, parental education and parents' labor status.

The second source of data is an administrative record from the Ministry of Education that tracks enrollment in all higher education institutions. For the high school cohort of 2006, the data correspond to an 11-year panel of students, containing information about yearly registration in each specific program.

The third source of information is the FUAS form, also compiled by the Ministry of Education, which provides information on the family income quintile determined by the tax authority. This income classification defines the eligibility for the two loan programs and the six scholarships supported by the government, including the Bicentenario Scholarship. Moreover, the data contain the assignment to financial aid and loan take-up of the TUL program. We can follow students' eligibility up to 2016. The fourth data set identifies the loans approved under the SGL program, as recorded by the INGRESA commission, the organization created in 2006 to manage the program.[20]

3.1.2 Labor Market data

We obtain information on labor market outcomes from the unemployment insurance records of Chile's Ministry of Labor, which keeps track of the monetary contributions to the individual unemployment insurance account of each worker. The unemployment insurance covers almost the entire formal sector, equivalent to 63 percent of the total labor force in 2016.[21] The groups excluded from the insurance are workers with training contracts, workers under the age of 18, those in domestic service, pensioners, self-employed or own-account workers, and public-sector employees. Workers in the informal sector are encouraged to buy unemployment insurance, but only 2.2 percent do so.[22]

[20]The assignment rule for SGL was in place only from late 2006. During the first year of implementation, in 2005, the SGL program erroneously assigned the loans to the wealthiest families among the applicants due to a severe mistake in the earnings ranking. Once the critical error was public, the students already had been informed about the approved loans. The solution was to issue a new set of credits based on the correct earnings ranking. We do not consider the cohort 2005 in the analysis.

[21]Source: The National Institute of Statistic of Chile, INE.

[22]See Berstein [2010].

The data contain individual-level records with information on participation in the formal sector and workers' labor income. The files for all students from January 2002 to February 2018 are available. From these data, we define five labor market outcomes: 1) annual earnings (sum of monthly labor income in a given year); 2) participation in the formal sector (indicator variable equal to one if the individual has positive labor income in any calendar month of a given year); 3) labor intensive margin (sum of months with positive earnings in a given year); 4) job stability (indicator variable if the individual has 12 consecutive months with positive labor income in a given year); and 5) accumulated experience (sum of months with positive earnings since high school graduation until February 2018).

3.2 Sample

We restrict the analysis to students who are pre-selected for loans and are first-time PSU-takers. We refer to students who belong to any of the four poorest earnings quintiles as pre-selected. The tax authority determines the earnings quintile for the students who complete the FUAS form. Students who do not complete the FUAS are ineligible at either side of the cutoff and, thus, are unaffected by the policy.[23] For pre-selected students, obtaining at least 475 PSU-points implies a change in their eligibility status for college loans.

Students can become eligible in future PSU attempts, creating a dynamic selection problem. We address this problem by limiting the sample to students who are first-time takers, to avoid initial self-selection to eligibility. To be more precise, we restrict the sample to students who have just graduated from high school and, therefore, have not taken the test before. This restriction prevents over-representation of high-earnings students, who may have more chances to prepare for and retake the admission test, self-selecting into the treatment. However, the first-time takers also select dynamically, once they take the test and improve their scores. We use the initial position around the cutoff as an instrument for the college enrollment in any year as described in Section 5.

The sample of students in our analysis is similar to the average student in Chile. First, on average, 80 percent of students graduate from high school.[24] Second, the cutoffs for loans and the Bicentenario

[23]In turn, we use the group of ineligible students as a placebo test.

[24]We use administrative records to follow the population of students in 8th grade where we observe 98 percent of the children. From that group, about 80 percent graduate from high school, and conditional on high school graduation, over 80 percent take the PSU test.

scholarship are 475 and 550, respectively, where the average PSU score is standardized to have a mean of 500 and a standard deviation of 110, which means that the complier in the RD setting should be quite similar to the average student.

4 Estimation Strategy

In this section, we describe the empirical strategy to overcome the selection problem when estimating returns to higher education. The selection problem arises since education is expected to be correlated with unobserved characteristics of the individuals, such as ability. Hence, we need a source of exogenous variation in education to estimate the parameters while avoiding the standard endogeneity bias.

We use the fuzzy discontinuity in college enrollment around the eligibility cutoff as an instrument for education choice. Intuitively, students who score just above and just below a given eligibility cutoff are very similar in all respects, but only those who are above the threshold are eligible for some benefits (scholarship or loan programs) and, therefore, enroll in college with higher probability. Thus, in a neighborhood around the cutoff, the college enrollment is as good as randomly assigned (Lee [2008] and Lee and Lemieux [2010]).

Following Lee and Lemieux [2010], we estimate the effects of education on different outcomes using a two-stage least squares estimator (2SLS):

$$E_i = \alpha_1 + \beta_1 \cdot \mathbb{1}(T_{i0} \geqslant c) + f_E(T_{i0}) + u_i \qquad \text{(First Stage)}$$

$$y_i = \alpha_0 + \beta_0 \cdot E_i + \gamma_0 \cdot \mathbf{X}_i + v_i, \qquad \text{(Second Stage)}$$

where y_i represents a labor market outcome; E_i corresponds to an education variable (college enrollment, vocational enrollment, years of college, etc.); and $\mathbf{X}_i$ is a vector of predetermined characteristics. The variable $\mathbb{1}(T_{i0} \geqslant c)$ is an indicator function on whether the score of the student i in her first attempt at the college admission test, T_{i0}, is at least as large as the eligibility cutoff (c) and f_E corresponds to a smooth function to control for the influence of the running variable (T_{i0}) away from the cutoff.[25] The random shocks u_i and v_i are assumed to be uncorrelated with the PSU results of student i. The parameter of interest is β_0, which is the marginal effect of education on outcome y.[26] We also estimate the so-called reduced form:

$$y_i = \alpha_2 + \beta_2 \cdot \mathbb{1}(T_{i0} \geqslant c) + f_y(T_{i0}) + \varepsilon_i, \qquad \text{(Reduced Form)}$$

where $\beta_2 = 0$ is a sufficient condition for $\beta_0 = 0$.

Although some students below the cutoff manage to enroll in college ("always takers," as they are probably not credit-constrained), we look for the existence of compliers—i.e., individuals who enroll in college if and only if they score at or above the cutoff (See Angrist et al. [1996]).[27] Since our exogenous variation in education affects only this group, we interpret our estimates as local average treatment effects, LATE (See Hahn et al. [2001] and Imbens and Lemieux [2008]).

Note that eligibility for the loan program ($c = 475$) also affects the amount of the student's debt since college has higher tuition and requires more years to graduate relative to vocational programs. That change in outstanding debt may not be relevant from the policymakers' perspective, as they are interested in the net effect of loan availability. However, to compare our findings with those of the previous literature, we have to separately identify the impact of education and debt on the outcomes of interest.[28]

We also use the cutoff rule on the eligibility for the BC scholarship ($c = 550$) to shed light on the effect of debt on labor market outcomes and college choice, overcoming the endogeneity issue. The Bicentenario scholarship described in Section 2.1 generates a sizable variation in the student's

[25] Namely, f_E is a local linear regression with $f_E(T_{i0} - c) = \phi_0(T_{i0}) + \phi_1(T_{i0}) \cdot \mathbb{1}(T_i \geqslant c)$ in a window of 45 PSU-points to each side of the cutoff. We obtain this bandwidth using the Imbens and Kalyanarman [2012] optimal bandwidth procedure for the first stage. We test the robustness of the specification using other functional forms, the inclusion of a rich set of covariates, and several bandwidths. In particular, we compute the optimal bandwidth of Calonico et al. [2014], which yields a similar window of about 45 PSU-points. We keep the Imbens and Kalyanarman [2012] optimal bandwidth throughout the paper to have a consistent and comparable sample.

[26] A note regarding standard errors in our application: Since the PSU score is a discrete variable in intervals of 0.5 points, we are not able to observe observations below the cutoff in a neighborhood strictly smaller than 0.5 and need to adjust the standard errors to this fact. Consequently, we rely on some functional forms to use remote data. Given that any misspecification induces a group correlation in the error term, we test the robustness of our findings by using standard errors that are clustered at the different discrete values of the PSU test (See Lee and Card [2008] for details). In general, the corrected standard errors are slightly smaller than the robust to heteroskedasticity alternatives. To be conservative, we report the latter.

[27] We also assume that no student chooses not to enroll in college because of being eligible for student loans or scholarships ("no defiers" as in Angrist et al. [1996]).

[28] See exclusion restrictions in (Angrist et al. [1996]).

outstanding debt at the eligibility cutoff. We use our estimation strategy in both cutoffs ($c = 475, 550$) to separately identify the effects of students' debt on their educational and labor outcomes.

One possible threat to our identification strategy is the fact that students just below the cutoff have strong incentives to retake the admission test to gain access to the benefits in subsequent years. However, if some students do not retake the test or retakers fail to reach the cutoff, then the instrument is still valid. We explicitly address this potential problem of self-selection into treatment in Section 5.

5 Validity of the Regression Discontinuity Design

In this section, we validate the assumptions that ensure a causal interpretation of the RD estimates for the complier—i.e., the local average treatment effect. We follow Imbens and Lemieux [2008] and perform three tests to guarantee i) the existence of a first stage; ii) the balance of covariates; and iii) the absence of manipulation of the running variable.

First Stage: Figure 1 shows the take-up discontinuity in the student loans and the Bicentenario scholarship at the respective eligibility cutoffs. The vertical lines represent the two cutoffs, 475 for loan eligibility, and 550 for the BC scholarship. Moreover, we show the dynamics of the take-up after ten years in the figures at the right.

Panel A confirms that below the 475-point threshold, the student loans are unavailable; however, students self-select retaking the PSU test in subsequent years. The left figure in Panel A shows that at the 475-point cutoff, the take-up rate of college loans increase sharply from 0 to 21 percent (a 254 thousand pesos increase in debt). At 550-point cutoff, however, students substitute their loan for the BC scholarships, and the loan take-up rate decreases from 51 to 21 percent (a decrease of 463 thousand pesos in debt). The right figure shows that some selection appears in the long -run, but still, the probability of obtaining a loan for college education increases discontinuously at 475-point cutoff and decreases discontinuously at 550-point cutoff.

Panel B shows the assignment rule of the BC scholarship, displaying a sharp allocation of resources. The awarded amount is zero below 550-point and positive for students at or above this cutoff.[29] The

[29] Students below the 475-point cutoff but having a high school GPA above 5.3 can apply for public-sponsored loans

right figure in Panel B displays the dynamic selection to the scholarship, showing some dynamic selection but showing a large discontinuity on take-up.[30]

Consistently, Panels A and B of Table 1 present the estimates of Equation (First Stage), using the indicator variable of whether the student obtains a loan or a BC scholarship as dependent variables at the correspondent eligibility cutoffs. As in the rest of the paper, the sample considers PSU-takers classified between quintiles one to four for the cutoff at 475 points, whereas the estimates at the 550-point cutoff (Panel B) consider PSU-takers classified in quintiles one and two.[31,32]

Column (1) in Panel A shows that the loan take-up increases by 21 percentage points at the 475-point cutoff, while Panel B shows that the take-up decreases at the 550-point cutoff by 33 percentage points as the scholarship replaces the loan. Column (2) shows that the Bicentenario scholarship is not granted below the 550-point cutoff and increases sharply above the 550-point cutoff, by 41 percentage points. Column (3) shows that the probability of obtaining any public scholarship (including the other six programs) increases by 31 percent at the 550-point cutoff, while there is no variation at 475. Finally, Column (4) shows that there is a discontinuity at the 475-point cutoff (due to loans) and no differences at the 550-point cutoff because the sum of loans and scholarships remains constant, consistent with a one-to-one substitution between student loans and the BC scholarship.

Regarding educational choices, Figure 2 shows the different effects of the loan programs and the BC scholarship on the type of education in which students enroll—namely, college versus vocational. Panels A, B, and C show the enrollment rate for college, vocational, and aggregated higher education institutions, respectively. College enrollment increases significantly at the 475-point cutoff, as depicted by the left figure in Panel A, while the enrollment effect at the 550-point cutoff is negligible for the marginal student. The right figure of Panel A shows the overall effect ten years after initial enrollment. Students above and below the cutoff do retake the PSU test and enroll in college in the subsequent years, but this dynamic selection does not eliminate the effect on college enrollment in the long run,

to finance vocational education only.

[30] The positive slope in the relationship between PSU scores and loans (and the BC scholarship) indicates that students enroll in programs with more expensive tuition fees.

[31] See Appendix A.1 for the amounts granted and the take-up of loans and scholarships by cohort.

[32] All estimates consider students in eligible quintiles and local linear regressions in a window of 45 PSU-points at each side of the cutoff. The bandwidth corresponds to the optimal bandwidth from Imbens and Kalyanarman [2012] for the educational first stage. We use this bandwidth throughout the paper to have the same sample in each regression.

as we still observe a discontinuity of about ten percentage points.[33]

The bottom panel presents the general view, aggregating both types of education. The left figure shows that the immediate enrollment in higher education increases when a student becomes eligible for the loan program at the 475-point cutoff, and that the change in admissions is negligible at the 550-point cutoff. Nevertheless, the overall increase in higher education enrollment at the 475-point cutoff disappears when considering those students who retake the PSU test and successfully enroll in some higher education program afterward. Consequently, we do not observe an exogenous variation in enrollment in higher education relative to high school education.

Consistent with Figure 2, Table 2 presents the equivalent RD estimates using Equation (First Stage). Panel A shows the estimates around the 475-point cutoff and considers students classified between quintiles one and four, whereas Panel B shows the estimates around the 550-point cutoff and considers students classified in quintiles one and two.

In panel A, Column (1) shows that the effect of loan eligibility on immediate college enrollment (right after the first PSU attempt) is strong and significant. Compared to a baseline of 21 percent, immediate enrollment increases by 15 percentage points. However, when considering all of the subsequent PSU attempts until 2016 in Column (2), the probability that a student ever enrolls in college is nine percent higher above the 475-point threshold. Column (3) shows that the likelihood of enrolling in any higher education immediately after the first PSU attempt is ten-percent higher at the 475-point cutoff, but it goes down to one percent when considering the reshuffling of students up to 2016.

This result is essential for the interpretation of our results. Almost all the variation in education reflects the substitution of college for vocational degrees when high school graduates obtain eligibility for the loan programs at the 475-point cutoff. There is a negligible effect on the extensive margin (the probability of enrolling in any higher education), which precludes us from comparing high school graduates who enrolled in vocational education and those who enter the labor market directly after high school.

The choice between college and vocational training is the most interesting marginal decision because most students at this point in the PSU distribution are already enrolled in some form of

[33] Figure A.1 in Appendix A.3 shows further evidence that the impact of loan program eligibility on college and vocational enrollment has persisted for over ten years, despite allowing students to retake the PSU test.

higher education (94% according to Column (4)). Therefore, the primary choice that they make is what type of higher education to pursue rather than whether or not to continue their studies.

For students around the 550-point cutoff, Panel B shows that the enrollment effects are statistically insignificant, supporting the hypothesis that access to the scholarship does not change college or vocational enrollment. This result is consistent with the permanent income hypothesis (Friedman [1957] and Eisner [1967]), which argues that in the presence of complete credit markets, individuals can smooth consumption and make optimal investment decisions. At both sides of the scholarship cutoff, loans are available, thus reducing the credit restrictions that students face.

In summary, loan eligibility at the 475-point cutoff changes students' enrollment decisions in favor of college relative to vocational education—decisions that go hand in hand with the accumulation of outstanding debt. Scholarship eligibility, however, does not change students' educational decisions, despite the substantial reduction in the amount of debt. As a consequence, the 550-point cutoff is a valid instrument for students' debt. We exploit this instrument in the following sections.

Balance of Covariates The second test for the validity of the RD verifies whether groups with scores above and below the cutoffs are balanced regarding predetermined observable characteristics. Table 3 shows the balance of covariates. Each row represents the estimation of Equation (First Stage) where the dependent variable is the one listed in the first column. As a reference, Column (1) shows the population average (considering the universe of students who took the PSU and have been classified as pre-selected). Column (2) shows the average for students just below the 475-point cutoff (α_1 in Equation (First Stage)), and Column (3) presents the change in the average for the students at the 475-point cutoff (β_1 in Equation (First Stage)). Analogously, Columns (4) and (5) replicate the same estimates for the 550-point cutoff. The standard errors are robust to heteroskedasticity.

We find no evidence of discontinuities in the predetermined characteristics. We cannot reject the null hypothesis of no difference in 13 out of 14 tests in each cutoff. The exception is "age at the PSU," indicating that students just above the 475-point cutoff are about 0.04 years older (2.2 weeks). Similarly, the fraction of the students working when taking the PSU test is 0.006 larger above the 550-point cutoff. The t-tests for both differences have p-values between 0.10 and 0.05, consistent with a type I error since we might expect 1.4 false positives at 10% significance.

Manipulation of the running variable The third test for the validity of the regression discontinuity shows that students are not able to manipulate the running variable around the eligibility cutoffs, and, therefore, the assignment is as good as random (see McCrary [2008]). Figure 3 shows that the empirical density of students around the cutoffs is smooth. Each dot indicates the number of students in each bin of four points. The absence of bunching confirms that students are not able to manipulate the PSU score.[34]

6 Empirical Analysis

In this section, we present our main empirical analysis. In Subsection 6.1, we introduce the results on the graduation rates for the different types of institutions. All figures in this section correspond to the reduced-form regression and represent the intention to treat (ITT) estimates. We also present correspondent regressions in which we show the results for the reduced-form and the 2SLS estimates that represent the local average treatment effects. In Subsection 6.2, we study the impact of college and vocational enrollment on labor market outcomes.

6.1 Effects on Graduation

We focus on the effect of loan eligibility on graduation rates, which quantifies the efficacy of the policy to foster human capital formation. Figure 4 shows graduation rates for college, vocational schools and aggregated higher education. Panel A shows that, ten years after graduation from high school, 20 percent of the students just below the cutoff graduate from college. The graduation rate increases sharply, by about four percentage points, for students who score at or above the cutoff. Consistently, Panel B shows that about 30 percent of students just below the cutoff graduate from vocational programs and that the graduation rate decreases discontinuously by five percentage points at or above the cutoff. The reduction is explained by fewer students above the cutoff enrolling in vocational programs once loan programs allow them to pursue a college degree.[35] Finally, in Panel C, we observe that the overall graduation rates in higher education do not change discontinuously

[34] Anecdotally, the PSU test considers only multiple-choice questions that are answered by the students darkening circles on an answer sheet. The score is determined by a photo-optical device, which does not involve human interactions, limiting the scope for manipulation by third parties.

[35] In Appendix B we show the reduced-form estimates, which are consistent with the figures on graduation rates.

at the 475-point cutoff, as the loan programs bias the composition of graduates choosing a college education but do not alter the total number of graduates.

Table 4 shows the estimates for the local average treatment effects for the complier, in a 2SLS estimation described in Section 4.[36] Panel A shows that students who are induced to enroll in college because of the loan eligibility increase their college graduation rate by 44 percentage points. The graduation rate is very high relative to the overall graduation rate at this margin. To compare the size of the effect, we report the average graduation rate for the population of pre-selected students. The probability of graduation for an average student is 23 percent, implying an important success of the policy increasing the graduation rate of the students.[37]

Panel B in Table 4 shows the effects on the graduation rates of students in vocational programs. We observe that students induced to pursue vocational degrees increase their graduation rate by 69 percentage points with a higher baseline of 27 percent.

Therefore, the eligibility for loan programs biases the composition of higher education enrollees towards college, which, in turn, implies lower average graduation rates. The lower graduation rates come at the cost of students taking longer to graduate from college relative to vocational institutions. As shown in Appendix A.2, students above the 475-point cutoff have more years of enrollment. In fact, compliers take 1.75 additional years to graduate from college (expected duration is 3.7 years for vocational graduates and 5.45 years for college graduates at this margin).

6.2 Effects on Labor Outcomes

6.2.1 Labor Experience

Given the higher graduation rates shown in the Subsection 6.1, the first labor outcome we study is the effect on labor experience for the PSU takers. We measure labor experience as the number of months with strictly positive earnings in the formal sector since high school graduation. Figure 5 shows how students just above the 475-point cutoff have lower accumulated experience. For example, after eight years of high-school graduation, the average experience for somebody just below the cutoff is 32

[36]Tables in this section present the following structure: the first column shows the results for the three cohorts pooled together, while columns (2) to (4) show the effects by cohort.

[37]In Table B.1 in Appendix B we can see that the enrollment rate just below the cutoff is 20 percent, which offers a second comparison for the magnitude of the effects.

months, whereas students at or just above the 475-point cutoff have 1.3 fewer months accumulated. Notice that the shorter the time window, the more precise are the estimates as we can pool more observations. Table 5 shows the LATE, estimated by 2SLS. We find that eligibility for the loan programs reduces the labor market experience in about 16 months for the average complier when pooling the 2006-2008 cohorts.[38] These effects are more substantial for newer cohorts, consistent with some students still not being in the labor market.

6.2.2 Annual Earnings

The next labor outcome of interest is the annual earnings in the formal sector. To account for the evolution of earnings over time, we present four different horizons, eight through 11 years after high school graduation.[39]

Figure 6 shows the variation in annual earnings around the cutoffs. To provide a more accurate idea around the cutoff, we zoom in to the chart to show PSU scores between 300 and 700 instead of the full range.

The top-left figure depicts the most prolonged time window, 11 years, while the bottom-right figure corresponds to the shortest time window, eight years. We find that students just above and just below the 475-point cutoff have very similar yearly incomes. The top-right figure shows that at 475 PSU-points, students earn about five million pesos per year (approximately 10,000 dollars). The figure also shows a positive gradient between PSU and earnings, and, at the 550-point cutoff, the students earn about 5.6 million pesos per year. Importantly, we do not observe any significant discontinuity at either cutoff. All the figures show a similar pattern: annual earnings appear to increase over time (the average at the 475-point cutoff is 3.5, 4.0 and 4.5 million pesos after eight, nine and ten years, respectively. We do not observe any significant discontinuity in earnings at the cutoffs.

The precision in the figures increases for shorter horizons, as we can pool data from more cohorts. For example, the 11-year horizon can be studied only with the 2006 cohort, which we observed in

[38] The 2SLS estimates in 550 are not informative since there is no first stage at that cutoff. The results are presented in the appendix for completeness.

[39] The web appendix contains similar tables for the analysis based on findings by cohort. All earning are measured in 2017 pesos, adjusted by the national price index.

2017. Instead, for the ten-year horizon, we can pool data from the 2006 and 2007 cohorts observed, respectively, in 2016 and 2017. The bottom-right figure illustrates the situation for the eight-year time-window that combined cohorts 2006 to 2010 and shows a small reduction in earnings above the 550-point cutoff. We explore this finding further in the following sections.

6.2.3 Labor Participation, Intensity, and Stability

We now turn to three other labor outcomes that determine annual earnings: the rate of participation in the formal sector; the labor-intensive margin (number of months with positive earnings per year); and job stability (as an indicator for 12 consecutive months with positive earnings).[40] Notice that differences in participation or hourly wages can explain changes in labor income.

Figure 7 presents the three labor outcomes at 11 years after high school graduation, and they do not show any discontinuity at the 475- or 550-point cutoffs.[41] First, the top-left figure indicates that, at the loan cutoff of 475 PSU-points, 65 percent of students are participating in the formal sector after 11 years. Interestingly, the gradient for participation is slightly negative,[42] and, at the scholarship cutoff of 550 PSU points, the participation rate is slightly lower. Second, the top-right figure shows that 40 percent of the individuals at both cutoffs have stable earnings. Third, the bottom figure shows that students participate in the formal sector for roughly six months per year, implying similar unemployment rates across the eligibility cutoffs.

6.2.4 Static Analysis of Labor Outcomes

Table 6 presents reduced-form estimates at the 475-point cutoff and confirms no effect of college enrollment on labor outcomes, which is consistent with Figures 6 and 7.[43]

Panel A presents the effect of college enrollment on annual earnings at the 475-point cutoff, and the estimates are negligible, which is consistent with the figures. However, we find that the statistically insignificant impacts of college enrollment on earnings increase monotonically from -19

[40] See Section 3.1.2 for details about the definitions of the labor market outcomes.
[41] See Appendix C for shorter time windows displaying similar conclusions.
[42] This pattern is more pronounced for shorter horizons, which may signal that some students are still studying or that college students take more time to match with an employer.
[43] The reduced form estimates follow Equation (First Stage) and consider the labor outcome as the dependent variable. The 2SLS estimates are omitted since the reduced-form estimates are statistically insignificant.

to +14 thousand pesos over time.[44] The rising college premium is essential for the long-run assessment of the profitability of a college education. We think that we observe the cross-point of the two lifetime earnings patterns, but the trend suggests that the college premium could increase over time and leave the optimality of a college education as an open question.

Panel B shows the estimates for labor participation and finds the same insignificant impact of college enrollment. At the 475-point cutoff, the share of workers in the formal sector is about 65 percent and remarkably stable over time, with no change at the cutoff.

Panel C shows that the rate of stable jobs is increasing monotonically over time, from 27 percent after eight years to 38 percent after eleven years for students just below the 475-point cutoff. At the 475-point cutoff, the rate of having stable jobs presents a small discontinuity ten years after high school, equivalent to 1.3 percentage points, which is significantly different from zero at the 10% significance level. However, the rate becomes positive but statistically insignificant one year later.

Finally, Panel D shows that students around the 475-point cutoff work more intensively every year, as the months worked per year increases monotonically from 5.4 months after eight years to 6.3 months after 11 years. Nevertheless, no significant differences are found for students at or above the 475-point cutoff, implying no effect of college enrollment in this labor outcome.

6.2.5 Dynamic Analysis of Labor Outcomes

Motivated by the trends observed in the data, we focus on the pattern of differences in outcomes over time between the students just below and those just above the loan eligibility cutoff at 475. We seek to uncover whether the eligibility for student loans causes dynamic effects on the labor market, implying that we should account for trends rather than for levels of labor outcomes. Thus, we summarize the dynamics in figures that plot the RD estimates for each of the 11 years of analysis.

Figure 8 shows the effects on annual earnings, labor participation, the rate of stable jobs, and the intensive margin in the labor market. Each dot in the graph represents the estimated average at the cutoff for a given group of PSU takers ("just below" and "just above" the cutoff). Each point estimate displays a 95 percent confidence interval in the form of a gray vertical line. In general, the estimates are precise for short time windows of analysis as we have more observations. The estimated

[44] Panel A also shows the increasing level of earnings over time, about half a million pesos per year.

gaps correspond to the reduced-form estimates introduced above.

The top-left figure shows the estimated earning gap over time between the PSU-takers just below and just above the 475-point cutoff. The effects of reaching the 475-point cutoff are adverse for students above the cutoff in the first periods, with earnings of about 200,000 pesos less per year ($400 US) for the compliers.[45] However, the initial earning gap disappears in the seventh year after high school graduation. The earning gap remains close to zero until the tenth year and then becomes positive in the 11th. The precision of the estimates in the shorter time windows reflects only the possibility of pooling data from multiple cohorts.

This figure is consistent with the classical patterns of earnings of workers between the ages of 20 and 30 years. The slope in the earning function for the 475-point cutoff is consistent with a college premium (i.e., a higher slope favoring college graduates relative to vocational graduates). The figure also depicts a common stylized fact of first earnings being higher for those with low levels of education, explained mainly by their earlier participation in the labor market. Moreover, the figure in Panel A highlights that the horizon of the assessment is fundamental to understanding and measuring the returns to college education. In the next subsection, we perform a brief exercise to identify the necessary conditions for the optimality of college education relative to the vocational choice.[46]

The top-right figure shows the evolution over time of labor participation in the formal sector. Similarly, the effects on the earnings of the group above the 475-point cutoff are negative and statistically significant in earlier horizons of analysis but become insignificant after the seventh year. They become positive in the eighth year but, curiously, turn into a negative slope in the last period. Our findings are robust to conditioning the analysis to the sample of students with positive earning in a given year and by each cohort separately.

The bottom-left figure depicts a similar situation for the rate of students holding stable jobs. We find negative and significant effects on college graduates during the first years, but those gaps in payoffs become zero at the end of the period. The bottom-right figure shows the intensive margin in the labor market, the number of months of labor participation in a given year. The initial effects

[45] The effects for compliers use the first stage estimate of about 0.1, and, hence, the LATE equals the reduced-form estimate multiplied by 10.

[46] The top-right figure shows the earning dynamics for the PSU-takers at the 550-point cutoff. We discuss these results in Section 7.

are adverse for students above the cutoff and become close to zero eight years after high school graduation.

7 Debt Aversion and the Educational and Labor Market Outcomes

The estimates from previous sections suggest that the loan programs have succeeded in expanding college enrollment, but the labor outcomes of college graduates who receive loans have not been affected, at least not in the short run. To extrapolate these conclusions, we need to separately identify the effects of college enrollment and students' outstanding debt. In fact, many students could be debt-averse; as a consequence, due to the student loans, they may make sub-optimal decisions that negate the potential benefits of a college education. Hence, separating the effects of college enrollment and debt aversion requires an exogenous variation that affects one but not the other. Importantly, since the loans are tied to college enrollment at the 475-point cutoff, the identification is impossible using the discontinuity rule. However, the cutoff rule at the 550 PSU score, which grants eligibility to the BC scholarship, creates an exogenous variation in the amount that students borrow, but it does not affect the overall rate of enrollment. We use the indicator variable of whether the student reaches the 550-point cutoff as an instrument for the amount of debt the student borrows to enroll in college. Section 5 contains the support for this regression discontinuity approach.

Figures 4 to 7 have already shown the absence of any discontinuity at the 550-point cutoff.[47] Figure 4 shows that holding debt does not affect the graduation rates of any educational type, consistent with the ability to smooth investments over time in the presence of credit markets.

Figure 5 shows that 11 years after high school, the accumulated experience of those who hold debt to finance education is not statistically different from those who fund education with a grant. Figure 6 shows that, over the longest horizon, we cannot reject the zero null hypothesis. However, for shorter periods, we observe a small but significant effect that can be estimated precisely given the availability of several cohorts, allowing an increased estimation power.

Figure 7 also points in the same direction, as the amount of debt held by the students just below and above the 550-point cutoff seems not to affect their labor participation, the rate of stable jobs

[47] The bottom-right graph in Figure 6 shows a small discontinuity eight years after high school graduation. Since the effects are minimal, we might need the aggregation of four cohorts to be able to detect it statistically.

and the intensive margin of workers. In fact, the initial periods show an adverse effect for college graduates, consistent with the results in Field [2009] and Rothstein and Rouse [2011], as the students holding debt perform slightly better in the labor market.

Thus, based on the evidence at the 550-point cutoff, we observe a significant effect for earlier periods after graduation from higher education. Nevertheless, for the most extended horizon available, we can reject the null hypothesis of debt aversion. Importantly, because students are eligible for loan programs at either side of the 550-point cutoff, we can assume that the incidence of credit constraints seems strongly reduced around that cutoff. If the trend continues, a reversal of the effects could occur, as discussed in the previous section for the returns to college.

The zero effects, when considering the longest observed period, could be interpreted as evidence that individuals behave like permanent income agents over their life cycle. The most common problem that challenges the permanent income hypothesis is the existence of credit constraints. After a windfall, an agent following a permanent income would not change her consumption dramatically, as she prefers to smooth consumption across periods. On the contrary, if we observed a change in consumption, it is difficult to know whether individuals are not behaving as permanent income agents or are affected by their credit constraints, so individuals are not choosing optimally.

In this case, the existence of college loans seems to significantly reduce the liquidity restrictions affecting students, and, therefore, the absence of a change in education choice suggests that individuals are choosing optimally as if the credit markets were complete. Although the credit market may have other sources of frictions, at least for the decisions to enroll in higher education, credit-constrained students have full access to college loans, and the availability of scholarships does not trigger any change in their college choice.

Table 7 presents reduced-form estimates of labor outcomes at the 550-point cutoff. The table shows negative and non-significant estimates. In the shorter horizons of eight to nine years after high school graduation, we can find some significant estimates. Annual earnings are statistically negative for the eighth year after high school. Table 7 also shows results for participation in the formal sector. In that case, all estimates are not significant and have point estimates below one percentage point. The rates of stable jobs and months of participation show significant negative effects, but they revert to no significance in the last period. Moreover, for the latter three outcomes, the point estimate is decreasing monotonically in almost all cases.

In short, our evidence indicates that labor market outcomes of students holding outstanding debt do differ from those of students who finance their education with scholarships or other sources, especially in earlier periods. However, for the most extended analysis horizon, we observe no differences between the two groups. Our results show that a sizable decrease in the debt amount of students near the 550-point cutoff does not affect labor outcomes. Thus, should the effects at the 475-point cutoff be stronger or milder? Recall that students who score barely above the 475-point cutoff have more college education, but also a more onerous debt burden, than similar students just below the cutoff. Given that the change in financial burden is stronger at the 550-point cutoff, we can argue that debt-aversion effects at the loan eligibility cutoff of 475 should be milder.[48] Because the effects of debt burden on labor outcomes are zero, we conclude that the results at the 475-point cutoff should be negligible.

8 Net Present Value Analysis

The decision on human capital investment is difficult, as it requires the evaluation of the net benefits of different inter-temporal patterns of costs and revenues.

On the cost side, the evaluation should account for the initial gap in investments due to the differences in tuition fees and opportunity costs. In effect, the choice between college and vocational education shows an initial investment gap, as college tuitions are typically more expensive than vocational or technical school fees. Also, there is a significant cost differential due to the delayed entry into the labor market by college graduates relative to vocational graduates, who enroll in shorter degree programs.

On the revenue side, the evaluation should account for the uncertain flow of earnings coming from future labor market participation. Furthermore, the streams of labor income for vocational and college graduates show different starting levels and growth rates over the life cycle. In particular, we observe quite similar initial earnings between both groups, but it seems that college graduates have a positive premium over time that can compensate for the lower accumulated labor experience.

[48] We also need the assumption that the impact of an increase in debt is symmetric relative to a decrease in student debt, which is consistent with our linear specifications.

Thus, we compute the net present discounted value of the educational investment (NPV) to summarize all the relevant dimensions in a single figure. For the sake of simplicity, we calculate the present discounted value (PDV) of direct costs and earnings separately and consider a six-percent rate of discount (all values are in pesos of December 2017). In our analysis, we present 2SLS estimates of college enrollment on the NPV that capture the LATE of college enrollment. Table 8 shows our estimates: Panel A shows the NPV; Panel B shows the PDV of direct costs (tuition); and Panel C shows the PDV of earnings. These calculations are based on the labor records between January 2002 and February 2018. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts in February 2018, while Columns (2) to (4) show the 2SLS estimates using different time windows.

Panel A presents the effect of college enrollment on the NPV of college education. Panel A presents a sizable negative and significant estimate, but with a strong trend towards zero. The trend is explained by a stable PDV of costs and a shrinking gap between PDV of earnings. Columns (2) to (4) show three different horizons. While, in column (4), nine years after high school, the negative effect is about three times the average NPV, in Column (2), the negative effect is equal to one times the average NPV.

We compute the PDV of tuition fees using the detailed information on individual enrollment in each degree over time. Due to the complete information on individual enrollment, our cost calculation accounts for the potential change of programs or higher-education institution and the graduation status. Panel B in Table 8 presents the effect of college enrollment on direct costs. The additional years of education and the more expensive college tuition translate into a significant gap in the initial investment. The reduced-form estimates show that the PDV of the costs increases by 1.5 million pesos ($3,000 US) at the cutoff.[49] This amount translates into 15 million 2017 pesos for the complier (Panel B, Column (1)), which is equivalent to doubling the cost of education for an average student (equivalent to 14 million pesos, as shown in the row labeled “Mean of dep. var.”). The subsequent columns present stable estimates, suggesting that most students have finished their education. We also compute the PDV of labor income using the actual earnings in our dataset. Panel C in Table 8 presents the effect of college enrollment on the NPV of earnings, which are not statistically different

[49]We use the face value of tuition fees without any penalty for late payments or interest rates. This calculation yields a lower bound of the costs of higher education.

between college and vocational graduates. Column (1) shows a gap in favor of vocational graduates that is not statistically significant. Columns (2) to (4) show the NPV for different time windows, suggesting a positive trend in favor of a college premium, but it, too, is not statistically significant.

8.1 Net Present Value Analysis using Forecasts

We assess the optimality of the educational choice by calculating the NPV, including future expected earnings. To study whether college is optimal relative to vocational education in financial terms, we forecast earnings of our sample several years ahead for college and vocational graduates and compare them.

To predict future earnings, we use the estimates of Mincer equations for college and vocational graduates separately.[50] The Appendix section E provides further details on the estimation and additional data that we use. We use actual earnings between 25 and 30 years old, while we forecast using our Mincer estimates for ages older than 31.

We consider two horizons in our calculations of the NPV. The first is the legal age for retirement (65 years old), covering the entire life cycle of the worker. Also, we consider 20 years after college graduation, which is the SGL program's default repayment schedule. The 20 years horizon tests whether the flow of college earnings can cover the financial cost of the loan and still being optimal relative to vocational education.

Our exercise also identifies the minimum annual growth rate of college earnings needed to obtain the same net present value of vocational graduates under different discount rates and time windows.

We use two values for the discount rate: two percent and six percent. The former is the interest rate of the TUL program, while the latter is the interest rate of the SGL program. The larger the discount rate, the less favorable are the calculations for the option of pursuing a college degree since it involves a more considerable initial investment.

Panel A in Table 9 presents the annual growth rate estimated by the model for both time horizons.

[50] We estimate the following OLS regression: $\ln(w_i) = \alpha + \beta E_i + \gamma_1 S_i + \gamma_2 S_i^2 + \delta X_i + v_i$, where $\ln(w_i)$ is the log of earnings, E_i is education and S_i is the accumulated labor experience, and X_i are other controls for individual i such as gender, health-status or productive-sector fixed effects. v_i is the unobservable random shock. β is the marginal return to an extra year of education, and $\gamma_1 - 2\gamma_2 S_i$ is the marginal return to an extra year of labor experience. We estimate the model separately for workers with high school education, vocational education (less than a four-year degree) and college education (more than a four- year degree).

Column (1) shows that the yearly growth rate of college graduates is 5.5 percent for the ages between 25 and 45, and 3.2 percent for ages between 25 and 65. This reduction in growth rate of earnings over time is due to the concave pattern of the earnings as captured by the Mincer estimates in Table E.1 . Column (2) shows that the yearly growth rate of vocational graduates is 4.8 percent for the ages between 25 and 45, and 2.7 percent for the full range of age 25-65.

Not surprisingly, our estimates show a path of earnings of college graduates that exceeds vocational earnings over time. Recent work has found that more-educated workers have steeper experience-wage profiles than uneducated ones (Lemieux [2006]). However, our focus is to assess whether the college premium is high enough to support the more substantial investment already documented.

Panel B in Table 9 show the minimum yearly growth rate for college earnings in order to have the same NPV of vocational graduates. Using the 20 years time-window, the growth rate of 4.3 percent ensures that the net present value (NPV) of the college education is equal to the NPV of vocational education under a discount rate of two percent (Column (1)), whereas the growth rate should be about 6.6 percent if there is a more demanding discount rate of six percent. If we extend the time horizon to the entire life-cycle of workers, age 25-65, the growth rate of college earnings should be 2.6 percent under 2 percent discount and 3.7 percent under a six percent discount rate.

In summary, a discount rate of two percent ensures that the college choice is optimal in any time window, as the required growth rates are below the predicted value by the wage equation. When considering a discount rate of six percent, however, the expected growth rate is below the requirement, but the gap is not sizable.

9 Conclusion

We present evidence of the effects of college choice and student debt on labor market outcomes, using a regression discontinuity design. We exploit the eligibility rules for two loan programs and one scholarship that create exogenous variation in higher education, diverting students from vocational to college enrollment and, as a consequence, increasing students' outstanding debt. In fact, the loan program induces students above the 475-point cutoff on the admission test to pursue a college education that requires more years of training and higher tuition fees per year, and that displays a higher dropout rate, relative to vocational education. Also, the scholarship program induces students above the 550-point cutoff to replace debt with the public scholarship, thus reducing their debt burden at the margin. We combine the exogenous variations caused by both cutoff rules with detailed administrative data on earnings from the formal sector to identify the impact of education and debt on labor outcomes several years after students take the higher education admission test for the first time.

The loan policy is effective in promoting college education. More students pursue college degrees at the eligibility cutoff, at expenses of vocational programs. However, the graduation rate is lower in college, and the time to graduation is longer than in vocational education. This combination decreases the student's labor experience significantly.

We cannot reject the hypothesis of zero effects in any labor outcome at the 475-point cutoff. Some adverse impacts on college students appear in the investment period. However, those effects are statistically zero and probably trending towards a positive effect in the long run.

We explore some mechanisms—specifically, the existence of debt aversion (Thaler [1990]). We use the scholarship cutoff at 550 points as an instrument for the size of the debt. We find no statistical effect on labor market outcomes for the longest time window available. However, for shorter time windows for which more data are available, we find negative and significant effects appearing in most outcomes. The dynamics do not allow us to distinguish between reverting patterns or problems relative to statistical power. The zero effect of the BC scholarship on college choice is consistent with students behaving according to the permanent income hypothesis (see Friedman [1957] and Eisner [1967]). This result is especially provocative since loans are available around the scholarship cutoff, and, therefore, credit constraints are less binding.

Given that the educational decision requires weighting several outcomes that are affected by the policy—tuition costs, the probability of graduation, the time to graduate, likelihood of employment and earnings— to summarize in a single number the profitability of the investment relative to other educational choices, we compute the net present discounted value of the education investment. For the complier, we find that choosing college implies a negative effect of equal size to the average NPV in the sample, indicating that the loans retard the investment break-even point. However, we observe a positive trend that may reverse this negative effect in the future. To better understand this outcome, we also present the decomposition of the NPV into tuition and earning components. Regarding the present value of costs, students have completed their investment history. For the complier, the investment implies doubling the monetary cost in education 11 years after high school. Importantly, we show that the present value of income is growing fast in favor of college graduates. However, the earnings in the recent periods are not enough to compensate for the more substantial difference in investments.

Overall, this paper presents a detailed picture of the dynamics of education and the labor market. Educational investments take time to produce better earning flows, making age and years after high school a crucial variable to consider when studying returns to college. However, this paper concludes that for individuals up to age 30 in Chile, college does not pay off relative to vocational education. However, the college premium seems to increase over time, possibly offsetting the initial experience gap and covering cost differences under moderate discount rates in the long run.

A possible future venue of research could be to characterize scenarios where this policy on student loans is optimal. Besides the inherent heterogeneity of individuals (demographics and regional factors), we could study different features of the credit conditions (interest rate, length, amount, penalties, etc.) and educational characteristics (degrees, higher education, duration) that can help to improve the outcomes of the policy.

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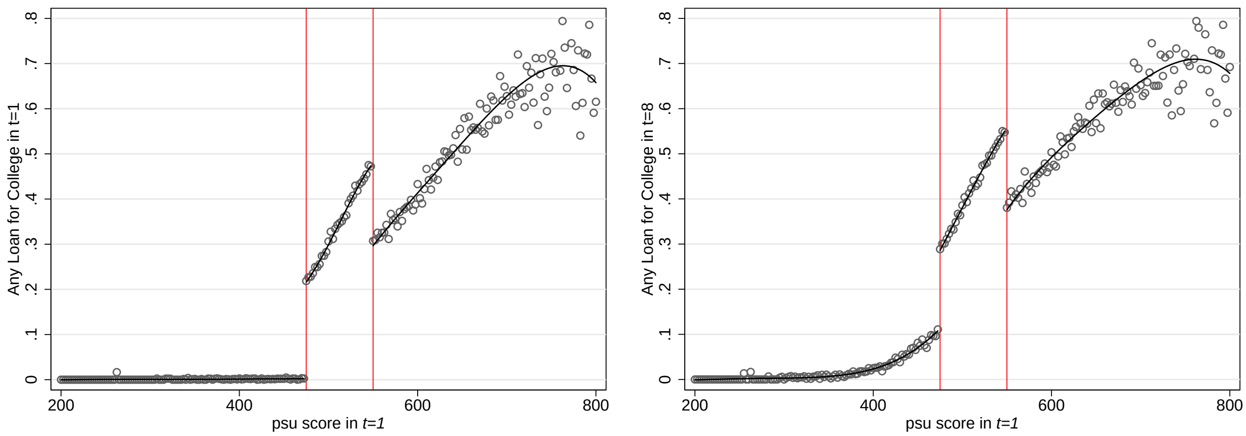
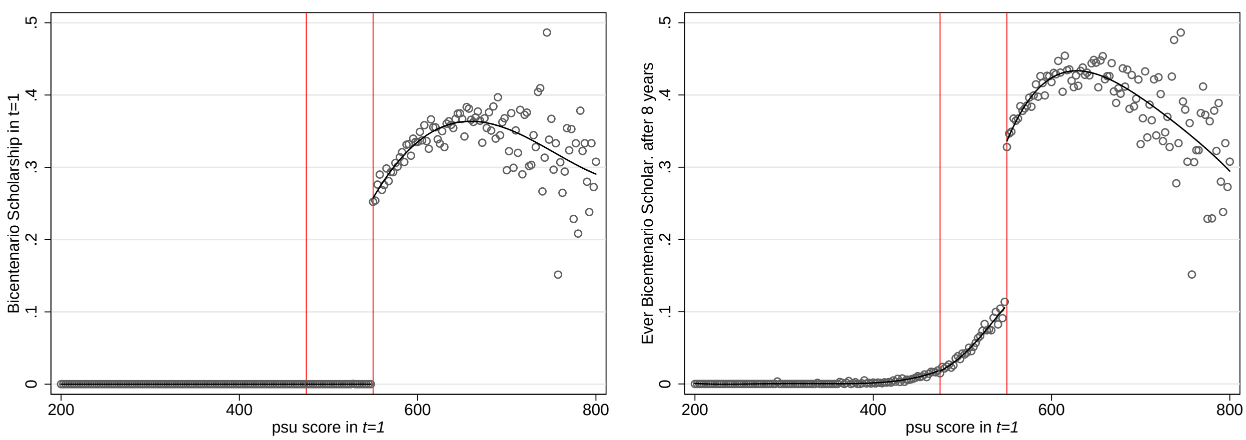
10 Figures and Tables

10.1 Figures

Figure 1: Loan Amounts and Scholarships around the Eligibility Cutoffs
[Panel A.] [Left] College Loans, 1st year, [Right] College Loans, Any year



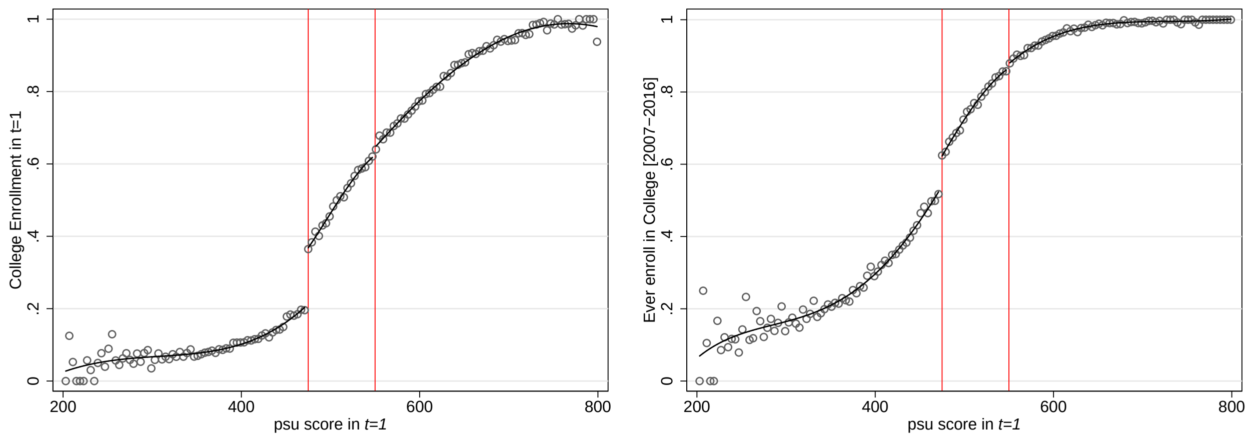
[Panel B.] [Left] BC, 1st year, [Right] BC, Any year



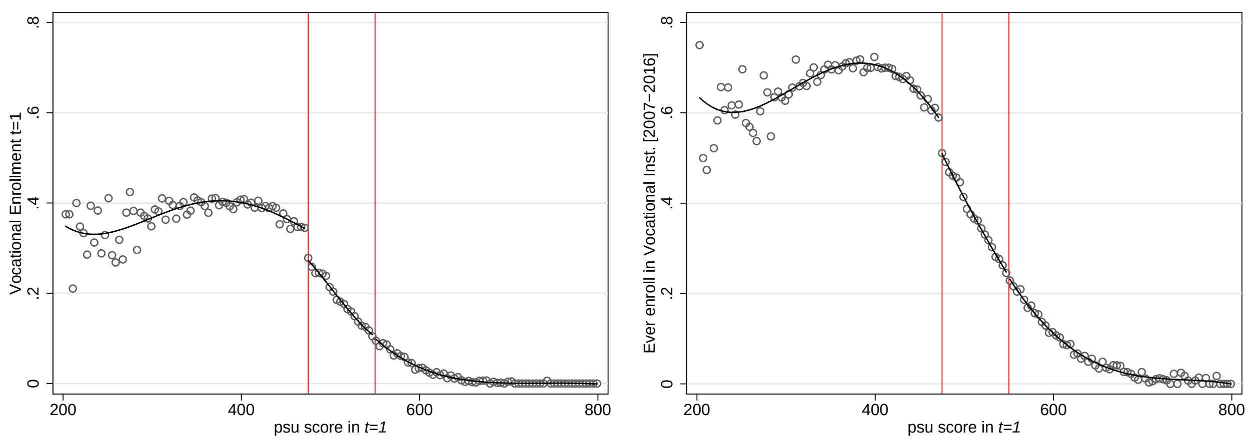
***Note*:** The figures show the loan amounts and scholarships as a function of the PSU scores. The figures show college loans (Panel A), any loan (Panel B), Bicentenario scholarship (Panel C) and any aid that is the sum of all loans and scholarships (Panel D). The left figures show the amounts awarded in the same year of the PSU test for first-time takers. The right figures show the amounts ten years after the PSU test for first-time takers. Each dot represents the average among students in a bin of 4 PSU-points. The solid line represents fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550).

Figure 2: Higher Education Enrollment around the Eligibility Cutoffs

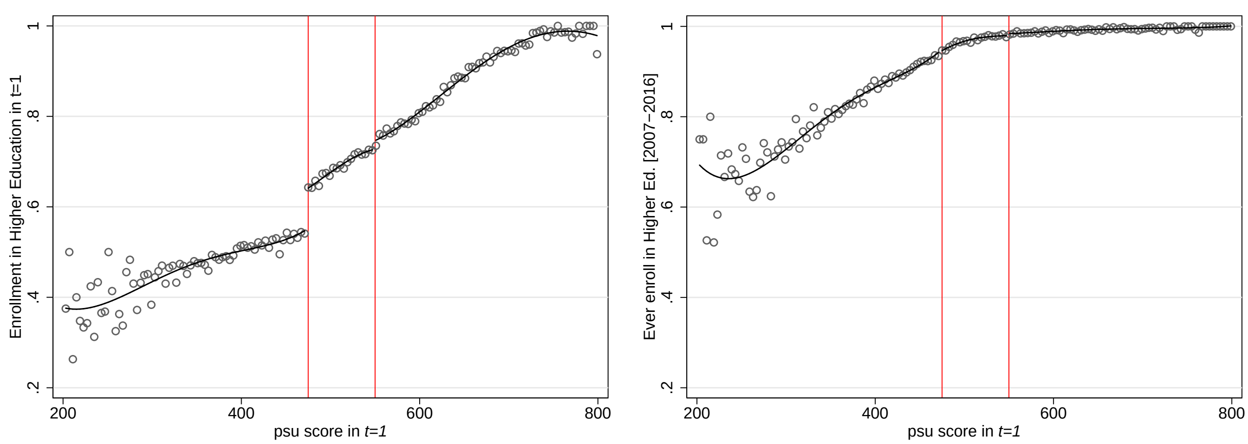
[Panel A.] College Enrollment



[Panel B.] Vocational Enrollment

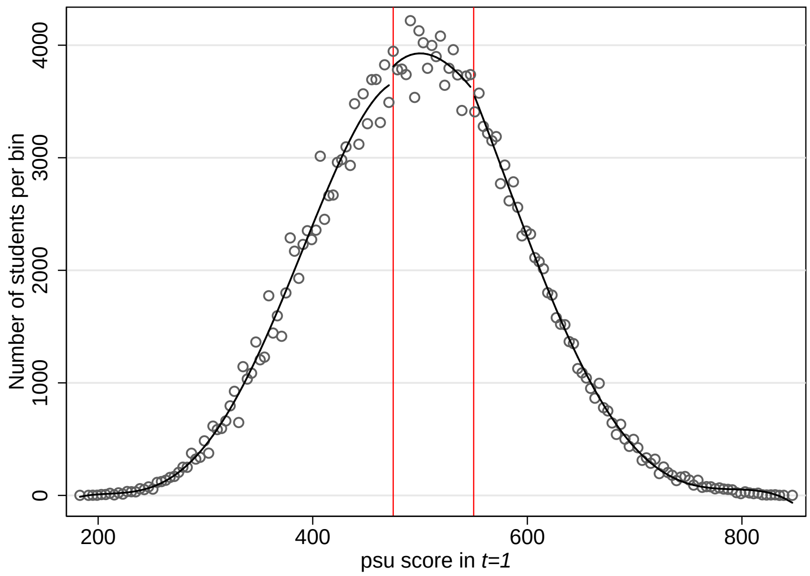


[Panel C.] Aggregated High Education Enrollment



***Note*:** The figures show higher education enrollment as a function of the PSU scores. The figures show the college enrollment (Panel A), vocational enrollment (Panel B), and the aggregated enrollment in any higher education (Panel C). The left figures in each Panel show the enrollment in the same year of the PSU test for the first-time takers. The right figures in each Panel show the enrollment ten years after the PSU test for the first-time takers. Each dot represents the average among students in a bin of 4 PSU-points. The solid line represents fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SGL loan cutoff (475) and the Bicentenario scholarship cutoff (550).

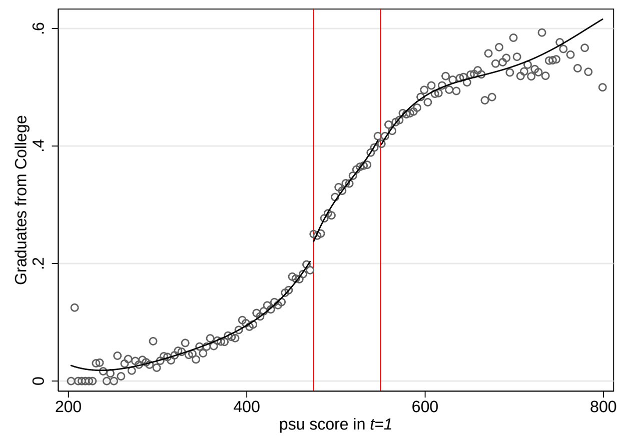
Figure 3: The McCrary Test



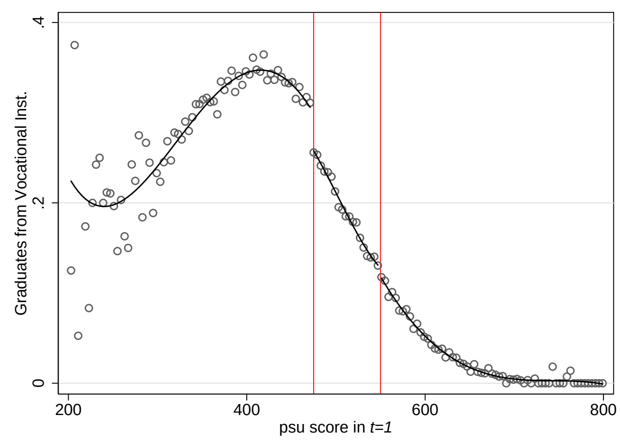
***Note*:** The figure shows the frequency of different PSU scores. Each dot represents the number of students in a bin of 4 PSU-points. The solid line represents fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The sample corresponds to the universe of students who took the PSU in the admission cohorts from 2006 to 2008 and who are outside the top quintile in the earnings distribution.

Figure 4: Graduation Rates around the Eligibility Cutoffs

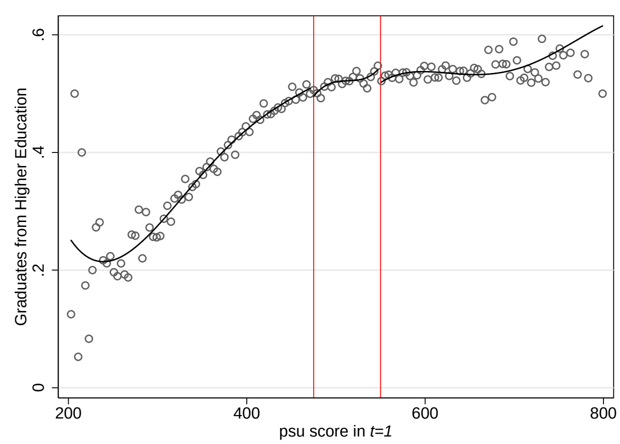
[Panel A.] College Graduation



[Panel B.] College Graduation

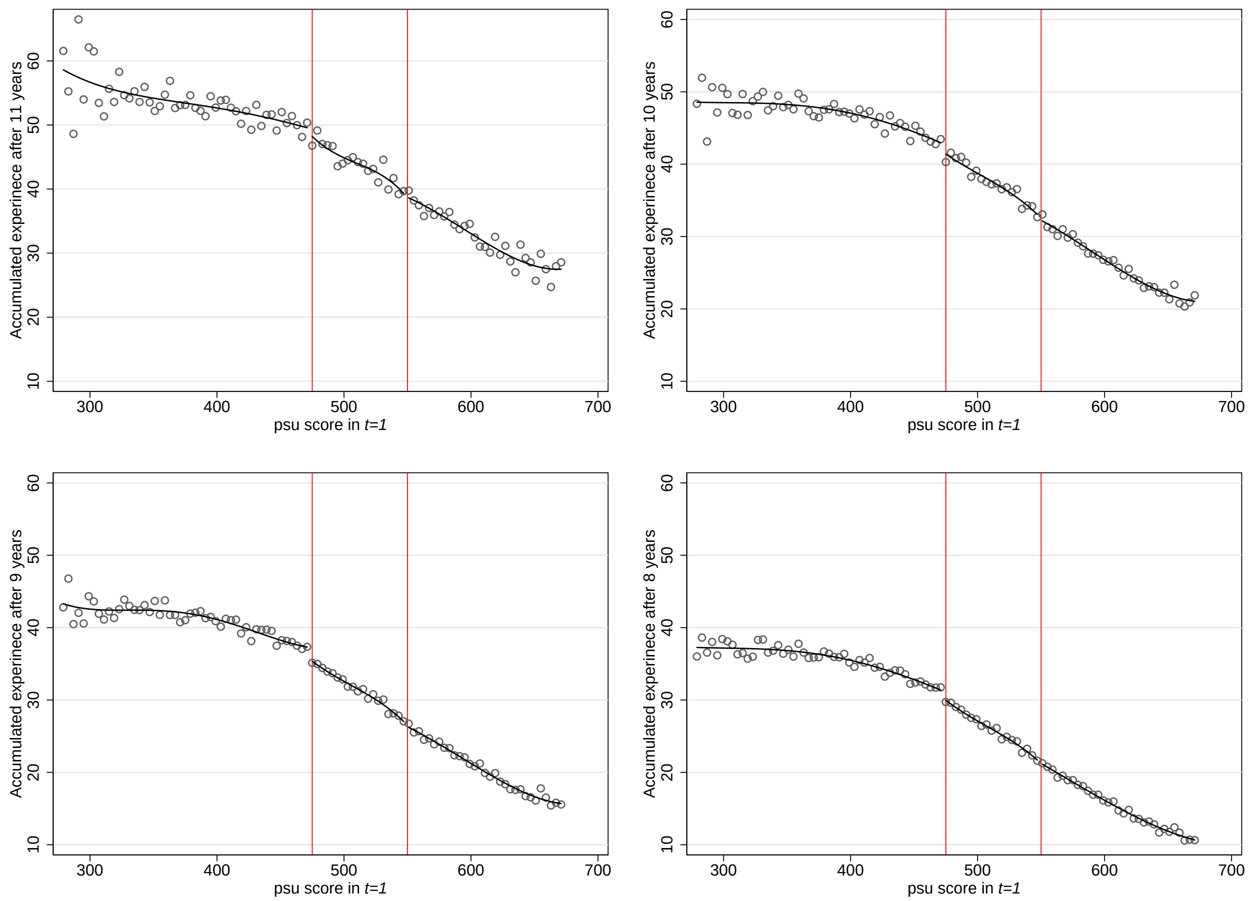


[Panel C.] Aggregated Higher Education Graduation



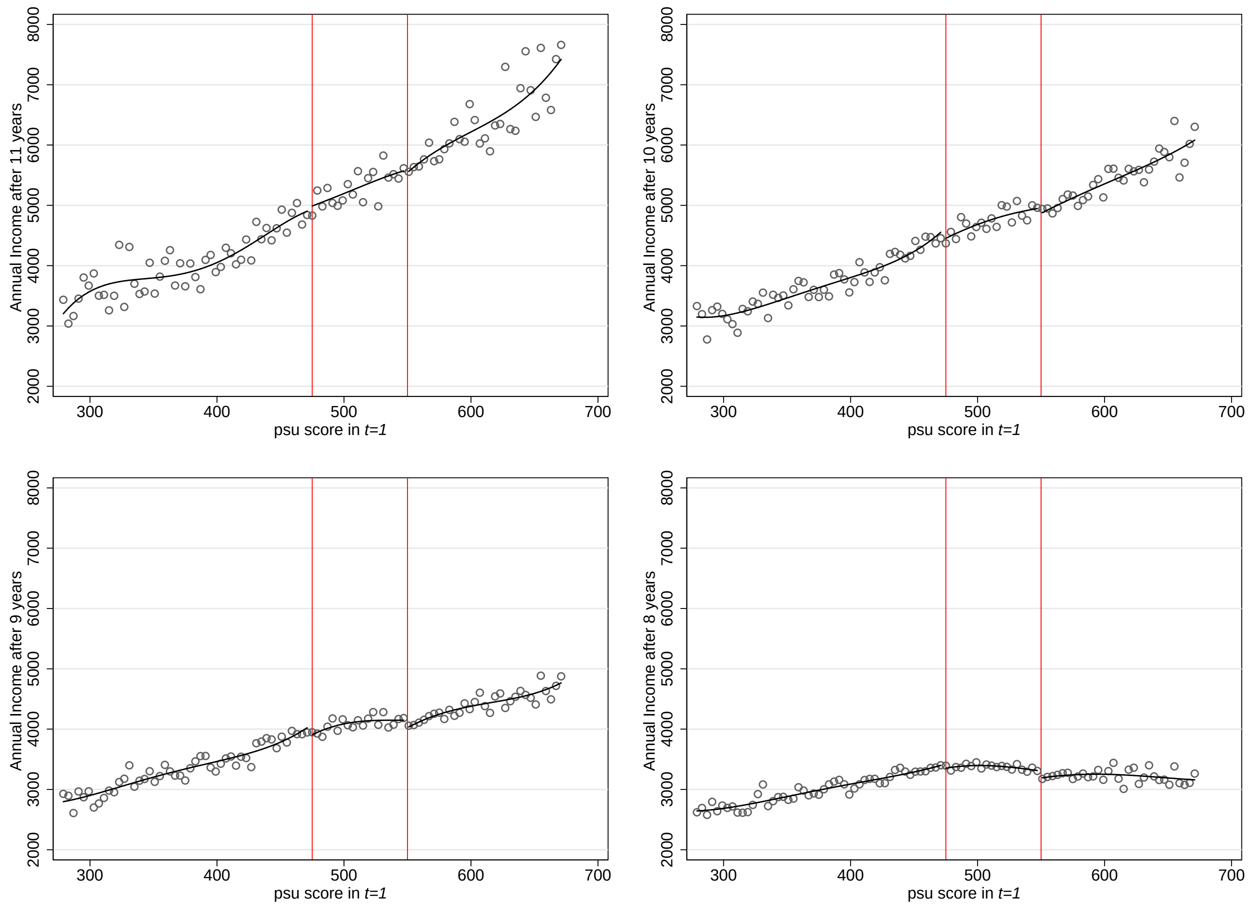
***Note*:** The figures show the graduation rates as a function of the PSU scores. The figures show the college graduation (Panel A), vocational graduation (Panel B), and the aggregated graduation in any higher education (Panel C). Each dot represents the average among students in a bin of 4 PSU-points. The solid line represents fitted values from a fourth-order polynomial for the PSU score, as described in Equation (First Stage). The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The sample corresponds to the pool of PSU takers.

Figure 5: Labor Experience around the Eligibility Cutoffs after t years



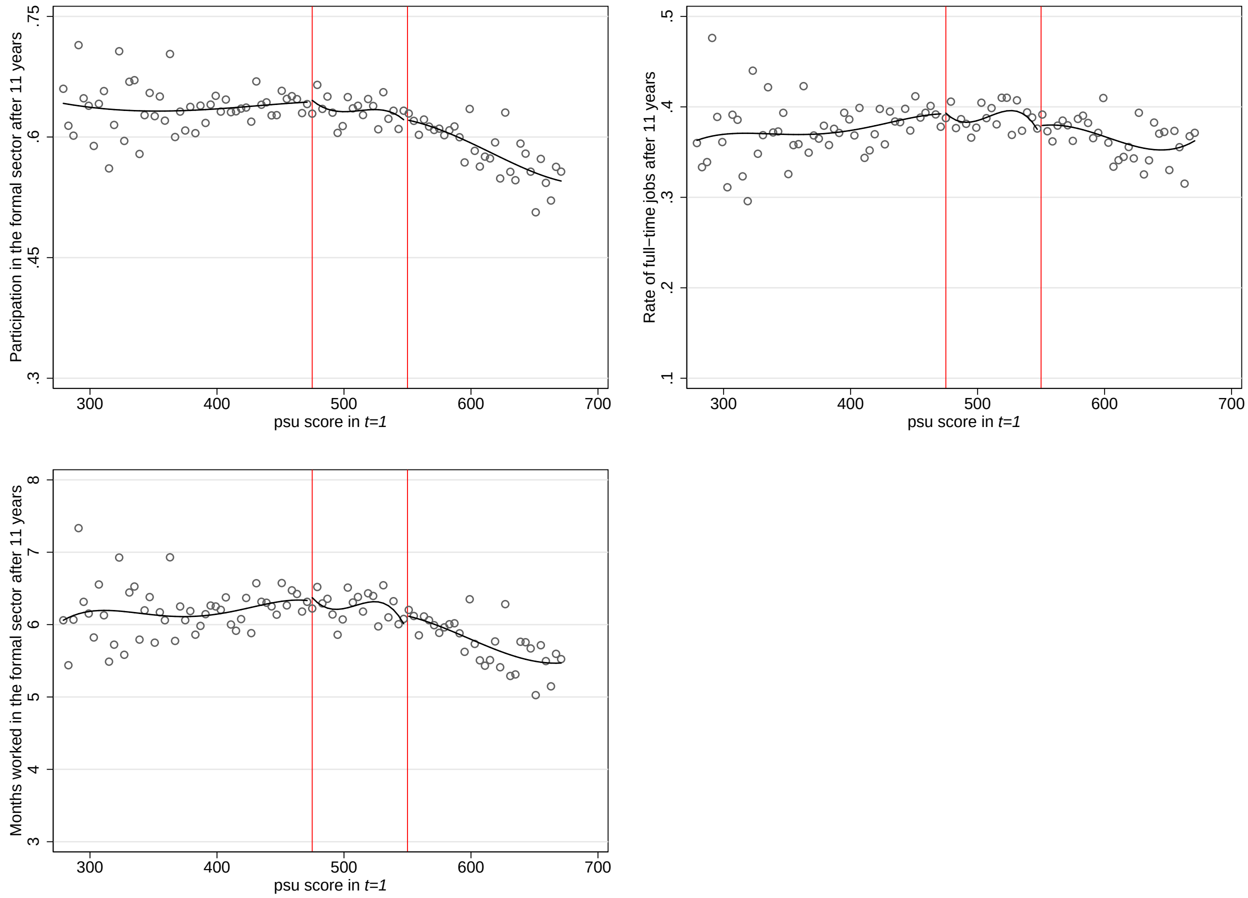
***Note*:** The figures present the average of the accumulated labor experience of students t years after their first attempt at the PSU admission test. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The top-left figure shows the 11-year analysis; hence, it considers the first-time PSU takers in November of 2006 (cohort 2006) in the labor market in 2017. Similarly, the top-right figure shows the ten-year analysis; hence, it considers the first-time PSU takers in November of 2007 (cohort 2007) in the labor market in 2017 and the admission cohort 2006 in the labor market in 2016. The bottom-left figure shows the nine-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of 2015, 2016 and 2017, respectively. The bottom-right figure shows the eight-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of the years 2014, 2015 and 2016, respectively.

Figure 6: Labor Market Outcomes: Annual Earnings around the Eligibility Cutoffs after t years



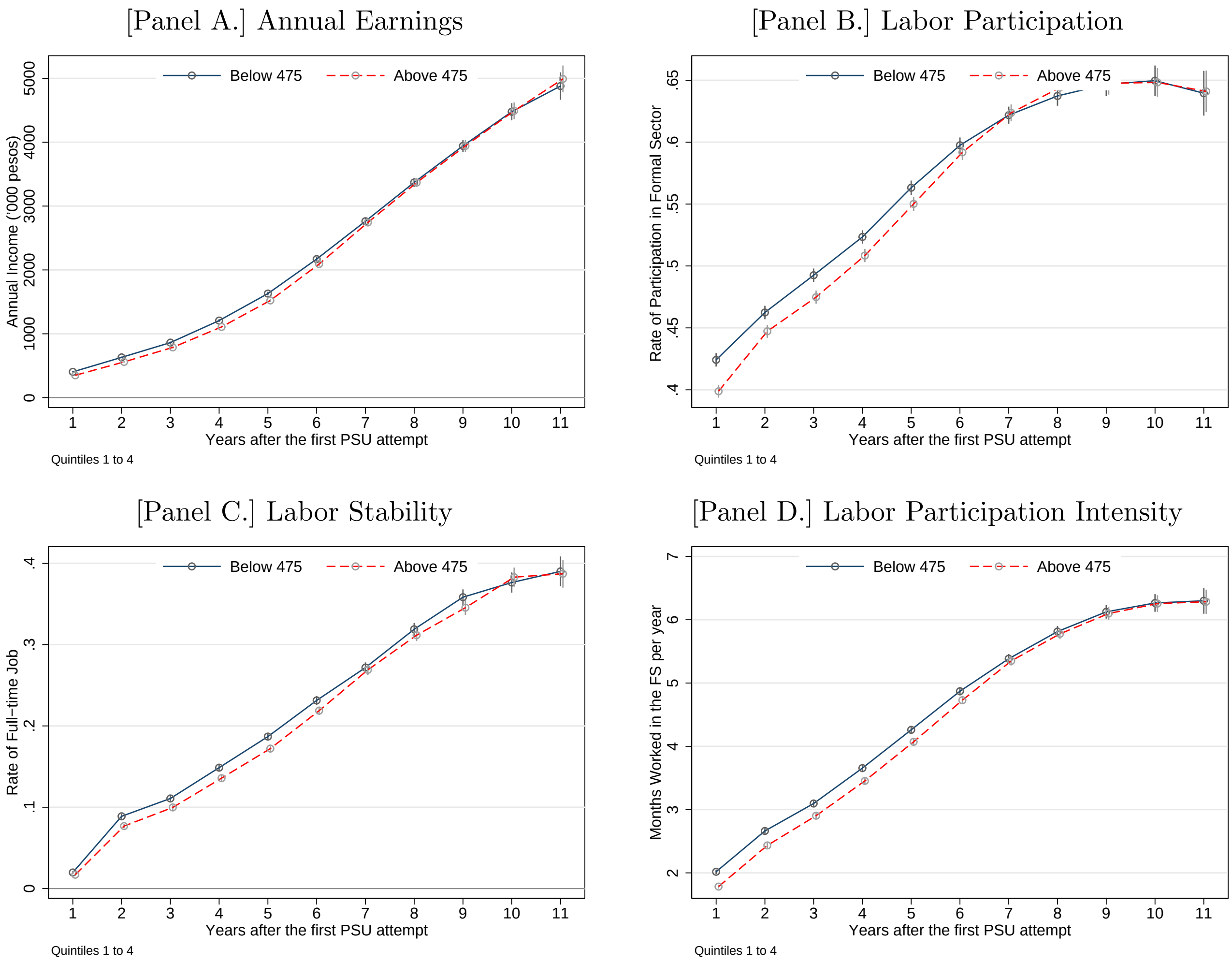
***Note*:** The figures present the average of the annual earnings of students t years after their first attempt at the PSU admission test. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The top-left figure shows the 11-year analysis; hence, it considers the first-time PSU takers in November of 2006 (cohort 2006) in the labor market in 2017. Similarly, the top-right figure shows the ten-year analysis; hence, it considers the first-time PSU takers in November of 2007 (cohort 2007) in the labor market in 2017 and the admission cohort 2006 in the labor market in 2016. The bottom-left figure shows the nine-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of 2015, 2016 and 2017, respectively. The bottom-right figure shows the eight-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of the years 2014, 2015 and 2016, respectively.

Figure 7: Labor Participation, Job Stability, and Intensive Margin at 11 years after High-School Graduation



***Note*:** The figures present the Labor Participation, Job Stability, and Intensive Margin as a function of the PSU scores of students t years after their high school graduation. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth-order polynomial for the PSU score. The vertical lines correspond to the SGL loan cutoff (475) and the Bicentenario scholarship cutoff (550). The figures show a time window of 11 years, as it considers the first-time PSU takers in November 2006 in the labor market in 2017.

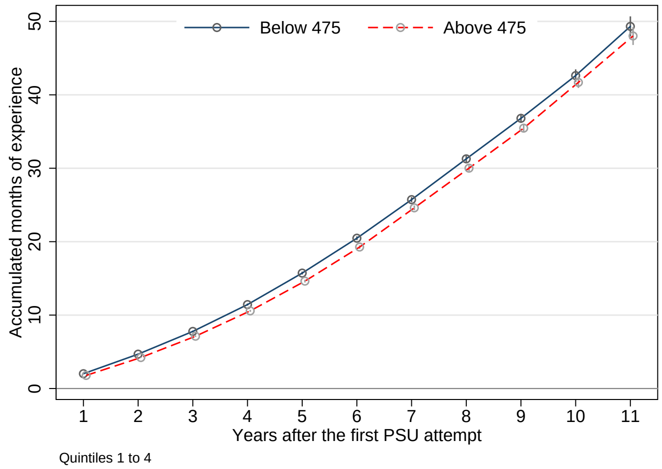
Figure 8: Annual Earnings, Participation, Job Quality and Labor Intensity over time



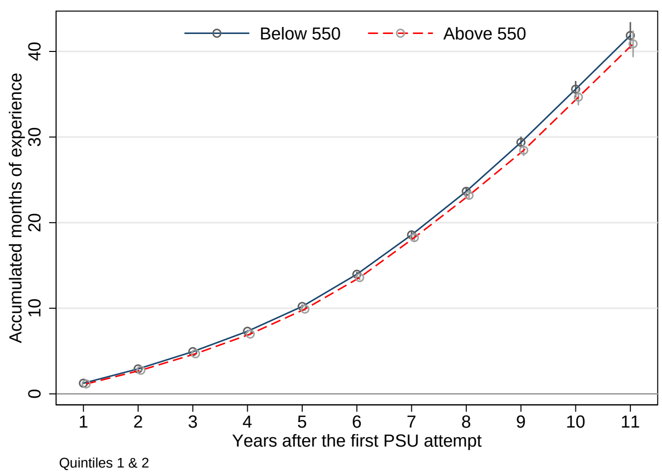
***Note*:** The figures plot the point estimate of the RD estimates for a given group of PSU takers ("just below" and "just above" the cutoff) over time. Each point estimate displays a 95 percent confidence interval in a form of gray vertical line. The dependent variable is the annual earnings in Panel A, labor participation in panel B and the rate of stable jobs in panel C. The left figures consider the loan program cutoff (475), while the right figures consider the BC scholarship cutoffs (550). Hence, the left figures consider the PSU-takers classified between quintiles one to four, whereas the right figures consider the PSU-takers classified in quintiles one and two.

Figure 9: Accumulated Experience over Time

[Panel A.] Accumulated Experience at 475



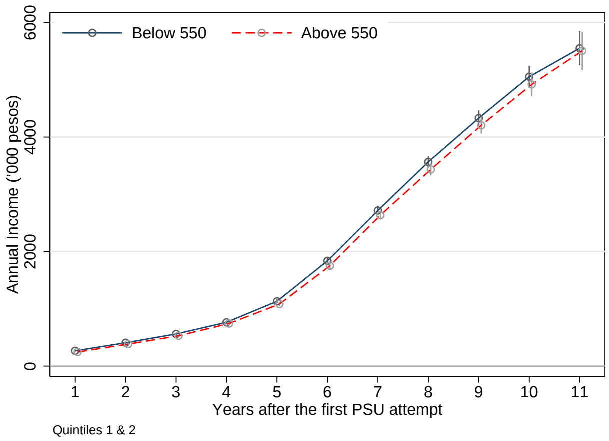
[Panel B.] Accumulated Experience at 550



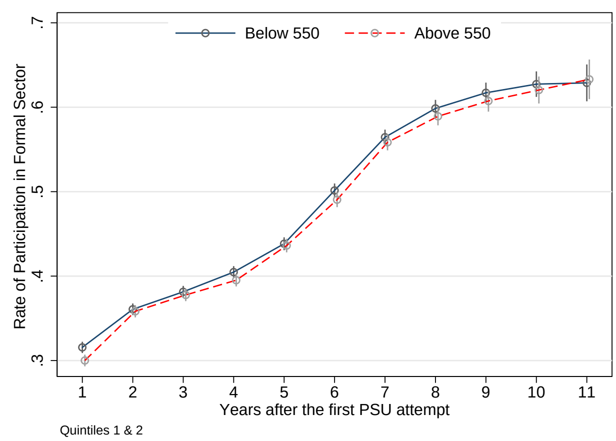
***Note*:** The figures plot the point estimate of the RD estimates for a given group of PSU takers ("just below" and "just above" the cutoff) over time. Each point estimate displays a 95 percent confidence interval in a form of gray vertical line. The dependent variable is the accumulated experience at 475-point cutoff (Panel A) and at the 550-point cutoff (Panel B). The top figure considers the PSU-takers classified between quintiles one to four, whereas the bottom figure considers the PSU-takers classified in quintiles one and two.

Figure 10: Annual Earnings, Participation, Labor Stability and Labor intensity over time

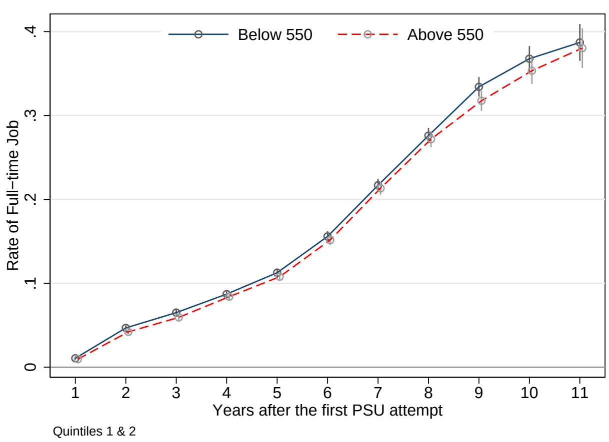
[Panel A.] Annual Earnings



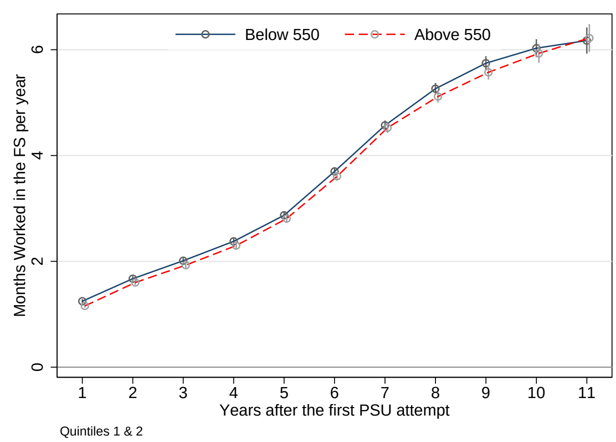
[Panel B.] Labor Participation



[Panel C.] Labor Stability



[Panel D.] Labor Participation Intensity



***Note*:** The figures plot the point estimate of the RD estimates for a given group of PSU takers ("just below" and "just above" the 550-point cutoff) over time. Each point estimate displays a 95 percent confidence interval in a form of gray vertical line. The dependent variable is the annual earnings in Panel A, labor participation in panel B, the rate of stable jobs in panel C, and the labor participation intensity in Panel D rate of stable jobs in panel C. The figures consider the PSU-takers classified in quintiles one and two.

10.2 Tables

Table 1: Loan and Scholarships around the Eligibility Cutoffs. First-Stage Estimates

	College loan	Bicentenario grant	Any grant	Any aid
	(1)	(2)	(3)	(4)
[Panel A.] Take-up at the 475 cutoff				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.21***	0.00	-0.01	0.18***
	(0.004)	(.)	(0.005)	(0.006)
Const.	0.00	0.00	0.17***	0.22***
	(0.000)	(.)	(0.004)	(0.004)
Obs.	80372	80372	80372	80372
[Panel B.] Take-up at the 550 cutoff				
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.30***	0.41***	0.31***	0.01
	(0.008)	(0.007)	(0.008)	(0.009)
Const.	0.51***	0.00	0.18***	0.61***
	(0.006)	(0.000)	(0.005)	(0.006)
Obs.	47687	47687	47687	47687

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation(First Stage) using take-up as dependent variable. Panels A estimates the effects at the 475 PSU score cutoff, and Panels B at the 550-point cutoff. Column (1) shows the estimates for the college loan programs; Column (2) shows estimates for the Bicentenario scholarship; Column (3) shows the estimates for any public scholarship; and Column (4) shows estimates for the sum of loans and scholarships. All the regressions consider local linear regressions. The sample corresponds to the pool of admission cohorts 2006, 2007 and 2008. Estimates at 475-point cutoff (Panels A) consider PSU-takers classified between quintiles one to four, whereas estimates at the 550-point cutoff (Panels B) consider PSU-takers classified in quintiles one and two.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table 2: Higher Education Enrollment around the Eligibility Cutoffs. First-Stage Estimates

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
[Panel A]. Higher Education Enrollment at the 475-point cutoff				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.152***	0.083***	0.096***	0.007**
	(0.006)	(0.007)	(0.007)	(0.003)
Const.	0.209***	0.546***	0.546***	0.946***
	(0.004)	(0.005)	(0.005)	(0.003)
Obs.	80,372	80,372	80,372	80,372
[Panel B.] Higher Education Enrollment at the 550-point cutoff				
$\mathbb{1}(T_{i0} \geqslant 550)$	0.014	0.009	0.006	-0.003
	(0.009)	(0.006)	(0.008)	(0.003)
Const.	0.622***	0.859***	0.738***	0.983***
	(0.006)	(0.005)	(0.006)	(0.002)
Obs.	47,687	47,687	47,687	47,687

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation(First Stage) using different educational outcomes as dependent variables. Panel A shows the estimates around the 475 PSU score cutoff, and Panel B shows the estimates around the 550-point cutoff. As the dependent variable, we consider a dummy indicator if the student enrolled in college after her first PSU attempt (Column (1)), a dummy indicator if the student ever enrolled in college (Column (2)), a dummy indicator if the student enrolled in higher education (college or vocational) after her first PSU attempt (Column (3)), and a dummy indicator if the student ever enrolled in higher education (college or vocational) (Column (4)). All the regressions consider local linear polynomials. The sample corresponds to the admission cohorts 2006, 2007 and 2008.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table 3: Balance of Covariates around the Cutoffs

	Pooled cohorts (2007-2009) and Eligible quintiles (1st to 4th)				
	Population Mean	Average at 475	Change at 475	Average at 550	Change at 550
	(1)	(2)	(3)	(4)	(5)
Female	0.57***	0.59***	0.0018	0.55***	-0.0015
	(0.0010)	(0.0035)	(0.0069)	(0.0036)	(0.0072)
Income quintile	1.99***	1.81***	0.020	2.16***	0.0090
	(0.0023)	(0.0073)	(0.015)	(0.0082)	(0.016)
Age at PSU	18.9***	18.9***	0.042*	18.7***	-0.0077
	(0.0038)	(0.011)	(0.023)	(0.0070)	(0.014)
High School GPA	5.71***	5.60***	0.0049	5.82***	-0.00020
	(0.00099)	(0.0030)	(0.0059)	(0.0030)	(0.0060)
Public School	0.45***	0.48***	0.010	0.39***	-0.0059
	(0.0010)	(0.0035)	(0.0070)	(0.0035)	(0.0070)
Father Edu. (years)	11.1***	10.6***	-0.035	11.7***	0.040
	(0.0082)	(0.027)	(0.055)	(0.027)	(0.054)
Mother Edu. (years)	11.1***	10.7***	-0.018	11.6***	0.048
	(0.0074)	(0.025)	(0.050)	(0.024)	(0.048)
Not Single at PSU	0.013***	0.012***	0.00092	0.0074***	0.0011
	(0.00023)	(0.00077)	(0.0015)	(0.00063)	(0.0012)
Work at PSU	0.073***	0.077***	-0.0030	0.059***	0.0058*
	(0.00053)	(0.0019)	(0.0037)	(0.0017)	(0.0034)
Household Size	4.46***	4.49***	-0.024	4.43***	0.014
	(0.0037)	(0.013)	(0.026)	(0.012)	(0.024)
Father Work Formal	0.66***	0.67***	0.0070	0.68***	-0.010
	(0.00097)	(0.0033)	(0.0066)	(0.0034)	(0.0067)
Mother College	0.066***	0.041***	0.0011	0.074***	-0.0010
	(0.00051)	(0.0014)	(0.0028)	(0.0019)	(0.0038)
Father College	0.073***	0.045***	-0.00099	0.087***	0.0023
	(0.00053)	(0.0015)	(0.0030)	(0.0020)	(0.0041)
Mother housewife	0.50***	0.52***	0.0025	0.48***	-0.012
	(0.0010)	(0.0035)	(0.0070)	(0.0036)	(0.0072)
Obs.	238,895	80,372	80,372	75,225	75,225

Note 1: The universe of students considers all the PSU takers in the admission cohorts from 2006 to 2008 and those students outside the top quintile in the earnings distribution. Each row represents the regression of the dependent variable listed in the first column on a constant, the indicator function and a local linear regression. Column (1) shows the population means considering the entire sample. Column (2) shows the estimated average for the students just below the 475-point cutoff, and Column (3) presents the change in that covariate for the group just above the 475-point cutoff, while using a local linear regression around the cutoff in a window of 45 points for each side. Columns (4) and (5) replicate the same estimates at and above the 550-point cutoff, respectively.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

10.3 Educational outcome: Causal effect of Enrollment on Graduation rates

Table 4: Graduation Rates at 475-point Cutoff. 2SLS Estimates

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
[Panel A]. Graduation Rates from College				
Ever Enrolled College	0.441***	0.484***	0.378**	0.429***
	(0.066)	(0.114)	(0.173)	(0.085)
Mean of dep. var.	0.23	0.29	0.25	0.18
[Panel B.] Graduation Rates from Vocational				
Ever Enrolled Vocational	0.691***	0.769***	0.574***	0.718***
	(0.083)	(0.169)	(0.168)	(0.114)
Mean of dep. var.	0.27	0.27	0.27	0.27
Obs.	80372	23063	26296	31013

Note 1: The table shows the 2SLS estimates that capture the causal effect of college enrollment on college graduation rates (Panel A) and the effect of vocational enrollment on vocational graduation rates (Panel B). Column (1) shows the results for the three cohorts pooled together, while columns (2) to (4) show the effects by cohort. All the regressions consider local linear polynomials. The sample corresponds to the pool of admission cohorts 2006, 2007 and 2008 classified between quintiles one to four.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

10.4 Labor Market Outcomes

Table 5: Labor Experience at 475-point Cutoff. 2SLS Estimates

[Panel A] Experience at the 475-point cutoff

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-16.24***	-14.18	-10.91	-21.39***
	(5.687)	(10.210)	(14.656)	(7.023)
Mean of dep. var.	42	49	42	37
Obs.	80372	23063	26296	31013

Note 1: : The table shows the 2SLS estimates that capture the causal effect of college enrollment on labor experience at the 475-point cutoff (Panel A). Column (1) shows the results when pooling the 2006-2008 cohorts, while columns (2) to (4) show the effects for each cohort separately. All the regressions consider local linear polynomials.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table 6: Labor Outcomes at the 475-point cutoff. Reduced Form Estimates

	After 11 Years	After 10 Years	After 9 Years	After 8 Years
	(1)	(2)	(3)	(4)
[A.] Anual income after t years				
$\mathbb{1}(T_{i0} \geqslant 475)$	111.8	15.1	2.24	1.54
	(153.0)	(97.3)	(69.2)	(51.5)
Const.	4879.3***	4534.2***	4058.6***	3527.3***
	(109.5)	(69.6)	(48.8)	(36.2)
[B.] Formal sector participation after t years				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.0015	-0.0014	0.00083	0.0068
	(0.013)	(0.0086)	(0.0067)	(0.0056)
Const.	0.64***	0.65***	0.65***	0.64***
	(0.0092)	(0.0062)	(0.0049)	(0.0040)
[C.] Full-time job after t years				
$\mathbb{1}(T_{i0} \geqslant 475)$	-0.0029	0.0066	-0.013*	-0.0073
	(0.013)	(0.0087)	(0.0067)	(0.0054)
Const.	0.39***	0.38***	0.36***	0.32***
	(0.0094)	(0.0063)	(0.0049)	(0.0039)
[D.] Month of work After t years				
$\mathbb{1}(T_{i0} \geqslant 475)$	-0.015	-0.0095	-0.027	-0.036
	(0.14)	(0.097)	(0.075)	(0.062)
Const.	6.30***	6.26***	6.12***	5.81***
	(0.10)	(0.071)	(0.055)	(0.045)
Obs.	23,063	49,359	80,372	115,552

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (2) using different labor outcomes as dependent variables. Each column shows the estimates at a different time horizon of analysis. Column (1) uses the different labor outcomes 11 years after the workers took the PSU admission test—for example, labor outcomes in 2017 for those students who took the PSU exam 2006. Column (2) considers a ten-year horizon—for example, labor outcomes in 2016 and 2017 for the students in the 2006 and 2008 cohort, respectively. Column (3) and Column (4) consider the nine- and eight-year horizon, respectively. Each panel uses different dependent variables. Panel A uses the annual earnings as the dependent variable; Panel B uses the indicator of whether the worker participates in the formal sector; Panel C uses an index of whether the worker has a stable job; and Panel D uses the accumulated months of work per year. All the regressions consider a local linear polynomial with a rectangular kernel with the optimal bandwidth of Imbens and Kalyanarman [2012].

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

10.5 Debt Aversion

Table 7: Labor Outcomes at the 550-point cutoff. Reduced Form Estimates

	After 11 Years	After 10 Years	After 9 Years	After 8 Years
	(1)	(2)	(3)	(4)
[A.] Anual income after t years				
$\mathbb{1}(T_{i0} \geqslant 550)$	-45.61	-133.86	-125.44	-131.91*
	(227.959)	(142.963)	(101.163)	(73.640)
Const.	5551.08***	5053.59***	4331.43***	3565.90***
	(151.308)	(96.438)	(68.807)	(50.548)
[B.] Formal sector participation after t years				
$\mathbb{1}(T_{i0} \geqslant 550)$	0.00	-0.01	-0.01	-0.01
	(0.016)	(0.011)	(0.009)	(0.008)
Const.	0.63***	0.63***	0.62***	0.60***
	(0.011)	(0.008)	(0.006)	(0.005)
[C.] Full-time job after t years				
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.01	-0.01	-0.02*	-0.00
	(0.016)	(0.011)	(0.009)	(0.007)
Const.	0.39***	0.37***	0.33***	0.28***
	(0.011)	(0.008)	(0.006)	(0.005)
[D.] Month of work After t years				
$\mathbb{1}(T_{i0} \geqslant 550)$	0.05	-0.10	-0.17*	-0.15*
	(0.185)	(0.126)	(0.098)	(0.080)
Const.	6.17***	6.03***	5.75***	5.26***
	(0.126)	(0.087)	(0.068)	(0.056)
Obs.	13,705	29,387	47,687	67,799

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 550)$ in Equation (2) using different labor outcomes as dependent variables. Each column shows the estimates at a different time horizon of analysis. Column (1) uses the different labor outcomes 11 years after the workers took the PSU admission test—for example, labor outcomes in 2017 for those students who took the PSU exam 2006. Column (2) considers a ten-year horizon—for example, labor outcomes in 2016 and 2017 for the students in the 2006 and 2008 cohort, respectively. Column (3) and Column (4) consider the nine- and eight-year horizon, respectively. Each panel uses different dependent variables. Panel A uses the annual earnings as the dependent variable; Panel B uses the indicator of whether the worker participates in the formal sector; Panel C uses an index of whether the worker has a stable job; and Panel D uses the accumulated months of work per year. All the regressions consider a local linear polynomial with a rectangular kernel with the optimal bandwidth of Imbens and Kalyanarman [2012].
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

10.6 NPV

Table 8: Net Present Value of the Investment at the 475-point cutoff. 2SLS Estimates

	Pooled cohorts 2007-2009 in Feb 2018	NPV after 11 years	NPV after 10 years	NPV after 9 years
	(1)	(2)	(3)	(4)
[Panel A] Net Present Value, NPV				
Ever Enrolled College	-20276.414***	-17895.551*	-18763.788**	-21523.493***
	(5201.301)	(10604.858)	(7856.054)	(4481.121)
Mean of dep. var.	10846.31	17118.95	11233.85	6679.79
[Panel B] Present Value of Direct Costs				
Ever Enrolled College	14824.407***	16635.253***	15779.250***	14781.294***
	(1405.064)	(2671.792)	(2192.217)	(1388.834)
Mean of dep. var.	14274.51	16371.78	15478.69	14201.63
[Panel C] Present Value of Earnings				
Ever Enrolled College	-5452.007	-1260.298	-2984.538	-6742.198*
	(4844.754)	(10003.812)	(7276.365)	(4044.439)
Mean of dep. var.	25120.83	33490.73	26712.53	20881.42
Obs.	80372	23063	49359	80372

Note 1: The table shows the 2SLS estimates that capture the causal effect of college enrollment on different discounted values around the 475-point cutoff. Panel A uses the NPV of earnings minus costs; Panel B uses the present value of Direct Costs; and Panel C uses the present value of earnings. Each column shows the estimates for different time horizons. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts, while Columns (2) to (4) show the same estimates but considering different time windows in the NPV calculations. The different horizon implies a different representation of the various cohorts. For example, the NPV after 11 years includes only the 2006 cohort observed in 2017, whereas the NPV after ten years includes the 2006 cohort in 2016 and 2007 the cohort in 2017). We consider the records between 2014 and February 2018. We use a six-percent discount rate and express the values in 2017 pesos. All the regressions consider local linear polynomials.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table 9: Growth Rate for College Optimality

[Panel A] Estimated Yearly Growth Rate for College and Vocational Earnings

	College Estimated	Vocational Estimated
	(1)	(2)
Yearly Growth Rate Age 25-45	5.5%	4.8%
Yearly Growth Rate Age 25-65	3.2%	2.7%

Note 1: The table shows the yearly growth rate of College and Vocational graduates, combining the first observed earnings (age 25-30) and the forecasted earnings for ages above 30. We assume the standard Mincer equation with returns to experience and squared experience as described in Appendix E. We consider that vocational graduates have two years more of experience than college graduates. The first row uses a horizon of 20 years, while the second row uses the entire life-cycle. The concave pattern of the estimated returns leads to lower profits at older ages.

[Panel B] Minimum Yearly Growth Rate for College Earnings to have the same NPV of Vocational Education

	Discount Rate 2%	Discount Rate 6%
	(1)	(2)
Required Growth Rate of College Earnings at Age 25-45	4.3%	6.6%
Required Growth Rate of College Earnings at Age 25-65	2.6%	3.7%

Note 2: The table shows the yearly growth rate required for college earnings to have the same net present value (NPV) of those of vocational education under a discount rate of 2 percent (Column (1)) and 6 percent (Column (2)). The NPV of Vocational education considers observed cheaper tuition fees and flatter pattern of earnings than college graduates at older ages, as captured by the estimates of experience squared presented in Table (E.1). The first row uses a horizon of 20 years (age 25-45), while the second row uses the entire life-cycle (age 25-65). The concave pattern of the estimated returns leads to lower profits at older ages.

Web Appendix[For Online Publication Only]

A Appendix: First Stage Details

A.1 Debt By Cohort

Table A.1: First Stage Estimates. Loan Amounts and Scholarships at the 475-point cutoff by Cohort.

	College loan	Bicentenario grant	Any grant	Any aid
	(1)	(2)	(3)	(4)
[A.] Cohort 2006				
$\mathbb{1}(T_{i0} \geqslant 475)$	297.63***	0.00	18.88***	310.42***
	(10.184)	(.)	(5.011)	(13.450)
Const.	0.24	0.00	58.07***	179.22***
	(0.167)	(.)	(2.745)	(6.973)
Obs.	23063	23063	23063	23063
[B.] Cohort 2007				
$\mathbb{1}(T_{i0} \geqslant 475)$	237.75***	0.00	25.28***	265.94***
	(9.448)	(.)	(4.574)	(11.364)
Const.	1.02	0.00	45.60***	103.27***
	(0.800)	(.)	(2.328)	(4.977)
Obs.	26296	26296	26296	26296
[C.] Cohort 2008				
$\mathbb{1}(T_{i0} \geqslant 475)$	244.74***	0.00	-3.12	234.20***
	(9.605)	(.)	(5.598)	(12.347)
Const.	5.52***	0.00	115.44***	214.54***
	(1.321)	(.)	(3.711)	(6.412)
Obs.	31013	31013	31013	31013

Note 1: The table shows the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (First Stage) using the amount in student loans and scholarships as dependent variables for different admission cohorts. We use the sample of admission cohort 2006, 2007 and 2008 in Panels A, B, and C respectively. Each column shows the estimates using different dependent variables: Column (1) uses the amount in student loans; Column (2) uses the amount in the Bicentenario scholarship; Column (3) uses the amount in any public scholarship, and Column (4) uses the sum in all loans and scholarships. All the regressions consider local linear regressions. The sample corresponds to PSU-takers classified between quintiles one to four.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table A.2: First Stage Estimates. Probability of Loans and Scholarships at the 475-point cutoff by Cohort.

	College loan	Bicentenario grant	Any grant	Any aid
	(1)	(2)	(3)	(4)
[A.] Cohort 2006				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.25***	0.00	-0.01	0.22***
	(0.008)	(.)	(0.009)	(0.012)
Const.	0.00	0.00	0.14***	0.22***
	(0.000)	(.)	(0.007)	(0.008)
Obs.	23063	23063	23063	23063
[B.] Cohort 2007				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.19***	0.00	0.02**	0.19***
	(0.007)	(.)	(0.008)	(0.011)
Const.	0.00	0.00	0.11***	0.16***
	(.)	(.)	(0.006)	(0.007)
Obs.	26296	26296	26296	26296
[C.] Cohort 2008				
$\mathbb{1}(T_{i0} \geqslant 475)$	0.19***	0.00	-0.03***	0.13***
	(0.007)	(.)	(0.009)	(0.011)
Const.	-0.00	0.00	0.22***	0.28***
	(.)	(.)	(0.007)	(0.007)
Obs.	31013	31013	31013	31013

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (First Stage) using the take-up of student loans and scholarships as dependent variables for different admission cohorts. We use the sample of admission cohort 2006, 2007 and 2008 in Panels A, B, and C respectively. Each column shows the estimates using different dependent variables: Column (1) uses the indicator variable whether the student borrows a student loans; Column (2) uses the indicator variable whether the student obtains the Bicentenario scholarship; Column (3) uses the indicator variable whether the student receives any public scholarship, and Column (4) uses the indicator variable whether the student obtains any loan or scholarships. All the regressions consider local linear regressions. The sample corresponds to PSU-takers classified between quintiles one to four.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table A.3: First Stage Estimates. Loan Amounts and Scholarships about at the 550-point cutoff by Cohort.

	College loan	Bicentenario grant	Any grant	Any aid
	(1)	(2)	(3)	(4)
[A.] Cohort 2006				
$\mathbb{1}(T_{i0} \geqslant 550)$	-382.22***	486.75***	402.24***	10.06
	(20.239)	(13.974)	(15.476)	(22.711)
Const.	723.48***	0.00	141.43***	924.15***
	(15.544)	(0.000)	(7.136)	(15.551)
Obs.	13705	13705	13705	13705
[B.] Cohort 2007				
$\mathbb{1}(T_{i0} \geqslant 550)$	-491.43***	571.48***	489.31***	-1.39
	(17.845)	(16.645)	(17.874)	(23.274)
Const.	611.25***	0.26	132.09***	767.17***
	(15.263)	(0.264)	(7.182)	(15.967)
Obs.	15682	15682	15682	15682
[C.] Cohort 2008				
$\mathbb{1}(T_{i0} \geqslant 550)$	-475.66***	606.35***	523.40***	41.30*
	(19.219)	(17.029)	(17.824)	(23.612)
Const.	663.82***	-0.00	143.94***	856.00***
	(15.777)	(0.000)	(6.744)	(16.165)
Obs.	18300	18300	18300	18300

Note 1: The table shows the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 550)$ in Equation (First Stage) using the amount in student loans and scholarships as dependent variables for different admission cohorts. We use the sample of admission cohort 2006, 2007 and 2008 in Panels A, B, and C respectively. Each column shows the estimates using different dependent variables: Column (1) uses the amount in student loans; Column (2) uses the amount in the Bicentenario scholarship; Column (3) uses the amount in any public scholarship; and Column (4) uses the sum in all loans and scholarships. All the regressions consider local linear regressions. The sample corresponds to PSU-takers classified in quintiles one and two.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table A.4: First Stage Estimates. Probability of Loans and Scholarships at the 550-point cutoff by Cohort.

	College loan	Bicentenario grant	Any grant	Any aid
	(1)	(2)	(3)	(4)
[A.] Cohort 2006				
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.12***	0.43***	0.33***	0.00
	(0.017)	(0.012)	(0.015)	(0.015)
Const.	0.60***	-0.00	0.18***	0.70***
	(0.011)	(0.000)	(0.009)	(0.011)
Obs.	13705	13705	13705	13705
[B.] Cohort 2007				
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.39***	0.41***	0.32***	0.00
	(0.013)	(0.011)	(0.014)	(0.016)
Const.	0.47***	0.00	0.16***	0.56***
	(0.011)	(0.000)	(0.008)	(0.011)
Obs.	15682	15682	15682	15682
[C.] Cohort 2008				
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.35***	0.39***	0.30***	0.03*
	(0.012)	(0.010)	(0.014)	(0.014)
Const.	0.47***	-0.00	0.20***	0.59***
	(0.010)	(.)	(0.008)	(0.010)
Obs.	18300	18300	18300	18300

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 550)$ in Equation (First Stage) using the take-up of student loans and scholarships as dependent variables for different admission cohorts. We use the sample of admission cohort 2006, 2007 and 2008 in Panels A, B, and C respectively. Each column shows the estimates using different dependent variables: Column (1) uses the indicator variable whether the student borrows a student loans; Column (2) uses the indicator variable whether the student obtains the Bicentenario scholarship; Column (3) uses the indicator variable whether the student receives any public scholarship; and Column (4) uses the indicator variable whether the student obtains any loan or scholarships. All the regressions consider local linear regressions. The sample corresponds to PSU-takers classified in quintiles one and two.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

A.2 Enrollment by Cohort

Table A.5: First Stage Estimates: College, Higher Education and Ever Enrollment. Cohort 2006
[A]. At 475-Point Cutoff

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	0.14***	0.10***	0.08***	0.01**
	(0.012)	(0.013)	(0.013)	(0.006)
Const.	0.24***	0.55***	0.57***	0.94***
	(0.008)	(0.010)	(0.010)	(0.005)
Obs.	23063	23063	23063	23063

[B]. At 550-Point Cutoff

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	0.03	0.02	0.01	-0.00
	(0.016)	(0.012)	(0.015)	(0.005)
Const.	0.64***	0.86***	0.76***	0.98***
	(0.011)	(0.009)	(0.010)	(0.003)
Obs.	13705	13705	13705	13705

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation(First Stage) using different educational outcomes as dependent variables. Panel A shows the estimates around the 475 PSU score cutoff, and Panel B shows the estimates around the 550-point cutoff. As the dependent variable, we consider a dummy indicator if the student enrolled in college after her first PSU attempt (Column (1)), a dummy indicator if the student ever enrolled in college (Column (2)), a dummy indicator if the student enrolled in higher education (college or vocational) after her first PSU attempt (Column (3)), and a dummy indicator if the student ever enrolled in higher education (college or vocational) (Column (4)). All the regressions consider local linear polynomials. The sample corresponds to the admission cohort 2006.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table A.6: First Stage Estimates: College, Higher Education and Ever Enrollment. Cohort 2007

[A]. At 475-Point Cutoff

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	0.15***	0.06***	0.11***	0.00
	(0.011)	(0.012)	(0.012)	(0.006)
Const.	0.21***	0.57***	0.51***	0.95***
	(0.007)	(0.009)	(0.009)	(0.004)
Obs.	26296	26296	26296	26296

[B]. At 550-Point Cutoff

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-0.01	-0.01	-0.01	-0.01
	(0.015)	(0.011)	(0.014)	(0.005)
Const.	0.63***	0.87***	0.72***	0.98***
	(0.011)	(0.008)	(0.010)	(0.003)
Obs.	15682	15682	15682	15682

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation(First Stage) using different educational outcomes as dependent variables. Panel A shows the estimates around the 475 PSU score cutoff, and Panel B shows the estimates around the 550-point cutoff. As the dependent variable, we consider a dummy indicator if the student enrolled in college after her first PSU attempt (Column (1)), a dummy indicator if the student ever enrolled in college (Column (2)), a dummy indicator if the student enrolled in higher education (college or vocational) after her first PSU attempt (Column (3)), and a dummy indicator if the student ever enrolled in higher education (college or vocational) (Column (4)). All the regressions consider local linear polynomials. The sample corresponds to the admission cohort 2007.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table A.7: First Stage Estimates: College, Higher Education and Ever Enrollment. Cohort 2008

[A]. At 475-Point Cutoff

	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	0.16***	0.09***	0.09***	0.00
	(0.010)	(0.011)	(0.011)	(0.005)
Const.	0.19***	0.52***	0.56***	0.95***
	(0.006)	(0.008)	(0.008)	(0.004)
Obs.	31013	31013	31013	31013

[B]. At 550-Point Cutoff

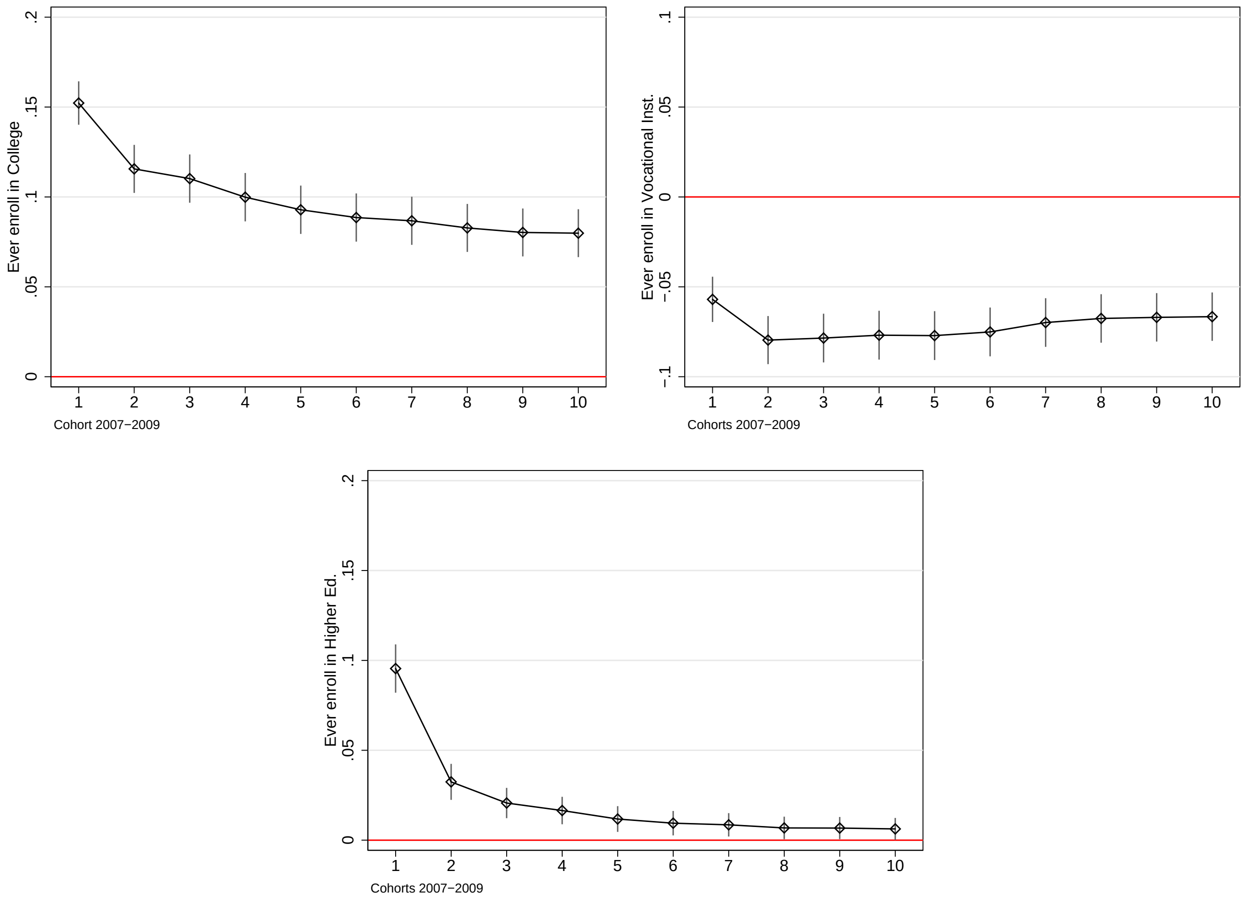
	College Enrollment	Ever enrolled College	Higher Ed. Enrollment	Ever Higher Education
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	0.03**	0.02*	0.02*	0.00
	(0.014)	(0.011)	(0.013)	(0.004)
Const.	0.60***	0.84***	0.74***	0.98***
	(0.010)	(0.008)	(0.009)	(0.003)
Obs.	18300	18300	18300	18300

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation(First Stage) using different educational outcomes as dependent variables. Panel A shows the estimates around the 475 PSU score cutoff, and Panel B shows the estimates around the 550-point cutoff. As the dependent variable, we consider a dummy indicator if the student enrolled in college after her first PSU attempt (Column (1)), a dummy indicator if the student ever enrolled in college (Column (2)), a dummy indicator if the student enrolled in higher education (college or vocational) after her first PSU attempt (Column (3)), and a dummy indicator if the student ever enrolled in higher education (college or vocational) (Column (4)). All the regressions consider local linear polynomials. The sample corresponds to the admission cohort 2008.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

A.3 Long-run effects on Higher Education Enrollment

Figure A.1: Higher Education enrollment at the 475-point Cutoff over time



***Note*:** The figures show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant c)$ in Equation (2) for a different number of years after school graduation of the first-time PSU takers. The dependent variable is the enrollment for different types of higher education. The figure at the top presents the college enrollment; the middle figure shows the vocational enrollment and the bottom figure depicts the overall enrollment in any higher education institution. The sample corresponds to the universe of students who took the PSU in the admission cohorts from 2006 to 2008, and who are outside the top quintile in the earnings distribution. The figure shows after ten years the gap created by the loan programs persist. These results support a long-run effect of the loan program in educational choices that validate our approach.

B Appendix: Details on Graduation Rates

Table B.1: Graduation Rates at the 475-point cutoff. Reduced Form Estimates

[A] Graduation rates from College. Reduced Form

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	0.04***	0.04***	0.02**	0.04***
	(0.006)	(0.012)	(0.010)	(0.008)
Const.	0.20***	0.25***	0.22***	0.15***
	(0.004)	(0.008)	(0.007)	(0.006)
Mean of dep. var.				
Obs.	80372	23063	26296	31013

[B] Graduation rates from Vocational. Reduced Form

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	-0.05***	-0.05***	-0.03***	-0.06***
	(0.006)	(0.012)	(0.011)	(0.010)
Const.	0.31***	0.32***	0.30***	0.31***
	(0.005)	(0.009)	(0.008)	(0.008)
Obs.	80372	23063	26296	31013

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (2) using graduation rates as dependent variables. The estimate captures the effects of being eligible for the loan programs on college graduation (Panel A) and vocational graduation (Panel B). The first column shows the results for the three cohorts pooled together, while column (2) to (4) show the effects by cohort. All the regressions consider local linear polynomials. The sample corresponds to the pool of admission cohorts 2006, 2007 and 2008.

Note 2: *: p-value<.1; **: p-value<.05; ***: p-value<.01. Robust to heteroskedasticity standard errors in parenthesis.

C Appendix: Details on Labor Market Outcomes

Table C.1: Labor Experience at 550-point cutoff. 2SLS Estimates
[Panel A] Experience at the 550-point cutoff

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-128.35	-38.98	1566.17	-38.19
	(160.762)	(146.946)	(32292.578)	(84.564)
Mean of dep. var.	34	40	34	28
Obs.	75225	22162	24989	28074

Note 1: The tables show the 2SLS estimates of college enrollment on labor experience at the 550-point cutoff (Panel B). Column (1) shows the results for the three cohorts pooled together, while columns (2) to (4) show the effects by cohort. All the regressions consider local linear polynomials. The sample corresponds to the pool of admission cohorts 2006, 2007 and 2008.
Note 2: *: p-value$< .1$; **: p-value$< .05$; ***: p-value$< .01$. Robust to heteroskedasticity standard errors in parenthesis.

Table C.2: Effects on Annual Earnings at the 475-point cutoff by cohort

[Panel A]. Cohort 2006

	Earnings in 2017	Earnings in 2016	Earnings in 2015	Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	111.82	22.53	62.04	108.25
	(152.993)	(141.667)	(131.822)	(118.746)
Const.	4879.29***	4595.60***	4232.26***	3629.78***
	(109.453)	(101.563)	(94.000)	(83.855)
Obs.	23063	23063	23063	23063

[Panel B]. Cohort 2007

	Earnings in 2017	Earnings in 2016	Earnings in 2015	Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	6.87	19.22	53.99	-7.74
	(133.853)	(122.038)	(110.937)	(99.741)
Const.	4480.41***	4034.13***	3508.70***	3033.16***
	(95.502)	(86.417)	(78.430)	(71.705)
Obs.	26296	26296	26296	26296

[Panel C]. Cohort 2008

	Earnings in 2017	Earnings in 2016	Earnings in 2015	Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	-63.95	-146.81	-108.36	-112.33
	(108.799)	(98.672)	(87.992)	(74.704)
Const.	3951.16***	3576.25***	3014.77***	2407.15***
	(76.031)	(69.287)	(61.891)	(53.128)
Obs.	31013	31013	31013	31013

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (2) using annual earnings as dependent variables. Panel A uses the 2006 cohort, Panel B uses the 2007 cohort, and Panel C uses the 2008 cohort. Column (1) shows the estimates when considering the Earnings in 2017. Columns (2) to (4) use the Earnings from 2016 to 2014 respectively. All the regressions consider local linear polynomials.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table C.3: Annual Earnings at the 550 by cohort. Reduced Form Estimates

[Panel A]. Cohort 2006

	Annual Earnings in 2017	Annual Earnings in 2016	Annual Earnings in 2015	Annual Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	77.37	52.77	-26.24	48.73
	(180.958)	(167.725)	(153.311)	(133.178)
Const.	5524.05***	5013.80***	4408.36***	3595.98***
	(122.208)	(113.646)	(104.443)	(91.172)
Obs.	22162	22162	22162	22162

[Panel B]. Cohort 2007

	Annual Earnings in 2017	Annual Earnings in 2016	Annual Earnings in 2015	Annual Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-174.25	-144.20	-164.05	-220.28**
	(155.805)	(140.661)	(123.801)	(102.812)
Const.	5067.46***	4384.58***	3614.26***	2727.03***
	(107.953)	(97.789)	(86.890)	(73.392)
Obs.	24989	24989	24989	24989

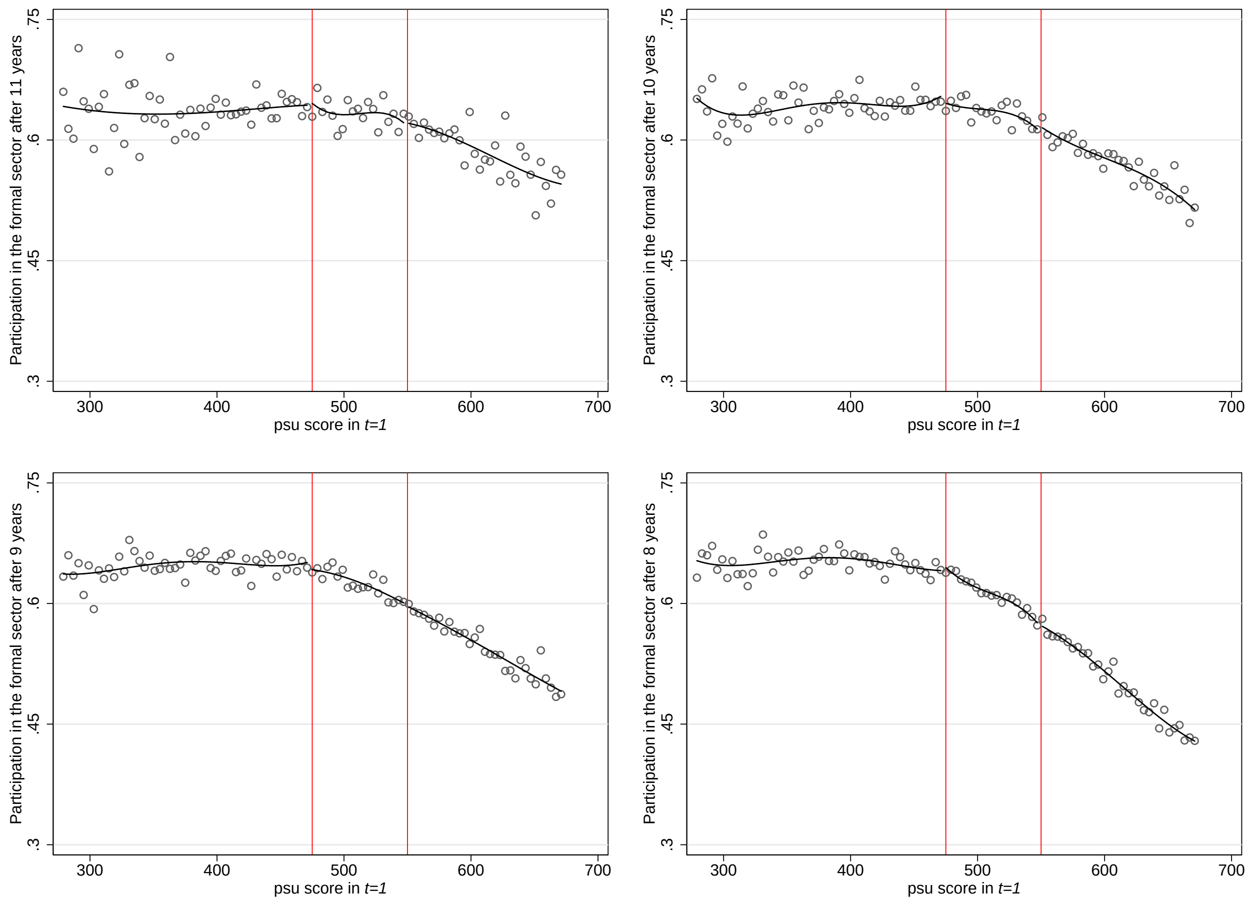
[Panel C]. Cohort 2008

	Annual Earnings in 2017	Annual Earnings in 2016	Annual Earnings in 2015	Annual Earnings in 2014
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-74.41	-20.82	59.22	-6.50
	(130.091)	(114.278)	(97.147)	(75.075)
Const.	4111.52***	3361.10***	2575.87***	1737.29***
	(90.618)	(80.176)	(69.111)	(54.312)
Obs.	28074	28074	28074	28074

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 550)$ in Equation (2) using annual earnings as dependent variables. Panel A uses the 2006 cohort, Panel B uses the 2007 cohort, and Panel C uses the 2008 cohort. Column (1) shows the estimates when considering the Earnings in 2017. Columns (2) to (4) use the Earnings from 2016 to 2014 respectively. All the regressions consider local linear polynomials.

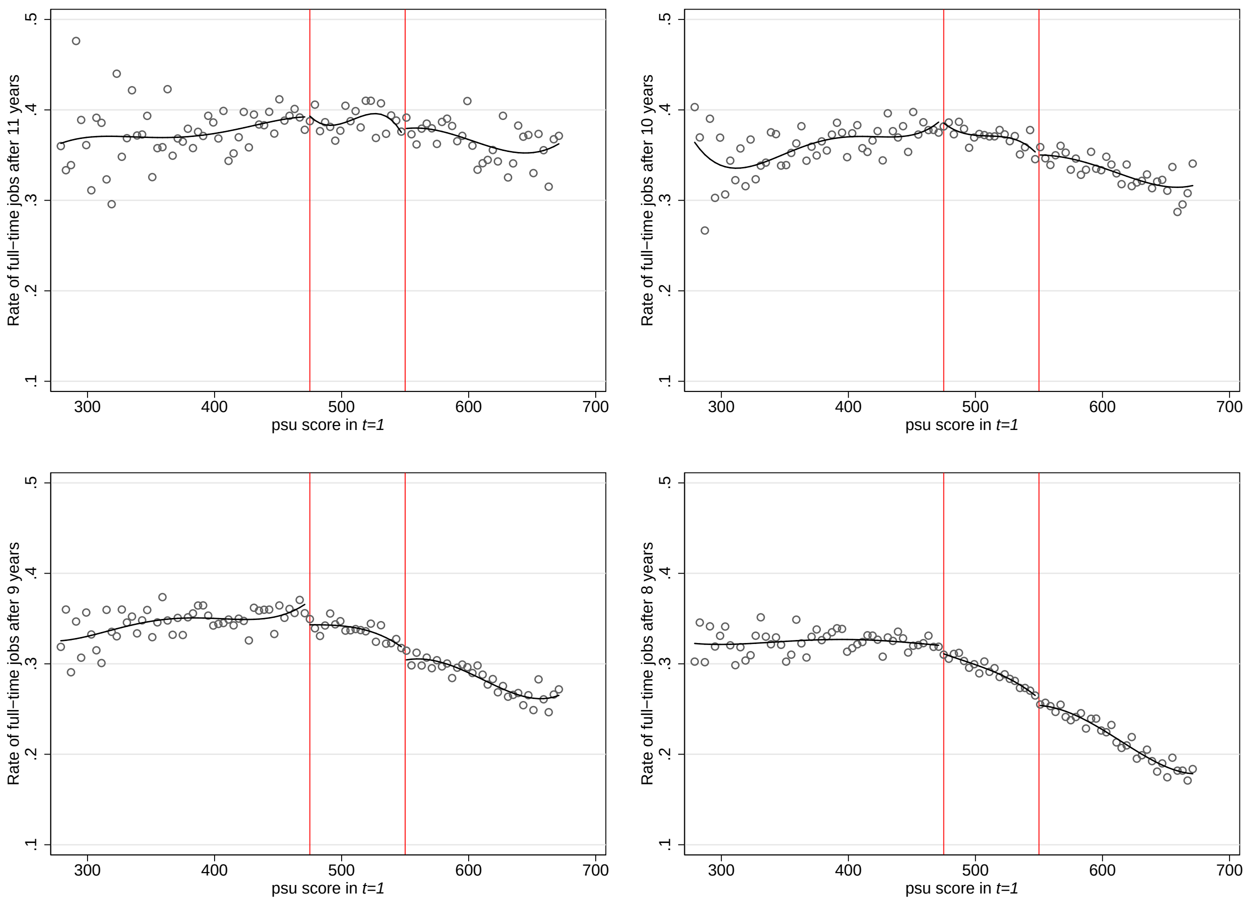
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Figure C.1: Labor Participation around the Eligibility cutoffs after t years



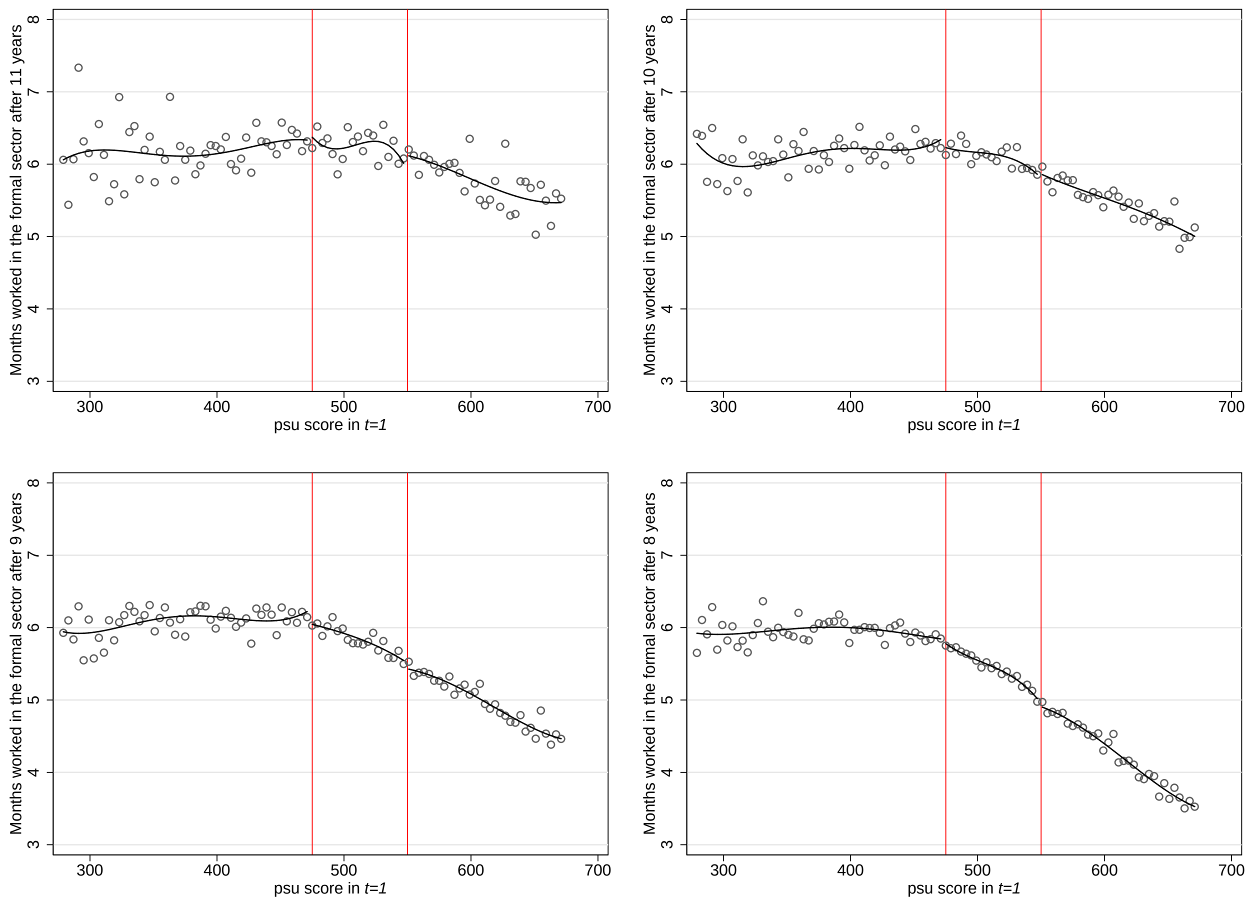
***Note*:** The figures present the average formal sector participation of students after t years of their first attempt at the PSU admission test. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The top-left figure shows the 11-year analysis; hence, it considers the first-time PSU takers in November of 2006 (cohort 2006) in the labor market in 2017. Similarly, the top-right figure shows the ten-year analysis; hence, it considers the first-time PSU takers in November of 2007 (cohort 2007) in the labor market in 2017 and the admission cohort 2006 in the labor market in 2016. The bottom-left figure shows the nine-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of 2015, 2016 and 2017, respectively. The bottom-right figure shows the eight-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of the years 2014, 2015 and 2016, respectively.

Figure C.2: Job Stability around the Eligibility cutoffs after t years



***Note*:** The figures present the average rate of stable jobs of PSU takers after t years of high-school graduation. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The top-left figure shows the 11-year analysis; hence, it considers the first-time PSU takers in November of 2006 (cohort 2006) in the labor market in 2017. Similarly, the top-right figure shows the ten-year analysis; hence, it considers the first-time PSU takers in November of 2007 (cohort 2007) in the labor market in 2017 and the admission cohort 2006 in the labor market in 2016. The bottom-left figure shows the nine-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of 2015, 2016 and 2017, respectively. The bottom-right figure shows the eight-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of the years 2014, 2015 and 2016, respectively.

Figure C.3: Labor Intensive Margin around the Eligibility cutoffs after t years



***Note*:** The figures present labor intensive margins measured as the average number of months worked by the students after t years of their first attempt at the PSU admission test. Each dot represents a bin of 4 PSU-points, and the solid line represents the fitted values from a fourth order polynomial for the PSU score. The vertical lines correspond to the SG loan cutoff (475) and the Bicentenario scholarship cutoff (550). The top-left figure shows the 11-year analysis; hence, it considers the first-time PSU takers in November of 2006 (cohort 2006) in the labor market in 2017. Similarly, the top-right figure shows the ten-year analysis; hence, it considers the first-time PSU takers in November of 2007 (cohort 2007) in the labor market in 2017 and the admission cohort 2006 in the labor market in 2016. The bottom-left figure shows the nine-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of 2015, 2016 and 2017, respectively. The bottom-right figure shows the eight-year analysis, so it considers the admission cohort 2006, 2007 and 2008, in the labor markets of the years 2014, 2015 and 2016, respectively.

D Appendix. Details on Present Discounted Values

D.1 Reduced form

Table D.1: Net present value of the Investment at the 475-point cutoff. Reduced Form Estimates

	Pooled cohorts 2007-2009 in Feb 2018	NPV after 11 years	NPV after 10 years	NPV after 9 years
	(1)	(2)	(3)	(4)
[Panel A] Net Present Value, NPV				
$\mathbb{1}(T_{i0} \geqslant 475)$	-1618.988***	-1617.390	-1331.317**	-1718.562***
	(436.275)	(997.855)	(587.043)	(381.438)
Const.	12368.898***	18789.511***	12688.445***	8207.974***
	(310.177)	(717.647)	(423.211)	(271.942)
N	80372	23063	49359	80372
[Panel B] Present Value of Direct Costs				
$\mathbb{1}(T_{i0} \geqslant 475)$	1183.668***	1503.485***	1119.560***	1180.225***
	(129.212)	(275.602)	(178.547)	(127.375)
Const.	13248.346***	15071.028***	14438.505***	13169.302***
	(89.281)	(195.746)	(125.185)	(87.868)
N	80372	23063	49359	80372
[Panel C] Present Value of Earnings				
$\mathbb{1}(T_{i0} \geqslant 475)$	-435.320	-113.905	-211.757	-538.337
	(391.064)	(906.399)	(520.073)	(328.584)
Const.	25617.244***	33860.539***	27126.950***	21377.276***
	(280.455)	(654.641)	(377.836)	(237.251)
Obs.	80372	23063	49359	80372

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (2) using different present values as dependent variables. Panel A uses the NPV of earnings minus costs, Panel B uses the present value of Direct Costs, and Panel C uses the present value of earnings. Each column shows the estimates for different time horizons. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts while Columns (2) to (4) shows the same estimates but considering different time windows in the NPV calculations. The different horizon implies a different representation of the different cohorts. We consider records between 2014 and February 2018. We use a 6 percent discount rate and express the values in pesos of 2017. All the regressions consider local linear polynomials.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

D.2 NPV Analysis by Cohort

Table D.2: Net Present Value of the Investment by cohorts at 475. 2SLS Estimates
[Panel A] Net Present Discounted Value, NPV

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-12317.92***	-8149.06	-9966.82	-17463.50***
	(4211.844)	(8023.921)	(11046.050)	(4778.437)
Mean of dep. var.	11105	15756	11049	7694
Obs.	80372	23063	26296	31013

[Panel B] Present Value of Direct Costs

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	8862.5***	8901.1***	8141.6**	9198.6***
	(9.25)	(5.36)	(3.22)	(7.45)
Mean of dep. var.	9522	9720	9762	9172
Obs.	80372	23063	26296	31013

[Panel C] Present Value of Earnings

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-3455.43	752.04	-1825.26	-8264.90*
	(3963.580)	(7653.662)	(10359.261)	(4394.739)
Mean of dep. var.	20628	25476	20811	16867
Obs.	80372	23063	26296	31013

Note 1: The tables show the 2SLS estimates that capture the causal effect of college enrollment on different discounted values around the 475-point cutoff. Panel A uses the NPV of earnings minus costs, Panel B uses the present value of Direct Costs, and Panel C uses the present value of earnings. Each column shows the estimates for different time horizons. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts while Columns (2) to (4) shows the same estimates but considering different cohorts of PSU-takers. The calculations use the earnings in 2017. We use a 6 percent discount rate and express the values in pesos of 2017. All the regressions consider local linear polynomials.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table D.3: Net Present Value of the Investment by cohorts at 550. 2SLS Estimates

[Panel A] Net Present Discounted Value, NPV

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-89626.25	-10466.42	1631850.45	-2859.06
	(120310.575)	(136701.630)	(33601218.207)	(68440.177)
Mean of dep. var.	4910	10834	4681	438
Obs.	75225	22162	24989	28074

[Panel B] Present Value of Direct Costs

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-10726.6	1933.9	423159.3	1839.5
	(-0.32)	(0.06)	(0.05)	(0.08)
Mean of dep. var.	14093	13926	14428	13928
Obs.	75225	22162	24989	28074

[Panel C] Present Value of Earnings

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
Ever Enroll College	-100352.86	-8532.57	2055009.84	-1019.61
	(131869.534)	(126079.917)	(41986803.249)	(58455.868)
Mean of dep. var.	19003	24760	19109	14365
Obs.	75225	22162	24989	28074

Table D.4: Net Present Value of the Investment by cohorts at 475. Reduced Form Estimates

[Panel A] Net Present Discounted Value, NPV

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	-1618.99***	-1525.84	-1014.49	-2301.34***
	(436.275)	(941.373)	(776.756)	(581.144)
Const.	12368.90***	17725.95***	11933.41***	8719.61***
	(310.177)	(677.025)	(559.920)	(406.936)
Obs.	80372	23063	26296	31013

[Panel B] Present Value of Direct Costs

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	1183.67***	1418.38***	813.15***	1305.89***
	(129.212)	(260.002)	(231.792)	(187.582)
Const.	13248.35***	14217.95***	13797.63***	12049.24***
	(89.281)	(184.666)	(160.645)	(126.022)
Obs.	80372	23063	26296	31013

[Panel C] Present Value of Earnings

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 475)$	-435.32	-107.46	-201.34	-995.45**
	(391.064)	(855.093)	(689.351)	(503.870)
Const.	25617.24***	31943.90***	25731.04***	20768.84***
	(280.455)	(617.586)	(501.732)	(358.863)
Obs.	80372	23063	26296	31013

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 475)$ in Equation (2) using different present values as dependent variables. Panel A uses the NPV of earnings minus costs, Panel B uses the present value of Direct Costs, and Panel C uses the present value of earnings. Each column shows the estimates for different time horizons. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts while Columns (2) to (4) shows the same estimates but considering different cohorts of PSU-takers. The calculations use the earnings in 2017. We use a 6 percent discount rate and express the values in pesos of 2017. All the regressions consider local linear polynomials.
Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

Table D.5: Net Present Value of the Investment by cohorts at 550. Reduced Form Estimates

[Panel A] Net Present Discounted Value, NPV

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-463.48	-209.37	-735.05	-51.49
	(462.334)	(1008.638)	(788.549)	(607.792)
Const.	1082.14***	7138.92***	758.92	-3745.39***
	(327.005)	(703.544)	(559.723)	(432.300)
Obs.	75225	22162	24989	28074

[Panel B] Present Value of Direct Costs

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-60.61	20.74	-209.16	74.42
	(155.455)	(302.947)	(274.747)	(233.346)
Const.	21374.45***	22444.94***	22066.72***	19854.83***
	(107.750)	(209.315)	(190.139)	(161.609)
Obs.	75225	22162	24989	28074

[Panel C] Present Value of Earnings

	Pooled cohorts 2007-2009	Cohort 2007	Cohort 2008	Cohort 2009
	(1)	(2)	(3)	(4)
$\mathbb{1}(T_{i0} \geqslant 550)$	-524.09	-188.63	-944.22	22.92
	(400.895)	(896.131)	(669.679)	(496.570)
Const.	22456.60***	29583.86***	22825.64***	16109.44***
	(284.260)	(625.473)	(475.582)	(356.806)
Obs.	75225	22162	24989	28074

Note 1: The tables show the estimated coefficient of $\mathbb{1}(T_{i0} \geqslant 550)$ in Equation (2) using different present values as dependent variables. Panel A uses the NPV of earnings minus costs, Panel B uses the present value of Direct Costs, and Panel C uses the present value of earnings. Each column shows the estimates for different time horizons. Column (1) shows the estimates when considering the 2006-2008 pool of cohorts while Columns (2) to (4) shows the same estimates but considering different cohorts of PSU-takers. The calculations use the earnings in 2017. We use a 6 percent discount rate and express the values in pesos of 2017. All the regressions consider local linear polynomials.

Note 2: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.

E Appendix. Details on Mincer Estimation

Table E.1: Mincer Equation Estimates

Dep Var log(Earning)	(1) High School	(2) Vocational	(3) College
Education	0.0659***	0.1638***	0.1860***
Experience	0.0287***	0.0437***	0.0540***
Experience Squared	-0.0004***	-0.0006***	-0.0008***
N	28413	6099	11943
r2	0.2460	0.3461	0.4125

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note 1: We estimate the following OLS regression: $\ln(w_i) = \alpha + \beta E_i + \gamma_1 S_i + \gamma_2 S_i^2 + \delta X_i + v_i$, where $\ln(w_i)$ is the log of earnings (plus one to keep observations with zero earnings), E_i is education and S_i is the accumulated labor experience, and X_i are other controls for individual i such as gender, health-status or productive-sector fixed effects. v_i is the unobservable random shock. β is the marginal return to an extra year of education, and $\gamma_1 - 2\gamma_2 S_i$ is the marginal return to an extra year of labor experience. We estimate the model separately for workers with a high school education, vocational education (less than a four-year degree) and college education (more than a four- year degree). We use the household survey CASEN 2011.

Note 2: Variable earning corresponds to the individual's annual labor income in 2011, accumulated work experience is approximated as the individual's age minus schooling minus 6 years, the accumulated experience variable is also squared to consider a concave pattern of wages over the life cycle. We use the state of health of the individual self-declared by the individual, measured categorical variable 1 if the health is very bad to 7 considering a very good health, and also county fixed effects.

Note 3: *: p-value< .1; **: p-value< .05; ***: p-value< .01. Robust to heteroskedasticity standard errors in parenthesis.