STUDENT LOANS, COLLEGE CHOICE AND THE RETURNS TO HIGHER EDUCATION

by

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This paper studies how access to student loans affects where and what students choose to study, and whether loan access effects vary depending on information students have on likely financial outcomes. We first document that labor market outcomes for observationally equivalent students are highly heterogeneous across degree programs, with larger returns for more selective degrees. We then use a regression discontinuity design based on a cutoff for student loan eligibility to show that although access to loans increases the probability students enroll in college, the expected labor market return from loan access is insignificant and near zero. This is because loan access shifts students into higher-cost, lower return degrees. Surveys suggest one possible explanation: potential loan recipients often have little information on the financial outcomes associated with different degree programs. We test the efficacy of informational interventions through large-scale field experiment in we provided students with information on financial outcomes for graduates of degrees in their choice sets. We find that access to this information shifts students without loan access towards degrees with higher returns, but does not affect choice for students with loan access. Our results suggest a role for supply-side policies in matching students to high return degree programs, and help interpret changes in the Chilean higher education market following a student loan reform in 2006.

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1 Introduction

Expanding access to tertiary education is a critical tool for policymakers aiming to promote economic growth and equity of opportunity. Federal student loans and grants form a key component of the policy effort to expand access to higher education for students from low-income backgrounds. If these programs succeed in helping liquidity-constrained students make profitable investments in their future earnings, the social returns could be large. However, if students taking loans have limited information about their educational options, face biases or high decision making costs, their loan-funded educational investments may not raise income prospects or social welfare more broadly. There may also be unintended secondary market impacts. Increased demand and dollars in the hands of limited decision makers may change which institutions target loan-taking students (Deming, Goldin and Katz 2012), raise the price of education, and change market structure more generally.

In the context of rising default rates on student loans, policy makers and economists hypothesize that loan takers may choose lower-return, higher-cost degrees based on poor information and marketing. This has led to higher-education reform proposals ranging from regulating which institutions can receive loan dollars, to rating schools, to indirectly capping tuition by tying federal aid to tuition costs.[1] However, there is little research to guide policy reforms; data on returns to specific degree programs are limited, as are data on how students make educational investment decisions, how loans impact those decisions, and the resulting impact on market structure.

We investigate these questions by combining large-scale natural- and field-experimental research designs with new administrative data on educational and labor market outcomes for fourteen cohorts of Chilean high school graduates. Chile, a middle-income OECD member country, implemented a major student loan reform in 2006. The Programa de Credito con Aval del Estado (CAE) expanded access to federally subsidized student loans to students at all accredited degree programs. Previously, federally subsidized loans had been available only to students in elite universities. Following the reform, the fraction of higher education revenues in Chile coming from loan dollars rose by 170%, and college enrollment rates rose by more than 50% as a fraction of the college-aged population, from 48% in 2005 to 74% in 2012.[2] Today, rates of educational attainment and the share of higher education revenues coming from loans are similar to those in the US.[3] These changes occurred in the context of a higher education

[1] U.S. Gainful Employment Act, 2014. 2012 U.S. presidential State of the Union Address.
[2] Source: World Bank (2014). http://data.worldbank.org/indicator/SE.TER.ENRR/countries?page=1
[3] 38 percent of adults between 25 and 24 years old in Chile in 2010 had tertiary degree, compared to 42% in the US. Source: OECD 2013.

marketplace that is in many ways similar to that in the US. As in the US, the higher education market in Chile contains a mix of public, private non-profit, and private for-profit firms.

Our paper has three main components. First, we construct estimates of the earnings gains associated with enrollment in nearly all of the degree choices available to Chilean students. We benchmark our results to regression discontinuity estimates reported in Hastings, Neilson, and Zimmerman (2013). Second, we combine these estimates with a regression discontinuity in loan eligibility to evaluate how loan access affects the types of degrees that students choose. Third, we present the results of a field experiment in which we randomized the provision of information about degree-specific labor market outcomes to a large sample of college applicants, and describe how treatment effects vary with loan access. We conclude with a discussion of the way the effects we document can help rationalize broad changes in the Chilean higher education market since the 2006 loan reform.

We conduct these analyses using an administrative database compiled from electronic and archival records in collaboration with the Chilean government. Our data cover fourteen cohorts of high school graduates surrounding the 2006 introduction of the loan program. It links individual-level high school records, entrance exam records, higher education applications, matriculation and graduation records, and federal loan and repayment data to labor market outcomes from tax returns for students completing high school between 2000 and 2013. We link these records to survey and experimental outcomes that designed and collected in collaboration with the Chilean Ministry of Education (MINEDUC).

Our first step is to create a measure of expected returns to enrollment choices, which in Chile consist of an institution and a field of study (e.g. nursing at University of Chile). We will refer to an institution-field combination as a degree. To construct predicted earnings from enrolling in each degree, we use a linear regression model to measure expected labor market returns by degree as a function of student baseline characteristics and field of study. We estimate best linear predictors of degree-level deviations in earnings by freshman cohort following Chetty et al. (2014). We compare our best linear predictors to regression discontinuity estimates of the return to admissions to the largest class of universities taken from Hastings, Nielson and Zimmerman (2013). We find that the two very different estimation approaches yield quite similar magnitudes and patterns in expected earnings gains from admissions across degrees. To our knowledge, these are the first estimates of population earnings returns to higher education enrollment by higher education degree.

We use cohorts entering college before the loan program began, for whom we observe several years of labor market returns post enrollment. We also combine these with earnings profiles from tax data by field of study and overall institution selectivity to estimate long-run (25 year) earnings gains over not enrolling in any degree post high school graduation. We convert both short-run (seven years of

experience) and long-run (twenty-five years of experience) earnings predictions into annualized modified real internal rates of return versus not going to college, assuming foregone earnings and tuition costs given expected length of enrollment.

Descriptively, we find that expected returns to degrees are very heterogeneous. For non-selective technical, professional and university degrees, real annualized returns are on average small in the short run, at -0.40%, and growing to an average of 0.23% over the long run. For selective university degrees (those admitting students with PSU's of 600 or higher) annual returns average 3.0% in the short run and 6.4% in the long run. Even within selectivity tier, returns are highly variable. For low-selectivity degrees, approximately 41.5% have negative estimated returns over the first seven years of employment, and 15.3% have negative returns over the long run. For degrees consistently admitting the top third of entrance-exam scores, returns to enrollment are uniformly positive across all degrees.

We show that variation in returns is explained in part by field of study, with science, health, and technology fields offering the highest returns. However, about half of the variation is explained within field across peer institutions admitting students of similar caliber. Importantly, for a given entrance exam score, we find that students from low-income and low-parental-education backgrounds choose lower-return degrees for them (conditional on their baseline characteristics) than the average student does. In other words, the average degree a low-income student could be admitted to would add more value to his or her labor market outcomes than the degree he or she chooses. The opposite is true for students coming from higher-income backgrounds. The enrollment choice earnings gap is largest for low-income students who could just qualify for admission to the least selective university degrees.

We next estimate the impact of qualifying for a loan on degree choice. We show that crossing the loan-qualification threshold increases the probability of enrollment in any degree by 10%[4]. However, we show that the expected labor market return from crossing the threshold is insignificant and near zero. This stems from the impact of student loans on the type of degree chosen. Loan recipients substitute away from technical and professional degrees towards non-selective private university degrees. These degrees are longer and offer on average lower labor market returns than the most selective technical and professional degrees. We show that crossing the loan qualification threshold based on entrance exam scores decreases the probability of enrolling in a technical or professional degree by 7 -8 percentage points off of a base of 39%, but increases the probability of enrolling in a non-selective private university degree by 11-12 percentage points off a below-threshold mean of 17 percent. Using the impact of threshold crossing on overall enrollment, the impact on overall expected returns to enrollment and the McDonald and Moffit

[4] This result is consistent with Solis (2013) which uses a regression discontinuity research design to study the effects of loan eligibility and enrollment.

(1980) decomposition formula, we show that crossing the threshold causes students to choose degrees with -0.23 to -0.31 percentage points off a mean of 1.2%.

These findings are consistent with the view that low-income students make decisions with limited information, which may result in lower returns to educational investments for them and perhaps contrary to their prior expectations. For example, uninformed students may use degree level as an approximation for fundamental value of the degree. Indeed, survey evidence shows that loan-taking students have limited access to college guidance, college prep, and emphasize proxies for quality such as number of years of accreditation and type of degree as reasons for selecting a particular degree (Hastings, Neilson and Zimmerman 2014). This explanation supports policy efforts to compile and disseminate information on earnings returns as part of the loan application process.

To test whether information can be used to push students towards choices with positive financial returns, we implemented a field experiment with MINEDUC to provide randomly-selected loan applicants with information on earnings returns and tuition costs to degree graduation. The experiment was conducted as part of the 2013 loan application process. Loan applicants were sent an email from MINEDUC requesting that they log into a secure website to fill out an additional set of questions post-application. Applicants logged in, were given an informed consent, and were asked six questions including questions about their enrollment plans and their expectations for earnings and tuition costs for themselves and typical graduates from their planned enrollment degree. Upon completing the questions, randomly-selected students were shown information on actual earnings gains (versus no tertiary enrollment) in monthly terms, tuition costs in monthly payments and a "net value" which was the difference in monthly gains and payments in pesos. Costs and benefits were amortized over the fifteen year loan repayment term. Treated applicants were then prompted with suggestions for alternative universities and degrees related to their interests, which they could get into and which offer higher net value. They were then taken to a searchable database that allowed them to select a major, enter an entrance exam score, and it would populate a table of degrees they could get into sorted in descending order by net value.

We measure the impact that information treatment had on the net value of the degree students enrolled in for the 2013 school year. We find the following. First, information is least likely to reach the least informed: low income students are the least likely to complete the survey overall and to search the database conditional on being in the treatment group. Second, there is no significant impact of information treatment on the net value, tuition costs or earnings estimates of the enrolled degree or the probability of enrolling in a degree. However, cutting the data by those who qualify versus do not qualify for loans, we find positive and significant impact of information on the net value of the enrolled degree among those who did not qualify for a loan. On average, treated non-qualifiers enroll in degrees with

13.7% higher net value than the control group, while qualifiers have no significant change in net-value of enrolled degree as a result of exposure to information. In other words, loan applicants appear to ignore information on relative earnings gains and costs of a degree if they receive federal loan dollars, but pay attention to it and incorporate it in their enrollment decisions if they must pay out of pocket. In addition, those not receiving loans (among new high school grads) are more likely to matriculate to a degree if they are treated with information. In other words, information may act to encourage enrollment in higher-return technical and professional degrees when students use it. Students are more likely to use information if they are paying out of pocket rather than through a government-subsidized loan.

To confirm that loan qualification causes students to discard information they would have used to choose a higher net-value degree, we cross our treatment with the effect of crossing the threshold for loan qualification. The regression discontinuity results interacted with information treatment confirms that crossing the threshold negates the positive impact of information on the net value of the degree enrolled in. The effect size is large, erasing half of the gains in net value from loan qualification. These effects suggest that students treat loan dollars and out-of-pocket dollars differently; they are much less sensitive to costs and earnings returns when investing loan dollars.

Together, results from the regression discontinuity design, field experiment analyses, and direct surveys of students suggest that students make education investment decisions based on out-of-pocket costs and proxies for quality such as prestige, selectivity or degree level (two versus four year). In the conclusion we describe how these behavioral biases may explain broad changes in the market for higher education post loan-expansion. We discuss the implications for loan policy design.

We contribute to several literatures. We add to the recent literature estimating returns to higher education using application or enrollment records linked to administrative data on labor earnings (Hoekstra 2009; Saavedra 2009; Ockert 2010; Ozier 2012; Hastings et. al 2013; Zimmerman 2014), as well as the literature comparing estimates of educational outcomes using experimental and non-experimental frameworks (Deming et al. 2011, Kane et al. 2013). We contribute to the literature estimating the causal impact of student loans, grants and financial aid on educational investment decisions (Dynarski 2003; Bettinger 2004; Bettinger et al. 2012; Solis 2013; Turner 2013) as well as the literature on how decision-making costs and limited access to relevant information drive tertiary enrollment decisions and appear to particularly impact students from low- -income backgrounds (Avery and Kane 2004; Jensen 2010; Wiswall and Zafar 2013; Bettinger et al. 2012; Avery and Hoxby 2012; Hoxby and Turner 2013). Finally, we contribute to research understanding how behavioral biases, limited information and decision making skills can influence the impact of social safety net programs (Thaler and Benartzi 2004; Hastings and Weinstein 2008; Duarte and Hastings 2011; Bhargava & Manoli 2011; Bettinger et al. 2012; see Madrian 2014 for a complete review).

2 Background: Chilean Higher Education System

2.1 Overview of the Chilean postsecondary education system

Chilean postsecondary students have a variety of options in terms of degree level and institution type. There are three major institution types: technical schools (CFT) offer two- to three-year technical degrees, professional institutes (IP) offer both technical and vocationally-oriented four-year degrees, while universities offer traditional undergraduate and graduate degrees.[5] In 2012, universities held 58.4% of all undergraduate matriculation while professional institutes and technical schools had 28.1% and 13.5% respectively.

Universities can be public or private-not-for-profit. IPs and CFTs are private and can be for-profit or not-for-profit. Even though for-profit universities have never been legal in Chile, in practice, portions of some universities are owned by for-profit parent companies.[6] Not-for-profit universities have outsourced enrollments to for-profit international education investment groups like Laureate International Universities, an international chain which owns five universities in the U.S. (including Walden University and Kendall College) and thirty institutions in Latin America.[7] In Chile, Laureate institutions have a 12% market share of all higher education enrollment.[8] The Apollo Group, which owns the University of Phoenix in the U.S., also participates in this market having recently purchased the university UNIACC, a "leading arts and communications university in Chile."[9]

The oldest and most selective set of universities is collectively called the CRUCH (Council of Chilean University Rectors) as they jointly run applications and admissions processes. These traditional universities have participated in a centralized, score-based application process since the late 1960s. The central piece of this process is a standardized test called the PSU -*Prueba de Selecion Universitaria* (Test

[5] Some universities, particularly public universities, also offer two-year technical degrees.
[6] "Las 11 instituciones de Educación Superior cuestionadas por irregularidades en 2012." *La Tercera*. 27 November 2012. http://www.latercera.com/noticia/educacion/2012/11/657-495574-9-las-11-instituciones-de-educacion-superior-cuestionadas-por-irregularidades-en.shtml. Accessed 2 May 2013.
[7] http://www.laureate.net/, accessed 7 May 2013.
[8] Universidad Nacional Andres Bello has 6.4% of all undergraduate college enrollment and is the largest university in Chile.Universidad de las Americas has 5 % of all undergraduate enrollment and is the second largest.
[9] Apollo Global Fact Sheet, accessed 7 May 2013. http://www.apollo.edu/sites/default/files/files/Apollo-Group-Apollo-Global-Fact-Sheet.pdf

for University Selection).[10] The entrance exam is constructed, administered and scored by a central testing agency under the authority of the CRUCH.

Entrance exam takers complete exams in Mathematics and Language. Scores are scaled to a distribution with range 150 to 850 and a mean and median of 500. Entrance exam scores are the key component to admissions, loan and scholarship qualification. For CRUCH admissions, students submit one application with up to eight degree choices in order of preference. Students apply to degree (e.g. Sociology at the University of Chile), a process common to many countries in Europe, Asia and Latin America. Degrees rank students based on their entrance exam scores, and the central admission algorithm assigns one admission slot to each student. Admission is given to each student's most preferred degree conditional on there being a seat open for that student (i.e. there are fewer, higher-scoring applicants than total seats available). Thus CRUCH degrees each have an annual admissions cutoff based on the entrance exam scores (cites – Hastings et al. 2013, other cites on efficient algorithms).[11] The least selective CRUCH degrees have admission score cutoffs near 450.

Outside of CRUCH, private universities will still rely on the PSU and GPA for admissions decisions. Students admitted to these universities typically have entrance exam scores over 350. Most technical and vocational schools do not require an entrance exam score for admission.

2.2 Federally subsidized student loan and grant programs

There are two types of student loans in Chile. The smallest and oldest type of loan is the Fondo Solidario de Crédito Universitario (FSCU). It is both need- and merit-based. It has existed since 1981[12]. To qualify for a FSCU loan, students must be Chilean citizens, have "family income that makes payment of tuition difficult or impossible", and an average PSU score in Math and Language of at least 475 points. FSCU loans can only be used at CRUCH institutions. The interest rate is set at 2% and the loans are administered directly by the universities and funded by the government. The FSCU program was small and targeted the poorest students.

To increase higher-education opportunities for low-income students, the government introduced the the *Crédito con Garantía Estatal* (Loan with State Guarantee, most commonly known as CAE, for

[10] Prior to 2003, the entrance exam was called the PAA, *Prueba de Aptitude Academica*.
[11] Hastings, Neilson and Zimmerman (2013) describes the process in detail and use the score-based cutoffs to measure long-run returns to CRUCH degrees.
[12] Originally called *Crédito Fiscal Universitario*, it was first introduced in 1981 by *D.F.L N°4* and modified in 1994 to its current state by *Articulo 70*.

Crédito Aval del Estado) beginning with the 2006 school year.[13] CAE can be used to finance education at any accredited postsecondary institution: CRUCH universities, accredited private universities, professional institutes and technical schools are eligible. It is both need- and merit-based; for studying at a university, first-time applicants need to have scored an average of 475 on the PSU (the same as the Fondo Solidario loan program). To enroll in a technical or professional degree, students need either a high school GPA of 5.3 (approximately the median GPA, or a C average), or an average PSU score of 475. Recipients must be from the first four income quintiles.[14]

To expand PSU-taking among low-income students, the government also introduced a grant which waived registration fees for the PSU for students coming from qualified high-poverty high schools. This policy increased PSU registration and PSU taking. To expand PSU-taking among low-income students, the government also introduced a grant which waived registration fees for the PSU for students coming from qualified high-poverty high schools. This policy increased PSU registration and PSU taking. The combined policies resulted in large changes in the students enrolling in tertiary degrees. Table I shows key differences between the 2005 graduating senior class and the 2010 graduating senior class. The average fraction of students taking the PSU increased from 55.5% to 76.6%. The fraction of students enrolling in a tertiary degree after high school graduation increased from 50.3% to 63.8%. The mean high school tenth grad test score of enrollees decreased from 278 to 274. The fraction of enrollees with at least one parent with a college degree increased slightly from 23.3% to 21.0%, and the fraction of enrollees coming from high-poverty high schools increased from 36% to 40.4%.

Students apply for the FSCU and CAE as well as several federal grant programs using Chile's *Formulario Unico de Acreditación Socioeconómica* (FUAS), a unified financial aid form which is like the FAFSA in the United States. Applications for FCSU are completed online with an application deadline in the beginning of November. PSU is given at the end of November or beginning of December. PSU scores are released at the end of December. CRUCH admission forms are submitted during the first two weeks in January. Admissions notifications are made one week later. The school year starts at the end of February or start of March.

Importantly, the Chilean government established caps on the amount of loans students could take out for higher education in an effort to control loan costs. Loan caps were set at historic averages within degree type and selectivity tier and allowed to increase only with wage inflation each year. Within year

[13] CAE was created by the passage of a new law in 2005, "*Crédito de la Ley 20.027 para Financiamento de Estudios de Educatión Superior*."
[14] "Quality Assurance in Higher Education in Chile." OECD. November 2012. http://www.oecd.org/chile/Quality%20Assurance%20in%20Higher%20Education%20in%20Chile%20-%20Reviews%20of%20National%20Policies%20for%20Education.pdf. Accessed 31 May 2013. Law 20,027. Article III, paragraph 2, section 9.3. NB. In the law itself, no mention is made of socioeconomic quintiles.

and selectivity tier, loan caps were allowed to vary slightly across degrees with measures of input costs and quality such as faculty-to-student ratio and first-year retention rates.

To illustrate the impact of the loan expansion on the market for higher education, Figure 1 shows the change in the fraction of total tuition revenue (students enrolled times annual tuition and matriculation fees) coming from student loans (total annual loans granted to enrollees). We present these statistics as the mean characteristic of degrees that a student with a PSU score of X could likely get into, to illustrate how degree characteristics vary with selectivity as measured by entrance exam scores of admittees. For degrees that do not require a PSU, we assume that anyone with a PSU score less than 425 (or no PSU score) could be admitted, generating a flat line in mean characteristics in for PSU scores less than 425.

The red line plots the fraction of total revenue coming from student loans in 2007 – the first full year of the CAE loan program and the first year for which data are available on loan applications and grants. The blue line plots the same statistic for 2012. Because most loan students come from backgrounds with less college preparation and lower entrance exam scores, the increase in loan revenue is highest for technical and professional degrees, as well as for less-selective private university and CRUCH degrees. Private university degrees serving the just-outside-of-CRUCH admissions area of PSU scores between 425 and 475 saw a particularly large percentage increase in loan-dollars as a fraction of total tuition. The impact of loans on degree revenue abates substantially among highly selective degrees serving students with PSU scores of 600 or higher. (This same break point in the data will be apparent later when looking at earnings returns as well as response of tuition to the loan program).

3 Data

3.1 Administrative data

In collaboration with MINEDUC and the Chilean government, we constructed a database spanning high school records, college records, loan records and tax records for cohorts of Chilean students from 1982 through 2013. The purpose of the database construction was to conduct research to inform upcoming policy decisions on if and how to reform the student loan system.

3.1.1 High school records

Student-level high school records include gender, high school of graduation and nationally standardized test scores. Standardized test scores are called the SIMCE (Sistema Nacional de Medición de la Calidad de la Educación). Students are tested approximately every other year (2001, 2003, 2006, 2008, 2010) in tenth grade on math and language In addition, like many US state tests, the test includes survey questions measuring variables such as parental education for mothers and fathers as well as parental income and variables such as whether the household has internet, TV, computers, etc.

Chile has a universal voucher system, and all schools (municipal/public, private-voucher-accepting and private-non-voucher-accepting) report enrollments, grades, standardized test scores, and graduation rates to MINEDUC. School-level characteristics include the type of school – municipal, voucher, and private (not accepting vouchers) – as well as a school-level poverty rating based on the poverty concentration of enrolled students. The poverty rating categorizes schools from A (highest poverty) through E (lowest poverty). We will often use the high school poverty rating as a categorization of low- versus high-socio-economic-status (SES). Students coming from A and B poverty schools are categorized as low-socio-economic-status.

High school records were available in electronic form from 2003 to 2013. We digitized records for graduation back through 1995.

3.1.2 Entrance exam records and CRUCH applications

We constructed a database of entrance exam registration, scores, full CRUCH applications and admission decisions. Electronic records were available from MINEDUC from 2000- 2013. We digitized data from original hard-copy archives for test scores data from 1980-1999 and admissions data for years before 1982 through 1999. These data allow us to construct admissions cut-off scores by degree and year as described in Hastings, Neilson and Zimmerman (2013).

3.1.3 Federal loan and scholarship applications and awards

Individual records on FUAS (unified loan and scholarship) applications and awards were available from 2007 to 2013. Registering students provide limited demographic information about themselves and their family, as well as income information. .

3.1.4 College matriculation and graduation

As part of the new loan system, all higher education institutions (HEI's) are required to report student-level enrollment and graduation data to MINEDUC each year. These data were available from 2007 through 2013 in a standardized format which included information such as tax ID number (called a RUT – Rol Único Tributario), unique school-degree code, birthday, gender, semester enrolled and graduation

status. To complete the necessary data for the research projects, we assisted MINEDUC in designing an additional data requirement for HEI's to provide additional historic enrollment and graduation data back to 2000. These data show semester-by-semester enrollments by degree within an institution. They also provide graduation lists by year with degree conferred. These data cover almost all institutions, CRUCH and non-CRUCH, and all postsecondary programs including night degrees, technical degrees, professional degrees, bachelors, masters, and doctorate degrees.

We use these data to construct a degree enrollment history for each student. The data allow us to measure drop-out rates, changes in degree within an institution, changes in institutions. They also allow us to track if students are enrolled in a degree or a graduate degree, which is important when measuring earnings.

3.1.5 Earnings by institution and degree

Through an agreement with the tax authority, and for the purpose of informing specific higher education policy, we were permitted to link our database of student records to their tax returns from the 2005-2012 earnings years on a secure computer within the tax authority. Over 99% of individuals in our data have matches in the tax records. Tax returns include earnings information from wages, contracts, partnerships, investments and retirement income. Hastings, Neilson and Zimmerman (2013) describe the tax data in detail, and provide an example of a tax form to illustrate the components used to calculate employment income.

Tax data were only accessible inside the Chilean tax authority on a secure, dedicated computer. In compliance with Chilean law, we were permitted to take out aggregate earnings information and regression output. In addition, we were able to merge parental identifiers to our student-level database using family linkage data from the Civil Registry. This allowed us to to calculate parental income for most students and use it to control for student characteristics when estimating earnings impact of degree enrollment.

3.1.6 Survey and experimental data

As part of our research partnership with MINEDUC, we designed several surveys and a field experiment which was administered by MINEDUC as part of the loan application process for the 2013 school year. The field experiment consisted of an online survey coupled with randomly assigned access to expected wage earnings and loan costs for each degree that a student could qualify to get into (based on their own expectations of entrance exam results). The earnings and costs were presented as monthly gains or losses

over not enrolling in any higher education degree amortized over the fifteen year federal student loan term.

The survey component of the experiment give us information on which degrees the loan applicant was planning to enroll in, the applicants own forecast of earnings upon graduating from their chosen degree (up to the first three degrees listed) and obtaining a full-time steady job, the applicant's forecast of the typical graduate's earnings, and the applicant's belief about annual tuition costs of enrolling in their chosen degrees, and their expected PSU scores in math and language. The experiment gives us data on their searches and the information the web-based program displayed for them. These data include personal identifiers, allowing us to link the survey responses and experimental treatment to individual data on baseline characteristics and loan qualification as well as outcome data on tertiary enrollment decisions.

We describe the survey questions and field experiment in more detail in Section 4 when we present results from the field experiment. The online appendix gives the survey question text as well as screen shots from the information presented to treated students.

4 Empirical Analysis

We first develop measures of predicted earnings returns to degree enrollment to understand how returns vary across degrees, and to develop an earnings metric with which to compare enrollment decisions across students from low- versus high-income and education backgrounds. We use our enrollment panel linked to tax records to construct degree-specific earnings estimates. To our knowledge this is the first comprehensive look at earnings returns to enrollment for the population of higher-education options in any country (Altonji et al. 2012).

4.1 Measuring earnings returns to degree enrollment

4.1.2 Estimation Framework

We measure returns to enrollment using our linked database for freshman enrolling cohorts from 2000 through 2005, the baseline years before the student loan expansion. We adapt the value-added estimation approach in Chetty et al. (2014) to our context of higher-education degree enrollment in order to generate

predicted earnings gains by degree accounting for the fact that estimates of effects are noisier within some degree program-cohort cells than in others.

Let earnings in year *t* for individual *i* who enrolled in degree *j* be a function of individual characteristics, the degree field of study and higher education institution they enrolled in and an idiosyncratic error term.

(1) $$y_{it} = X_{it}\beta + Z_j\gamma + W_{itj}\delta + \mu_{jc} + \varepsilon_{it}$$

Where X_{it} includes baseline characteristics (socio-economic status, entrance exam scores, gender), years of labor market experience, interactions between experience and baseline characteristics, and tax year dummies; Z_j are dummy variables for majors, and W_{ijt} are interactions between majors and baseline characteristics and majors and experience years, μ_{jc} is component of residual earnings that varies by degree and freshman cohort, and ε_{it} is a mean zero idiosyncratic error term.

We are interested in estimating the expected earnings over *T* years for an individual *i* enrolling in degree *j*, $\hat{y}_{ij}^{T}$, Most degrees are large, but many small degrees exist as well. Obtaining estimates of $\hat{\mu}_{jc}$ requires adjusting for small sample sizes as a small degree may draw higher- or lower-than-average earners by chance. We follow Chetty et al. 2014 and estimate the best linear predictor of $\hat{\mu}_{jc}$, which is essentially the predicted value of enrolling in a degree using the OLS coefficients from cohort *c's* mean residuals from equation (1) on prior cohorts' mean residuals.

We estimate (1) by degree and selectivity level securely within the tax authority in Chile, taking out parameter estimates and freshman-cohort-level mean residuals needed to estimate $\hat{\mu}_{jc}$. Selectivity tier has five categories: no college enrollment, technical degrees, and three selectivity tiers for professional and university degrees defined by the median entrance exam scores of enrollees over our sample period. Thus the parameter estimates from (1) for a nursing degree, for example, can vary by whether it's a technical nursing degree, an average nursing degree, or a very selective nursing degree.

We then generate predicted earnings for experience years two through seven for the students in enrolling cohorts of 2000 through 2005 using the student's characteristics, the regression estimates and the expected mean value added of each degree. This effectively adds the student-level predicted earnings based on observable characteristics back into the mean predicted earnings by degree.

Two to seven years of experience reflects only a relatively short-run return to an educational investment choice. To scale earnings predictions to lifetime (25 years) earnings, we add to each prediction

an expected earnings growth rate over 25 years which we estimate from the tax data within the tax authority. Specifically, we estimate the following equation separately by major, type of degree and selectivity tier.

$$y_{it} = \alpha_j + X_{it}\beta + E_{it}\gamma + \varepsilon_{it} \quad (2)$$

Where α_j are degree-specific fixed effects, X_{it} includes tax year dummies and individual, time-invariant baseline characteristics (entrance exam score, gender and socio-economic status), and E_{it} is either a vector of labor-market experience year dummies or a linear term for years of experience, depending on the specification. The years of experience in the base data set span one to 12 years of experience. For experience years two through twelve, earnings growth appears approximately linear for most fields of enrollment as well as for high school graduates who never enroll (see online appendix for further details). We use these growth estimates to grow earnings from years seven through fifteen, and then hold them constant through twenty-five years of experience to approximate lifetime earnings gains. We will focus on these lifetime earnings estimates in the results section, but we also present analogous results using just the two-through-seven-years of experience earnings estimates from (1) in the online appendix.

Finally, to help with interpretation, we convert these long-run earnings estimates in annual rate of return units by calculating an annualized Modified Internal Rate of Return (MIRR) for the educational investment. We set the reinvestment rate and financing cost equal to the federally subsidized loan rate of 2%. The cost of the degree at enrollment is the cost of tuition and fees as well as foregone earnings for the expected length of enrollment in the degree.

Equation (1) estimates earnings returns using ordinary least squares which may be subject to substantial selection bias if students select degrees strongly based on personal information and individual-degree match-specific returns. Hastings et al 2013 estimate returns to CRUCH university degree admissions using score-based centralized admission cutoffs to CRUCH degrees. They focus on older cohorts of Chileans, 1982-1992, when non-CRUCH options for university degrees were more limited. We use the same regression discontinuities for the 2000-2005 admission cohorts to obtain threshold crossing estimates of returns to short-run earnings. We then use the same data set, and replace actual earnings with predicted short-run earnings as calculated by (1). We again calculate threshold crossing estimates and compare the results. The online appendix describes the relationship between the threshold crossing estimates of returns to admission using actual versus our predicted earnings. We find similar results using these two different estimation procedures.

4.1.2 Earnings gains

Figure 2 shows the distribution of predicted long run returns to enrollment across all degrees in 2005. To facilitate presentation, we present the distribution graphically, plotting returns on the vertical axis versus PSU score on the horizontal axis. The figures show the distribution of returns that a student scoring X on their entrance exam realizes in expectation. We average within each score bin over predicted returns for observed 2003-2005 enrollment outcomes. We group all non-selective degrees together (those not requiring a PSU), and assume that they are options for anyone who does not take the PSU or who takes it but scores less than 425 (the lowest upper percentile for private universities outside of CRUCH). This generates the horizontal segment of the returns distribution. There is a jump in the distribution at 450, the lower threshold for admissions to CRUCH degrees.

There are two key features in this distribution. First, over the long run, the average annualized return to enrollment in any higher education degree is positive with an overall average of 4.2% in real terms per year. Even among non-selective schools the enrollment-weighted mean is a positive 2.5%. However, more selective degrees clearly have substantially higher returns. The mean annual predicted real return to enrollment is over 5% for degrees enrolling students with PSU scores of 575 or higher. The upward, convex shape of mean returns reflects the regression discontinuity estimates found in Hastings et al. 2013 when examining returns to admittees from the 1980's into CRUCH degrees. In addition, their finding that less selective CRUCH degrees offer near zero returns over the outside option of technical degrees is consistent with the near zero increase in mean returns between non-selective technical degrees and the least selective CRUCH degrees (admitting students in the 450-475 PSU score range).

There is substantial variation in long-run predicted real returns. Among technical and professional degrees, the lower 9% of degrees have negative returns relative to not enrolling. While it is possible that there are non-pecuniary benefits to attending these degrees, non-pecuniary benefits can be subsidized outside of an individual loan which must be repaid from labor wages. Figure 2b shows just the short run real returns, amortized over seven years (calculated on earnings data without added long-run growth rates). In the short-run, the variance in real returns is even larger, with substantially negative returns for non-selective university, technical and professional degrees. If loan-takers focus on the short-run, the burden of paying back loan debt may loom substantially larger for nearly half of enrollees relative to the low-to-zero earnings gains versus those who entered the labor market right after high school graduation.

Much of the variation in earnings gains can be explained by the degree field. Figure 3 breaks shows enrollment-weighted mean returns by broad area of study used in Hastings et. al 2013 and based on the CINE UNESCO categorizations. For non-selective and technical degrees, long-run annual real returns are highest for science and technology degrees, and small and very negative for degrees in humanities (e.g. professional degree in journalism). Interestingly, technical degrees in health fields are not

high return relative to other fields despite the fact that health degrees are high return overall. Most of those high returns are driven by returns to selective degrees in medicine, which at the top of the selectivity distribution offer the highest returns on average out of all fields. Overall, a little over half of the distribution of long-run returns is explained by major, and the other half is explained by the degree,[15] meaning that within the same major, and within a similar entrance exam score range, which institution one chooses has a substantial impact on later earnings – almost the same impact as which major one chooses.

Finally, our predicted earnings are a function of individual characteristics such as SES, PSU score and gender. To explore this variation, we use our estimates to calculate mean predicted earnings and mean predicted long-run annualized returns for each degree by SES category (high versus low). Figure 4 shows mean predicted long-run annualized returns by SES category and PSU score bin, calculating the weighted means using either a) overall enrollment weights (the average person's enrollment choice) or b) SES-specific enrollment weights (adjusting for the fact that high- versus low-SES students may make different degree choices). Comparing the lines Low SES – Pop weight with High SES – Pop weight gives the mean difference within degree between predicted earnings gains for high and low SES students. Comparing the lines Low SES – SES weight and Low SES – Pop weight shows how much of the mean difference in low- versus high-SES students can be explained by the differences in the returns at degrees they choose. Similarly, the difference in High SES – SES weight and High SES – Pop weight shows the extent to which higher returns for High SES students can simply be attributed to which degrees they choose.

This graph points generates several interesting points. First, for the most part, the difference within degree between returns for High- versus Low-SES students is negligible. This holds true at almost all points of the selectivity distribution. The Low SES and High SES – Pop weight lines are very close to each other both in the non-selective technical and professional degree range as well as in the selective degree range. The only range that they diverge in is in the non-selective university degree area. These degrees appear to do relatively worse at adding earnings value to low-SES versus high-SES students. Second, and more importantly, the Low SES – SES weight line lies significantly below the Low SES – Pop weight line over the entire selectivity distribution. Low- SES students choose lower return degrees to enroll in than the population-weighted average degree. These are either degrees that have worse value-added for the typical low-SES students, or are just lower return degrees overall. The difference in choice-driven SES returns gap is lowest for selective university degrees, but it is highest for non-selective private and public university degrees. Here, on average, low-SES students enroll in degrees which have near zero

[15] Calculated as the fraction of variation in returns explained by dummies for major within majors serving students with PSU scores divided into 50 point bins.

returns for them, despite the fact that the average degree offers a positive return to low-and high-SES students. Note that the opposite is true for high-SES students; weighting their returns by their enrollment choices leads to higher mean returns than weighting them by average enrollment.

This difference in choices is consistent with lower information on educational choices among low-SES students. As we will show in our survey and field experiment results, students coming from low-income backgrounds have on average worse information on potential earnings returns and tuition costs when making education investment decisions. They are less likely to have parents with college education, and they come from high schools with historically fewer students matriculating to higher education degrees. Further survey evidence in Hastings et al. (2014) shows that students coming from low-income backgrounds are less likely to rely objective information from government sources or their schools (e.g. school college fairs and events) on education options. They are more likely to choose a degree based on rough heuristics such as accreditation, which is a very lower-bound on potential value-added of a degree. They are less aware of other majors outside of the major they plan to enroll in, consistent with less personal and social/familial-network information on higher education.

4.2 The causal impact of student loans on education investment returns

This choice differential may feed directly into the efficacy of student loans. If low-income students use loans but choose low-return options in lieu of higher-return options for them, loans may not be adding the value to personal productivity or to society more broadly. Figure 4 suggests that loans targeted even at relatively high performing low-SES students – those scoring at least a 475 on their PSU or graduating with a high enough GPA – may not result in earnings gains equal to the average if those students persistently make poor education investment choices.

To further investigate the interaction of loans and choices, we exploit discontinuities in loan qualifications for the CAE loan. Recall that CAE requires a PSU score of 475 or higher to use a loan to attend a university degree, or a GPA of 5.3 or higher to use a loan to attend a technical or professional degree. We can use these qualification cutoffs to estimate the impact of loan receipt on education investment choice characteristics such as type of degree enrolled in and expected real annualized earnings returns.

Figure 5 plots mean educational investment outcomes by 5-point PSU score bin, transformed into distance in PSU points from the loan qualification cutoff of 475. The first plot, 5a, shows the impact of crossing the loan qualification threshold on the probability that a PSU taker matriculates to any higher-education institution. There is a clear discontinuity at zero, implying a 7-10 percentage point increase in

the probability of matriculating anywhere. Loans increase the number of marginal students enrolling in higher education degrees, but they also cause substitution between types of degrees. Figure 5b-5d show how the probability of matriculating to various types of degrees changes as students cross the loan-qualification threshold. Based on the plot crossing the threshold decreases the probability of enrolling in a technical or professional degree by five to ten percentage points – a sizeable decrease off of a mean technical/professional school enrollment rate of 39% to the left of the cutoff. Panel 5c shows that many loan qualifiers opt to enroll in a university degree at a private, non-selective university. The probability of enrolling in a private university increase by 10-15 percentage points off a base of about 17 percent to the left of the threshold. The change represents a doubling in the probability of enrolling in a private, non-selective degree. The final panel shows that loan qualifiers are also more likely to enroll in less-selective CRUCH degrees. However the size of the substitution towards CRUCH degrees is much smaller in absolute value than the substation towards private university degrees serving the less-selective degree market.

Table II reports regression discontinuity regression results from regressions of the following form.

$$y_i = \alpha + \theta T_i + \lambda d_i + \delta d_i^2 + \phi T_i d_i + \varphi T_i d_i^2 + \varepsilon_i \tag{3}$$

where y_i is the outcome of interest, for example an indicator if student *i* matriculated to any higher education degree, T_i is an indicator if *i*'s PSU score was higher than the cutoff score of 475, and d_i is the distance of *i*'s PSU score from the cutoff score of 475. We estimate (3) using all loan applicants from 2008-2012 whose PSU scores fell within a 50 point window around the cutoff score (PSU scores from 450 to 500).

Table II presents results from (3). The first row of results corresponds to a specification with only linear-in-distance terms ($\varphi = \delta = 0$), while the second row specification allows for quadratic terms in distance from the threshold. The first row of results shows that the probability of receiving a loan increases by approximately 29 percentage points as a result of crossing the threshold for PSU-based loan-qualification. The below threshold mean loan recipient rate conditional on application is 18.9%.

The next set of results show the reduced form impact of crossing the threshold on educational investment choices, the coefficients θ from regressions with measures of education decisions as the dependent variable. Dividing these estimates by the impact of threshold crossing on loan receipt (about 29%) gives the impact of receiving a loan on the outcome of interest if threshold crossing was used as an instrument for receiving a loan.

The second column reports the impact of threshold crossing on the probability of matriculating to any higher-education degree. The impact is positive and significant in both specifications at 11.1% and 10.4% respectively off a base below-threshold mean of 58.7%. The third column reports the effect of crossing the threshold on the probability of matriculating to a technical degree. Here the coefficient is negative and significant in both specifications with the impact of crossing the threshold of -7.52% and -8.35% off a base below-threshold mean of 38.9%. The fourth column shows that crossing the threshold to receive a loan increases the probability of matriculating to a non-selective, private university degree by 11.4 % and 11.9% of a base below-threshold mean of 17.19%. The fifth column shows that crossing the threshold causes a 6.92% to 7.16% increase in matriculation to a less-selective CRUCH degree off a base below-threshold mean of 2.8%.

The sixth column shows the impact of crossing the threshold on the long-run annualized real return on investment of the degree enrolled in. This includes both the extensive margin – the impact of crossing the threshold on enrolling in any tertiary degree – as well as the intensive margin – the impact of crossing the threshold on the projected earnings returns of the degree enrolled in (i.e. which degree a student chooses). The seventh column shows just the intensive margin impact using the McDonald-Moffit decomposition (McDonald and Moffit, 1980) to solve for the intensive margin impact given the estimated impact of threshold crossing on matriculation to a higher degree and the combined-margin impact estimate from column six and the impact of crossing the threshold on overall matriculation probability from column 2.[16]

The threshold crossing impacts on the expected real annualized return of the degree enrolled in is slightly positive in the linear specification and slightly negative in the quadratic specification, but insignificant in both. Given that overall matriculation increases as a result of threshold crossing, and that the average degree in this range has a long run real annual rate of return of 1.2% over not enrolling in any degree, the point estimates suggest that the intensive margin is negative. Column 6 shows that this is indeed the case. Both specifications imply that students who would have still matriculated to the left of the threshold now matriculate to a degree with 0.231 to 0.309 lower expected annual real returns than the

[16] Specifically, let R denote long-run annualized real return of the degree enrolled in, let M be an indicator if a student matriculates to any tertiary degree, and let T be an indicator if the student crosses the threshold for loan qualification based on PSU score. Then $\frac{dE(\mathrm{R})}{d(T)} = \frac{d\,\Pr(\mathrm{M}=1)}{dT} \cdot E\left(R \mid M=1\right) + \frac{dE\left(R \mid M=1\right)}{dT} \cdot \Pr(M=1)$. We are interested in the intensive margin impact of crossing the threshold, namely $\frac{dE\left(R \mid M=1\right)}{dT}$. The left-hand term is given by the estimates in column 6. The first right-hand-side term is given by the estimates in column 2. The conditional mean and the probability terms on the right-hand-side are calculable from the data, thus allowing us to solve for the term of interest. Note that we could replace T with L, an indicator of loan receipt, and perform the same calculation.

degree they would have enrolled in had they not qualified for the loan. Using the same decomposition and combining the coefficients in column 1 with those in columns 2 and 6, the estimates imply that receiving a loan decreases has no overall expected impact on real return (-0.034 to 0.185), but that is due to the fact that while it increases matriculation to some degree by 36 to 38 % (column 2 divided by column 1), it decreases the expected return to education investment conditional on enrollment somewhere by -0.791 to -1.070.

4.3 Information, Degree Choice and Loans: Field-experimental Evidence

4.3.1 Survey and Field Experiment Design

These findings support the view that low-income students make decisions with limited information, which may result in lower returns to educational investments for them and perhaps contrary to their prior expectations. For example, uninformed students may use degree level as an approximation for fundamental value of the degree. Indeed, survey evidence shows that loan-taking students have limited access to college guidance, college prep, and emphasize proxies for quality such as number of years of accreditation and type of degree as reasons for selecting a particular degree (Hastings, Neilson and Zimmerman 2014). This explanation supports policy efforts to compile and disseminate information on earnings returns as part of the loan application process.

To test if information can be used to impact choices towards positive financial investment returns, we implemented a field experiment with MINEDUC to provide randomly-selected loan applicants with information on earnings returns and tuition costs to degree graduation. The purpose of the survey and field experiment was to measure how informed enrollment choices are, and to test if information could improve loan efficacy by nudging loan takers towards positive-expected-value investments (and thus also exerting demand-side pressure on HEI's to add value to enrollees in the long run).

Students in the 2012 graduating high school cohort and all other PSU registrants (including those from older high school cohorts) were pre-assigned to treatment and control groups. Treatment status was randomly assigned by high school for the current graduation cohort and by prior-PSU score bin for prior high school graduates. Upon completing a FUAS application, students were sent an email from MINEDUC requesting that they complete six additional survey questions related to the FUAS process. Students were assured that their responses would not impact their FUAS outcome, but that the questions were important and would be used by MINEDUC to help improve the education system in Chile.

The field experiment was constructed as follows. First, the universe of high school seniors and PSU registrants were merged together, and assigned a treatment status by high school for current high

school seniors,[17] and by prior PSU test score (50 point bins) for PSU registrants who had graduated in the two prior cohorts.[18] This list was merged to loan applications as the loans were completed. Loan applicants then received an email from MINEDUC with a subject line "Código Confirmación FUAS" (FUAS Confirmation Code).. The email requested applicants to participate in a brief survey that would be used by MINEDUC to make decisions about higher education. The email requested applicants to participate in a brief survey that would be used by MINEDUC to understand how students make decisions about higher education. They were told that they would receive a confirmation code at the end of the survey, and that their survey responses would be kept anonymous, used only for research and would not affect their FUAS applications in any way. Emails were managed through Constant Contact, allowing us to track bounce-back, open and click-through for each email address.

Upon opening the email, applicants could click a link which would then take them to a customized website. They logged in with their identification number and email address, were given an informed consent to accept or reject. Conditional on acceptance, they began the survey. The survey asked them six questions, each of which appeared on its own page, with participants clicking a “next” button to proceed to the next question. Each question could only be completed once (if a respondent left the survey and started again it would start them where they left off).

The survey adapted questions based on responses. The first question asked students about their current education status. The second question asked them to list at least the top, but up to the top five, institutions and majors (degrees) they planned to apply to (chosen from a nested set of drop down menus that filtered results to make options of manageable size). The third question asked them how certain they were of these choices. The fourth question asked them what they thought the annual cost of studying (tuition plus registration) at each of their choices would be. Their choices were piped in from their prior responses. They could a click “No Sabé” (I do not know) button or slide a slider to indicate the total annual cost. The fifth question asked them about expected earnings upon graduation (the survey and experiment focused on graduation rather than enrollment consistent with MINEDUC’s objectives at that time). They were asked to estimate what their monthly salary would be once they started in a stable, full-time job after graduating from each of their choices. They were also asked to estimate what a typical

[17] Note, high school classes in Chile are small because most schools are private or private-voucher-accepting. Median graduating class size in 2012 was XX. Schools were broken into groups based on high school type (private not-accepting-vouchers, private voucher-accepting, and municipal), the fraction of students taking the PSU and the average PSU score from the prior two senior cohorts. Half of the schools within each randomization block were assigned to treatment.

[18] PSU registrants for the 2013 college entering class could use old PSU scores. This was a new policy. Hence the PSU registration list consisted of those who currently wanted to take the PSU, as well as those who had taken the PSU in prior years in case colleges requested their prior test score for admissions. Thus the PSU registrant list consisted of new test takers, test re-takers and prior test takers who were not retaking the test. This gave us a sample of older graduates who may apply for a loan.

graduate in each degree would earn. They were allowed to choose "I do not know" for each sub-question or fill in earnings amounts with a slider. The sixth question asked them what they expect to get on their PSU in language and math. The exact questions in Spanish (with English translations) are in the online appendix.

Upon completing the final question, control subjects were shown a Thank you page with their confirmation code. They also received a thank you email with the same message. Treated students continued to a new page which showed them five key pieces of information. At a table at the top, they were shown estimated monthly earnings gains (estimated from tax returns) for graduates from their top-choice degree relative to a high school graduate, projected and amortized over fifteen years (the length of a student loan). They were also shown monthly payment costs for a loan covering tuition and registration through expected degree length. And they were shown a "Net Value" – the difference between earnings gains and costs. Below the table, in a highlighted box, they were told whether there were other institutions they could get into which offered the same degree with a higher Net Value, and they were told the additional Net Value they could gain by switching institutions (though they were not told which institution offered this better Net Value). The gain was actually calculated by the web program by referencing a back-end database and using the chosen major and the PSU score the respondent entered. Finally, treated participants were shown in a second highlighted box indicating whether or not there were other majors related to their major of interest that offered higher Net Value (again based on degrees they could get into with their expected PSU score), and they were shown the expected Net Value gain from switching majors.

After the information and suggestion page, treated subjects clicked through to the final page, which gave them the ability to enter a PSU score , select a degree level (technical or university/professional) and a major at the top of the page to populate a table of comparative Net Values underneath their selections. The comparative table displayed institutions offering their chosen major which they could get into with their stated PSU score and would want to go to given their PSU score. Specifically, the web program selected all degrees in the same major for which the stated PSU score fell within the 5^{th} and 95^{th} percentile of their first chosen degree. Students were informed at the top of the page that this new database was being produced by MINEDUC using tax records of past graduates, and that they could log back in at any time and compile and view up to ten comparative tables to use in choosing their degree by entering their expected PSU score and selecting a major.

This final page also contained a thank you message and the confirmation code. Note that students were not required to search the database once there. Approximately 45% percent of students who were shown this page searched at least once. We will use treatment assignment to test for an impact of information on the characteristics of the degree enrolled in. The degree enrolled in comes from matching

student records from the survey and field experiment to MINEDUC's 2013 enrollment and matriculation files.

Table III shows demographic characteristics for the students in our invitation sample from sample design to final experiment participants. The first column is the union of 2012 High School Graduates and PSU registrants who filed a FUAS application form and received a recruitment email from us. The second column is the subset of students who we were able to reach by email (they opened the email). Students could be unreachable either because their email was invalid (2.9%) or because our requests went to spam or remained unread for various reasons. The third column shows the characteristics of those who accepted the informed consent and started the survey. The fourth column shows information for those who completed the survey and were randomly exposed to information on comparative net returns from degrees they could get into. The important take-away from this table is that among loan applicants, higher-income applicants from higher education backgrounds are more likely to be reached by information. Respondents, while similar to the overall applicant pool, have 31 point higher average PSU scores, are about 7 percentage points more likely to come from private or private-voucher high schools, score on average 0.265 student-level standard deviations higher on the 10^{th} grade SIMCE tests, and are 1.8 percentage points more likely to be female.

Within respondents, half were pre-assigned treatment status by us. Treatment appeared after all survey questions were answered. In the online appendix we confirm randomization into treatment among the final respondents by confirming that on average, baseline characteristics (including survey responses) are similar across treatment and control groups. We find no significant difference between treatment and control groups. The p-value on the joint test that baseline characteristics explain treatment status is 0.70 among current graduating seniors, and 0.13 among those graduating in prior cohorts.

Hastings et al. 2014 use the survey results preceding the experiment along with results from several other surveys we ran to describe how tertiary degree applicants make choices among degrees, how informed they are about loan terms, degree characteristics, and which sources of information they relied on to make their decisions. They find that approximately 40% of loan applicants do not know the amount they can expect to earn upon graduating from their degree of choice, nor do they know what the average graduate from their chosen degree will earn. A similar fraction does not know the tuition costs they can expect to pay. In addition, lack of knowledge and errors in predictions are higher among those coming from low-SES backgrounds. Given the survey results, it is possible that information may result in large changes in choices.

Table IV shows the impact of information on educational investment decisions. We present all results separately for 2012 and pre-2012 high school grads. The first two columns present results within these two groups. The first two rows of estimates show that information did not impact the PSU score or

loan qualification for either subsample. Exposure to information did not prompt students to study harder for their entrance exam and increase their chances of loan qualification. The third row shows the impact on matriculation to a tertiary degree, the fourth shows the impact on Net Value of the enrolled degree, the fifth and sixth show the Monthly Gains and the Monthly Debt Payments of the enrolled degree respectively. The Net Value, Monthly Gains and Monthly Debt payments are zero by construction for non-matriculators. Overall, Information has no significant impact in educational investment decisions.

The next four columns break up 2012 and pre-2012 grads into those who qualified for a loan and those who did not qualify for a loan (those who received grants are excluded). Among 2012 grads who did not qualify for a loan, receiving information had a marginally significant (p-value of 0.052), positive impact on matriculation. Receiving information appears to slightly increase matriculation to tertiary education among new high school grads who do not qualify for a loan for university degrees. One interpretation is that these students learned that technical and professional degrees they could get into offered substantial net returns, and often higher than their university degree of choice. Among this same subsample, information had a significant, positive impact on Net Value of the degree enrolled in. The impact is a 6.2% increase off the mean Net Value of enrolled degrees in the sample. This gain comes from an increase in Monthly Gains rather than a decrease in Monthly Debt (tuition costs). Among pre-2012 grads, we find a similar point estimate, but without the same statistical precision. Overall, information has a positive impact the Net Value and Earnings Gains for 2012 grads who do not qualify for loans.

In comparison, among loan qualifiers, information has no significant impact on educational investment decisions. The coefficients are all close to zero. These results suggest information only influences choices when students must finance their degree without a government loan, or equivalently that students are less sensitive to fundamentals such as potential earnings or tuition costs when paying with loan dollars instead of personal dollars.

Loan qualifiers are also higher-scoring on average. To investigate if receiving a loan itself causes information to lose its impact on choice, we can interact our treatment effect with crossing the loan-qualification threshold for the 2013 loan application process. While this will substantially reduce our sample size substantially, it will combine the causal impact of loan qualification with the causal impact of information treatment to test if loan qualification decreases the impact of treatment on enrollment choice.

We estimate regressions of the following form.

(4) $$y_i = \alpha + \phi I_i + \theta T_i + \delta I_i T_i + \lambda d_i + \delta d_i^2 + \eta T_i d_i + \varphi T_i d_i^2 + \varepsilon_i$$

where y_i is the Net Value of the degree *i* matriculated to in 2013, I_i is an indicator if *i* received information treatment, T_i is an indicator if *i*'s PSU score was higher than the cutoff score of 475, and d_i is the distance of *i*'s PSU score from the cutoff score of 475. We estimate (4) using all survey and field experiment respondents whose PSU scores fell within a 50 point window around the cutoff score (PSU scores from 450 to 500). The coefficient ϕ measures the impact of information on applicants who do not qualify for a loan, while δ measures the added impact of crossing the threshold for loan qualification and receiving information.

Table V reports regression results for $\hat{\phi}$, $\hat{\delta}$, and $\hat{\theta}$ respectively. We present results for 2012 grads, pre-2012 grads and both groups pooled. The impact of threshold crossing on Net Value is positive and significant for 2012 grads, and similar in magnitude to the effects of information identified in Table IV. Among 2012 High school graduates to the left of the loan-qualification threshold, the impact of information is positive and significant, increasing the Net Value of the degree enrolled in by 27.8% over the mean of 420,864 pesos. Crossing the threshold appears to erase this impact. The interaction between treatment and threshold crossing is negative and of similar magnitude to the impact of treatment below the threshold. The sum of the $\hat{\phi}$ and $\hat{\delta}$ is not significantly different from zero in either the linear or quadratic model among 2012 high school grads.

Among pre-2012 high school grads, we do not see significant impacts of information treatment, though the sample size is very limited in this subset. Pooled estimates are consistent with the 2012 HS graduate effects but noisier. Though, overall, the combination of the regression discontinuity and information experiment yields noisier estimates, they support the finding that information can impact enrollment choices, but receipt of federally subsidized loans reverses this impact.

5 Conclusion

This paper combines regression discontinuity and field-experimental research designs with new administrative data on educational and labor market outcomes for Chilean students to explore the earnings returns associated with enrollment at different degree programs and the effect of loan access on extensive- and intensive-margin college choice. We find that returns to tertiary education are highly variable and increasing in degree selectivity. This is important for policies subsidizing tertiary education for low-income students, who often enroll in less selective degree programs but have loans that must be repaid.

We examine disparities in choices of degrees between higher and lower income students qualifying for admissions to similar sets of tertiary degrees. We show that low-income students do as well as high-income students in terms of expected labor market returns conditional on degree choice, but tend to choose degrees associated with lower earnings levels. This gap is particularly large for students who score highly enough on entrance exams to qualify for less selective university degree programs, as opposed more selective university degrees or less selective technical or vocational degrees.

We also show how choice behavior varies with access to student loans. We demonstrate using a regression discontinuity framework that access to student loans increases the probability that students enroll in a tertiary degree. However, it also causes them to substitute away from technical and professional degrees and towards low-selectivity university degrees. These degrees are longer, cost more, and result in lower expected labor-market returns. We show that, for students on the margin, loan-induced substitution from technical to university degrees erases most of the expected labor market gains one might expect based on large matriculation effects. This finding is consistent with survey evidence and cross-sectional evidence on education investment choice decisions: students from non-college, lower-income and lower-achieving backgrounds are more likely to take out student loans and are less likely to be informed about their educational options. They choose degrees based on rough quality measures like accreditation or degree type (technical versus university), and in the low-selectivity range uninformed choices can lead students to very low or negative return degrees.

Despite this, informational demand-side policies are unlikely to nudge loan takers towards financially sound educational decisions. Nor are they likely to nudge firms that rely on loans for revenue towards the provision of higher value-added per tuition dollar in the low-selectivity market. Using a large-scale informational field experiment embedded in the 2013 administrative loan application process, we demonstrate that information is effective at directing students towards higher-expected-return-degrees only so long as they do not qualify for loans and must pay out-of-pocket. For students just below the score threshold for loan access, information on earnings gains and tuition costs has a positive impact on the net value of the degree chosen. However, for students just above the threshold, information has no impact. Students appear to be less sensitive to fundamentals when receiving a loan.

Overall, our results are consistent with the idea that students make decisions primarily based on heuristics like prestige and degree length, and primarily consider out-of-pocket costs. In Hastings, Neilson and Zimmerman (2014), we examine how this behavior can help explain the overall changes in enrollment and tuition across tertiary degrees following the loan program expansion. Descriptively, the largest increase in loan dollars as a fraction of revenue following loan introduction was in the private, non-selective university segment of the market. Within this market segment, degrees with lower expected returns experienced the highest increase in the fraction of revenues coming from loan dollars, as they

expanded enrollment to meet increased demand from student-loan qualifiers. Our findings here suggest one possible explanation: students, and particularly students from low-SES backgrounds, have limited access to information on the returns associated with enrolling in different degree programs, and become less sensitive to this information when granted access to loans.

At higher levels of selectivity, patterns in institutions' enrollment and tuition responses to loan expansion are consistent with a world in which students value prestige (Grossman and Shapiro 1988, Becker 1991) and out-of-pocket costs when choosing degrees. Specifically, high-selectivity institutions responded to increase demand by increasing selectivity (entrance exam requirements), and holding enrollment down, consistent with the predicted response for prestige products. These degrees increased tuition by 15% on average in real terms, capturing rents from higher selectivity. Non-selective schools act as a competitive fringe, expanding enrollment to admit all applicants but holding tuition at government-determined loan caps in response to competition on out-of-pocket costs. In the absence of loan caps, tuition in the competitive fringe may not have been so disciplined.

Taken together, our results and those of Hastings, Neilson and Zimmerman (2014) suggest that capping loans in a way that directs students with limited information and decision-making ability towards higher value investments may be a more effective policy than providing information for nudging students toward financially viable choices. Beyer et al. 2014 discuss a loan cap policy designed in collaboration with MINEDUC as a result of this research and integrated into the Chilean loan cap policy for the 2014 school year.

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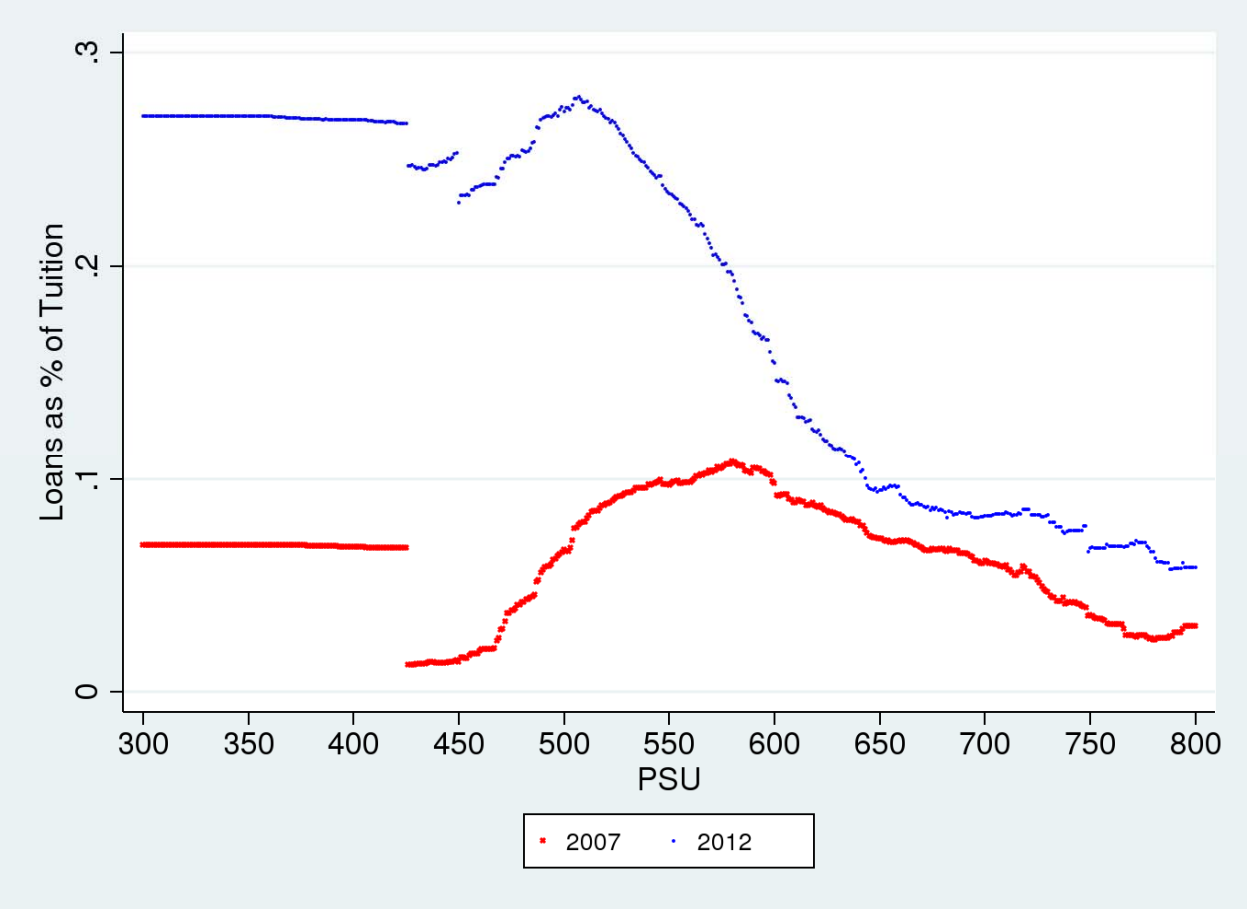
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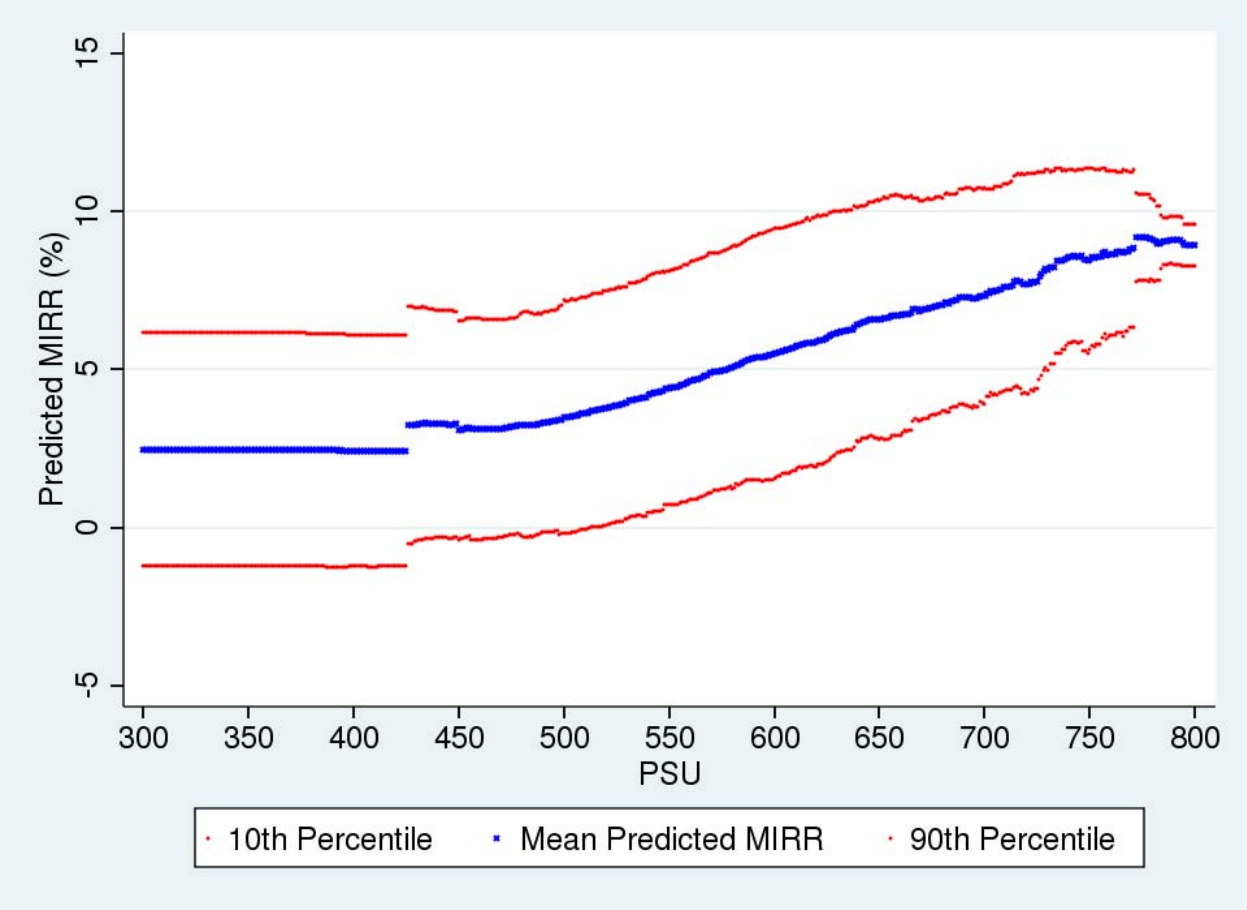
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FIGURE 1
Loans as a fraction of Tuition Revenue



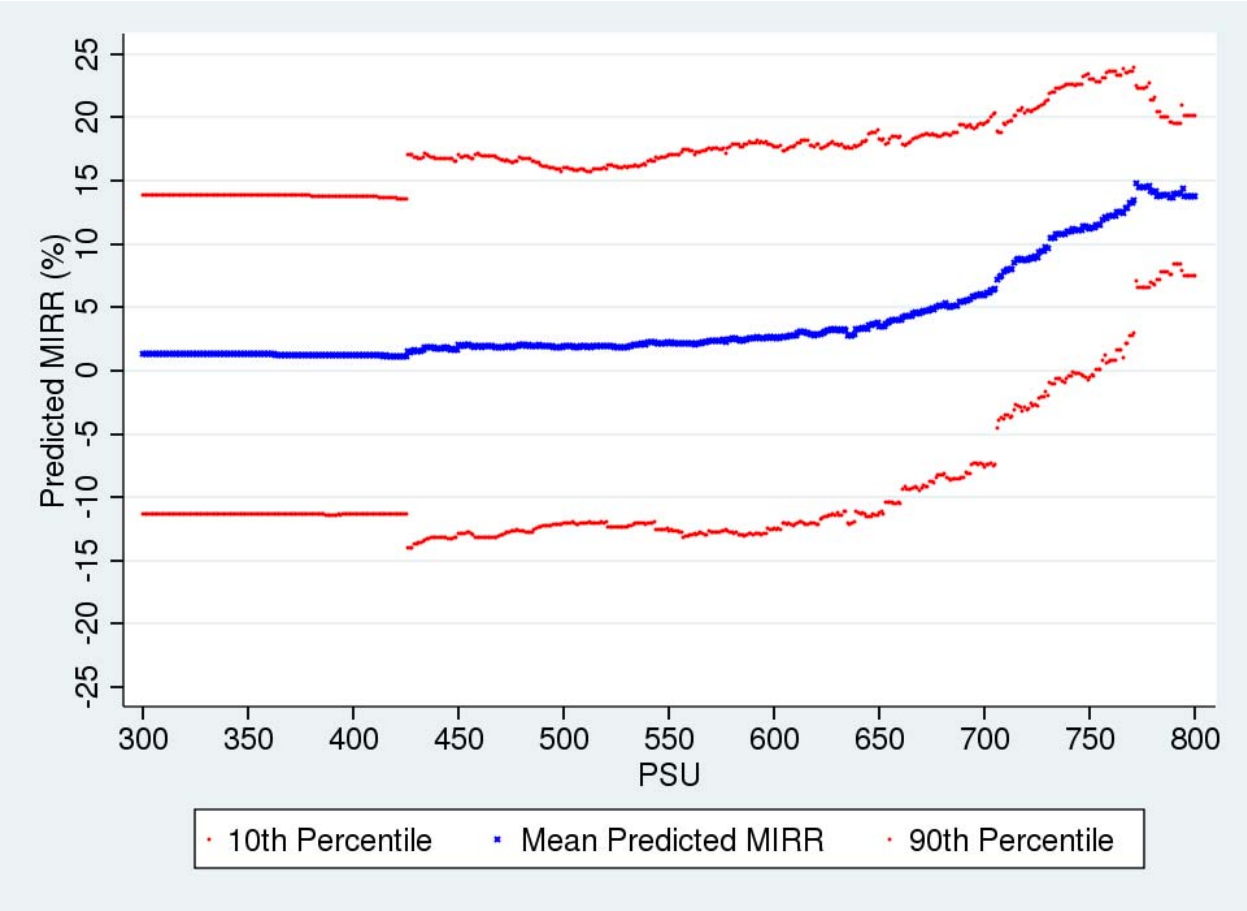
Notes: The loans included in these calculations are Crédito con Garantía Estatal (CAE) and Fondo Solidario de Crédito Universitario (FSCU). CAE is both need- and merit-based; students must be Chilean citizens or permanent residents. Generally, for CAE use at universities, the student must have scored an average of 475 on the PSU in Math and Language; for IPs and CFTs, students need either a high school GPA of 5.3 or an average PSU score of 475. FSCU is both need- and merit-based; students must be Chilean citizens, have family income within the first four socioeconomic quintiles and have a minimum average PSU score of 475 for Language and Mathematics. FSCU can only be used at CRUCH Universities. Each degree is assigned to a PSU 25^{th}-90^{th} percentile range. Within each PSU score, the weighted average of loans as a fraction of tuition revenue is taken, and this is what is presented in the graph above.

FIGURE 2a
Predicted Long-Run MIRR



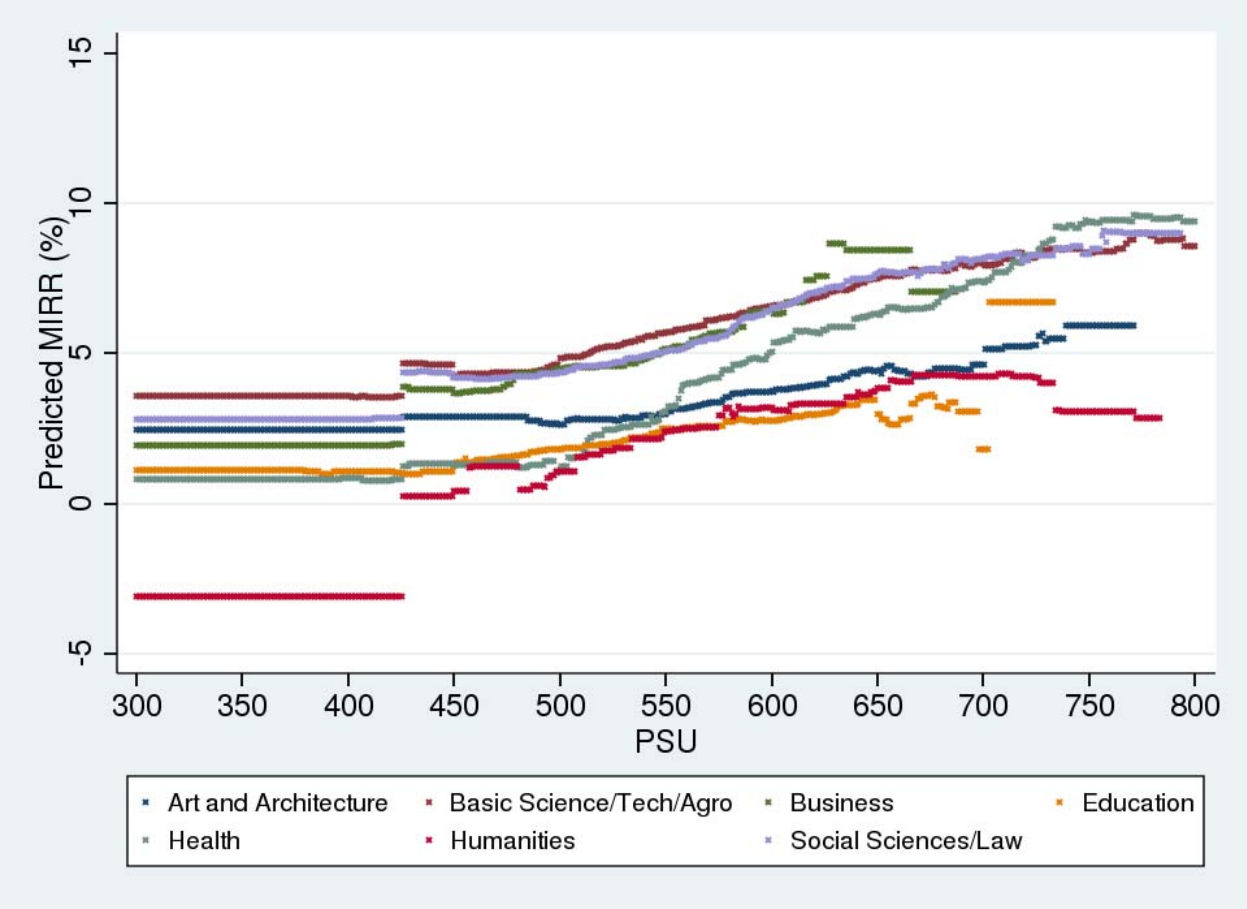
Notes: Figure presents the mean Modified Internal Rate of Return (MIRR) using predicted earnings with value-added estimates, weighted by probability of enrollment for 2003-2005 freshman cohorts across each degree's range of PSU from the 25th-90th percentile. MIRR is defined as = FV(earnings) / PV(tuition + opportunity costs + no-college earnings); where earnings are projected for 25 years of experience using our value-added prediction model. We use predicted earnings for experience years 1-7, then use a linear degree-selectivity-level growth rate to project earnings through experience year 15; then keep earnings constant through experience year 25. Tuition is calculated for the expected time to complete the degree. Opportunity costs are the no-college earnings for the expected time to complete the degree. No-college earnings are the earnings for no-college in the experience year that the student would be in had the student not enrolled in a higher-education degree (i.e. for a student in a degree that is expected to take 5 years to complete, the student's earnings in experience year 1 would correspond to no-college earnings for experience year 6.) The FV of earnings is evaluated at the end of experience year 25 using a reinvestment rate of 2%. The PV of tuition, opportunity costs and no-college earnings are evaluated at the time of enrollment using a borrow rate of 2% APR.

FIGURE 2b
Predicted Short-Run MIRR



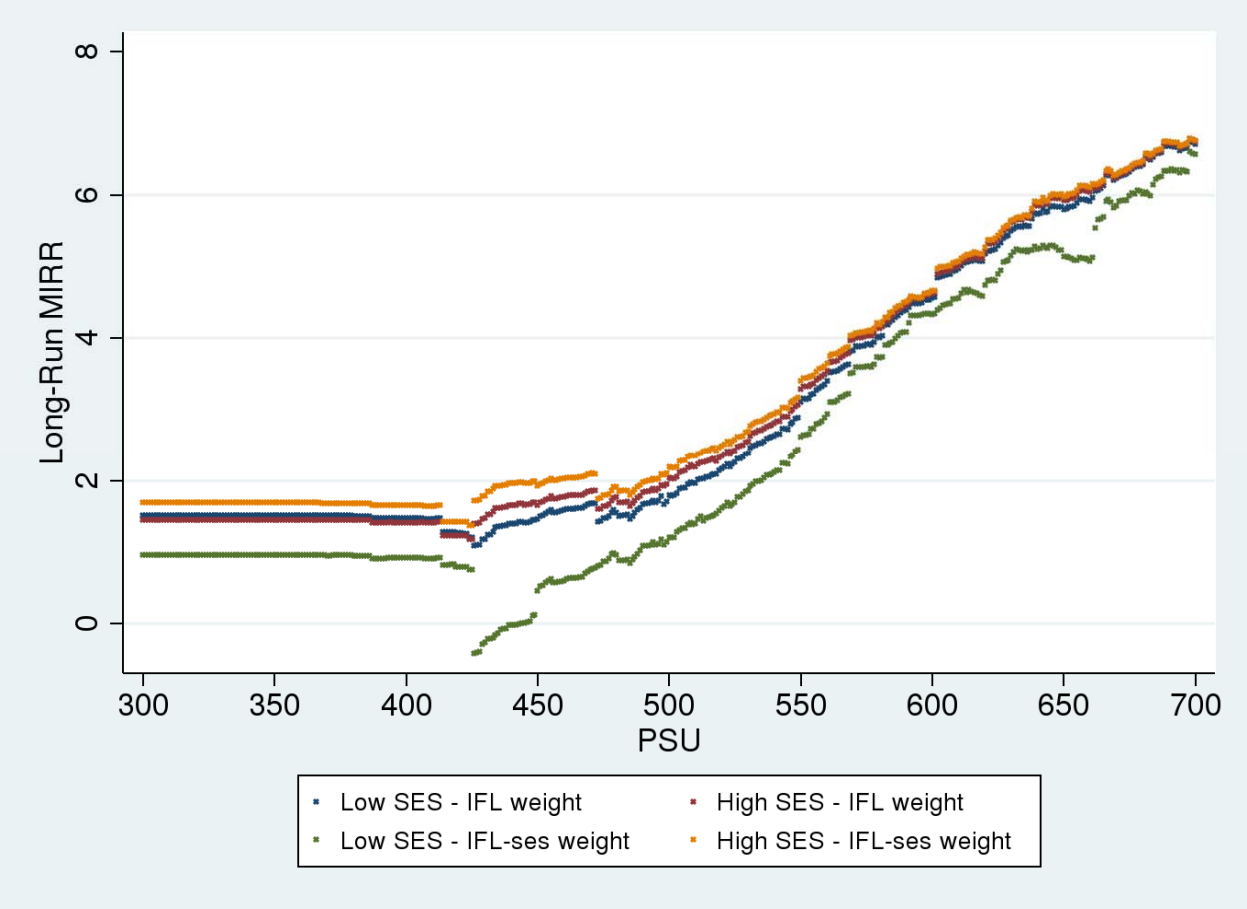
Notes: This figure presents the mean Modified Internal Rate of Return (MIRR) using predicted earnings and a weighted average for each PSU score within each degree's 25th-90th percentile range, weighted by the 2003-2005 freshmen enrollees. MIRR is defined as = FV(earnings) / PV(tuition + opportunity costs + no-college earnings); where earnings are projected for 7 years of experience using our value-added prediction model. Tuition is calculated for the expected time to complete the degree. Opportunity costs are the no-college earnings for the expected time to complete the degree. No-college earnings are the earnings for no-college in the experience year that the student would be in had the student not enrolled in a higher-education degree (i.e. for a student in a degree that is expected to take 5 years to complete, the student's earnings in experience year 1 would correspond to no-college earnings for experience year 6.) The FV of earnings is evaluated at the end of experience year 7 using a reinvestment rate of 2%. The PV of tuition, opportunity costs and no-college earnings are evaluated at the time of enrollment using a borrow rate of 2% APR.

FIGURE 3
Long-Run Predicted MIRR by Area



Notes: Figure presents the mean Modified Internal Rate of Return (MIRR) using predicted earnings with value-added estimates, weighted by probability of enrollment for 2003-2005 freshman cohorts across each degree's range of PSU from the 25th-90th percentile. Degrees are categorized into one of seven academic fields (defined in Hastings et al. 2013a). MIRR is defined as = FV(earnings) / PV(tuition + opportunity costs + no-college earnings); where earnings are projected for 25 years of experience using our value-added prediction model. We use predicted earnings for experience years 1-7, then use a linear degree-selectivity-level growth rate to project earnings through experience year 15; then keep earnings constant through experience year 25. Tuition is calculated for the expected time to complete the degree. Opportunity costs are the no-college earnings for the expected time to complete the degree. No-college earnings are the earnings for no-college in the experience year that the student would be in had the student not enrolled in a higher-education degree (i.e. For a student in a degree that is expected to take 5 years to complete, the student's earnings in experience year 1 would correspond to no-college earnings for experience year 6.) The FV of earnings is evaluated at the end of experience year 7 using a reinvestment rate of 2%. The PV of tuition, opportunity costs and no-college earnings are evaluated at the time of enrollment using a borrow rate of 2% APR.

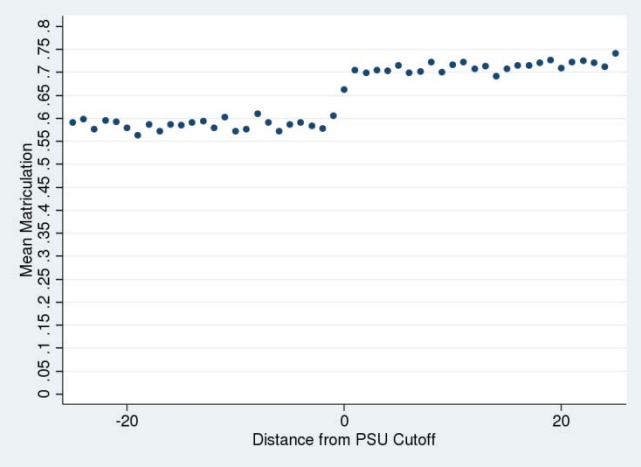
FIGURE 4
Long-Run Predicted MIRR by Socioeconomic Status



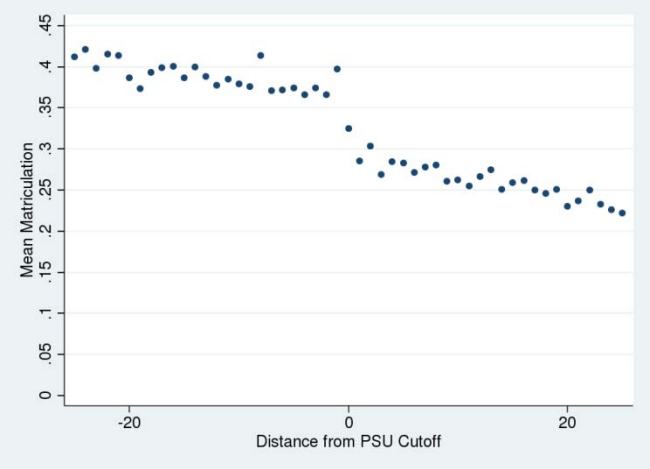
Notes: This figure presents mean predicted long-run MIRR for experience years 2-7 for the 2003-2005 freshman cohorts across the degree's 25th-90th PSU percentile. Means are weighted by probability of enrollment; the "IFL weight" lines are weighted by the probability of enrolling into an IFL, not conditional on SES. The "IFL-ses weight" lines are weighted by the probability of enrolling into an IFL, conditional on SES. These means are predicted using a vector of observable characteristics as well as degree-level value added estimates. Low-SES is defined as the student's high school (RBD) having an RBD poverty rating of "A" or "B"; these are the two lowest income quintiles.

FIGURE 5
Impact of Loan Qualification Test Score Threshold Crossing on Matriculation

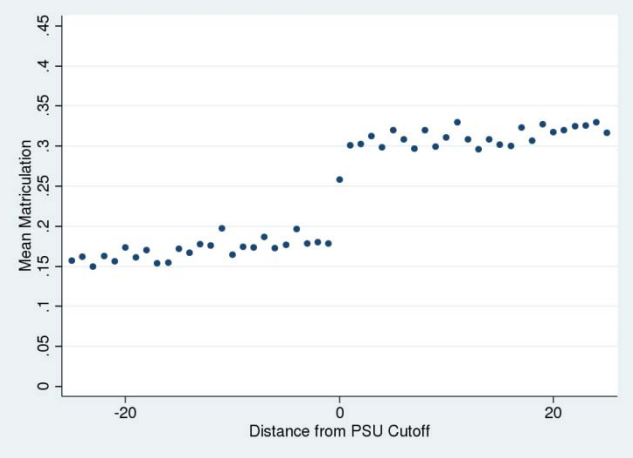
(a) Matriculation to any Higher Education Institution



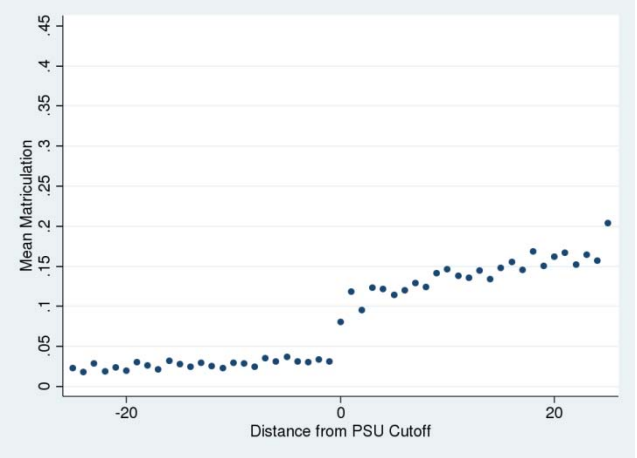
(b) Matriculation to Professional or Technical Institution



(c) Matriculation to Private University



(d) Matriculation to Elite University



Notes: The figure above shows the probability of matriculating to higher education institutions within one point PSU score bins. PSU score is calculated as the average of Math & Language score. PSU score is given as a raw score centered to 475 (the minimum score to receive CAE aid). A raw score of 475 would correspond to a score of 0 in the figures above. Base sample was the set of all loan applicants from 2008-2013.

Table I. Summary Statistics for Students Before/After Loan Reform

	(1) 2005 HS Graduates	(2) 2010 HS Graduates
% Graduates took PSU	55.5%	76.6%
	(213,786)	(210,870)
% Graduates Enrolled in Higher Ed	50.3%	63.8%
	(213,786)	(210,870)
Mean SIMCE Score for Enrollees	277.8	273.8
	(93,794)	(117,938)
% Enrollees with At Least 1 parent College Degree	23.3%	21.0%
	(81,751)	(122,721)
% Enrollees from High Poverty HS	36.0%	40.4%
	(107,553)	(134,597)

Notes: Sample sizes are in parentheses. Graduates were counted as enrollees in higher education if they enrolled within two years of graduation (i.e. years 2006, 2007 for 2005 graduates and 2011, 2012 for 2010 graduates).

Table II. Impact of Threshold Crossing Among FUAS Applicants

	(1) Approved for Loan	(2) Matric. Anywhere	(3) Prof./Tech. Matric.	(4) Private Univ. Matric.	(5) Elite Univ. Matric.	(6) LR MIRR	(7) Intensive Margin
PSU Linear Threshold	0.292***	0.111***	-0.0752***	0.114***	0.0716***	0.0542	-0.231
	(63.56)	(23.15)	(-16.00)	(26.51)	(25.54)	(0.62)	tba
PSU Quadratic Threshold	0.289***	0.104***	-0.0835***	0.119***	0.0692***	-0.00975	-0.309
	(41.92)	(14.50)	(-11.83)	(18.38)	(16.43)	(-0.07)	tba

Notes: Displays regression coefficients with t-statistics in parentheses. Threshold is a dummy variable indicating if an applicant received a combined PSU math and language score of at least 475, which is the minimum score to qualify for a CAE loan or if the applicant had a cumulative high school GPA of 5.3 or greater, which is the an alternative minimum requirement to qualify for a CAE loan. PSU Score is raw PSU score centered to 475, that is, a raw PSU score of 475 would be set to a score of 0 in the table above. For the regressions based on the GPA cutoff, a GPA of 5.3 is set equal to 0. Base sample is the set of all FUAS applicants 2008 – 2012. MIRR is defined as = FV(earnings) / PV(tuition + opportunity costs + no-college earnings); where earnings are projected for 25 years of experience using our value-added prediction model. We use predicted earnings for experience years 1-7, then use a linear degree-selectivity-level growth rate to project earnings through experience year 15; then keep earnings constant through experience year 25. Tuition is calculated for the expected time to complete the degree. Opportunity costs are the no-college earnings for the expected time to complete the degree. No-college earnings are the earnings for no-college in the experience year that the student would be in had the student not enrolled in a higher-education degree (i.e. For a student in a degree that is expected to take 5 years to complete, the student's earnings in experience year 1 would correspond to no-college earnings for experience year 6.) The FV of earnings is evaluated at the end of experience year 7 using a reinvestment rate of 2%. The PV of tuition, opportunity costs and no-college earnings are evaluated at the time of enrollment using a borrow rate of 2% APR. A detailed discussion about the construction of the Intensive Margin in (7) is found in the body of the paper.

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

Table III. Comparison of PSU Takers, Survey Sample Invitees, Opened Email, Consenting Sample & Respondents

	(1) Invited Sample	(2) Opened	(3) Consent	(4) Respondents
PSU - Average of Math & Language	505.4	521.5	524.5	536.3
	(165,591)	(95,864)	(72,474)	(47,568)
Municipal High School	38.70%	36.20%	36.50%	33.10%
	(189,554)	(100,381)	(83,346)	(49,166)
Private or Voucher High School	59.20%	63.30%	60.80%	66.60%
	(189,554)	(100,381)	(83,346)	(49,166)
Mother Some Tertiary Education	24.80%	27.60%	26.90%	29.80%
	(141,263)	(79,090)	(60,616)	(40,744)
Father Some Tertiary Education	26.20%	29.30%	28.60%	31.70%
	(136,676)	(76,603)	(58,722)	(39,511)
SIMCE RBD Poverty Rating	2.663	2.809	2.760	2.928
	(173,750)	(94,079)	(76,476)	(46,444)
SIMCE 10th grade Math (Z-score)	0.295	0.429	0.454	0.560
	(130,803)	(75,127)	(56,172)	(38,563)
SIMCE 10th grade Language (Z-score)	0.311	0.445	0.477	0.577
	(130,802)	(75,112)	(56,159)	(38,554)
Female	55.70%	57.30%	58.20%	57.50%
	(189,309)	(100,375)	(83,215)	(49,166)
Delayed College Entrance	34.50%	29.70%	39.60%	24.50%
	(189,554)	(100,381)	(83,346)	(49,166)
Total Observations	189,554	100,381	83,346	49,166

Notes: In this table, "2013 PSU Takers" are all those who took the 2012 PSU for application and enrollment in the 2013 school year. The “Invited Sample” is all valid email addresses that were sent an invitation to participate in the survey. The "Opened" are those that opened the email inviting them to participate in the survey; if the images were disabled and they did not click on the link, they are not included here. The "Consent" column refers to those that began the survey and clicked to indicate that they were giving informed consent. The "Respondents" are classified as those who completed the entire six question survey with no errors. Calculations are based on survey responses linked to administrative data from the Chilean Ministry of Education (Mineduc). Sample sizes for each calculation are in parentheses. These values differ from total observations because of partially incomplete administrative data. The survey reported in this table is the P3E 2012 survey which recruited HS seniors and PSU registrants as part of the November 2012 FUAS application process for the 2013 school year. RBD Poverty Ratings are the modal poverty ratings for each high school, produced by Mineduc in 2001, 2003, 2006, and 2008. A (set = 1 in this table) is the highest poverty level, B (=2) the next highest, and so on, until E (=5) is the lowest poverty rating. SIMCE scores are results from standardized high school test scores that were nationally administered to all students enrolled in the 10th grade in 2001, 2003, 2006, 2008, and 2010. The results for these test scores are normalized to z-scores within each testing year because the scale for the raw scores changed over time. Delayed college represents those that were not directly coming from high school and were generally older students that had taken a few gap years between high school and college.

Table IV. Impact of Treatment on Outcome Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled		Did Not Receive Loan		Received Loan	
	2012 HS Grad	2009-11 HS Grad	2012 HS Grad	2009-11 HS Grad	2012 HS Grad	2009-11 HS Grad
Received Loan	-0.005	-0.004	--	--	--	--
	(0.006)	(0.006)	--	--	--	--
2013 PSU	2.060	-2.199	5.705	-3.831	1.481	-1.636
	(1.801)	(1.290)	(3.129)	(4.815)	(1.618)	(1.151)
Matriculated Anywhere	0.008	-0.006	0.023	-0.017	0.006	-0.003
	(0.006)	(0.006)	(0.012)	(0.023)	(0.006)	(0.006)
Net Value of Matriculated Degree	11,455	-223	25,918**	24,311	9,325	-3,179
	(6,297)	(7,578)	(8,893)	(20,189)	(7,263)	(8,301)
Earnings Gains of Matriculated Degree	12,271	-617	27,986**	27,532	9,922	-3,929
	(6,896)	(8,312)	(9,797)	(22,336)	(7,932)	(9,090)
Monthly Debt of Matriculated Degree	684	-183	2,007	278	495	-278
	(695)	(898)	(1,087)	(2,518)	(783)	(974)

Notes: The statistics reported above are the coefficients on a treatment indicator that is set =1 if the student was treated with degree information in our survey experiment. Standard errors are in parentheses. The variables in the left-side column are the dependent variables in each regression that includes independent variables: treatment indicator, controls for higher-education major of their first-choice in the survey, and randomization group for the 2012 high school graduates clustered by high school, PSU score-bin for the 2009-2011 high school graduates. Received Loan is an indicator whether the student received any federal loans. 2013 PSU is the average Math + Language PSU score for just the 2013 test year (test actually administered in 2012). Matriculated Anywhere is an indicator if the student matriculated to any higher-education institution. Net Value of Matriculated Degree is the monthly value of the average earnings of the matriculated degree less the no-college average earnings less the total tuition for duration of the degree. The earnings are average earnings from 5 years of experience that are grown using an area level linear growth rate through experience year 15. The present value of the 15 years of earnings is taken using 2% APR. Monthly Debt of Matriculated Degree is the total tuition for duration of the degree amortized over 180 months (15 years). The following are all stated in 2011 Chilean pesos: the average Net Value of Matriculated Degree is 420,864, average Earnings Gains of Matriculated Degree is 474,793, average Monthly Debt of Matriculated Degree is 57,874.

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

Table V. Impact of Treatment and Threshold Crossing on Net Value of Matriculated Degree

		(1) Treated	(2) Treated * Threshold	(3) Threshold
2012 HS Graduates	Linear	58,081*	-45,487	117,146***
		(26,072)	(36,136)	(25,296)
	Quadratic	82,637*	-63,586	160,144***
		(39,268)	(54,431)	(38,479)
2009-11 HS Graduates	Linear	33,925	-14,601	68,934
		(51,800)	(69,401)	(48,629)
	Quadratic	8,157	105,429	29,987
		(77,151)	(102,481)	(71,366)
Pooled	Linear	48,077*	-40,080	103,964***
		(22,965)	(31,550)	(22,039)
	Quadratic	52,607	-13,718	120,209***
		(34,549)	(47,333)	(33,189)

Notes: The regressions reported above include the net value of the matriculated degree as the dependent variable with the following independent control variables: indicator for treatment in survey experiment, indicator for crossing the 475 PSU score CAE loan threshold, interaction between treatment and threshold crossing, distance in PSU score from threshold, interaction between distance an threshold, interaction between distance and treatment, interaction between treatment and threshold, net value of first-choice degree, first-choice degree indicators, indicator for 2009-2011 high school graduate, indicator for gender, and controlling for randomization group fixed effects. These regressions are run for students with PSU scores between 450-500 (50 point window around the CAE threshold). The regressions are then run with distance variables and coinciding interaction variables as squared terms (these results are the quadratic estimates shown above).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$