CAUSAL RETURNS TO POSTSECONDARY EDUCATION IN CHILE: FIELDS, SELECTIVITY, STUDENTS AND LUCK

by

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Abstract

We use new administrative data from Chile from 1985 through 2010 to estimate the causal returns to a college degree as a function of field of study, course requirements, selectivity, measures of school quality, and student socio-economic status. It is to our knowledge the first study to examine the causal impact of these factors on short and long-run labor market outcomes. Our data link high school records to entrance exam records to college applications, admission, matriculation, and finally labor market earnings from tax records. Because the Chilean admission system for most universities is centralized and test-score based, we are able to exploit hundreds of regression discontinuities to estimate the causal impacts of interest. We use the reduced-form estimates to estimate a simple wage model, which allows us to compare the earnings effects of each program to a common outside option. We find that returns are highly heterogeneous by field of study, with particularly large returns in health, technology and business. Earnings gains are larger for more selective programs, with little to no gains from admission to low-selectivity degrees or degrees with vocational curriculum focus. Heterogeneity in gains are not fully captured by differences in tuition across institutions and degrees. We do not find differential outcomes for students coming from low versus high SES backgrounds. Our results support the claim that persistent frictions exist in supply of institution-degrees relative to demand for skills, or in demand response to returns through informed student choice. Both suggest a role for public policy in decreasing frictions.

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1 Introduction

The college wage premium in the United States has risen dramatically since the early 1980s (Cutler & Katz 1992; Karoly & Burtless 1995; Bound & Johnson 1992; Katz & Murphy 1992; Murphy & Welch 1993; Juhn, Murphy & Pierce 1993; Goldin & Katz 2007; Autor, Katz & Kearney 2008; Acemoglu & Autor 2010). Concerns over the growing college-high school wage gap and its implication for income inequality led to Federal and state expansions of student loan programs in the 1990s and 2000s (e.g. the 1993 Student Loan Reform Act and the 2007 College Cost Reduction Act). From 1990 to 2010, U.S. college going rates increased by 52%.[1] In Chile, student loan program expansions were introduced in the 2000s, and total enrollment grew by 94% between 2000 and 2009.[2] But by 2010, protests over student loan debt and *ex-post* regret of higher educational investments abounded in the U.S. and abroad. This called into question the idea that returns to college education identified by panel regression correlations applied to students induced into postsecondary degrees by expanded student loan programs.

Returns to education may vary with student characteristics, such as innate hard and soft skills. They may also vary with institution characteristics, such as selectivity, and with field of study (e.g. history major versus engineering major). Both differences in students' ability and differences in their postsecondary field and institution of choice could drive differences in returns to education. Understanding how student, degree and institution factors influence the returns to education is crucial for designing successful loan and higher-education policy. However, there is relatively little causal evidence regarding heterogeneity in returns to college along these three important dimensions (Dale & Krueger 2002; 2011, Deming, Katz & Goldin 2012; Altonji et. al 2012). A few recent studies use regression discontinuity designs to provide convincing evidence on the returns to admission to particular institutions. Hoekstra (2009) studies admissions to a flagship state university in the U.S., while Zimmerman (2012) focuses on students crossing the margin from community college to university attendance in the Florida State University System. Saavedra (2008) uses a similar design to estimate employment and earnings returns one year after college for applicants to the top university in Colombia, and

[1] U.S. Department of Education, NECS, 2011, Digest, Table 198. "Degree-granting institutions include almost all 2- and 4-year colleges and universities; they exclude institutions offering only career and technical programs of less than 2 years' duration and continuing education programs."
[2] Rolando et al. (2010).

Öckert (2010) estimates long-run earnings returns to a year of schooling for Swedish college applicants. While these studies offer a significant improvement in causal identification over studies controlling for observable characteristics alone (Monks 2000; Black and Smith 2004;, Lindahl and Regner 2005; Long 2008; Dale and Kruger 2011; Hoxby 2004; Brewer et al. 1999; Kane 1998, among others), the narrow data and scope of these studies limit their ability to address the broader economic and policy questions at hand.

This paper provides new evidence on the determinants of returns to college education using a unique and extensive database constructed from high school, college and tax return records for 26 cohorts of high school graduates in Chile. We compiled these data in conjunction with the Chilean Ministry of Education (MINEDUC) to provide empirical facts to guide and shape sweeping student loan policy reforms for the 2014 school year.

In this study, we use these data to estimate short- and long-run labor-market returns, employing a regression discontinuity design which, coupled with a simple model of earnings determination, allows us to decompose returns into the contributing factors of interest; field of study, vocational focus, and institution selectivity for students coming from different socio-economic backgrounds. Examining these questions in the Chilean context provides several benefits. First, to our knowledge this is the first data base that has linked administrative data from high school, college entrance exam, college choice, college admission, college matriculation, and tax return data for a population of students across multiple cohorts. Second, Chilean students apply to a career (major/degree) and a university simultaneously (e.g. Civil Engineering at UC Berkeley), a process common to many countries in Europe, Asia and Latin America. The centralized application and score-based admission system results in thousands of regression discontinuities, effectively randomizing students near admissions cutoffs between fields of concentration and institutions of varying selectivity.

Students apply using a central application system, ranking up to eight institution-degree choices. Students are ranked by a score composite comprised of standardized admissions tests and high school GPA. Universities order by their score, and student's choices are evaluated beginning with the highest scoring student. Within student, choices are evaluated in rank order, placing each student in her most preferred option with available slots by the time her application comes up in line. This process continues until all admission slots are full or demand is satiated. The assignment algorithm is similar to that used in the U.S. medical residency market.

Students typically list different careers and institutions of varying selectivity in their application. Students have some idea of which school-career combinations they could get into based on their exam scores, and often list "reach" and "safety" options in their applications. Actual cutoff scores in any given year-institution-career combination are unknown, and cutoff scores within institution-career can vary substantially across years. The cutoffs for most programs depend in a complex way on the scores and preferences of other applicants. Demand shocks to one institution or career can ripple through the system. This generates sharp discontinuities in admission probabilities which are unpredictable within a window of scores around the cutoff. It also generates exogenous variation in the characteristics of the institution and career attended, as students often cross the threshold for admission to degrees with different fields of study and selectivity tiers than those to which they would otherwise have been admitted.

In partnership with MINEDUC and several other agencies, we constructed from hard copy or electronic copy high school, entrance exam, college choice, admissions and matriculation data for cohorts of admissions test takers beginning in 1980 through the present. We then linked these data to labor market earnings from tax records from 2005-2011 (accessed securely within the tax authority), providing labor market returns from 1 year after high school graduation for the youngest cohorts to 26 years post-graduation for the oldest cohorts.

We use thousands of regression discontinuities to examine how returns to college education vary with career, institution and individual characteristics for students who are ex ante the same on observable and unobservable characteristics (Pop-Eliches and Urquiola , 2011). We first present a straightforward summary of the effects of admission to different types of degree programs. Interpreting these reduced-form effects is challenging, since the earnings effects of threshold-crossing depend on both the characteristics of the target degree and the characteristics of the degrees to which students would otherwise be admitted. To address this problem, we integrate the many regression discontinuity estimates into a coherent framework using a simple model of wage determination, which allows us to estimate the earnings effects of each degree program for different types of students relative to a common outside option.

Our analysis reveals several interesting patterns. First, we find statistically and economically significant increasing returns to selectivity of the degree as measured by entrance exam cutoff-scores. In particular we find small and even negative returns to university degrees at non-selective institutions across all fields of study. When tuition costs are taken into account, we

find negative returns to admission at non-selective institutions. This finding is important as this enrollment in non-selective universities saw the preponderance of growth as a result of Chilean student loan program expansion. Hastings, Neilson and Zimmerman (2013a) use cutoffs for loan qualification to show that student loan receipt caused students to substitute away from technical degrees into non-selective college degrees. Our results suggest that these degrees have low-to-negative net-present-value returns. In contrast, admission to selective programs causes positive and economically significant labor market returns even once tuition costs are accounted for. Returns to selectivity increases, with the largest returns realized at the most selective institutions.

Second, we find persistent returns to field of study. Being admitted into a Health degree increases earnings by 15.1 to 19.1 percent of an average wage. Being admitted into a Business degree has a similar size impact on earnings (16.7-16.8), and being admitted to Social Science/Law or Technology/Science degrees also have positive impacts on earnings of 9.9-10.3 and 7.2-9.1 percent, respectively. In contrast, admissions into Art and Architecture and Humanities degrees result in lower earnings relative to no admission at all. Art and Architecture admittees stand to lose 1.1-5.5 percent of an average wage while Humanities admittees lose 9.1-14.9%. Our results suggest that just failing to be admitted to a program of choice could be one of the luckiest or unluckiest events for a person's expected future earnings. For students who chose degree combinations like Art versus Computer Graphic Design or Health versus Education or History versus Economics, just missing admission to your target of choice could substantially impact your average annual earnings by 12.7, 14.3, or 25.9%, respectively. Moreover, when we use tuition costs and convert our annual earnings gains into present discounted values of lifetime earnings, we find that differences in tuition costs across programs and institution selectivity are not nearly enough to even out the disparate returns we identify.

Third, we examine the extent to which returns to field of study and institution-career selectivity can be attributed to course requirements. To do this, we digitized and matched on core major requirements by institution-career. Although the requirement data was only available for recent years, we find significant differences in the quantitative (math, computer science, statistics), qualitative (language, humanities) and vocational (internship and practitioner coursework) core requirements both within and across institutions and general field of study. We find that, students admitted to degrees in which required coursework has a strong vocational focus rather than a traditional math-science-language focus have lower earnings returns across

areas of study and program selectivity. This suggests that more vocational-focus in curriculum may not raise labor market returns for loan-eligible populations.

Finally, we find no significant difference in returns along each of these dimensions by measures of socio-economic status of the applicant. This suggests that subsidizing admission for students from low-socio-economic students can be successful if the right degrees and institutions are targeted.

These findings speak to key economic and policy questions. They suggest that frictions exist in the markets that match students to postsecondary degrees. Constraints on the supply of high-return degrees (see Bound and Turner, 2007) may push students into programs with lower economic returns at many margins. Admitting the marginal applicant to a high-return program by lowering the score cutoff a small amount likely represents a policy change with a positive social return. At the same time, we observe excess demand for degrees that lead to zero or, in some cases, large and negative earnings returns for admitted students. This could be because these degrees offer high non-pecuniary compensation that is valued by all students, or because some students have very strong tastes for the coursework or careers associated with these degrees.

That said, several recent papers present evidence suggesting that students may base college and career choices on beliefs about economic returns that are systematically biased and uniformed (Arcidiacono et al. 2010; Zafar 2011; Hastings et al. 2013b; Wiswall and Zafar 2013). The existence of oversubscribed degrees with zero or negative returns thus suggests two possible avenues for welfare-improving policy intervention. First, if information aggregation is a public good, policymakers supply centralized ranking and earnings information to guide to provide students with accurate information needed before making life-long decisions. Second, loan policy could be used to provide additional supply-side incentives to ease frictions in supply of high-return degrees (Hastings et al. 2013a,b).

2 College applications in Chile

All students take a standardized test for college admission. This test was called the PAA until 2002 (taken for the 2003 college entering year), and the PSU after 2002. It is constructed and

administered by the central testing authority, DEMRE, which is under the authority of the Council of Rectors of Universities of Chile (CRUCH). Together with high school grades, which are submitted to DEMRE and converted to a standardized score, this universal entrance exam is the primary component of postsecondary admissions, scholarships, and student loan eligibility. Online Appendix, Section 1 describes the scoring system in detail. All students take entrance exams in language and mathematics, with some degree programs requiring additional subject tests in areas like history or chemistry. Scores range from a minimum of 150 to a maximum of 850. A minimum score of 450 is required for admission to a CRUCH institution. The distribution is standardized so that the mean and median are 500.

CRUCH institutions are the core set of universities in Chile. Students apply to CRUCH institution-career combinations through a central application process. The CRUCH are all not-for-profit, but can be either public or private or private parochial. Importantly, universities of various selectivity levels are members of the CRUCH. An appropriate analogy might be a combination of the University of California system, the Cal State system, and the major private universities in California. The two most selective Universities are Universidad de Chile (UC, a public university) and Pontificia Universidad Católica de Chile (PUC, a private catholic university), both of which send top students to some of the most selective graduate programs in the world.

Table 1 lists these universities and the interquartile range of entrance exam scores of graduating classes from 1995 to 2010 as well as their overall share of college graduates. There is a wide selectivity range within the CRUCH universities, and the relative selectivity is fairly constant over time for top- versus bottom-ranked schools. In the 80s and 90s CRUCH universities made up over 80% of all University degree granting institutions by students graduating.[3] Over time, there has been entry by new universities, typically serving lower-scoring students.[4] Figure 1 shows the fraction of high school graduates taking the college entrance exam in Chile from 1995 through 2011, and the fraction of students who scored above the minimum score to apply to CRUCH. Overall, entrance exam taking has been increasing over time in Chile,

[3] Rolando et al. (2010), MINEDUC report on aggregate trends in postsecondary education provides similar statistics for the 1980s.

[4] Hastings et al. (2013b) show that entry in this non-profit segment was related in part to the expansion of student loans which caused expansion in non-for-profit university degrees as students used loans to substitute away from professional and technical degrees towards more expensive university degrees.

though it has persistently been higher in Chile than in the US, if we consider the SAT an analogous college entrance exam.

Application to CRUCH is centralized; students submit one application with up to eight choices for institution and career.[5] Unlike the US, but similar to many other postsecondary education systems in Europe, a choice is an institution and a career. Most degrees are licenciatura (licenture) degrees which take an average of 5 years to complete. These degrees are similar to a combined bachelor's and 1 year master's degree. Professional degrees are also offered in more recent years by for-profit and not-for-profit Professional Institutes. These are 3-4 year degrees, similar to a combination of two year degree with professional training. CRUCH institutions also offer 2 to 3 year technical degrees, as do the newer for-profit Professional Institutes and Technical Institutes. These are similar to an Associate of Art, or a technical degree from a two year college in the US. These degrees were rare in earlier years, but have grown in the past decade.

Students apply with some knowledge of where they might be admitted. Institution-degrees currently post statistics such as interquartile range of PSU scores for admittees on their websites to aid students with gauging their likelihood of admission, and students can look up cutoff scores from past years in publicly available sources. Students know that they are ranked based on a scoring system driven predominantly by their PAA/PSU score and high school grades. However, they still face substantial uncertainty, since the cutoff score fluctuates year to year as the number of available spots and the profile of the other applicants changes. Even if students can predict their own admissions score perfectly, marginal students will be unable to predict their admissions outcome, since the cutoff score is only known ex post.

Table 2 shows summary statistics from CRUCH applicants for years 2001-2011, years for which we have full preference rankings from electronic records. For 1985 to 2000, we do not have full ranked choices but instead digitized admission, waitlist and score data from hard records (to our knowledge, full applications in these earlier years do not exist in any form). Column 1 shows the mean and standard deviation of choices listed (1 is the min and 8 is the max). Students on average do not list a full set of eight, but list on average 4-5 choices. On

[5] Other systems that use centralized applications include the University of California system where students can list up to 10 universities and the California State University system where students can list up to 23 choices. See more on: http://en.wikipedia.org/wiki/University_of_California for UC system description; http://en.wikipedia.org/wiki/California_State_University

average their first choice school is one they could get into with some probability based on historic admissions; on average their own PSU score is slightly higher than the cutoff for their year of admission. They are on average more comfortably over the cutoff score for their last choice school, indicating that students apply for reach options on their first choice and safer options for their lower-ranked choices.

On average there is a lot of variation in the careers, areas of study and universities a student lists in their application. Out of their average 4-5 choices, they list 3-4 different careers in close to 2 different CINE-UNESCO (UNESCO Normalized International Classification of Education) areas, at 2.5 different universities crossing 1.6 -1.7 selectivity tiers (tiers are defined based on a median split of the distribution of program-level average scores for accepted students; see below). CINE-UNESCO categories are broad. There are ten categories: Agriculture, Art and Architecture, Basic Science, Business Administration, Education, Health, Humanities, Law, Social Science, and Technology. On average, students are selected to a little less than their second choice. About 68% of students are admitted to at least one choice, and of those 70-75% eventually matriculate to that choice.

There are two important things to note with this centralized process. First, centralization leads to many random shocks and difficult-to-predict cutoff scores. Figure 3 illustrates the variation in mean peer quality within institution-career from 2000-2011 as a function of overall selectivity of the institution-career. Second, students only receive *one* admission ticket – the highest ranked school on their application with an open seat when they come up in the score line, so that admission to a particular choice translates much more clearly into matriculation to that choice relative to the system in the US where students may field many offers from institutions.

3 Data

3.1 Administrative records on college applicants

We compiled several databases for this study, often from original hard-copy records. Compiling these data required coordinating cooperation between several Chilean institutions, the impetus

for which was a need for better data-driven policy response to the student loan debt crisis in Chile.

First, we compiled historic records on scores, admissions, and waitlist for all CRUCH schools and careers from 1985 through 2000, which we digitized from original paper copies. Second, we digitize data on PAA/PSU scores from 1985-2000 from hard records at the testing authority, and match these by individual identifiers to the admissions data. These records also include information on high school of graduation and gender (we are currently working to complete this information by matching records to alternative government sources). In addition to this, we digitized high school graduation records from hard-copy paper archives for 1995-2001. These data include gender, GPA, attendance and high school for almost all high schools. These data give us not just entrance exam takers, but a large sample of high school graduates in Chile that may or may not have taken the PAA college entrance test. Online Appendix Section 2 provides further detail on the data digitization and construction.

Starting in 2001, we are able to use electronic records on the college application process. These records include high school graduation records with gender, GPA and high school of graduation. We link these records to digital applications to CRUCH schools. These digital applications include all choices, admissions and waitlist decisions, as well as demographic information such as gender and family income. Additionally, we link these records to entrance exam test outcomes from the test authority.

For the years 1995, 1998, 2000 through 2011 we have data on graduates from each postsecondary degree-granting institution in Chile. For 2000 through 2011 we have data on matriculation on a semester-by-semester basis for all degree-granting institutions.
These data combined give us a panel of college applicants and graduates from 1985 through 2010 – twenty-six cohorts of students. We have cutoffs for admissions and scores used for admissions to each CRUCH University and career over that time period. We also have high school of graduation and handful of demographic variables for a subset of years beginning in the late 1990s.

We match these data to individual tax records at the Chilean tax authority in compliance with privacy laws in Chile. Over 99% of individuals in our data have matches in the tax records. The tax records are available for tax years 2005 to 2011, and include all labor earnings. Prior to 2005, administrative earnings microdata are not available for a significant portion of wage

earners. Online Appendix Section 3 describes the tax records in Chile in detail and explains how we construct labor earnings. All values are reported in 2011 pesos.

Our earnings analysis includes zero earnings values; we do so to ensure we capture returns due to changes in the extensive labor supply margin as well as increases in productivity and movement along the intensive labor supply margin. In Online Appendix Section 4 we show results for participation effects and earnings that exclude zeros; in practice our results are driven largely by changes in earnings conditional on some work. To reduce the effect of earnings outliers on our analysis, we exclude the top 1% of values conditional on cohort and experience. Specifically, we regress earnings on a set of cohort dummies and a quadratic in experience and compute the residuals. We then drop observations with residuals in the top 1% of the distribution. Our results are robust to moving this threshold up or down.

3.2 Administrative records on college applicants

We construct several measures of institution and career characteristics. First, careers come with administrative categorizations by CINE category (UNESCO Normalized International Classification of Education). There are ten categories: Agriculture, Art and Architecture, Basic Science, Business Administration, Education, Health, Humanities, Law, Social Science, and Technology. We group these ten categories into seven categories in most specifications to facilitate parsimony in our exposition and to improve statistical power.[6] These seven areas are Art and Architecture Agriculture; Basic Science and Technology; Business and Administration; Education; Health; Humanities; and Social Science and Law.

In addition to these broad categories, MINEDUC categorizes careers into 191 narrow majors. Within these categories, a major is essentially the same, but may have a slightly different name at different universities. For instance, the "Social work" code includes degrees titled "Social work", "Social service", and "Social service with a degree in social work". We will use this very detailed career categorization in some specifications. Online Appendix Section 5 details these field categorizations and provides further examples.

[6] Note that we chose these aggregate groupings prior to RD estimation. As we discuss in Online Appendix 5, we observe similar point estimates of earnings effects in the subcategories we combine to form our broader categories.

Second, we use course requirement data to categorize institution-careers by the amount of quantitative, qualitative or pre-professional course work they require. We use current course requirements as listed on institution and major websites as historic information is not available. Quantitative courses include math, statistics, computer science, physical sciences, and life sciences. Qualitative courses include language, literature, and history. Professional courses include internships and courses that teach students how to apply skills to problems specific to particular segments of the labor market. For example, a course on the operation and repair of medical devices would fall into this category, as would a course on the administration of medical tests. By contrast, a chemistry or cell biology course on the mechanisms underlying the function of the medical device or the effectiveness of the test would fall into the quantitative category. Each institution and career is then categorized into a career that focuses on professional coursework or one that focuses on quantitative and qualitative coursework. Within a narrow field or major, this distinguishes professional "how-to" oriented degrees from degrees focused on training in general skills in math, science and communication. Online Appendix Section 5 details this categorization process and provides additional examples.

We combine each of the data sets above to arrive at our estimation sample. Online Appendix Section 7 provides details on how this sample is constructed. Table 3 compares characteristics of the full sample with our current estimation sample and the sample of students near the score cutoff for admission to each institution-career in each application year. Column 1 shows summary statistics for all applications. Column 2 shows summary statistics for the marginal sample of applications – those within 25 points of the cutoff for each institution-career-year combination where we observe excess demand, defined as a minimum of 15 applications in the five points below the cutoff score. Column 3 shows summary statistics for students on the margin for which we have all data. We currently lose approximately 3% of our data due to either missing CINE-UNESCO classification or missing course requirement data. We are currently working to fill these in where possible. On average our marginal sample has higher entrance exam scores, are more likely to be applying to a degree in the Business area classification, and less likely to be applying to a degree in the Education area. They are more likely to be applying to high-selectivity degrees, since low selectivity ones may not have marginal students in many years. Their degrees are similarly likely to have course requirements with a vocational focus.

Marginal applicants are more slightly more likely to be male, and significantly more likely to come from private schools, which serve on average wealthier families and enroll/produce higher-scoring students. For the 2011 tax year, labor earnings for our marginal group are slightly higher than those for the total applicant population. If we convert Chilean pesos to USD using OECD Purchasing Power Parity for 2011, this results in an average income of $24,449 per person in 2011. Positive earnings probability per person is high at 85.6%.

4 Model and Empirical Framework

Our goal is to use this sample and sharp cutoffs in admissions to schools to estimate how the returns to college education vary with key characteristics of the degree and student socio-economic characteristics. Since individuals may positively select into careers and institutions for which they have higher unobservable expected labor market returns, coefficients from an OLS regression of labor market outcomes on admission program and individual characteristics do not have a causal interpretation.

To address selection problems, we exploit the discontinuities in admissions outcomes discussed above. In the first stage of our analysis, we obtain estimates of the effects of crossing the admission threshold at each degree program on earnings. Using data at the student-application-outcome year level, we estimate equations of the form

$$Y_{itpr} = f_p(d_{ipr}) + \delta_p Z_{ipr} + \varepsilon_{itpr} \quad (1)$$

Here, Y_{itpr} is total earnings in outcome year *t* for individual *i* who applies to program *p* in application process (application year) *r*; d_{ipr} is the difference between the admissions score assigned to *i*'s application to program *p* in application year *r* and the cutoff score for admission for that program in that year; $Z_{ipr} = 1\left(d_{ipr} \geq 0\right)$ is an indicator variable equal to one if *i*'s application to program-year *pr* is accepted (is above the cutoff score); $f_p\left(d_{ipr}\right)$ is a smooth

function of the score difference; ε_{itpr} is an error term. We can estimate equation (1) separately for every target degree in the system. Doing so gives us a reduced-form estimate of threshold crossing into each program, δ_p - the mean annual earnings impact of crossing the admission threshold into program *p*. We generally estimate (1) using data on all student-year observations for which between 6 and 26 years have elapsed since the year of college application. To test for changes in the effects of threshold-crossing over time, we also estimate complementary specifications focusing on student-year observations between 6 and 15 and between 15 and 26 years since college application. In addition, we can condition on baseline characteristics of interest, *c*, such as socio-economic status or measures of mathematics ability. As these characteristics are predetermined to application and threshold crossing, they are valid conditioning variables. Conditioning on observable characteristics of interest, *c*, yields separate reduced-form impacts of threshold crossing for individuals with characteristics *c* applying to program *p*, δ_{cp}.

The effects of threshold crossing are surely of interest for students on the margin of admission and for administrators evaluating admissions and tuition policies. However, we are interested in using these reduced-form estimates to understand the causal returns to institutions and degrees along key dimensions of field of study, selectivity and curriculum, and how these vary with key demographic characteristics like socio-economic status. These do not follow directly from the reduced-form estimates, since estimated threshold-crossing effects reflect differences between the earnings effect of the target degree and earnings effects of the degrees to which students would be admitted if their grades fell just below the threshold. In particular, direct comparisons between the effects of threshold-crossing at different degree programs may be misleading if they are measured relative to very different below-threshold outcomes. To facilitate cross-degree comparisons, we combine our knowledge of admissions outcomes for the full set of above- and below-threshold applicants with a simple model of earnings determination. This let us recover the underlying impact of each degree program on labor market earnings relative to a common outside option, which we choose to the "no acceptance" outcome. Students who are not accepted anywhere will typically attend a two-year program or not attend college at all.

The simplest form of our wage model is

(2) $$Y_{icp} = \beta X_i + \theta_{cp} + \omega_i$$

where Y_{icp} is labor market earnings for individual *i* with characteristics *c* who is admitted to program *p*. Y_{icp} can be decomposed into *i's* observable characteristics, X_i; a program effect for individuals with demographic characteristics *c* (e.g. impact of an elite engineering degree on males from low-income backgrounds), θ_{cp}, and an error component (unobservable characteristics), ω_i. Since ω_i will be the same on average for students above and below each threshold, we need not place restrictions on its mean or relationship with degree choice. We can therefore focus on recovering estimates of θ_{cp} from our threshold crossing estimates, δ_{cp}.

To do this, note that the impact of threshold crossing into program *p* for individuals in demographic group *c* is a function of the characteristics of the target degree for threshold crossers relative to those who just missed the threshold and the relative impacts those degree characteristics have on labor market earnings. Specifically, let Δ_c be a $p \times 1$ vector of reduced-form, target-program-level regression-discontinuity estimates for individuals in demographic group *c*, $\hat{\delta}_{cp}$, and let Π_c be a $p \times p$ matrix of with cells (p, q) equal to the impact of threshold crossing into program *p* on admissions to program *q* for individuals in demographic group *c*. Then we can recover $\hat{\theta}_{cp}$ as the solution to *p* equations with *p* unknowns: $\Theta_c = \Pi_c^{-1}\Delta_c$.

Note that can estimate the $\hat{\theta}_{cp}$ two ways: using a two-step approach as just outlined, or using an instrumental-variables regression of the following form for individuals in each demographic group *c*:

(3) $$\begin{aligned} Y &= X\mathrm{B} + A\Theta + \varepsilon \\ A &= X\Psi + Z\Pi + \upsilon \end{aligned}$$

where *X* is a matrix of polynomial terms in d_{ipr} (the distance between individual *i*'s score and the cutoff for program *p* in application year *r*), *A* is an $N \times p$ matrix of admissions outcomes, where each entry is equal to 1 if individual *i* in row *n* is admitted to program *p*, and *Z* is matrix of threshold crossing dummies. Because threshold crossing increases the probability of being

admitted to the target program, but decreases the probability of being admitted to other programs applicants to target program *p* applied to, the solution to the *p* equations with *p* unknowns within each demographic group *c* can be represented using this IV specification.

We consider several variations on this core specification. First, we consider coarser and finer definitions of characteristics *c*. Finer cuts by individual characteristics allow for richer heterogeneity, but at the cost of decreased statistical power. Second, we consider a set of related specifications that allow for differences in returns to different degrees (i.e., comparative advantage) within groups defined by *c* but restrict the main effect of each degree *p* to depend on observable characteristics: field of study, selectivity, and vocational focus. In these specifications, we parameterize the $\hat{\theta}_{cp}$ as functions of observable degree characteristics and interactions between degree characteristics and students' math and reading scores. These specifications can be estimated using specifications analogous to (3) but in which the IV model is overidentified. In practice, we obtain consistent results across models and definitions of *c*, which suggests that our choices of functional form are not driving our findings.

We present results three ways. We present reduced-form estimates from equation 1 estimated separately by program and demographic group. We also present estimates from (3) under an assumption of homogeneity of program impacts on students from different backgrounds (i.e. $\theta_{cp} = \theta_p, \forall c, p$). We also present results allowing program impacts to vary with socio-economic status and entrance exam math scores (a measure of baseline math ability).

We estimate equation 1 using a local polynomial regression in the neighborhood of the cutoff value. We focus on a specification that uses data within 25 points on either side of the cutoff and includes second-order polynomials in d_{ipr} that are different above and below the cutoff value. To assess the robustness of our results, we also present estimates for two other bandwidth/polynomial combinations. The first is a tight window that uses an 8 point interval and linear functions of d_{ipr} on either side of the threshold. The second is a wider specification that extends the above-cutoff window to 50 points and uses cubic polynomials above and below the threshold. We don't extend the below-cutoff window because few students with scores more than 25 points below the cutoff value apply. Results for these specifications are in Online Appendix 9. Note that in this specification, individuals who appear in multiple marginal applications may function as both treated students (in the application to which they are accepted) and control students (in the applications where they are rejected). To account for this, we allow for arbitrary

correlation between error terms at the individual level (as opposed to the application level) when computing standard errors and conducting hypothesis tests. This also allows for possible correlations within individuals over time; which could be important if persistent shocks affect the earnings process.

In addition, as discussed in Abdulkadiroglu et al. (2011), the presence of multiple application cutoffs could raise concerns about discontinuities in the conditional mean function at points other than the cutoff value, for example if many or all students applying to one program also apply to another with a very close cutoff score. This is much less likely to be a problem in our setting than in the Boston magnet school application process in Abdulkadiroglu et al. (2011) for two reasons. First, students have the option to choose from several hundred institution-degree combinations, and their preferences across these programs are heterogeneous as evident in summary statistics tables describing choices. For comparison, Abdulkadiroglu et al. focus on an application process to only three programs with a fairly distinct hierarchy in terms of desirability. Second, as described earlier, each institution-degree combination has a different scoring system. Accordingly, our data show no indication of discontinuities in matriculation or earnings functions over the windows we use.

5 Results

5.1 Validating the Regression-discontinuity Design

We start with several checks to confirm the validity of our regression-discontinuity design. If it is valid, observable and unobservable characteristics of students are the same on both sides of the discontinuity. Figure 4 plots the impact of threshold crossing on mean baseline characteristics in one-point-bins of the running variable (distance between score and the cutoff). Threshold crossing does not coincide with a change in the conditional mean of baseline characteristics. Baseline characteristics are gender and high-school type (voucher, public or private).

We also consider an index which is the portion of earnings predicted by these baseline characteristics in an OLS regression of labor market earnings that also controls for polynomials in score and cohort and experience effects. Figure 4 graphs balance of the baseline characteristics

pooled and for each of our application characteristic categories of interest. Table 4 shows the corresponding regression results from equation (1) where baseline characteristics instead of wages are the dependent variables. We conclude that baseline characteristics are balanced above and below the threshold.

Finally, Figure 5 plots the density of score in 2 point bins around the cutoff, verifying that there is continuous density in the running variable across the cutoff.

5.2 Treatment Size and Impact

Figure 6 plots matriculation into the target institution-degree against distance from the cutoff score from applications from 2004 to 2010. Recall that we currently only have matriculation files for 2004 through 2011 and are currently building the data back to 2000. Overall, threshold crossing causes a 54.2 percentage point increase in enrolling in the target degree. This is less than 100 percentage points because students may 1) opt not to enroll to pursue alternative plans or try again next year for a higher ranked choice or 2) be pulled off the waitlist, which is visible among score bins just to the left of the cutoff. This implies that the ITT results of the impact of admission on labor market outcomes are approximately half the size of the effects of matriculation on labor market outcomes.

Table 5 shows the impact of threshold crossing on matriculation by our institution-degree characteristics of interest. Business, Science/Tech and Humanities degrees have the highest causal impact of admission on matriculation. Art and Education are the lowest. Degrees with Vocational vs. Non-Vocational (traditional) focus have similar matriculation rates. Highly selective institutions have higher matriculation rates as a result of admission, which may be because they are higher ranked choices on average. Online Appendix Section 7 shows the coefficients on threshold crossing for all combinations of these categorical variables.

These differences will be important to keep in mind when interpreting the ITT results. In future results, we will present specification checks including two-sample-two-stage least squares (2S2SLS) estimates of effect of matriculating in degrees with characteristics *c* on labor market earnings.

In addition, note that threshold crossing identifies the impact of being admitted to a degree program of characteristic *c* relative to that of being admitted to one of characteristic *k* for

students applying to degrees of type *c*. For applications pre-2000, we know where the student was admitted, where they were waitlisted, and their score. For application years 2000 and later, we additionally have the full rank-ordering of student choices from their electronic applications. Thus in the full sample, we can identify the impact of gaining admission to a degree of characteristic *c* relative to the average characteristics of degrees those who applied to *c* with scores below the threshold were admitted to instead.

Table 6 shows the impact of NOT crossing the threshold in an application to a degree of the type given by the row label on the probability of being admitted to a degree of the type indicated in the column label. In other words, for students applying to a degree in each field/selectivity/curriculum category who do not cross the threshold, what fraction of them end up being accepted to a different degree indicated by the column headings. For example, those who did not cross the threshold into admission for a target Business degree, where most likely to be admitted to another business degree (36.2%) or to a Technology/Science degree (24.3%) though some also were admitted to degrees in the other fields. 26.9% were not admitted to any CRUCH degree. Interestingly, Art and Architecture students are very (22.9%) likely to be admitted to a Technology and Science degree if they fail to be admitted to their target Art/Architecture program. These transition probabilities will play a key role in our estimation strategy below as we will use them to recover mean earnings returns by degree type from program-specific threshold-crossing estimates as outlined in Section 4.

5.3 Impact on Labor Market Outcomes by Program Characteristics

Tables 7 through 9 present our key results.

The first row of Table 7 shows pooled results for the three regression models: 1) reduced-form ITT, 2) assuming homogeneous program effects ($\theta_{cp} = \theta_p, \forall c, p$), and 3) allowing program effects to vary with socio-economic status and baseline math entrance exam scores. Specifically, for socio-economic status we use MINEDUC's poverty categorization of the high school the student attended (MINEDUC scores high schools from A through E, where E is most economically disadvantaged). We classify students as coming from low-socio-economic backgrounds if they came from schools classified as D or E. For mathematics ability we use an

indicator if the student scored above the median of the math test-score distribution among CRUCH applicants.

To facilitate interpretation, we present earnings effects as percentages of average earnings in the tax records – 8.13 million pesos. A coefficient of X% implies that annual earnings gains are equal to X%*8.13 million pesos. Overall, crossing the threshold into a target degree increases labor market earnings by 3.6% of an average annual wage (Model 1: Reduced-form). Gaining admission to a target degree increases average annual wages by 8.3% in Model 2 and by 10% in Model 3. The mean impact on earnings is significant at the one-percent level in the reduced-form specification, and we will add standard errors for the other two specifications at the end of March when we can access raw data within the tax authority again.

The subsequent rows of Table 7 aggregate the estimated program or program-demographic-cell-level impacts into selectivity categories based on mean cutoff score for the program across all admissions years. The rows present aggregated average impacts for programs whose average cutoff score falls within 25 points on either side of the row label. Across all three models, we see that the labor market earnings (versus no admission) increases with selectivity of the program admitted to. The first column ITT does not adjust for probabilities and program characteristics on the other side (non-admission side) of each threshold. The second two columns do, and this increases the degree to which returns increase with selectivity. Interestingly there is little difference between specifications 2 and 3, suggesting that choices and returns to selectivity do not vary with our SES or Math Ability measures, something we explore in further detail in Section 5.4.

Figure 8 plots these three columns. Visually two points stand out. First, there is a small if not zero impact of being admitted to a less-selective program (575 or lower) relative to the no-admission alternative. In Chile, the majority of student loan recipients apply to schools in this category and these non-selective universities have seen the largest growth in demand during the past decade (see Hastings et al. 2013a). Hastings, Neilson and Zimmerman show that loan receipt causes students with test scores in the 475-575 range to substitute away from technical degrees into university degrees at low-selectivity institutions. They show that this results in higher tuition payments, but not higher expected earnings (using institution-degree means from prior cohorts). Figure 8 adds further causal evidence; being admitted to a low-selectivity institution offers little-to-no labor market returns over being admitted to no university at all. In

contrast, once selectivity passes into the 600's, returns to selectivity increase at an increasing rate.

Differences in returns to selectivity could be generated by differences in field of study or coursework requirements that vary systematically across selective and non-selective institutions. To explore this further, Table 8 shows program returns aggregated into high-selectivity and low-selectivity by general area of study. High-selectivity is defined as having an average admission cutoff above the median of admission cutoffs across all programs. Recall our fields of study are Business and Administration; Art and Architecture; Education; Social Sciences and Law; Health Humanities; and Technology and Basic Science. Again we present aggregated results from three models.

The results in Table 8 show some striking patterns. First, there are large and significant causal returns to field of study. Being admitted into a Health degree increases earnings by 15.1 to 19.1 percent of an average wage (columns 4 and 7). Being admitted into a Business degree has a similar size impact on earnings (16.7-16.8), and being admitted to Social Science/Law or Technology/Science degrees also have positive impacts on earnings of 9.9-10.3 and 7.2-9.1 percent, respectively. In contrast, admissions into Art and Architecture and Humanities degrees result in lower earnings relative to no admission at all. Art and Architecture admittees stand to lose 1.1-5.5 percent of an average wage while Humanities admittees lose 9.1-14.9%.

These results suggest that just failing to be admitted to a program of choice could be one of the luckiest or unluckiest events for a student's expected future earnings. For students who chose degree combinations like Art versus Computer Graphic Design or Health versus Education or History versus Economics, just missing admission to your target of choice could substantially impact your average annual earnings by 12.7, 14.3, or 25.9%, respectively, conditional on your observable and unobservable characteristics (using Model 2 estimates).

Looking at the field-by-selectivity results, disparity in earnings returns by field is generally higher for selective programs. Large gains for Health, Social sciences, law, business and technology accrue primarily to programs in the high-selectivity category. In the low-selectivity category are uniformly smaller and therefore closer in size to each other. The exception is Humanities, which have large and negative estimates on earnings for selective programs, but positive impacts on earnings for less selective programs.

Table 9 converts our annual earnings estimates into present-discounted value of lifetime earnings gains, amortized over forty years at a 5% annual interest rate. Next to PDV of earnings gains we show the estimated cost of a degree, calculated using annual tuition costs from current data (2000 to present) and expected time to degree completion. We use earnings gains for Model 2 to conserve space. Table 9 shows that while some degrees are more expensive than others, the variation is clearly not enough to erase gains in earnings across degrees. In fact, for programs in Art and Architecture, Education and Humanities, net present value of the degree is negative versus not being admitted to any degree. For Art and Architecture, admission to a selective program has a negative impact of -1.464 average annual wages on lifetime net earnings. For Humanities, this number increases to -2.921. Getting a degree from a selective institution in business instead of humanities would result in 4.339 average-wages increase in net PDV earnings despite the fact that selective humanities programs cost substantially less than selective business programs.

Interestingly, again less selective programs have very different net-earnings patterns across fields of study. The tuition costs of less-selective programs are uniformly lower than for highly-selective programs. However, although earnings for some of these programs were positive (for example, low-selectivity Humanities degrees), their net earnings are negative as the earnings gains do not outweigh tuition costs. This speaks to the student loan crisis in Chile as low-selectivity university degrees saw the preponderance of growth in demand from loan-eligible students as a result of student loan expansion programs.

One issue that has been raised is whether low returns at less selective institutions may be due to systematic differences in curriculum requirements within fields. For example, perhaps vocational-oriented programs serve this student population better than traditional programs focused on core but abstract skills in math, science and languages. To explore this pattern further we use our digitized course requirements by program to investigate how course requirements vary across field and program selectivity. Overall, both selective programs and non-selective programs vary in their core-requirement focus on Quantitative and Qualitative basics such as math, statistics, hard sciences, computer programing, language and writing. Some degrees and institutions are more likely to require an abstract skills course such as those just listed, while others require high amounts of professional or vocational coursework. These vocational courses

emphasize implementation rather than developing abstract skills. These are “how-to” courses specific to the profession the degree aims to graduate students into.

Table 10 presents PDV earnings and cost estimates by field, selectivity and curriculum (vocational vs. non-vocational). Across all fields of study, non-vocational programs have higher returns when pooled across selectivity groups. The same pattern appears to hold within selectivity category: in both high and low selectivity degrees non-vocational degrees outperform vocational degrees, though there are some exceptions. Our results suggest that differences in selectivity returns are not attributable to curriculum focus, and that overall, general education with emphasis in core maths, sciences and languages appears to have higher returns than vocationally-focused careers do.

5.4 Impact on Labor Market Outcomes by Socio-economic Status and Skill

TBA – we need to pull out additional information from the tax authority during our March visit to complete this section.

6 Conclusion

We estimate the impact of acceptance into colleges and fields of study on labor market earnings by exploiting thousands of regression discontinuities in admissions to university-degree combinations in Chile for 26 years of college applicants. We find significant returns to fields of study, course requirements, and selectivity and value-added measures of peer and institution-degree quality.

Importantly these differences are not caused by correlations in preferences and/or relative unobserved skill (e.g. Dahl 2002), as both are balanced across admission thresholds. Rather, they may be caused by persistent differences in demand and supply in the labor market and in the postsecondary education market. Such results are important for understanding how loan policy and information policy may reduce persistent market frictions in the long run.

Our findings suggest that frictions exist in the markets that match students to postsecondary degrees. Constraints on the supply of high-return degrees (see Bound and Turner, 2007) may push students into programs with lower economic returns at many margins. Admitting the marginal applicant to a high-return program by lowering the score cutoff a small amount likely represents a policy change with a positive social return. At the same time, we observe excess demand for degrees that lead to zero or, in some cases, large and negative earnings returns for admitted students. This could be because these degrees offer high non-pecuniary compensation that is valued by all students, or because some students have very strong tastes for the coursework or careers associated with these degrees. That said, Hastings et al. (2013b) present evidence suggesting that students may base college choices on beliefs about economic returns that are systematically biased and uninformed. The existence of oversubscribed degrees with zero or negative returns thus suggests two possible avenues for welfare-improving policy intervention. First, if information aggregation is a public good, policymakers supply centralized ranking and earnings information to guide to provide students with accurate information needed before making life-long decisions. Second, loan policy could be used to provide additional supply-side incentives to ease frictions in supply of high-return degrees (Hastings et al. 2013a).

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FIGURE 1: TRENDS IN COLLEGE ENTRANCE EXAM TAKING, CHILE AND U.S.

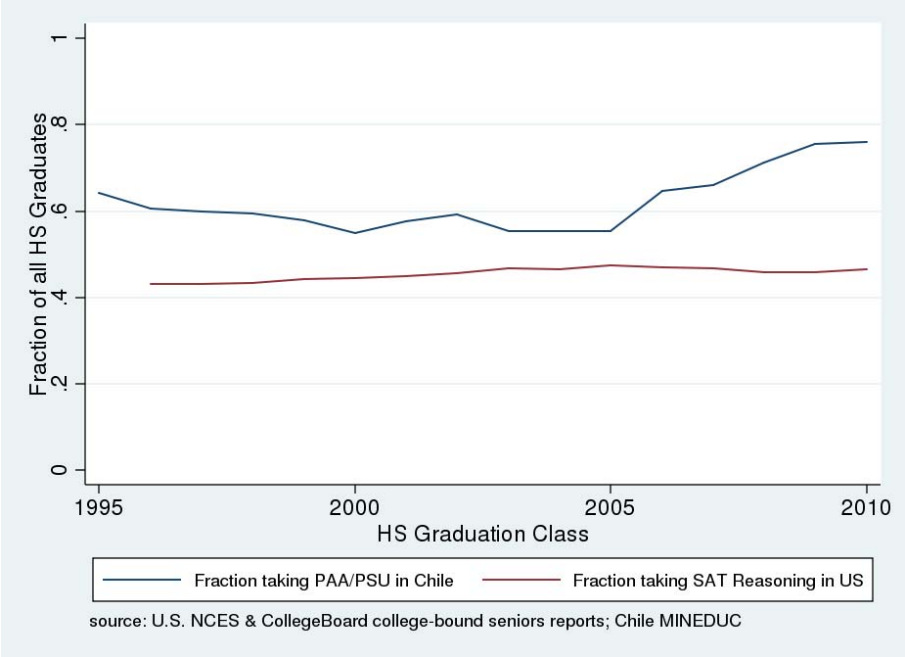


FIGURE 2: ENTRANCE EXAM SCORE DISTRIBUTION BY HIGH SCHOOL TYPE

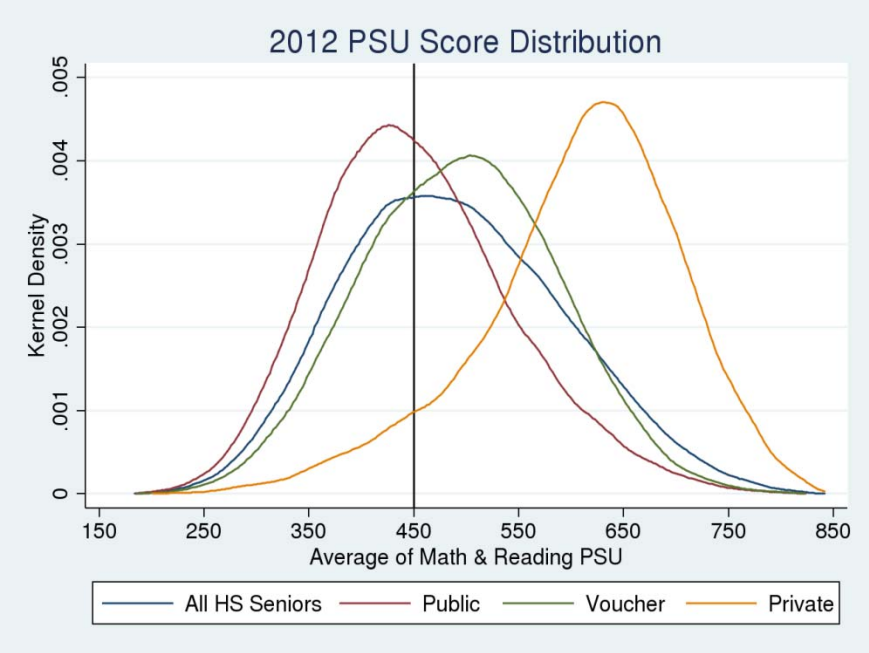


FIGURE 3: VARIATION IN MEAN ENTRANCE EXAM SCORES OF ACCEPTED COHORTS BY SELECTIVITY

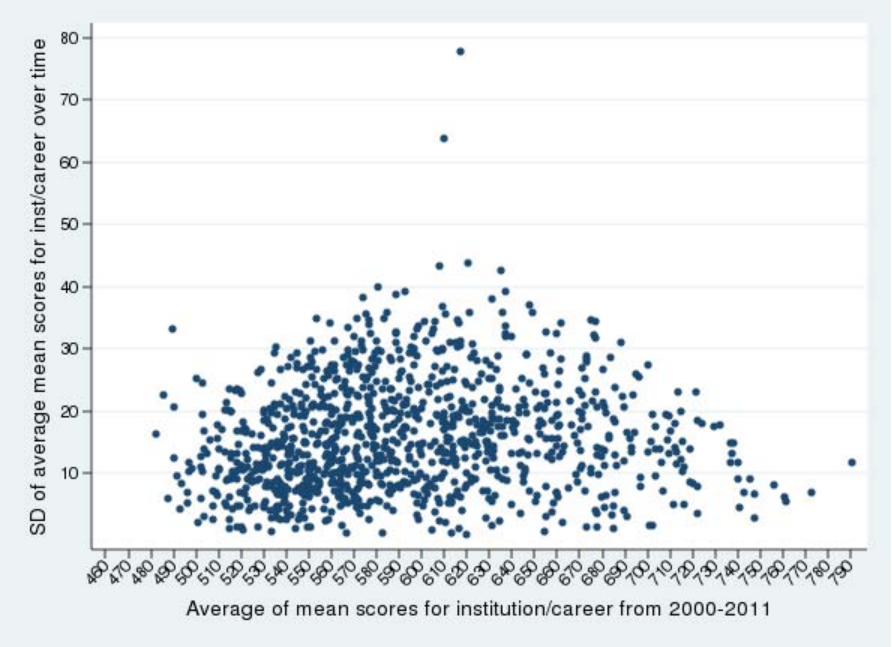
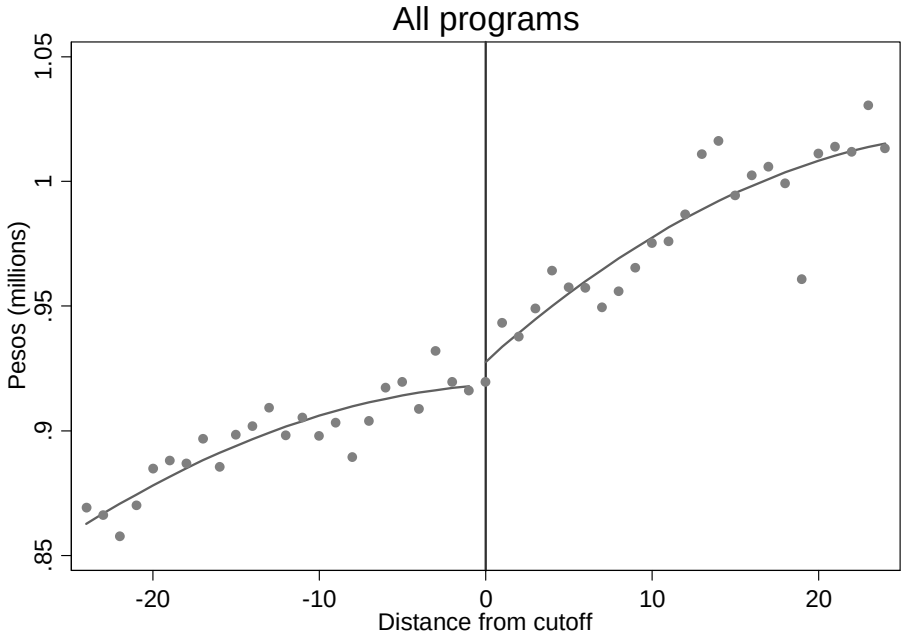
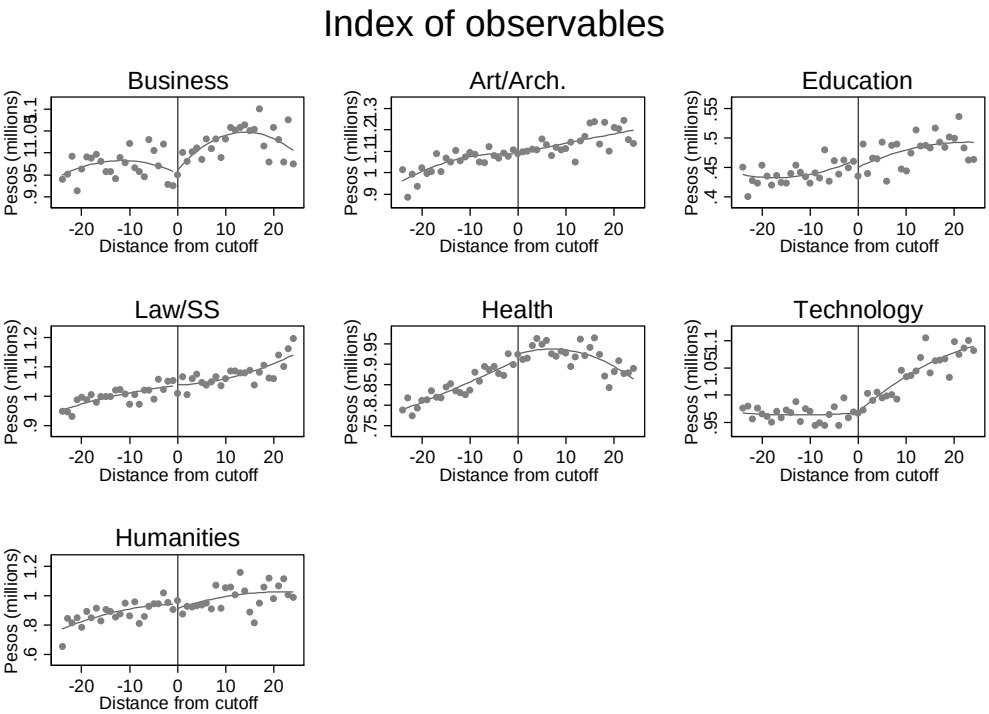


FIGURE 4: CONDITIONAL MEAN OF INDEX OF STUDENT DEMOGRAPHICS
(1 POINT SCORE BINS)

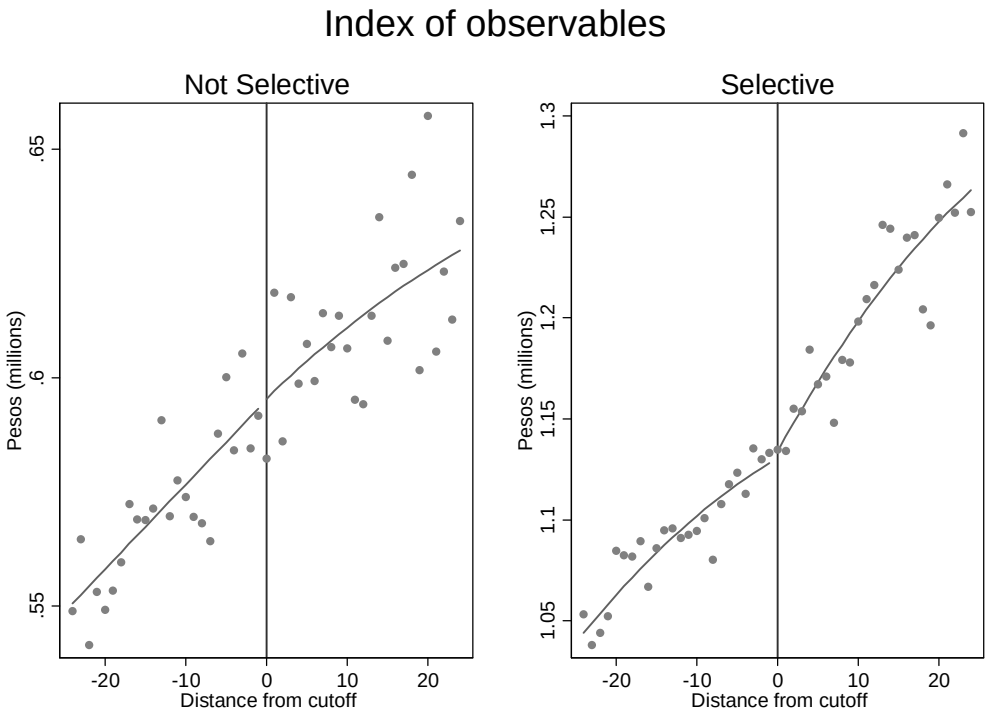
4.A. POOLED SAMPLE



4.B. BY AREA



4.C. BY SELECTIVITY



4.D. BY COURSE CATEGORY

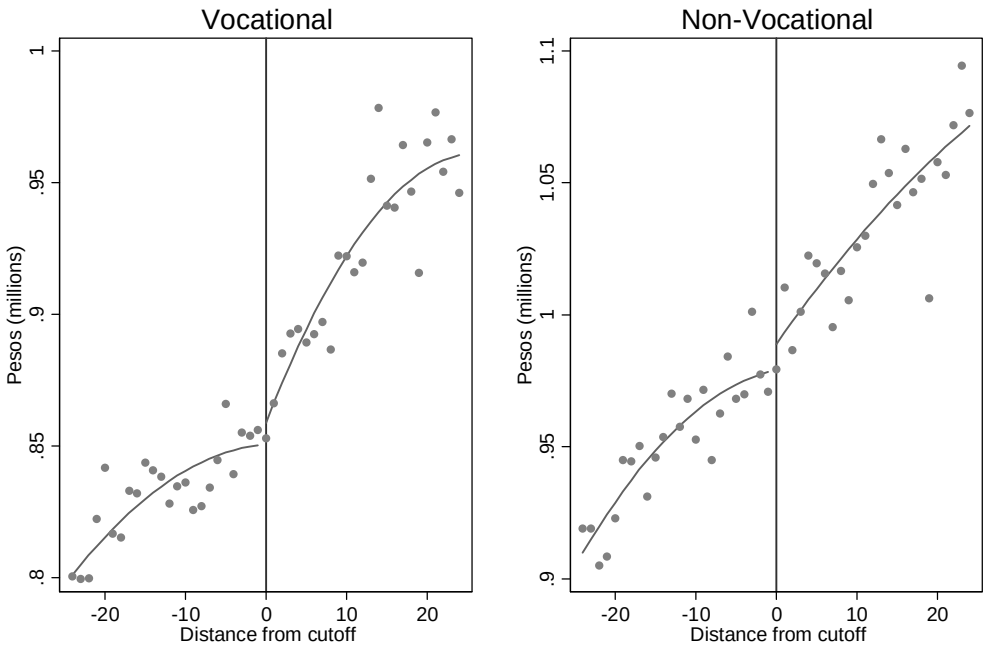


FIGURE 5: DENSITY OF RUNNING VARIABLE

(2 POINT BINS)

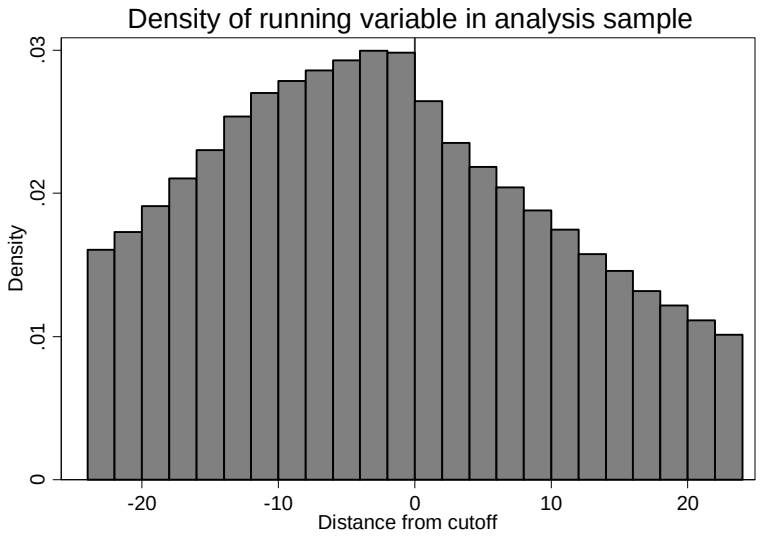
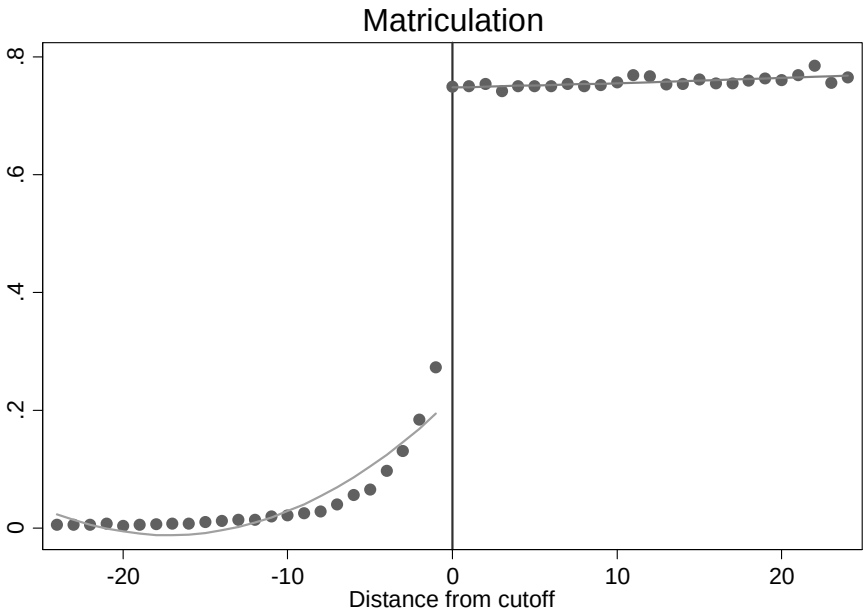
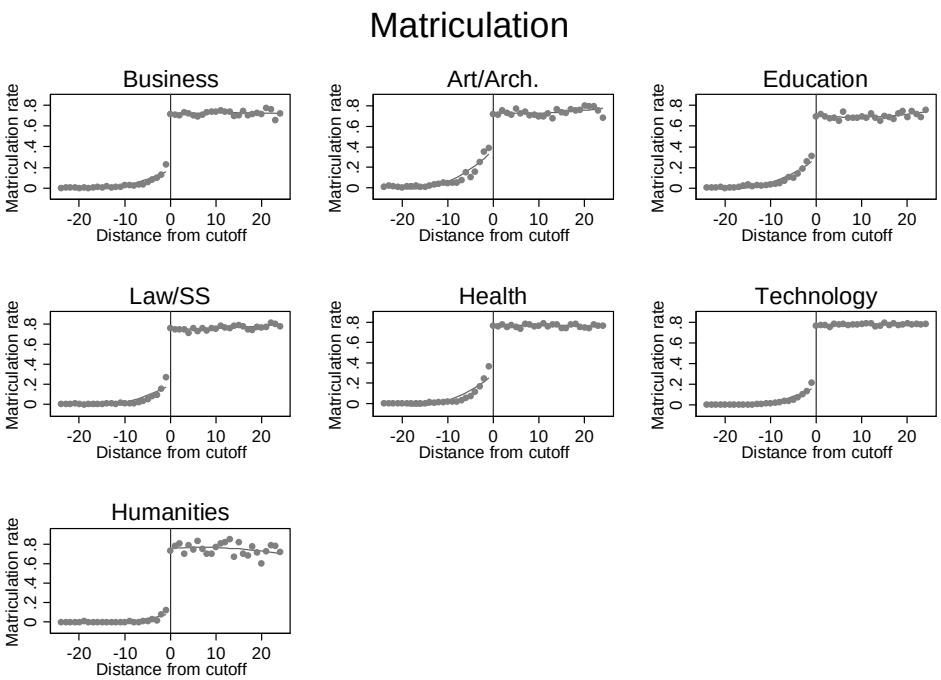


FIGURE 6: MATRICULATION BY POSITION RELATIVE TO CUTOFF
(1 POINT SCORE BINS)

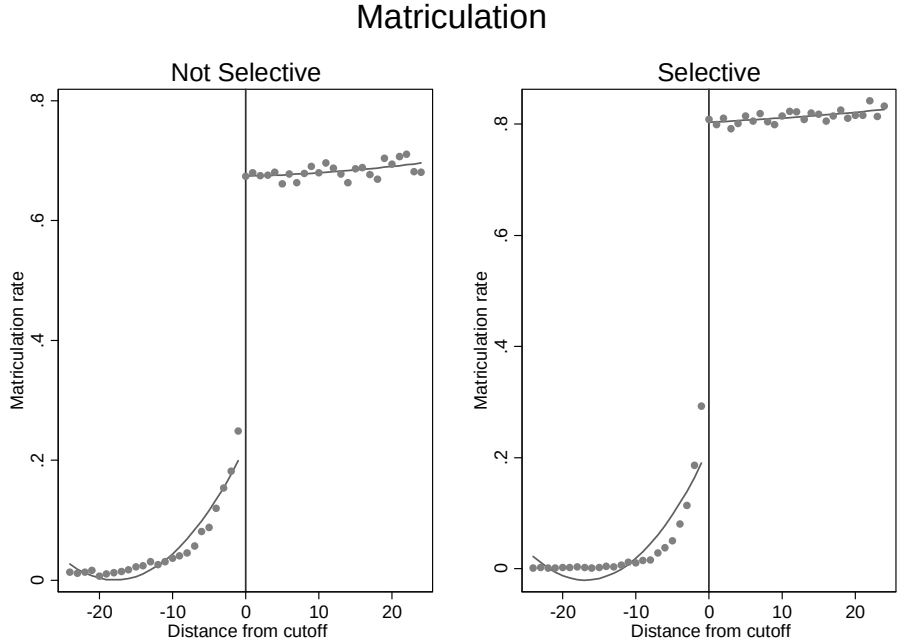
6.A. POOLED



6.B. BY AREA



6.C. BY SELECTIVITY



6.D. BY CURRICULUM TYPE

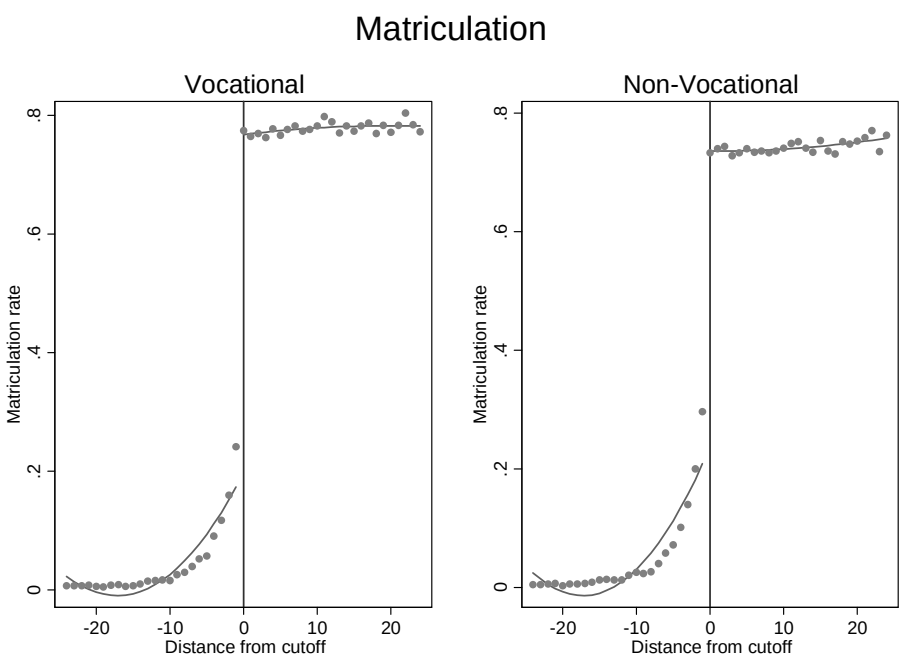
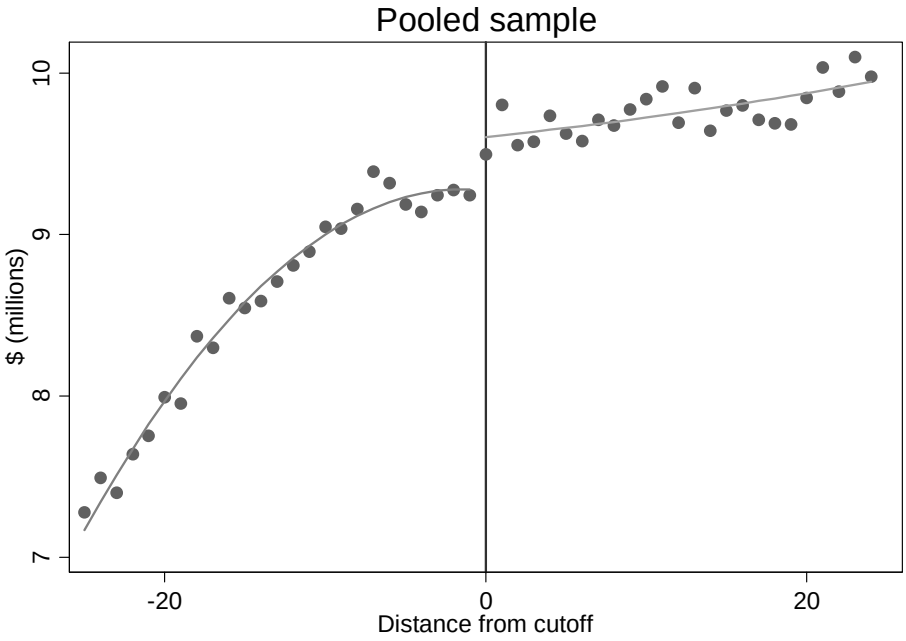
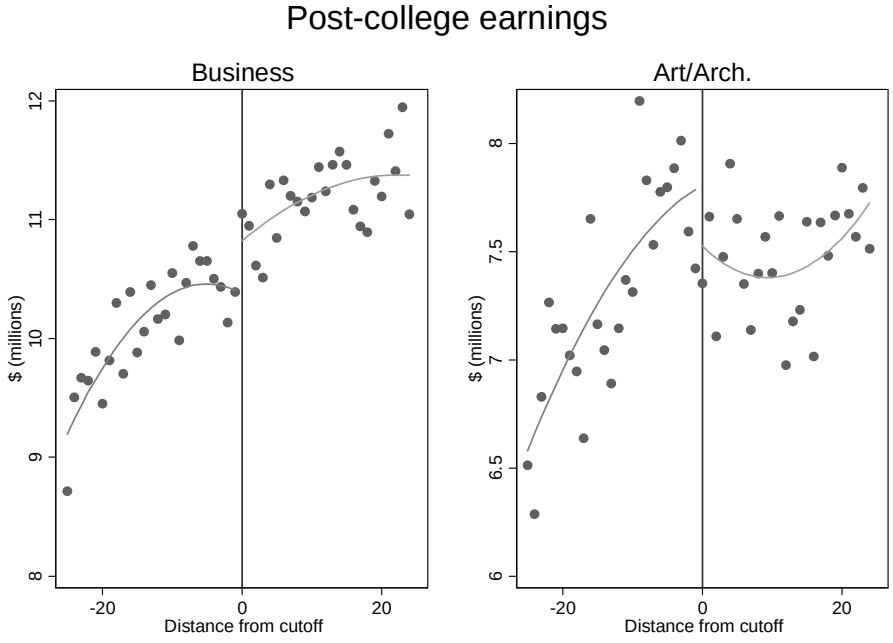


FIGURE 7: POST-COLLEGE EARNINGS BY POSITION RELATIVE TO CUTOFF

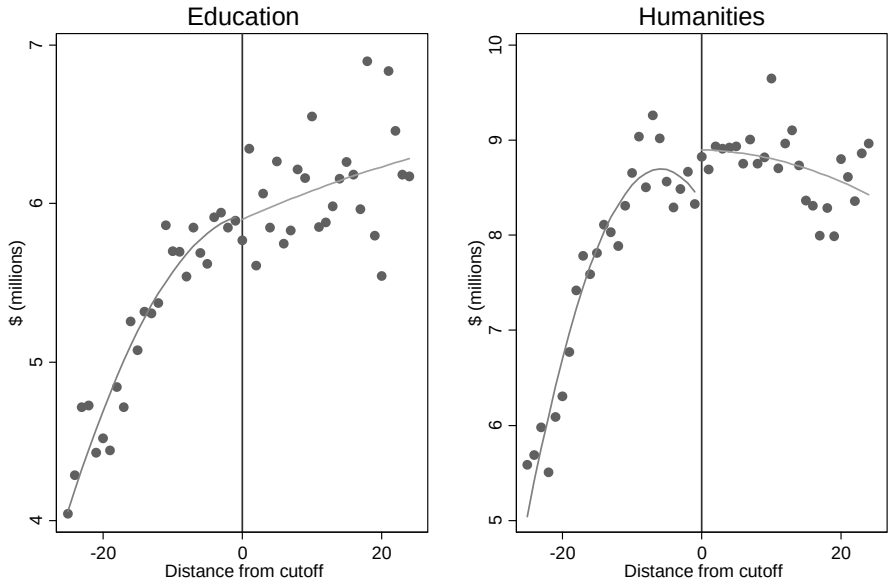
7.A. POOLED



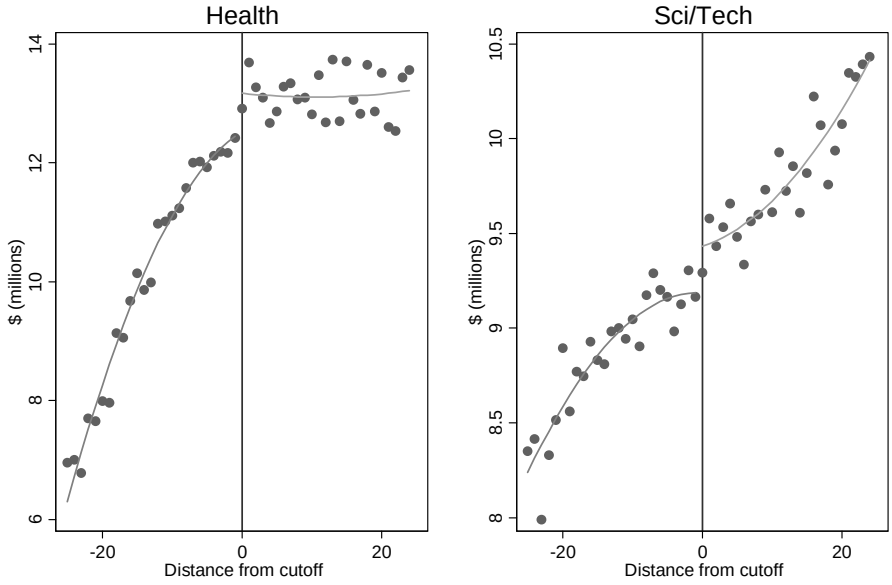
7.B. BY AREA



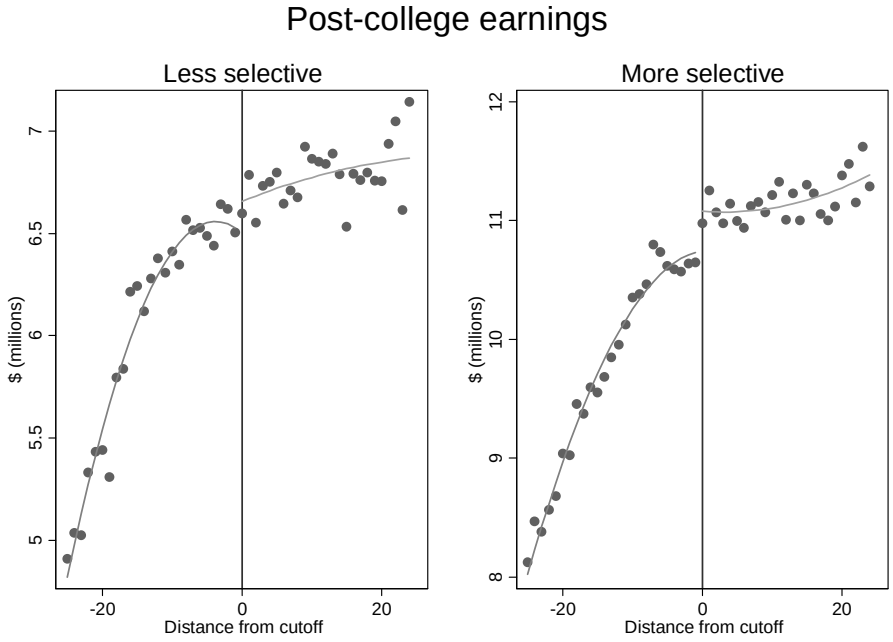
Post-college earnings



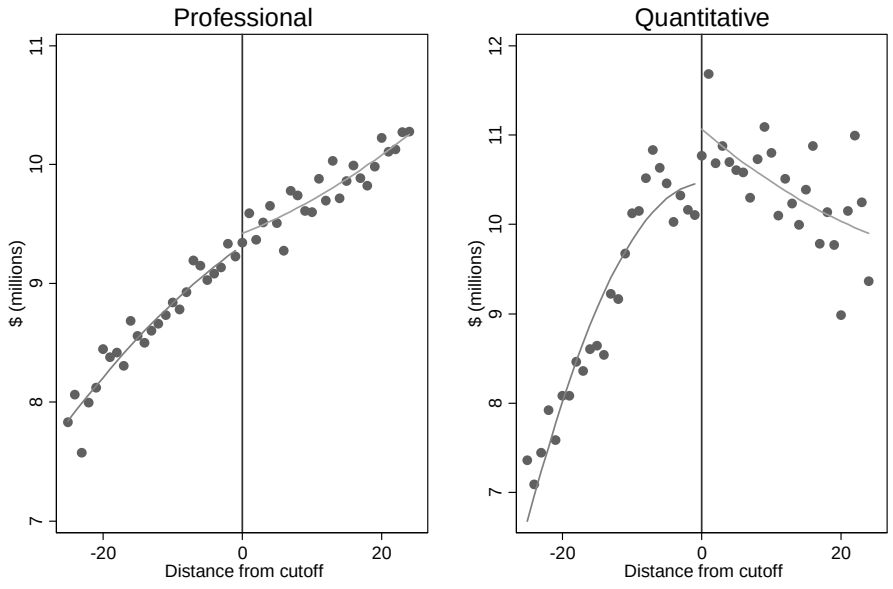
Post-college earnings



7.C. BY SELECTIVITY



7.D. BY CURRICULUM TYPE



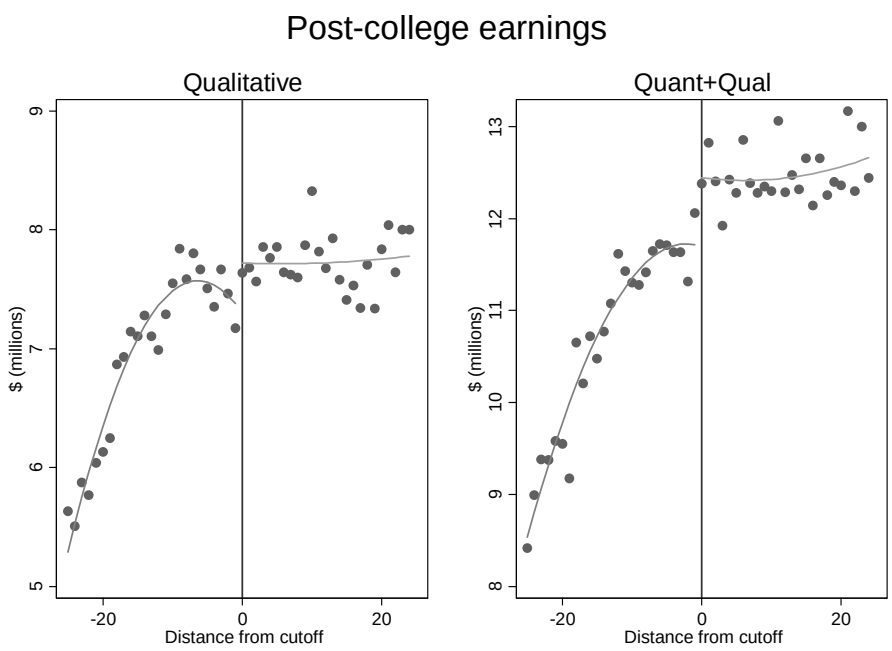

Post-college earnings
Qualitative
Quant+Qual
$ (millions)
Distance from cutoff
5
6
7
8
9
10
11
12
13
-20
0
20

FIGURE 8: IMPACT OF SELECTIVITY OF DEGREE ON ANNUAL EARNINGS

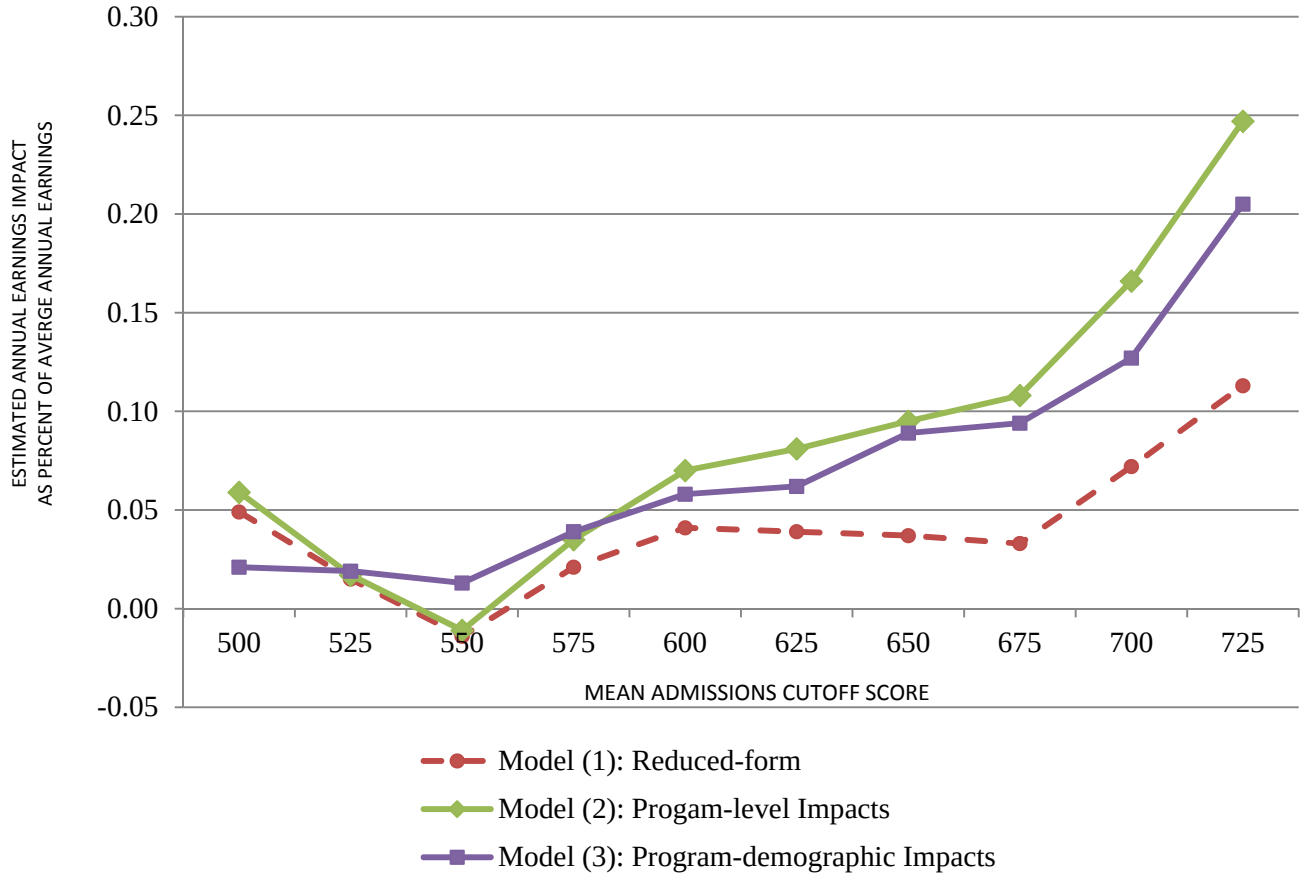


TABLE 1: DESCRIPTIVE STATISTICS ON UNIVERSITIES IN CHILE

	1995-2000			2000-2005			2006-2010		
	Share	PAA/PSU IQR		Share	PAA/PSU IQR		Share	PAA/PSU IQR	
University	of Grads	25th %tile	75th %tile	of Grads	25th %tile	75th %tile	of Grads	25th %tile	75th %tile
Pontificia Universidad Católica de Chile	10.1%	664	740	7.1%	668	740	5.0%	672	746
Pontificia Universidad Católica de Valparaíso	5.0%	614	689	3.3%	600	684	2.3%	600	681
Universidad Arturo Prat	0.7%	520	603	3.2%	432	547	5.5%	408	528
Universidad Austral de Chile	4.8%	558	666	2.6%	564	665	1.8%	562	657
Universidad Católica de la Santísima Concepción	0.3%	542	636	1.5%	526	616	1.4%	522	606
Universidad Católica de Temuco	0.8%	520	584	1.1%	504	588	1.1%	510	590
Universidad Católica del Maule	0.4%	558	658	1.8%	518	608	1.4%	529	628
Universidad Católica del Norte	1.7%	582	663	1.4%	567	648	1.6%	551	641
Universidad de Antofagasta	1.7%	565	640	1.4%	530	623	1.4%	510	632
Universidad de Atacama	0.9%	479	560	0.4%	470	576	0.6%	474	570
Universidad de Chile	10.0%	676	735	7.9%	666	732	5.1%	669	738
Universidad de Concepción	9.8%	608	700	6.5%	578	688	4.3%	572	681
Universidad de la Crontera	3.1%	587	668	2.8%	556	662	2.0%	557	664
Universidad de la Serena	2.4%	530	618	0.7%	523	614	1.7%	530	618
Universidad de los Lagos	1.2%	483	560	1.1%	484	560	2.3%	436	549
Universidad de Magallanes	0.9%	494	602	1.1%	475	578	0.7%	474	578
Universidad de Playa Ancha	2.1%	518	584	2.6%	494	582	2.3%	502	591
Universidad de Santiago de Chile	5.6%	612	687	6.7%	600	680	4.2%	587	676
Universidad de Talca	1.5%	588	658	1.6%	581	658	1.2%	584	674
Universidad de Tarapacá	1.6%	522	624	1.2%	502	606	1.8%	480	584
Universidad de Valparaíso	2.1%	619	698	2.1%	605	694	2.4%	572	669
Universidad del Bíio-bío	3.2%	567	644	2.1%	566	643	2.5%	538	626
Universidad Metropolitana de Ciencias de la Educación	2.8%	566	628	2.8%	522	606	1.5%	550	630
Universidad Técnica Federíco Santa María	4.6%	551	644	2.3%	557	684	2.8%	544	673
Universidad Tecnologica Metropolitana	2.6%	584	656	5.6%	538	636	3.1%	518	631
All Non-CRUCH Universities	*20.1%*	*508*	*648*	*29.1%*	*484*	*626*	*40.0%*	*460*	*606*

Sample is all university students graduating with a pre-grado degree of any type.
25th-75th percentile PAA/PSU is for most recent test score of graduates. PAA was last administered in 2002 and PSU was administered starting in 2003.

TABLE 2: DESCIRPTIVE STATISTICS ON APPLICATIONS AND CHOICES

Year	# Choices (SD)	PSU Distance from 1st Choice Cutoff	PSU Distance from Last Choice Cutoff	# diff FL's	# diff areas	# diff unis	# diff tiers	Acc 1st Choice	Acc Choice	Acc Any Choice	Matric to Adm Choice
2001	4.68 (2.05)	29.89	56.76	3.63	1.92	2.55	1.67	31%	2.21	68%	TBA
2002	4.65 (2.01)	34.71	60.64	3.60	1.91	2.53	1.66	34%	2.11	69%	TBA
2003	4.67 (1.99)	34.41	62.14	3.64	1.95	2.52	1.66	36%	2.02	70%	TBA
2004	5.02 (2.07)	38.45	69.97	3.74	1.95	2.66	1.70	41%	1.90	72%	75%
2005	5.18 (2.14)	15.94	45.07	3.71	1.90	2.66	1.70	30%	2.41	69%	74%
2006	4.99 (2.18)	8.43	37.53	3.63	1.89	2.54	1.69	29%	2.38	68%	74%
2007	4.92 (2.19)	8.85	35.76	3.56	1.86	2.53	1.68	27%	2.38	64%	71%
2008	4.87 (2.21)	14.58	39.56	3.52	1.84	2.50	1.64	31%	2.25	69%	71%
2009	4.74 (2.21)	8.94	34.20	3.41	1.80	2.47	1.63	26%	2.38	62%	69%
2010	4.68 (2.20)	16.97	41.30	3.36	1.78	2.43	1.61	33%	2.16	69%	70%
2011	4.45 (2.19)	21.82	44.63	3.21	1.73	2.37	1.59	37%	1.97	71%	69%
Total	4.80 (2.15)	20.09	46.89	3.53	1.86	2.52	1.66	32%	2.20	68%	71%

Sample is all students that applied to CRUCH in each year. # Choices is the mean number of institution/career choices listed on CRUCH applications out of a possible 8. PSU distance from cutoff is the average distance of the applicant's PAA/PSU score from the lowest admitted PAA/PSU score among all applicants to that career/institution. # diff FL's is the mean number of different careers applied to. # diff areas is the mean number of different career areas applied to. # diff Unis is the mean number of different universities applied,
diff tiers is the number mean of different university tiers applied to. We categorized each CRUCH University into one of 3 different tiers by their overall quality. Acc 1st choice is the percentage of applicants that were admitted to their first choice career, including those that were not admitted to any choice. Acc choice is the average admitted choice among applicants that were admitted to one of their CRUCH application choices. Acc any choice is the percentage of all applicants that were admitted to one of their CRUCH choices. Matric to Adm Choice is the percent of admitted students that actually matriculated to their admitted choice. Those that did not matriculate may have been admitted to a higher-choice career off of the waitlist, chosen to instead attend a non-CRUCH school, or not matriculated to any tertiary institution.

TABLE 3: APPLICATION CHARACTERISTICS, SAMPLE MEANS

	Full sample	Marginal	Marginal and Complete Data
Application Characteristics			
Math score	595	637	637
Read score	583	612	613
Accepted	0.340	0.410	0.409
Business	0.090	0.126	0.127
Art/Arch.	0.057	0.055	0.055
Education	0.159	0.096	0.095
Law/SS	0.131	0.137	0.139
Health	0.166	0.166	0.168
Sci/Tech	0.370	0.407	0.403
Humanities	0.027	0.013	0.014
Low Sel.	0.500	0.353	0.348
High Sel.	0.500	0.647	0.652
Vocational	0.477	0.484	0.491
Non-Vocational	0.523	0.516	0.509
Applicant Characteristics			
Male	0.491	0.524	0.524
Public HS	0.381	0.334	0.335
Voucher HS	0.442	0.398	0.400
Private HS	0.177	0.267	0.265
Post-college market outcomes, 2011 tax year, 6 to 26 years post application			
Non-zero earnings	0.837	0.856	0.853
Earnings (mil.pesos)	8.13	10.4	10.6
Earnings (USD)	$19,113	$24,449	$24,920
N apps	3,098,267	689,810	668,843
N students	1,120,882	442,306	432,862

Notes: Characteristics of full dataset and analysis sample. Data is at the application (i.e., person X program X application year) level. Columns: "Full sample" is the sample of all digitized applications. "Valid app" includes observations within program X year cells where all students with scores higher than that of the lowest admitted individual are recorded as being accepted. "Marginal" contains applications that a) are valid, b) have at least 15 waitlisted individuals with scores within five points of the cutoff, and c) subsets on individuals within 25 points above or below the cutoff value. "Marginal, all data" is the marginal sample with the additional restriction that data on the area, course content, and selectivity of the target application all be available. LF variables are for years 6-26 after the application year. Data reflect the 1985-2010 application cohorts.

TABLE 4: BALANCE OF BASELINE CHARACTERISTICS IN RD DESIGN

	Index	Male	Public HS	Private HS	Voucher HS
Pooled	6843	0.001	-0.006	0.003	0.004
	-7168	(0.004)	(0.004)	(0.004)	(0.004)
Within Area:					
Business	-417	-0.004	-0.006	0.000	0.006
	(22251)	(0.012)	(0.012)	(0.011)	(0.012)
Art/Arch.	1745	-0.004	-0.020	-0.002	0.022
	(32275)	(0.018)	(0.016)	(0.018)	(0.018)
Education	-14608	-0.003	0.004	-0.007	0.004
	(14664)	(0.012)	(0.013)	(0.007)	(0.013)
Law/SS	2398	-0.018	-0.012	0.005	0.008
	(19937)	(0.011)	(0.010)	(0.010)	(0.011)
Health	14696	0.004	-0.014	0.005	0.009
	(16953)	(0.009)	(0.009)	(0.009)	(0.009)
Sci/Tech	-1915	0.004	0.002	-0.002	0.000
	(11570)	(0.006)	(0.007)	(0.006)	(0.007)
Humanities	-31526	-0.005	0.021	-0.013	-0.008
	(53763)	(0.031)	(0.030)	(0.029)	(0.030)
Joint P-value:	0.952	0.846	0.469	0.966	0.838
By Sel. Group:					
Low Sel	1260	0.003	-0.002	-0.001	0.003
	(9765)	(0.005)	(0.005)	(0.005)	(0.005)
High Sel	469	-0.004	-0.008	0.000	0.008
	(8397)	(0.007)	(0.007)	(0.004)	(0.007)
Joint P-value	0.990	0.687	0.464	0.993	0.426
By Course Content:					
Vocational	4719	0.003	0.002	0.002	-0.004
	(10211)	(0.006)	(0.006)	(0.005)	(0.006)
Non-Vocational	8173	0.000	-.0121*	0.003	.00979+
	(10046)	(0.006)	(0.005)	(0.005)	(0.005)
Joint P-value	0.645	0.916	0.061+	0.804	0.165
Full interaction:					
Joint P-value	0.965	0.695	0.592	0.979	0.299
N apps	443,804	443,822	443,696	443,836	443,836
N students	282,294	282,305	282,225	282,319	282,319

Notes: +0.1, *0.05, **0.01, ***0.001; Results from estimates of equation (1) within group described in row for the dependent variables given in the column. "Full interaction" row is joint test of all coefficients on threshold-crossing within each group defined by the interaction between area, selectivity group, and course content. Data are at the person-application level and include 1998-2010 cohorts only due to availability restrictions.

TABLE 5: IMPACT OF ACCEPTANCE ON MATRICULATION, 2004-2010 SAMPLE

Program Field or Category	Coefficient	SE	N
Business	0.542***	(0.013)	30,232
Art/Arch.	0.389***	(0.021)	13,411
Educ.	0.431***	(0.015)	25,925
Law/SS	0.565***	(0.011)	41,548
Health	0.499***	(0.010)	56,002
Sci/Tech	0.608***	(0.007)	84,920
Humanities	0.677***	(0.031)	4,395
Vocational	0.583***	(0.007)	110,579
Non-vocational	0.514***	(0.006)	150,092
Low-Selectivity	0.463***	(0.007)	109,455
High-Selectivity	0.600***	(0.006)	152,059

Notes: ***0.001; Data are at the person-application level and include 2004-2010 cohorts. Dummy variables are equal to one if a person matriculates at a program of a given type, and zero otherwise.

TABLE 6: COUNTERFACTUAL ACCEPTANCE OUTCOMES

Target	*None*	*Business*	*Art/Arch*	*Educ.*	*Law/SS*	*Health*	*Sci/Tech*	*Hum.*
Business	0.269	0.362	0.022	0.029	0.060	0.005	0.243	0.007
	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.001)	(0.006)	(0.001)
Art/Arch.	0.287	0.037	0.326	0.048	0.051	0.006	0.229	0.013
	(0.009)	(0.004)	(0.009)	(0.004)	(0.004)	(0.001)	(0.008)	(0.002)
Education	0.437	0.022	0.016	0.360	0.039	0.009	0.089	0.025
	(0.007)	(0.002)	(0.002)	(0.007)	(0.003)	(0.001)	(0.004)	(0.002)
Law/SS	0.247	0.061	0.031	0.078	0.435	0.012	0.077	0.053
	(0.005)	(0.003)	(0.002)	(0.003)	(0.006)	(0.001)	(0.003)	(0.003)
Health	0.192	0.012	0.009	0.036	0.038	0.519	0.189	0.004
	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.004)	(0.001)
Sci/Tech	0.297	0.046	0.016	0.041	0.013	0.017	0.563	0.004
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.000)
Humanities	0.304	0.016	0.047	0.194	0.152	0.002	0.060	0.222
	(0.017)	(0.005)	(0.008)	(0.015)	(0.013)	(0.001)	(0.008)	(0.015)

Target	*None*	*Hi Sel*	*Low Sel*	*Voc*	*Non-Voc*
Hi Sel	0.196	0.157	0.647	0.396	0.407
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Low Sel	0.432	0.542	0.027	0.310	0.244
	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)
Voc	0.286	0.328	0.386	0.496	0.213
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Non-Voc	0.268	0.267	0.465	0.249	0.480
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Estimates of counterfactual acceptance outcomes at threshold. Data are at the person-application level and include 1985-2010 cohorts. Standard errors in parentheses. Rows are for target application, columns are counterfactual outcomes. Cells show the fraction of students admitted to a program in the column category for students just denied admission in an application in the row category.

TABLE 7: ESTIMATES OF RETURNS TO ADMISSIONS, AGGREGATED BY SELECTIVITY

Mean Score at cutoff	Model (1): Reduced-form (1)	Model (2): Program-level Impacts (2)	Model (3): Program-demographic Impacts (3)	N programs
All	0.04	0.08	0.10	684
500	0.05	0.06	0.02	62
525	0.02	0.02	0.02	147
550	-0.01	-0.01	0.01	198
575	0.02	0.04	0.04	209
600	0.04	0.07	0.06	196
625	0.04	0.08	0.06	153
650	0.04	0.10	0.09	94
675	0.03	0.11	0.09	53
700	0.07	0.17	0.13	40
725	0.11	0.25	0.21	22

Notes: Program level impacts of threshold crossing or attendance relative to no admission, by model, aggregated up to row-category levels. Mean earnings are displayed as a percentage of an average annual wage. Mean earnings within rolling 50 point bins centered at given value. Correct standard errors to be added during March visit to tax authority in Chile.

TABLE 8: ESTIMATES OF RETURNS TO ADMISSIONS,
AGGREGATED BY SELECTIVITY AND FIELD OF STUDY

	Model (1): Reduced-form			Model (2): Program-level Impacts			Model (3): Program-demographic Impacts		
	Pooled (1)	High-Sel. (2)	Low-Sel. (3)	Pooled (4)	High-Sel. (5)	Low-Sel. (6)	Pooled (7)	High-Sel. (8)	Low-Sel. (9)
Business	0.070	0.081	0.048	0.168	0.216	0.074	0.167	0.215	0.074
Art	-0.045	-0.056	-0.008	-0.055	-0.074	0.012	-0.011	-0.024	0.037
Education	-0.007	0.041	-0.021	-0.005	0.019	-0.012	0.012	0.073	-0.007
SS/Law	0.06	0.083	-0.016	0.103	0.137	-0.009	0.099	0.122	0.022
Health	0.079	0.085	0.027	0.151	0.162	0.038	0.191	0.204	0.058
Tech.	0.029	0.037	0.018	0.072	0.102	0.030	0.091	0.126	0.041
Hum.	-0.074	-0.151	0.084	-0.091	-0.183	0.101	-0.149	-0.258	0.076

Notes: Program level impacts of threshold crossing or attendance relative to no admission, by model, aggregated up to row-category levels. Mean earnings are displayed as a percentage of an average annual wage. Correct standard errors to be added during March visit to tax authority in Chile.

TABLE 9 NET PDV OF ADMISSIONS TO DEGREES
BY FIELD AND SELECTIVITY

	High-Selectivity			Low-Selectivity		
	Costs (1)	Earnings (2)	Net (3)	Costs (4)	Earnings (5)	Net (6)
Business	1.114	2.486	1.418	0.435	0.847	0.412
Art	0.732	-0.732	-1.464	0.482	-0.291	-0.773
Education	0.511	-0.047	-0.558	0.340	-0.045	-0.385
SS/Law	1.000	1.716	0.716	0.573	-0.143	-0.716
Health	1.161	1.908	0.747	0.483	0.445	-0.038
Tech.	1.220	1.209	-0.011	0.586	0.584	-0.002
Hum.	0.771	-2.150	-2.921	0.481	0.377	-0.104

Notes: Program level impacts of attendance relative to no admission using Model 2, aggregated up to row-category levels. Net Present Value calculations assume tuition accrues for expected career duration. Interest rate is 5%. NPV of earnings gains are displayed as a percentage of an average annual wage. Correct standard errors to be added during March visit to tax authority in Chile.

TABLE 10: NET PDV OF ADMISSIONS TO DEGREES
BY FIELD, SELECTIVITY AND CURRICULUM TYPE

	All Selectivity		High-Selectivity		Low-Selectivity	
	Vocational	Non-Vocational	Vocational	Non-Vocational	Vocational	Non-Vocational
	(1)	(2)	(3)	(4)	(5)	(6)
Business	0.697	1.324	1.207	1.434	0.166	0.801
Art	-2.374	-0.727	-2.811	-0.925	-1.596	0.391
Education	-0.537	-0.425	1.204	-0.563	-0.647	-0.375
SS/Law	-0.286	0.535	2.845	0.610	-1.035	-0.215
Health	0.271	1.021	0.208	1.158	0.713	-0.897
Tech.	-0.253	0.723	-0.390	0.984	0.008	0.011
Hum.		-2.093		-2.924		-0.184

Notes: Program level impacts of attendance relative to no admission using Model 2, aggregated up to row-category levels. Net Present Value calculations assume tuition accrues for expected career duration. Interest rate is 5%. NPV of earnings gains are displayed as a percentage of an average annual wage. Correct standard errors to be added during March visit to tax authority in Chile.