NBER WORKING PAPER SERIES

ARE SOME DEGREES WORTH MORE THAN OTHERS? EVIDENCE FROM COLLEGE ADMISSION CUTOFFS IN CHILE

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Working Paper 19241
http://www.nber.org/papers/w19241

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2013

We thank Noele Aabye, Phillip Ross and Unika Shrestha for outstanding research assistance. We thank Nadia Vasquez, Pablo Maino, Valeria Maino, and Jatin Patel for assistance with locating, collecting and digitizing data records. J-PAL Latin America and in particular Elizabeth Coble provided excellent field assistance. We thank Ivan Silva of DEMRE for help locating and accessing data records. We thank the excellent leadership and staff at the Chilean Ministry of Education for their invaluable support of these projects including Harald Beyer, Fernando Rojas, Loreto Cox Alcaíno, Andrés Barrios, Fernando Claro, Francisco Lagos, Lorena Silva, Anely Ramirez, and Rodrigo Rolando. We also thank the outstanding leadership and staff at Servicio de Impuestos Internos for their invaluable assistance. We thank Joseph Altonji, Peter Arcidiacono, Ken Chay, Raj Chetty, Nathaniel Hilger, Carolyn Hoxby, Wojciech Kopczuk, Thomas Lemieux, Costas Meghir, Jonah Rockoff, and participants at University of Chicago, the U.S. Consumer Financial Protection Bureau, the Federal Reserve Bank of New York, the NBER Public Economics and Education Economics program meetings, and Yale University for helpful comments and suggestions. This project was funded solely by Brown University, the Population and Studies Center at Brown, and NIA grant P30AG012810. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research. Online Appendix available at: http://www.justinehastings.com/images/downloads/HNZ_Chile_Appendix_2013a.pdf.

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July 2013
JEL No. H52,I23,I24,I25,I28,J24,J31

ABSTRACT

We use administrative data from Chile from 1985 through 2011 to estimate the returns to postsecondary admission as a function of field of study, course requirements, selectivity, and student socioeconomic status. Our data link high school and college records to labor market earnings from federal tax forms. We exploit hundreds of regression discontinuities from the centralized, score-based admissions system to estimate the causal impacts of interest. Returns are positive and significant only among more-selective degrees. Returns are highly heterogeneous by field of study, with large returns in health, law and social science, as well as selective technology and business degrees. We find small to negative returns in arts, humanities and education degrees. We do not find evidence that vocational curriculum focus increases returns for less selective degrees. We do not find differential outcomes for students coming from low- versus high-socioeconomic backgrounds admitted to selective degrees.

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1 Introduction

The college wage premium has risen dramatically since the early 1980s, causing concern over rising income inequality between those with and without a college education.[1] In response, federal and local governments in OECD countries, such as the U.S. and Chile, have expanded programs aimed at increasing access to higher education.[2] Many students have taken advantage of these programs. Rates of college-going in the U.S. increased by 52% between 1990 and 2010, while rates in Chile increased by 94% between 2000 and 2009.[3] However, by 2010, protests over student loan debt and *ex-post* regret of higher-education investments abounded in both countries, suggesting that cross-sectional returns to college may not accrue to likely loan-takers or to the institutions and degrees they select.[4] Disentangling the causal contributions of student background, institution and field of study to postsecondary educational returns is central to effective higher-education policy design.

In this paper, we provide 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 21 cohorts of college-bound students in Chile. These data were compiled as part of "Proyecto 3E: Expectativas. Estudiantes. Educación.", a research partnership with the Chilean Ministry of Education (Mineduc). The goal of the partnership is to develop datasets and provide rigorous empirical research to guide postsecondary education policy reforms.

In this paper, we use a subset of these data to estimate long-run labor market returns to postsecondary education by institution selectivity, curriculum focus (vocational versus basic math-science-language), field of study, and student socioeconomic status (SES). We use a

[1] See 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).

[2] Examples in the U.S. include the U.S. student Loan Reform Act of 1993 and the College Cost Reduction and Access Act (CRAA) in 2007. In Chile the largest expansion was the 2005 *Crédito con Garantía Estatal* (Loan with State Guarantee, commonly called CAE for *Crédito Aval del Estado*). See Crédito de la Ley 20.027 para Financiamiento de Estudios de Educación Superior.

[3] U.S. statistics: 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." Chilean statistics: Rolando et al. (2010).

[4] See for example: http://www.nbcnews.com/id/45040659/ns/us_news-life/t/another-idea-student-loan-debt-make-it-go-away/#.UYfDa8pbMyQ, and http://www.economist.com/node/21552566.

regression discontinuity design to estimate the earnings impact of crossing admission thresholds to degrees with different characteristics. We couple this with a simple model of wage determination to decompose threshold-crossing estimates into the underlying factors of interest.

Examining these questions in the Chilean context offers several benefits. First, the data available are unique. To our knowledge, this is the first database that has linked administrative data from high school, college entrance exam, college choice, college admission, college matriculation, and tax return data for a broad population. Our college application and admissions data cover 21 full student cohorts – from 1985 through 2005 – and were matched by unique national identification numbers to 2005-2011 tax returns within the Chilean federal tax authority. This allows us to measure long-run labor market impacts across a spectrum of postsecondary institutions and fields for students with diverse skills and backgrounds.

Second, the college admissions process in Chile generates exogenous variation in the assignment of students to institutions and fields of study. Chilean students apply to a career (major) and university simultaneously (e.g. Civil Engineering at the University of Chile) as part of a centralized, score-based application process that covers the majority of universities in the country (a process common to many OECD countries). We refer to an institution-career combination as a degree. Students rank up to eight degree choices in order of preference. The applicants are then scored by universities using a combination of entrance exam scores and GPAs. Students are admitted to at most one of their choices based on their preferences and their score using an algorithm similar to that used in the U.S. medical residency market. This process creates regression discontinuities which effectively randomize students near unpredictable admission cutoffs into institution-career combinations in different fields and selectivity tiers.

We use these discontinuities to estimate the impact of threshold-crossing into a target degree by selectivity, field of study and core curricular focus. Students on either side of each threshold are *ex-ante* the same on observable and unobservable characteristics. We estimate the impact of threshold-crossing on average annual earnings between 2005 and 2011, stacking regression discontinuities by target degree characteristics (Pop-Eleches and Urquiola, 2011). Students crossing the threshold for admission into their target degree realize statistically significant earnings gains equal to 2.9% of mean earnings in the population of applicants. Gains range from close to zero for admission to the least selective degrees to 9.2% for admission into the most selective degrees. We find positive and significant effects of threshold-crossing into health or law and social science degrees, and negative and significant effects for admission into degrees in the arts.

Threshold-crossing estimates measure the impact of admission to a particular degree relative to the mix of admissions outcomes for just-rejected students applying to that degree. We add a simple model of earnings determination to outline the assumptions needed to recover the effects of field of study and selectivity on earnings relative to no admission (Angrist and Imbens 1995; Angrist 2004; Heckman, Urzua, and Vytlacil, 2006). Using data on all admissions in the system, we can estimate the impact on earnings of being admitted to each degree *j* for each student of characteristics *c*, relative to being admitted to no university at all under the assumption that heterogeneity in returns to each institution-career depend only on students' observable characteristics. We then aggregate model estimates of degree-specific effects into categories, decomposing the earnings gains into contributions from selectivity, field of study and vocational study for students from different socioeconomic backgrounds.

We present estimates from three different models: a homogeneous effects model in which the earnings effects of each degree are the same for all students and two comparative advantage models that allow for heterogeneous returns by math and language ability, respectively. Overall, the specifications return similar results, suggesting positive and significant earnings returns for selective degrees and zero to negative returns to less-selective degrees. Annual gains from admission to the most selective degrees range from 20.3 to 22.8%. Earnings gains to low-selectivity degrees are near zero even before factoring in tuition costs. These findings are important, as low-selectivity universities saw the preponderance of growth as a result of 2005 Chilean student loan program expansion (Hastings, Neilson and Zimmerman, 2013).[5]

Earnings returns also differ across field of study. Being admitted to a health degree increases earnings by 15.6 to 18.4% of the average wage, and returns to law/social-science degrees are between 9.6 and 12.8%. In contrast, art and architecture admittees stand to lose 8.5 to 10.6% of average earnings. These magnitudes suggest that for students who list high- and low-return degrees on their applications, just failing to be admitted to the degree of choice could be one of the luckiest or unluckiest shocks to lifetime earnings.

While both high- and low-selectivity health degrees have positive earnings returns, we find that large earnings gains are concentrated in more selective degrees in the business, law/

[5] Deming, Goldin and Katz (2012) show similar enrollment growth patterns in the U.S.

social-science, and science/technology fields. However, for art and architecture, education, and humanities, less selective degrees have higher returns, perhaps because of differences in careers upon exiting the degree.

We examine the extent to which returns to institution-career selectivity can be attributed to course requirements. Policy makers have suggested that low returns to postsecondary education may be attributable to focus on core (abstract) math-science-language curriculum rather than vocational or "how-to" curriculum focus (Symonds, Schwartz, and Ferguson, 2011). We digitized data on course requirements by degree to classify degrees as "vocational" versus "core curriculum." We find that, students admitted to degrees with strong vocational focus have lower earnings returns. This holds within selectivity tier.

Finally, we investigate whether returns to field and selectivity differ across student SES. Students from low-socioeconomic backgrounds may benefit most (least) from postsecondary education if, for example, education is a substitute for (complement to) non-educational human capital (such as familial inputs and soft-skills). We use the federal poverty rating of the student's graduating high school to test for differential returns by socioeconomic status. Current results based on a subsample are noisy, but point estimates indicate, if anything, larger returns for students from low-SES backgrounds.

Our results contribute to the growing literature on causal returns to postsecondary education. To date, there is relatively little causal evidence regarding heterogeneity in returns across institution and degree types (Dale & Krueger 2002, 2011; Deming, Katz & Goldin, 2012; Altonji et. al, 2012). Several recent studies use regression discontinuity designs to estimate returns to admission at particular institutions: Hoekstra (2009) studies admissions to a flagship state university in the U.S., Zimmerman (forthcoming) focuses on students crossing the margin from community college to university attendance in the Florida State University System, and Saavedra (2008) uses a similar threshold-crossing design to estimate one-year labor market returns to the top university in Colombia. Öckert (2010) estimates long-run earnings returns to a year of schooling for Swedish college applicants, and finds no significant average impact of threshold-crossing, but does not address heterogeneous effects by degree or student characteristics. These studies offer a significant improvement in causal identification over studies controlling for observable characteristics alone,[6] but do not allow for the kinds of comparisons of long-run returns across institutions or fields of study that we present here.

Our findings also speak to key economic and policy questions. First, they suggest sizeable market frictions in the supply of and/or demand for high-return degrees. Marginally increasing offerings in particular fields could raise aggregate earnings, suggesting constraints on supply (Bound and Turner, 2007). On the other hand, while excess demand for degrees with zero to negative earnings returns may be driven by non-pecuniary factors, recent empirical evidence suggests that students may make uninformed or short-sighted college and career choices (Arcidiacono et al. 2010; Jensen, 2010; Hastings et al. 2013a,b; Hastings, Neilson and Zimmerman 2013; Jacob, McCall and Stange, 2013; Wiswall and Zafar 2013). Information aggregation may be a public good, suggesting a role for government to facilitate informed demand and responsive supply (Beyer et al. 2013). Finally, we show that students from low-SES backgrounds gain from attending selective programs and high-return fields as much or more than their high-SES counterparts, suggesting a role for targeted admissions, loan and recruitment policy (Hoxby and Avery 2012).

2 College Applications in Chile

2.1 Brief History of Chilean Postsecondary Education

The centralized university admissions system in Chile is run by the Council of Rectors of Universities of Chile (CRUCH).[7] CRUCH institutions are the core set of universities in Chile. They are all not-for-profit. They can be public, private or private-parochial. Universities of various selectivity levels are members of the CRUCH. 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

[6] Papers following non-experimental approaches include Kane, 1998; Monks, 2000; Brewer et al., 1999; Black and Smith, 2004; Hoxby, 2009; Lindahl and Regnér, 2005; Long, 2008; Dale and Kruger, 2011; and Rao, Rojas and Urzua 2013.
[7] Pronounced "Crooch." CRUCH is in similar in some ways to the Regents of the University of California, though both public and private schools are members of and therefore subject to the CRUCH.

selective graduate programs in the world. Most degrees at these institutions are licenciatura (licenture) degrees which take 5 years to complete on time. Overall, for those entering a CRUCH degree between 2000 and 2004, 45.7% graduated at their enrolled institution within 150% of expected degree completion time. The corresponding statistic for all four-year, Title IV-eligible institutions in the U.S. is 57.5%.[8]

During the 1980s and 1990s, CRUCH universities made up over 80% of all university degree-granting institutions (weighted by students graduating).[9] From the mid-1990s to present, there has been entry by new, predominantly private, universities typically serving lower-scoring students. By 2000 (one of the youngest cohorts in our sample) CRUCH's share of university enrollment had fallen to 67%.[10] Online Appendix Section I, Figures A.I.I through A.I.III show how outside postsecondary options in Chile have changed between 1983 and 2009.[11] These changes are important to keep in mind when interpreting the earnings gains relative to the outside options.

While we do not have universal enrollment outside of CRUCH in early sample years (see data description in Section 3), we do know that by 2000 16.6% of applicants who were not admitted to any CRUCH option enrolled in a private university that year,[12] while 5.7% enrolled in a technical or professional degree program and 77% did not enroll anywhere. By two years after initial application, these numbers were 37%, 13.8%, and 48.5% respectively (see enrollment tables in Online Appendix Section I).[13] For students from low-income backgrounds, the outside-option, two-year matriculation probabilities are skewed away from private university enrollment (24%) and towards technical/professional enrollment or no postsecondary enrollment (21%, and 55%, respectively).

Extrapolating back using overall market share of CRUCH vs. Private-non-CRUCH vs. technical/professional enrollment, about 16% of rejected applicants in 1990 (graduating in 1995

[8] U.S. Department of Education, NCES, 2011, Digest, Table 345. The value is the average of the 2000-2004 starting cohorts.
[9] Rolando et al. (2010), Mineduc report on aggregate trends in postsecondary education.
[10] 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.
[11] Online Appendix is here: http://www.justinehastings.com/images/downloads/HNZ_Chile_Appendix_2013a.pdf.
[12] From row 1 of Table A.I.I, 69.6% of applicants do not enroll in a CRUCH option (1 - 0.071 - 0.233). Of those 69.6%, 16.7% (0.116/0.696) enroll in a private non-CRUCH university.
[13] The large majority of students applying to postsecondary education in Chile are either just graduating high school, or graduated high school within the past two years.

or1996) would have enrolled in a private university within two years, with the large majority enrolling in no postsecondary education. Thus the non-CRUCH options for rejected applicants in the 1980s and 1990s can be thought of as consisting of a) eventual (within 2 years) CRUCH enrollment (about 26% of students), b) eventual private school enrollment (about 13% of students), c) eventual technical or professional enrollment (about 39% of students), or d) non-enrollment (about 22% of students).[14]

2.2 CRUCH Application and Admission Process

All students applying to CRUCH institutions must take a standardized test for admission. This test was called the PAA (*Prueba de Aptitud Académica*, or Academic Aptitude Test) until 2002 (taken for the 2003 college entering year), and the PSU (*Prueba de Selección Universitaria*, or University Section Test) after 2002. It is constructed and administered by the central testing authority, DEMRE (for *Departamento de Evaluación, Medición y Registro Educacional*, or the Department of Educational Evaluation, Measurement and Registration), which is under the authority of the CRUCH. All entrance exam takers complete exams in mathematics and language, and some students also take optional tests in other subjects. Scores are scaled to a distribution with range 150 to 850 and a mean and median of 500. Entrance exam scores, along with high-school GPA, are the primary components of the composite scores used for postsecondary admissions, scholarships, and student loan eligibility.

After taking the entrance exam and receiving their scores, students choose where to apply and submit their application to CRUCH. As in many other postsecondary education systems (though typically not the U.S.), a choice indicates both an institution and a career. We will refer to an institution-career combination as a degree. Students submit one application with up to eight ranked degree choices.[15] Once students apply, their entrance exam scores and GPAs are

[14] Extrapolated based on 22% of those not admitted in 2000 did not matriculate anywhere within 2 years (see Table A.I.I.) and 26% of rejected applicants from 1985-1999 were admitted to a CRUCH option within 2 years. The remaining 52% were extrapolated based on the fact that from 1985-1999, 25% of non-CRUCH enrollment was at private universities and 75% was at IPs (*Institutos Profesionales* or Professional Institutes) or CFTs (*Centros de Formación Técnica* or Technical Formation Centers.) See Figure A.I.II.

[15] 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

used by CRUCH members to assign a score for each degree. Students selecting a particular degree are admitted in order of their score until all slots are filled or demand is satiated. We observe excess demand for 65% of all degrees in our data, accounting for 90.2% applications.

Students are offered at most one admission slot: they are admitted to their most preferred degree for which they garnered a sufficiently high score. Online Appendix, Section II describes the CRUCH scoring and admission algorithm in detail. Students have an incentive to rank order their choices correctly (they should not list a less-preferred choice over a more-preferred choice), though they may incorporate overall probability of admission in deciding which options to list (as they are capped at eight options). While students apply with some knowledge of where they might be admitted (applications display “reach” and “safety” schools), cutoff scores vary unpredictably from year to year as shocks to demand for various degrees ripple through the system.[16] These sharp and unpredictable cutoffs generate exogenous variation in admissions outcomes.

3 Data

3.1 Administrative records on college applicants

We construct our analysis dataset from a variety of administrative and archival sources. We summarize the process here, with additional detail available in Online Appendix Section III. We digitized test score, admissions, and waitlist results for all CRUCH schools and careers between 1985 and 2000 from original paper copies. We then digitized data on PAA/PSU scores from 1985-2000 from hard copy records at the testing authority and matched these by individual identifiers to the admissions data. These records also include information on gender and, beginning in 1998, high school of graduation.[17]

[16] Admission cutoff scores vary significantly within a degree over time. The average standard deviation in cutoff score for a degree in our marginal sample is 19.4 points, making the actual cutoff in a particular year unpredictable.
[17] We are currently completing high school of graduation records back to 1982 to expand our analysis of differential returns to college education by socio-economic status.

Using high school of graduation, we construct measures of student socioeconomic status. Mineduc categorizes high schools by the poverty-level of their student-body. There are five categories, A through E, with A being the highest-poverty and E being the lowest-poverty. While poverty ratings have only been available during the 2000s, they are very persistent over time. We classify students as low-SES if they graduated from a high school with an A, B or C rating.[18]

Beginning in 2001, we have electronic records of the full college application process. These records include high school graduation records with gender, GPA and high school of graduation. We link these records to digital records of applications to CRUCH schools. These records 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 scores. For the years 2000 through 2011, we have data on college attendance and graduation from almost all postsecondary degree-granting institutions in Chile. We obtained these data as part of Proyecto 3E. Combined, these data give us a panel of college applicants and graduates from 1985 through 2005 – twenty-one cohorts of students.

We match these data to individual tax records at the Chilean tax authority in compliance with Chilean privacy laws.[19] 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 micro-data are not available for a significant portion of wage earners. Online Appendix Section IV 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 include zero earnings to 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 VII we present regression discontinuity estimates of participation effects by selectivity and field of study. These effects are generally quite small: our results are driven largely by changes in

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[18] The poverty ratings are highly correlated with family income. We measured family income in tax data using parental identifiers linked to student identifiers. Our family income measures are highly correlated with the Mineduc poverty rating. In addition, there are no municipal (public, non-voucher) schools with poverty-rating E, and no private schools with poverty-rating A.

[19] This disclosure is required by the Chilean government. SOURCE: Information contained herein comes from taxpayers' records obtained by the Chilean Internal Revenue Service (*Servicio de Impuestos Internos*), which was collected for tax purposes. Let the record state that the Internal Revenue Service assumes no responsibility or guarantee of any kind from the use or application made of the aforementioned information, especially in regard to the accuracy, validity or integrity.

earnings conditional on some work. We top-code the highest one percent of earnings, conditional on earnings and experience, to reduce the impact of earnings outliers in our analysis. Specifically, we divide earnings observations into cells based on a full interaction between application cohort and years since application. We then set observations in the top one percent of the distribution in each bin to the 99th percentile value for the bin. Our results are robust to moving this threshold up to the 99.5th percentile or down to the 98th percentile. We present regression discontinuity estimates by selectivity and field of study for these alternate top-code values in Online Appendix Section VII.

3.2 Administrative records on postsecondary institutions and degrees

We construct several measures of institution and career characteristics. First, careers come with administrative categorizations by CINE-UNESCO 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 improve statistical power.[20] These seven areas are: art and architecture, agriculture, basic science and technology, business administration, education, health, humanities, and law/social-science. Online Appendix Section V details these field categorizations and provides examples of specific careers in different field and selectivity categories.

Second, we use course requirement data to categorize degrees by the vocational coursework requirements. We use current course requirements as listed on institution websites as historic information is not available. Vocational courses include internships and courses that teach students how to apply skills specific to 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 non-vocational category. Each degree is then categorized as vocational if it has a larger share of vocational course requirements than the median degree. Within a field of

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

study, this distinguishes vocational "how-to" oriented degrees from degrees focused on training in general skills in math, science, language and writing. Online Appendix Section V details this categorization process and provides additional examples.

Finally, we categorize degrees into selectivity tiers based on quartiles of average math and language scores for admitted students. Two degrees within the same institution can fall into different selectivity categories; some institutions may specialize in certain fields and not in others. While selectivity is at the degree level, some institutions have more selective degrees across all fields than others. Table I lists the CRUCH universities as well as a handful of associated professional institutes that also participated in the centralized assignment system during our sample period. The table shows each institution, the average PSU score (combined math and reading scores) of admittees and the fraction of degrees that fall in the top two selectivity tiers (above median average cutoff score over our sample). It also shows the fraction of degrees by the seven broad fields of interest.

Pontificia Universidad Católica is the most selective private institution and Universidad de Chile is the most selective public institution. Both offer a wide range of degrees. Not all of their degrees are selective in part because of field (e.g., PUC offers degrees in education that tend to be less selective). Many universities offer some selective options, with the fraction of selective degrees increasing with overall university selectivity. Some universities focus on particular fields (e.g. education at U. Metro. en Ciencias de la Educación or U. de la Serena).

Table II shows summary statistics from CRUCH applicants for application years 2001-2011, the years for which we have full preference rankings from electronic records (recall that for 1985 through 2000 we do not have full ranked choices but instead have only digitized admission, waitlist and score data from hard copy records).[21] Column 1 shows the mean and standard deviation of the number of choices listed. Students must list one choice and can list up to eight. Students, on average, list only four to five out of eight possible choices. On average, students' scores slightly exceed admissions cutoffs at their first-choice degrees, and are even farther above admissions cutoffs for their last-choice schools. This is consistent with a story in which students apply to "reach" options with their first choice and safer options with lower-ranked choices. Students list an average of three to four different careers in close to two different CINE-UNESCO areas, at 2.5 different universities and crossing 1.6 to 1.7 selectivity

[21] To the best of our knowledge, full applications in these earlier years do not exist in any form.

tiers. On average, students who are admitted somewhere 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.

Combining each of the data sets above, we construct an estimation sample of applications that fall within 25 points on either side of the admission cutoff to a degree-year for which there was excess demand. We define degree-year combinations as having excess demand if we observe a minimum of 15 applications in the five points below the cutoff score.[22] These are the students on the margin of admission.

Table III compares characteristics of the full sample with our 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 applications in the estimation sample. Column 3 shows summary statistics for applications in the estimation sample for which we have full data on field of study and course requirements of the target degree. We are missing this data for approximately two percent of applications. On average, students in our marginal sample have higher entrance exam scores, are more likely to be applying to a business degree, and less likely to be applying to an education degree. 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 slightly more likely to be male, and significantly more likely to come from private schools. Average labor earnings between 2005 and 2011 (in constant 2011 pesos) for our marginal group are about 13% higher than those for the total applicant population. Converting to U.S. dollars using OECD Purchasing Power Parity data for 2011 indicates that mean earnings for students in the applicant population were roughly $25,200, compared to $28,400 for students in the marginal sample.[23] To facilitate interpretation, we will divide estimated effects by mean full sample earnings in much of what follows. We observe positive earnings for 82.8% of students in the full sample and 83.8% of students in the marginal sample.

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[22] Online Appendix Section VII presents regression discontinuity and model estimates for wider and narrower bandwidths and more and less inclusive definitions of excess demand.

[23] Exchange rate taken from OECD data on Purchasing Power Parities for actual individual consumption. Exchange rate of Chilean Pesos to U.S. Dollars was 334 to 1 in 2011. http://stats.oecd.org/Index.aspx?DataSetCode=SNA_Table4, accessed July 9, 2013.

There are 1,399 CRUCH degrees in our data. We observe marginal students subject to binding cutoffs in 914 of these degrees, accounting for 90.2% of applications. The remaining degrees for which there are no regression discontinuities are therefore part of the outside option. We also examine a more inclusive definition of binding admissions cutoffs as a robustness check. This alternative definition includes 1,025 of the 1,399 degrees and 94.6% of all applications. Our findings are robust to this change. See Online Appendix Section I for a more detailed discussion of the outside option and Online Appendix Section VII alternate estimates of earnings models.

4 Model and Empirical Framework

Our empirical approach has two parts. First, we use a stacked regression discontinuity design to identify the effect of crossing the threshold for admission to a given type of degree on earnings outcomes. Second, we use a simple model of earnings determination to outline the assumptions needed to recover the earnings effects of admission by selectivity, field of study and student characteristics relative to a common outside option from the threshold- crossing estimates.

Recall that students are admitted to at most one degree program. Average annual earnings for individual *i* admitted to degree *p* are given by:

$$Y_{ip} = \theta_p + \mu_i + \phi_{ip} + \omega_{ip} \tag{1}$$

where Y_{ip} is average annual earnings, θ_p is the mean earnings gain from admission to degree *p* in the population (relative to not being admitted to any degree, the effect of which is normalized to zero), μ_i is an individual-specific component of earnings that accrues regardless of admissions outcome, ϕ_{ip} is an individual-specific return to degree *p* known to individual *i* at the time of selecting a degree, and ω_{ip} is a mean-zero individual-specific return from attending degree *p* realized after attending *p*. While ϕ_{ip} may play a role in degree choice; ω_{ip} does not.[24]

Consider the group of students applying for admission to degree *p*. Those just below the threshold will be admitted to a mixture of other degrees *q*. The average effect of crossing the threshold for admission at degree *p* on earnings is given by:

$$E\left(\Delta_p\right)=\left(\theta_p-\sum_q \pi_{pq}\theta_q\right)+\left(\sum_q \pi_{pq}E\left(\phi_{ip}-\phi_{iq} \mid i \text{ chose } p>q\right)\right) \tag{2}$$

where π_{pq} is the probability that individuals just below the threshold of admission to degree *p* will be admitted to degree *q*. The first term is the probability-weighted difference in mean earnings gains from admission to degree *p* versus any other degree in the system. The second term is a probability-weighted average of individual-specific gains from admission to degree *p* relative to degree *q* given that individual *i* was on the margin of admission to degree *p* and would have attended degree *q* had he been rejected from *p*. Thus, threshold-crossing effects depend on a mix of mean earnings effects, conditional choice and admissions probabilities, and individual-specific earnings effects that may be related to choice and admissions probabilities.

We are interested in estimating θ_p in addition to the threshold-crossing effects. To do so, we need to place restrictions on ϕ_{ip}.[25] We take a simple approach: we assume that ϕ_{ip} is a function of observable characteristics of students and degrees. Students with certain observable characteristics may realize larger earnings gains if they choose certain degrees, and students may make choices with this in mind. Student characteristics we consider include math entrance exam scores, reading entrance exam scores. Students may choose degrees with an idea that they are relatively good at math versus language (Arcidiacono, 2004). We also consider socioeconomic status; students may know that they lack (or have) social capital or soft-skills which will impact

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[24] The ϕ_{ip} allow for essential heterogeneity in the sense of Heckman et al. (2006). For simplicity, this model abstracts from possible differences in the growth of earnings for students admitted to different degree programs.
[25] Even with our large database, we do not have sufficient observations to estimate separate threshold-crossing effects by degree and exact choices and choice order submitted.

their relative returns from a degree. We allow student characteristics to affect earnings returns through interactions with field of study and selectivity quartiles.

It is possible that ϕ_{ip} may also depend on student characteristics that we cannot observe. We present results from four main specifications to explore the sensitivity of our results to these alternative assumptions. First, we present estimates of Δ_p, the impact of crossing the admissions threshold to degree *p*,

$$(3) \qquad Y_{ip} = f_p(d_{ip}) + \Delta_p Z_{ip} + \varepsilon_{ip}$$

where Y_{ip} is average earnings over outcome years 2005-2011 for individual *i* who applies to degree *p*,[26] d_{ip} is the difference between the admissions score assigned to *i*'s application to program *p* and the cutoff score for admission to that program in the year *i* applies, $Z_{ip} = 1(d_{ip} \geq 0)$ is an indicator variable equal to one if *i*'s application to degree *p* is above the cutoff score (so *i* is accepted to program *p*), $f_p(d_{ip})$ is a smooth function of the score difference, and ε_{ip} is an error term. We estimate equation (1) separately for every target degree in the system. This yields 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*.

Our remaining three specifications add assumptions on ϕ_{ip} to uncover θ_p under different restrictions on ϕ_{ip}. The homogeneous effects model assumes that $\phi_{ip} = 0, \forall i, p$. In other words, students do not know of, or do not act on, individual-specific deviations from degree-specific mean earnings effects at the time of choice.[27] We then present two comparative advantage models which allow for heterogeneous returns by baseline math or language skills. Let *g* denote a cell defined by a triplet of student characteristics *c*, field of study *f*, and selectivity quartile *s*. We allow that $\phi_{ip} = \phi_{g(i,p)}$, so students select degrees based on a mean comparative advantage term for individuals with their demographic characteristics that may vary across field and

[26] These averages exclude earnings observations from fewer than six years after college application.
[27] See Hastings et al. 2013a for survey evidence on what information and factors Chilean students use when making their postsecondary educational choices.

selectivity tier. For the math and language skills models, *c* is an indicator if the student has above-median math or language entrance exam scores, respectively. For example, students with high math scores may realize particularly large earnings returns in high-selectivity science and technology degrees. We also estimate a model in Section 6 where *c* is an indicator equal to one if the student comes from a low-SES school to allow for heterogeneous effects by socioeconomic status. We present additional models and robustness checks in the Online Appendix Section VII, including some that allow for unrestricted heterogeneity in degree effects for students in the high and low math and reading score groups.

To estimate the homogeneous effects and comparative advantage models, we allow earnings for individual *i* to be a function of the homogeneous degree effect θ_p, and the additional comparative advantage impact of ϕ. For individual *i* with characteristics *c* applying to degree *p*,

$$Y_{icp} = f_{cp}(d_{ip}) + \sum_{r=1}^{P}\left(\theta_r + \phi' X_g\right) A_{ir} + \varepsilon_{ip} \tag{4}$$

where X_g is a vector of indicator variables for each group *g* defined above, ϕ is a vector of coefficients ϕ_g, *P* is the total number of degrees, A_{ir} is an indicator if *i* was admitted to program *r*, and $f_{cp}(d_{ip})$ is a smooth degree-and-student-characteristic-specific functions of d_{ip}. We instrument for A_{ir} and its interaction with X_g using a set of threshold-crossing indicators Z_{icr} which are equal to one if applicant *i* to degree *r* with characteristic *c* has $d_{ir} \geq 0$. In our homogenous effects model, we restrict the ϕ to be zero, restrict the $f_{cp}(d_{ip}) = f_p(d_{ip})$ for all *c*, and instrument using $Z_{ir} = 1[d_{ir} > 0]$. This yields a just-identified IV specification with *P* endogenous admissions outcomes and *P* threshold-crossing indicators.

Intuitively, estimating the homogenous effects model amounts to solving *P* equations of the form given in (2) for *P* unknowns, θ, using estimates of the threshold-crossing estimates Δ and transition probabilities π. For the comparative advantage models, we have a different threshold-crossing estimate of earnings effects for each degree-characteristic pair. This is an over identified specification with *2P* instruments for *P+G* parameters, where *G* is the number of categories generated by the area-selectivity quartile interaction.

We estimate (3) and (4) using data on mean 2005-2011 earnings. We exclude applicant-year observations for which fewer than six years have elapsed since the year of college application. We include observations with zero earnings values in our regressions. We focus our analysis on a 25-point window on either side of admissions cutoff values, and include second-order polynomials in score. The polynomials are allowed to change above and below the cutoff value. Because individuals can appear at more than one threshold (they may just fail to be admitted to p and just cross the threshold to q), we cluster standard errors at the individual level. Cluster – robust standard errors are computed using a wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). The wild bootstrap allows us to conduct analysis and robustness checks outside of the tax authority using only degree and characteristic specific threshold-crossing estimates. Online Appendix Section VI provides further details on the estimation procedure. After computing the threshold-crossing and model estimates for each degree program, we summarize the distribution of estimates by program selectivity, field of study, and course requirements. For purposes of comparison, we also present OLS estimates of the earnings effects of admission to different types of degrees. OLS models include controls for cubic terms in math and language test scores as well as cohort fixed effects.

We focus on group-specific means, but also present kernel density estimates of the distributions of different types of degrees. Online Appendix Section VII presents several robustness checks. We present standard robustness checks varying the bandwidth around the threshold and the polynomial degree (Imbens and Lemieux 2008; Lee and Lemieux 2010). We also vary our definition of degree-year pairs with excess demand. Our results are robust to these changes. We present results for men only, and results using an indicator for positive earnings as the dependent variable (extensive margin only). Our results for men are similar to our overall results and we find little impact on the extensive margin.

Finally, note that 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 (Abdulkadiroglu et al. 2011). This is much less likely to be a problem in our setting than in the Boston magnet school application process studied in Abdulkadiroglu et al.. Students in our setting have the option to choose from several hundred institution-degree combinations, and have very heterogeneous preferences for institutions and fields (in contrast to three magnet programs with distinct hierarchy). In addition, scoring systems vary across degrees. Accordingly, our data show no indication of discontinuities in matriculation or earnings functions away from the threshold over the windows we use.

5 Results

5.1 Validating the regression-discontinuity design

If the regression-discontinuity design is valid, observable and unobservable characteristics of students will be on average the same on both sides of the discontinuity. Figure I plots an index of baseline characteristics in one-point bins against distance from the admission cutoff. The index is the portion of earnings predicted by baseline characteristics in an OLS regression of labor market earnings that also controls for polynomials in score and cohort and experience effects. Baseline characteristics include gender and indicators for type of high school (municipal vs. private). The figure shows no visible discontinuity around the threshold. Table IV presents the impact of threshold crossing on baseline characteristics, pooled as well as by the degree characteristics of interest (field, coursework, selectivity). Joint tests are all insignificant indicating that baseline characteristics are balanced above and below the threshold.[28]

5.2 Impact of threshold-crossing on matriculation, degree characteristics and earnings

Figure II plots matriculation into the target institution-degree against distance from the cutoff score for applications from 2000 to 2010. Recall that we currently only have complete matriculation records for these years. Overall, threshold crossing causes a 49.2 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

[28] In the Online Appendix Section VII we plot one-point-bin averaged baseline characteristics for each baseline characteristics separately as well as the density of score in 2 point bins around the cutoff, verifying that there is continuous density in the running variable across the cutoff (McCrary, 2008).

ranked choice, or 2) be pulled off the waitlist, which is visible among score bins just to the left of the cutoff. If matriculation rates were similar in the 1980s, 1990s, and mid-2000s to what they were in the late 2000s, our estimated admission effects are approximately half the size of the effects of matriculation on labor market outcomes.

The final column of Table IV shows the impact of threshold crossing on matriculation by our institution-degree characteristics of interest. Business, science and technology and humanities degrees have the highest causal impact of admission on matriculation. Art and education are the lowest. Degrees with vocational vs. core-curriculum 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. These differences will be important to keep in mind when interpreting the threshold-crossing results.

Threshold-crossing identifies the earnings impact of being admitted to the target degree program relative to the mix of degrees students would otherwise have attended. This mix varies across target degrees. Table V describes acceptance outcomes for students just below the threshold for admission to different types of target degrees.[29] If rejected students are accepted elsewhere, they are most likely to be accepted to a degree in the same field. For instance, 33.4 % of rejected business degree applicants are accepted to another business degree. Outcomes also vary by selectivity of the target program. 61.3% of students rejected from programs of above-median selectivity are accepted at other such programs, while 14.2% are accepted at lower-selectivity programs and 24.5% end up in the outside option. The equivalent figures for students rejected from below-median selectivity programs are 2.3%, 45.4%, and 52.3%. These patterns suggest that threshold-crossing estimates understate the relative returns for students applying to high-return areas or high-selectivity degrees, since their below-threshold outcomes likely provide relatively large earnings gains compared to the below-threshold outcomes for applicants to lower-return degrees.

5.3 Impact on labor market outcomes by program characteristics

[29] These estimates are obtained using local polynomial regressions in the subsample of rejected marginal students.

5.3.1 Degree selectivity

The first row of Table VI shows pooled results for five regression models: 1) Threshold-crossing estimates, 2) Homogeneous program effects models ($\phi_{ip} = 0, \forall i, p$), 3) and 4) allowing program effects to vary with math or reading exam scores, respectively ($\phi_{ip} = \phi_g$), and 5) ordinary least squares. We present earnings effects as percentages of average earnings in the tax records – 8.43 million pesos. A coefficient of X% implies that annual earnings gains are equal to (X/100)*8.43 million pesos. Crossing the threshold into a target degree (column 1) increases labor market earnings by 2.9% and is significant at the 1% level. Figure III shows the threshold-crossing impact on earnings graphically by plotting mean earnings in 5-point bins of distance-from-threshold.

In the homogeneous effects model (column 2), gaining admission to a target degree increases average annual wages by 6.5% in the homogeneous effects model and by 5.8% in the model allowing for comparative advantage in math. Allowing for comparative advantage in language yields a similar estimate to the threshold-crossing model, but the impact is noisier. OLS regressions predict a 21.9% effect of being admitted to the target degree.

The subsequent rows of Table VI aggregate the estimated degree-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 the indicated range. Across all five models, labor market earnings increase with selectivity of the program admitted to. Significant positive returns generally do not appear until the third selectivity group, about one standard deviation above the mean admissions test score. In the threshold-crossing specification (column 1), returns rise from roughly 1% in the lowest selectivity category to 9.2%in the highest. Consistent with the idea that students applying to more selective degrees have better options if they are rejected, this pattern is even more pronounced in the model estimates. For instance, in the homogeneous effects specification (column 2), earnings effects relative to the outside option rise from 2.5% in the lowest selectivity group to 22.8% in the highest selectivity group. Interestingly there is little difference between the homogeneous effects model and the heterogeneous effects models (columns 3 and 4). OLS estimates imply negative and significant returns to the lowest selectivity tiers, and positive 101% returns to the highest selectivity tier. Comparison with the model estimates suggests that selection into degrees based on student skill levels may bias OLS estimates of earnings effects of low selectivity degrees downwards and high-selectivity degrees upwards.

Figure IV.A. plots point estimates by finer selectivity bins for the threshold-crossing, homogeneous effects and comparative-advantage in math models. Returns are flat and near zero until degree-average cutoff-scores reach 575, at which point returns appear to increase at an increasing rate. In Chile, the majority of student loan recipients apply to low-selectivity degrees, and non-selective universities have seen the largest growth in demand during the past decade.

Figure IV.B. shows the distribution of average entrance exam scores for CAE-loan-takers (the main federal loan program) versus non-takers. The bulk of loan takers have entrance exam scores in lower-selectivity range. Hastings, Neilson and Zimmerman (2013) 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. This results in higher tuition payments, but not in higher expected earnings (using institution-degree means from prior cohorts). Figure IV and Table VI add further causal evidence: being admitted to a low-selectivity institution may offer little to no labor market returns over the outside option (no university, technical or professional degrees per Online Appendix Section I).

5.3.2 Field of study

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 VII shows program returns aggregated by field of study. We present the same five specifications as in Table V. There is substantial variation in returns by field of study. Generally all models agree in sign and relative magnitudes, with OLS estimates yielding large effect sizes in absolute value. Admissions to degrees in business, law/social-sciences and health are generally associated with positive and significant earnings gains. Degrees in health have the highest returns. Students crossing the admissions threshold into health degrees (which increases the probability of being admitted to any health degree by 53.4%) realize earnings gains of 7.6%. The homogeneous effects model indicates that earnings gains are 18.4% when compared to the outside option, while the OLS specification indicates a 58.7% impact. Students crossing the threshold at art or architecture degrees see their earnings *decrease* by 7.5%.

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 15.2, 16.9, or 18.6%, respectively (using column 2 estimates).

Table VIII combines selectivity measures and field of study by reporting earnings impacts by field for degrees above or below median selectivity (more – or less – selective, respectively). We present the threshold-crossing estimates and the homogeneous effects model estimates only to conserve space. Additional heterogeneous effects models are in the Online Appendix Section VII. For Health degrees, returns are positive and significant regardless of selectivity level. Law and social science, science and technology and business have positive and statistically significant returns only among more-selective degrees. Interestingly, for art and architecture, humanities and education degrees, admission to a more selective degree is associated with more negative impacts (though these negative impacts differ significantly from zero only for art and architecture). This may be because these degrees direct students towards occupations that pay less than what high-ability students could expect to earn without a college degree.

Figure V plots the distribution of degree-level estimates for the threshold-crossing and homogeneous effects models by field. Each graph plots a field relative to the distribution for art and architecture. The variance of estimated returns within fields is large and partially attributable to sampling error. A rightward shift in the distribution of returns in higher-earnings careers is observable in the threshold-crossing estimates and is even more distinct in the model estimates. In part, this reflects the fact that students on the margin of admission to degrees in high-earning fields tend to have higher-earning below-threshold options.

5.3.3 Curriculum

Table IX asks whether differences in returns within selectivity tier vary with core course requirements. We categorize degrees into vocational versus core-curriculum based on whether the degree had an above-median fraction of applied (as opposed to math/science/language) courses among its course requirements. Some policymakers have argued that low-selectivity degrees specializing in vocational subjects have larger returns than other low selectivity degrees. We do not find evidence of this. Rather, we find that positive and significant returns are concentrated in degrees that are more selective and have a core curriculum heavy in math, science and language.

6 Extensions

6.1 Returns to selectivity by socioeconomic status

Table X uses data on student high school of graduation to categorize students into low versus high socioeconomic status. Students coming from Mineduc poverty-rated A, B, or C high schools are categorized as low-SES. We currently only have complete information on high school of graduation from 1998 onward. We are completing the data for the years 1982-1997. For now, we explore how admission varies with SES by selectivity. We first replicate our pooled results in columns 1 and 2 on the sample of applicants from 1998-2005. As a point of comparison, the pooled estimates for the threshold-crossing and homogeneous effect models in this sample are smaller in magnitude and insignificant. If we split the sample by SES category, we find larger point estimates for low-SES students from admission to high-selectivity degrees. This may be because low-SES students are less able to pursue beneficial non-CRUCH options, such as attending a private university or technical school. It may also be because a selective degree is a substitute for, rather than a complement to, forms of human capital that low-SES students lack. While the estimates are noisy, they do suggest that returns for students from low-SES backgrounds at selective degrees are at least as large as those for high-SES backgrounds, and support targeted admissions and scholarship programs.[30]

[30] Bertrand, Hanna and Mulainathan (2009) examine returns to affirmative action programs in India. They find that lower-scoring lower-caste entrants have positive returns to admission. However they find their returns are smaller than those for higher-scoring higher-caste members. Here, our regression discontinuity design implies that scores are on average the same across applicants from different socioeconomic backgrounds. Conditional on score, lower-socioeconomic students appear to gain the same if not more than higher-socioeconomic students.

6.2 Tuition versus returns

One concern is that the benefits students realize from admission to different degrees may simply be captured by universities through higher tuition costs. We construct estimates of the direct costs of college using tuition fees and expected time to degree completion from 2011, using data provided to Mineduc by postsecondary institutions. We convert these costs into fractions of the average annual wage, and compare them to our homogeneous effects model estimates. We do not have past tuition data for the cohorts in the bulk of the earnings estimation sample. We also do not have student-level information on realized outside options until 2000, and, as discussed above, these options have changed over time. We therefore interpret this side-by-side comparison as the cost-benefit tradeoff a student today would face when considering which degree to apply to, given information about earnings gains for past cohorts and current tuition costs. Because cost figures reflect the cost of degree completion, they may be inflated relative to per-admission estimates of earnings effects, which also reflect outcomes for students who do not complete degrees.

Table XI shows the estimated earnings gains and tuition costs by field and selectivity tier. The highest return fields in law and social-science and health have the highest tuition, but relative tuition costs are small relative to increased average annual earnings gains over lower-return fields. Degrees in art and architecture appear to be the worst deal, with negative expected earnings gains and higher average tuition costs than business (which has positive expected earnings gains), education or humanities degrees.

Tuition costs increase with selectivity of the degree. The most selective degrees charge almost 2.4 times the tuition than the least selective degrees do. However, expected annual earnings gains are almost ten times as high. While tuition costs increase steeply at the higher degrees, expected returns increase even more, implying that the highest-selectivity degrees are well worth the investment – institutions are not simply capturing differences in gains with increased tuition.

6.3 Selectivity and value-added through human capital accumulation

Across a variety of specifications, we find that selective degrees, degrees with core-curriculum focus, and degrees focusing on health and law/social-science exhibit positive and significant causal returns to admission. Our finding of heterogeneity in returns by field of study is consistent with a story about frictions in supply and demand for laborers across specialization field (Autor, Katz & Kearney 2008; Acemoglu & Autor, 2010). Our findings on the earnings benefits of core-curriculum, as opposed to vocational coursework, could suggest that students receiving broad training in logic and language skills may more successfully adapt to a changing labor market over their career. Our finding of high returns only in high-selectivity degrees is consistent with a pure signaling model of postsecondary education. It is also consistent with a model where high-selectivity degrees have higher value-added; they do more to raise the human capital of enrolled students.

Differences in retention and graduation are one measure of value-added, assuming that human capital gained is increasing in years of schooling completed. Using the complete matriculation and graduation records from 2000-2011, Online Appendix section VIII shows how matriculation translates into degree completion by selectivity and field of study. Overall, more selective degrees are more effective at graduating students; students crossing the threshold into a more selective degree are about 1.73 times more likely to graduate from the target degree than students crossing a threshold into a less-selective degree are. Core-curriculum degrees are 1.32 times more likely to graduate students than vocational degrees.[31] Of course, graduation and earnings gains are linked through student choice: if students realize after matriculation that their degree will result in lower earnings than expected they may be inclined to drop out sooner (Hastings et al. 2013a). They are both likely correlated with student ability and socioeconomic status as well. Decomposing the factors that contribute to the high returns observed for selective degrees is an important area for future research.

7 Conclusion

[31] Table A.VIII.I, 0.221/0.128 = 1.727, and 0.21/0.159 = 1.321.

We estimate the impact of acceptance into colleges and fields of study on labor market earnings by exploiting hundreds of regression discontinuities in admissions to university-degree combinations in Chile for 21 years of college applicants. We find statistically and economically significant heterogeneity in earnings returns by selectivity, field of study and course requirements. These differences are not driven by correlations in preferences and/or unobserved skill (e.g. Dahl, 2002), as both are balanced across admission thresholds. Rather, they may be caused by differences in the amount and types of skills acquired by students enrolled in different degree programs as well as differences in skill prices in the labor market.

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; Zimmerman, forthcoming) 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 would likely have 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. (2013a) 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 could supply centralized ranking and earnings information to provide students with added information needed for making life-long decisions (Beyer et al. 2013, Hastings et al. 2013a,b). Second, loan policy could be used to provide additional supply-side incentives to ease frictions in supply of high-return degrees (Beyer et al., 2013).

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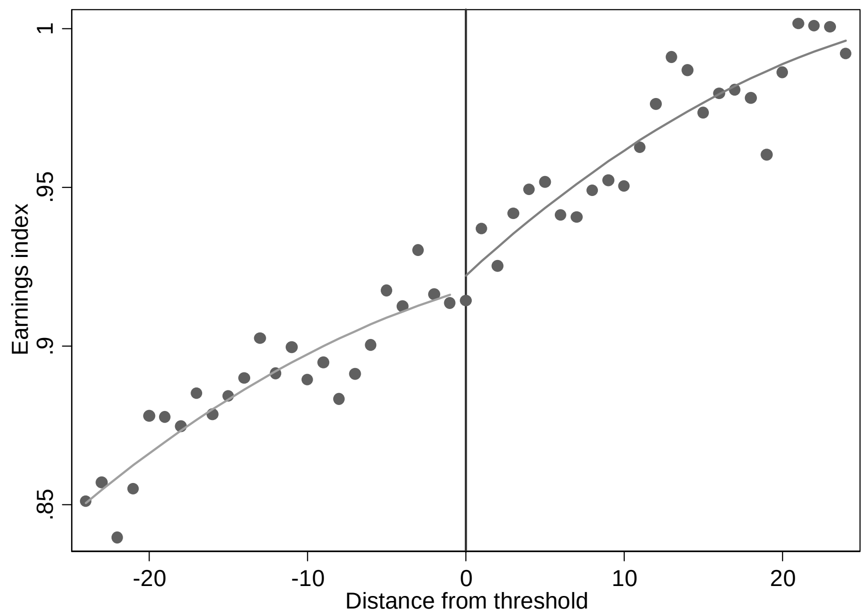


FIGURE I
Impact of Threshold-crossing on Baseline Characteristics Index

Notes: Plot of one-point-bin-averaged Baseline Characteristics Index. Index is the predicted mean earnings from a regression of average earnings from tax years 2005-2011 on gender, indicators for the type of high school graduated from and flexible second order polynomials in distance from the cutoff, excluding the mean shift for crossing the threshold. Sample is 1998 to 2005.

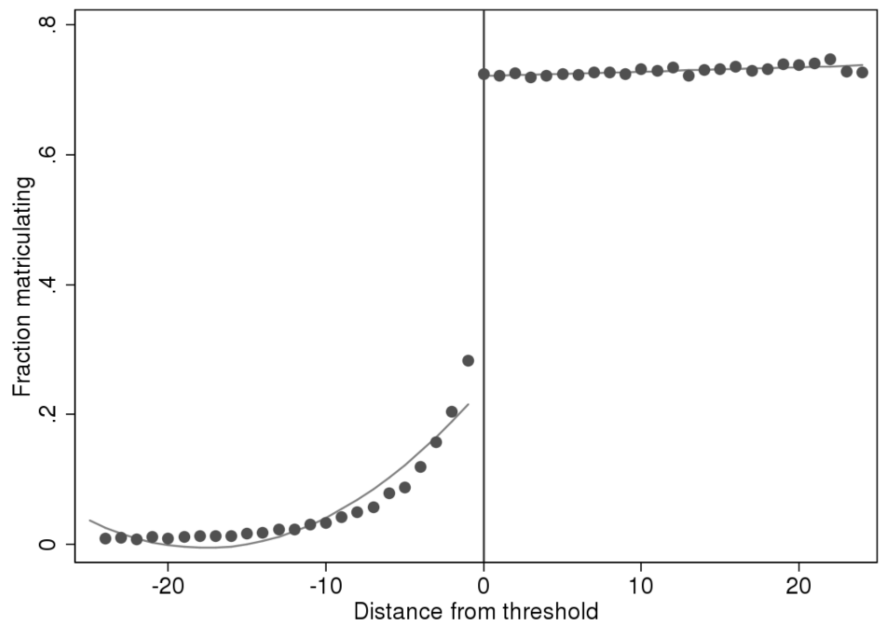


FIGURE II
Impact of Threshold-crossing on Matriculation
(2000-2010 Applicants)

Notes: Plot of one-point-bin-averaged matriculation probabilities into target degree. Sample is 2000 to 2010.

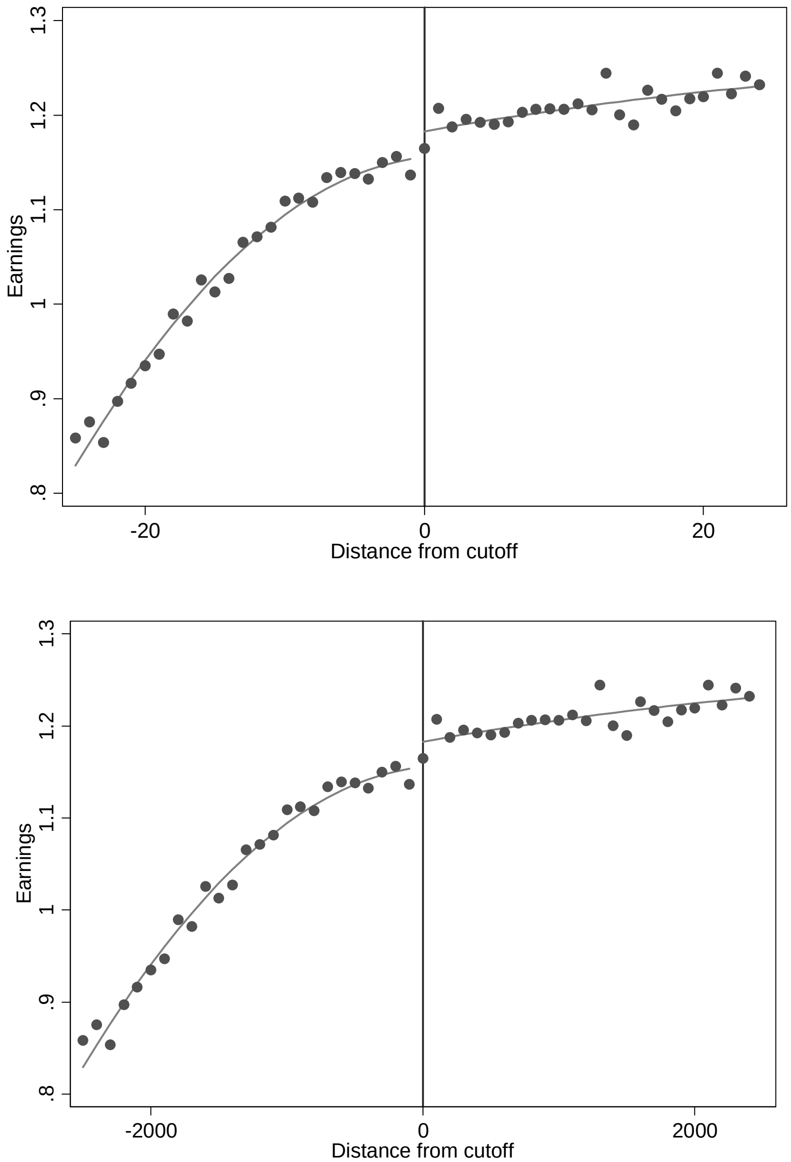


FIGURE III
Pooled Impact of Threshold Crossing on Earnings

Notes: Plot of one-point-bin-averaged mean earnings from tax years 2005-2011. Sample is 1985 to 2005.

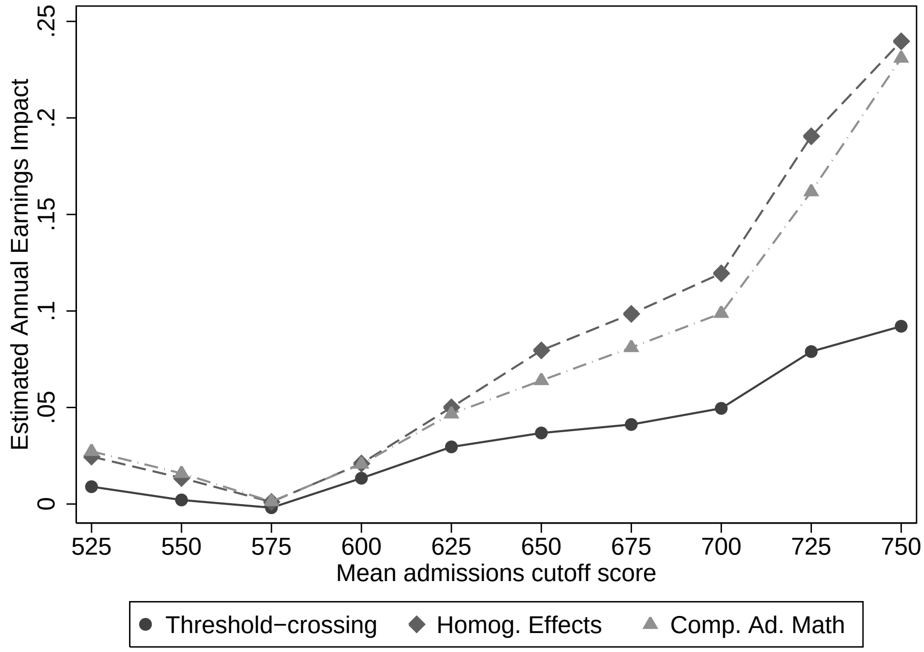


FIGURE IV. A:
Impact of Degree Selectivity on Annual Earnings

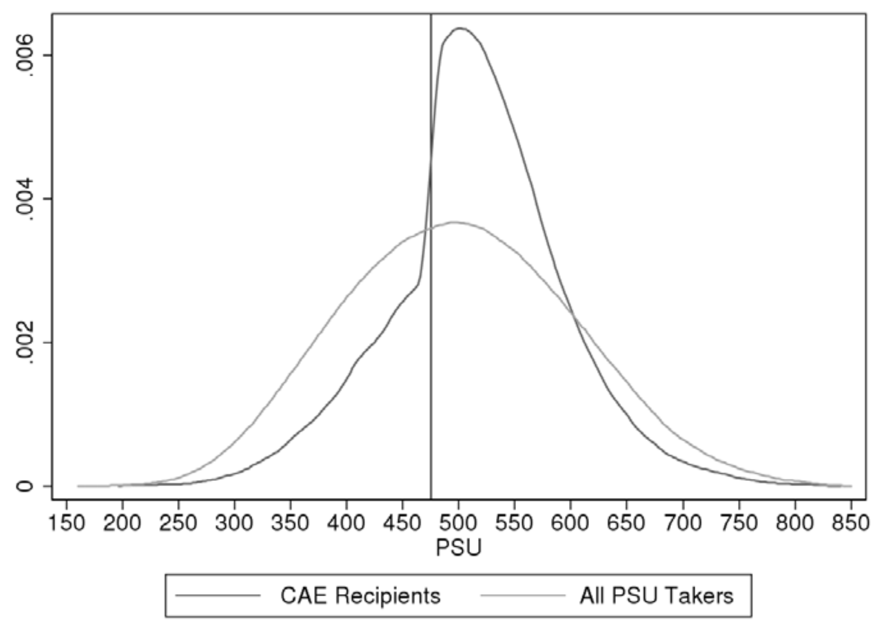


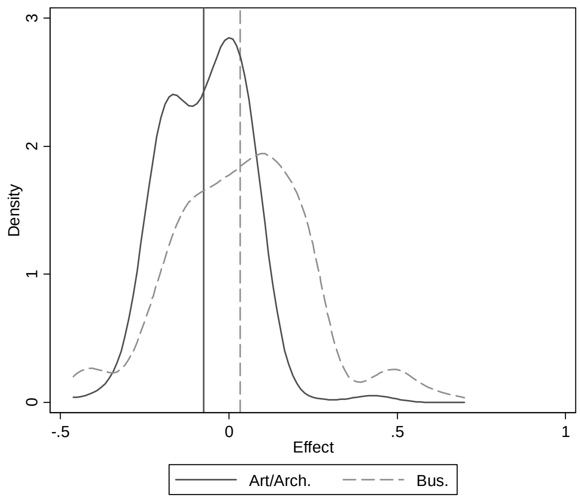
FIGURE IV. B:
Distribution of Entrance Exam Scores: CAE Loan-Takers vs. All PSU Takers

Notes: IV.A: (1) Plot of average point estimates of effect on a degree with mean cutoff within 25 points centered around each mark denoted in the graph. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that φ=0. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math scores. IV.B: average of math and language PSU scores from administrative data for the 2007-2011 PSU. Vertical line at a PSU score of 475, which is the cutoff for CAE eligibility.

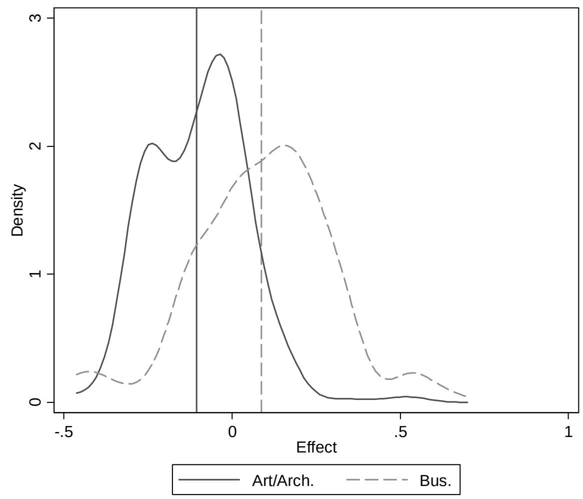
FIGURE V
Distribution of reduced form and structural earnings effects by Area. Distributions for Art/Architecture are reproduced in each subfigure.

V. A Business

(1) Threshold-crossing

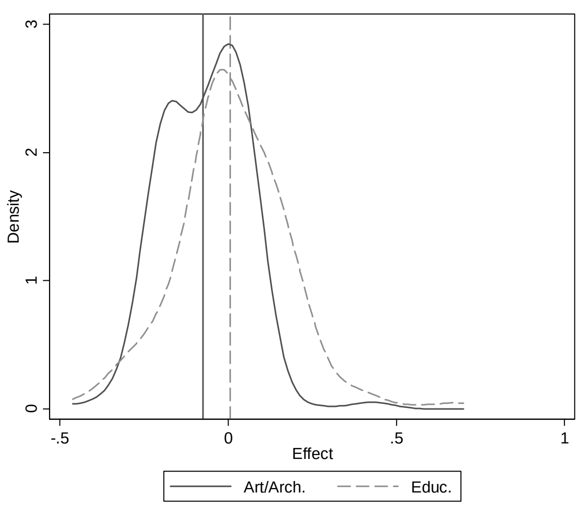


(2) Homogeneous Effects

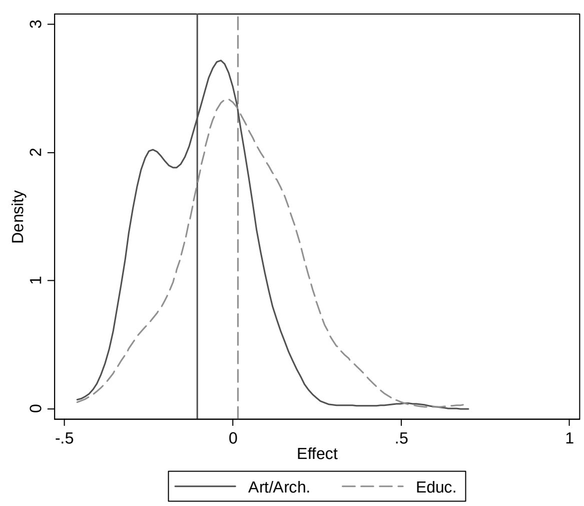


V. B Education

(1) Threshold-crossing

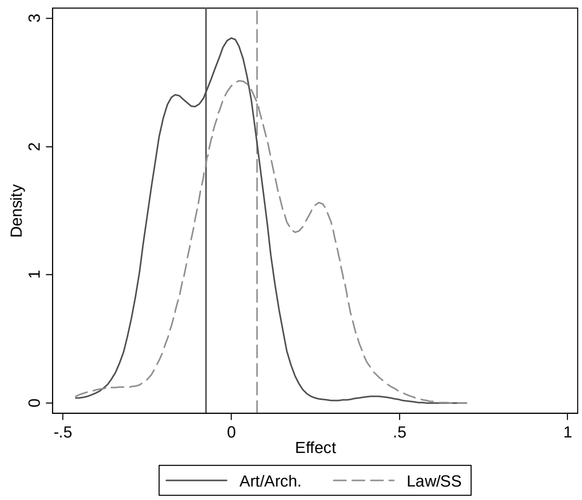


(2) Homogeneous Effects

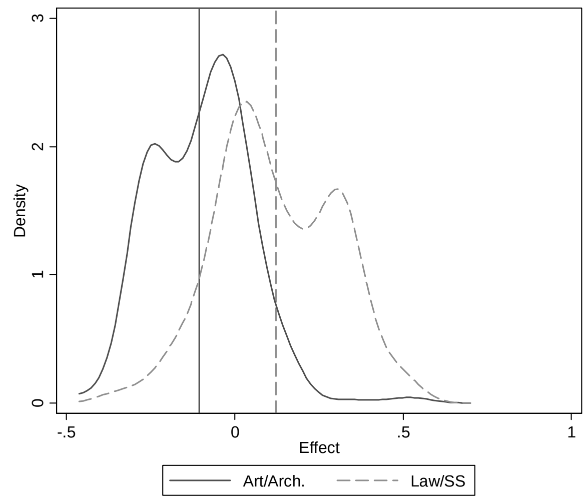


V. C   Law/Social-science

(1)   Threshold-crossing

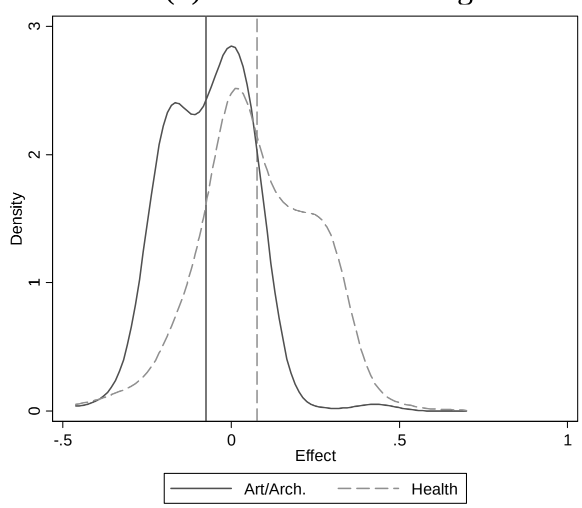


(2)   Homogeneous Effects

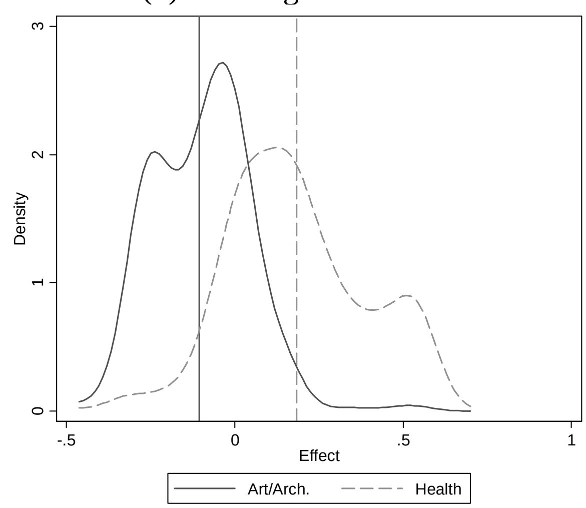


V. D   Health

(1)   Threshold-crossing

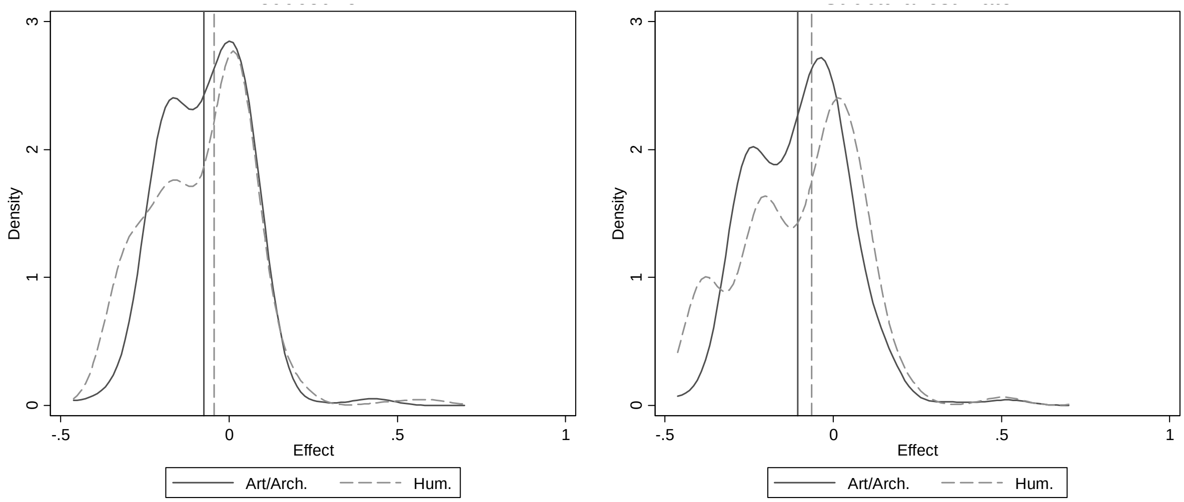


(2)   Homogeneous Effects



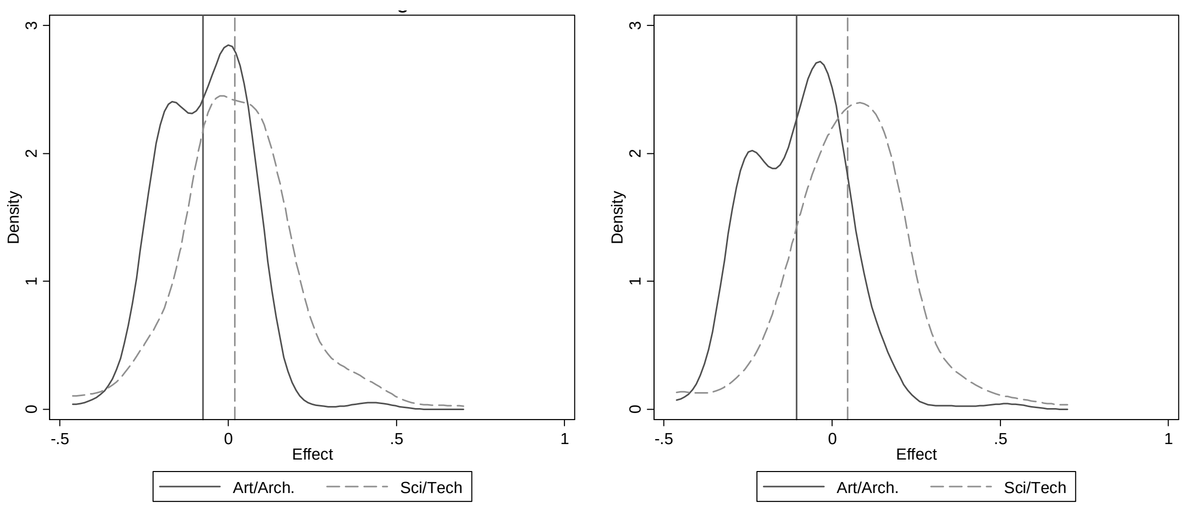
V. E Humanities

(1) Threshold-crossing (2) Homogeneous Effects



V. F Science/Technology

(1) Threshold-crossing (2) Homogeneous Effects



Notes: Density graph of estimated degree-level impacts for degrees in the specified fields. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that $\varphi=0$. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively.

TABLE I

CHARACTERISTICS OF ACCEPTED STUDENTS AT CRUCH UNIVERSITIES, 1985-2005

(1) Institution	(2) Ave. Score	(3) % Selective	(4) Bus.	(5) Art/Arch.	(6) Educ.	(7) Law/SS	(8) Health	(9) Science/Tech	(10) Hum.	(11) N
Universities:										
U. de Chile	696	0.99	0.08	0.19	0.00	0.17	0.18	0.31	0.06	90,316
Pontificia U. Catolica de Chile	685	0.86	0.05	0.12	0.15	0.17	0.05	0.36	0.10	83,890
U. de Santiago de Chile	647	0.79	0.17	0.02	0.06	0.05	0.04	0.65	0.01	72,528
Pontificia U. Catolica de Valparaiso	640	0.68	0.08	0.05	0.17	0.18	0.03	0.49	0.00	55,909
U. de Concepcion	628	0.57	0.08	0.03	0.16	0.12	0.14	0.45	0.01	82,012
U. de Valparaiso	624	0.54	0.16	0.16	0.03	0.24	0.20	0.21	0.00	35,240
U. Tecnologica Metropolitana	623	0.55	0.19	0.12	0.00	0.04	0.00	0.61	0.03	31,614
U. Tecnica Federico Santa Maria	611	0.42	0.03	0.01	0.00	0.00	0.00	0.96	0.00	42,200
U. Austral de Chile	610	0.42	0.11	0.01	0.07	0.10	0.14	0.54	0.01	35,851
U. de La Frontera	609	0.43	0.07	0.00	0.12	0.15	0.18	0.48	0.00	31,834
U. de Talca	605	0.37	0.27	0.03	0.09	0.19	0.08	0.34	0.00	31,880
U. Metropolitana En Ciencias de La Educacion	604	0.33	0.00	0.00	0.99	0.00	0.01	0.00	0.00	29,794
U. del Bio Bio	596	0.31	0.14	0.08	0.10	0.01	0.04	0.62	0.00	37,934
U. Catolica del Norte	594	0.28	0.16	0.05	0.03	0.15	0.03	0.57	0.01	26,506
U. Catolica del Maule	590	0.22	0.00	0.00	0.03	0.20	0.02	0.75	0.00	5,599
U. de La Serena	575	0.15	0.08	0.05	0.34	0.05	0.02	0.45	0.01	33,035
U. Catolica de La Santisima Concepcion	566	0.10	0.12	0.00	0.21	0.03	0.15	0.49	0.00	10,508
U. de Antofagasta	566	0.17	0.02	0.04	0.10	0.10	0.21	0.52	0.00	23,488
U. de Playa Ancha de Ciencias de La Educacion	562	0.08	0.00	0.10	0.62	0.04	0.03	0.10	0.12	33,835
U. de Tarapaca	559	0.10	0.18	0.00	0.10	0.13	0.10	0.47	0.02	23,729
U. de Magallanes	550	0.03	0.16	0.01	0.17	0.08	0.11	0.47	0.00	8,797
U. Catolica de Temuco	548	0.09	0.00	0.00	0.26	0.09	0.00	0.61	0.04	13,720
U. Arturo Prat	542	0.02	0.27	0.03	0.12	0.12	0.05	0.38	0.02	21,833
U. de Atacama	539	0.01	0.03	0.00	0.19	0.09	0.00	0.66	0.03	11,297
U. de Los Lagos	534	0.00	0.17	0.08	0.34	0.14	0.00	0.28	0.00	17,545
Professional Institutes:										
Instituto Profesional de Santiago	617	0.48	0.04	0.06	0.00	0.00	0.00	0.90	0.00	2,739
Instituto Profesional de Chillan	590	0.11	0.13	0.06	0.70	0.00	0.12	0.00	0.00	2,507
Instituto Profesional de Valdivia	564	0.00	0.11	0.00	0.00	0.00	0.00	0.89	0.00	1,805
Acad. Sup. Ciencias Pedagogicas de Valparaiso	561	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	133
Instituto Profesional de Osorno	539	0.00	0.06	0.00	0.40	0.14	0.00	0.39	0.00	4,143

Notes: Ave. score is the average entrance exam score of admittees from 1985 through 2005. Selective is defined as being above the degree-level median for average admission cutoff across the sample. Source: Administrative data from Proyecto 3E database.

TABLE II

DESCRIPTIVE STATISTICS ON APPLICATIONS AND CHOICES

(1) Year	(2) # Choices (SD)	(3) PSU Dist. from 1st Choice Cutoff	(4) PSU Dist, from Last Choice Cutoff	(5) Ave. # Dif. Narrow Fields Listed	(6) Ave. # of Dif. Areas Listed	(7) Ave. # of Dif. Institutions Listed	(8) # of Dif. Selectivity Tiers Listed	(9) Percent Accepted at 1st Choice	(10) Ave. Rank of Accepted Choice	(11) % Admitted to any choice	(12) % Matriculated to Admitted Choice
2001	4.68 (2.05)	29.89	56.76	3.63	1.92	2.55	1.67	31%	2.21	68%	68%
2002	4.65 (2.01)	34.71	60.64	3.60	1.91	2.53	1.66	34%	2.11	69%	70%
2003	4.67 (1.99)	34.41	62.14	3.64	1.95	2.52	1.66	36%	2.02	70%	69%
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%

Notes: 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 Narrow Fields is the mean number of different careers applied to. # diff areas is the mean number of different career areas applied to. # diff Institutions is the mean number of different universities applied to, # diff tiers is the mean number 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. Average rank of accepted choice is the average admitted choice among applicants that were admitted to one of their CRUCH application choices. Acc. to 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 III
SAMPLE DESCRIPTION: CRUCH APPLICANT RECORDS FROM 1985-2005

	(1) All	(2) Marginal Applicants	(3) Estimation Sample (Marginal Applicants with Complete Data)
Student Characteristics			
Male	0.525	0.543	0.545
Public High School	0.402	0.372	0.373
Voucher High School	0.362	0.341	0.341
Private High School	0.236	0.287	0.285
Math Test	615	632	633
Reading Test	593	603	603
GPA (scoring scale)	574	581	581
Application Characteristics			
Accepted	0.512	0.430	0.430
Business	0.101	0.124	0.121
Art/Architecture	0.060	0.056	0.055
Education	0.158	0.113	0.114
Law/Social-science	0.116	0.119	0.120
Health	0.106	0.127	0.128
Science/Technology	0.434	0.444	0.444
Humanities	0.026	0.018	0.018
Less-Selective+	0.468	0.388	0.385
More-Selective+	0.532	0.612	0.615
Vocational	0.525	0.528	0.532
Labor force outcomes			
Participation	0.828	0.838	0.839
Earnings (millions CLP)	8.43	9.49	9.55
N applications	1,977,898	675,064	649,588
N students	787,645	409,603	398,906

Notes: Data from Proyecto 3E database. Characteristics of full dataset and analysis sample. Data is at the application (i.e., person X program X application year) level. Marginal Applicants contain applications that a) are valid (all students with higher score than the lowest admitted score are accepted), 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 Applicants with Complete 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. Labor outcomes are for years 6-26 after the application year. Data reflect the 1985-2005 application cohorts. For high-school variables, currently only 1998 to 2005 data are available.

+Less-selective and more-selective are defined as degrees with below- or above-median average admission cutoff-score over the 1985-2005 sample.

TABLE IV

VALIDATING THE REGRESSION DISCONTINUITY

	(1) Baseline Char. Index+	(2) Male	(3) Public HS+	(4) Private HS+	(5) High SES+	(6) Low SES+	(7) Matriculation ++
Pooled	3,309.6	-0.001	-0.002	0.000	0.005	-0.005	0.492***
	(6,156.6)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
By Area:							
Business	-12,600.0	-0.017**	0.002	-0.011	0.007	-0.007	0.494***
	(20,093.6)	(0.008)	(0.010)	(0.009)	(0.011)	(0.011)	(0.010)
Art/Arch.	777.5	-0.004	-0.001	-0.002	-0.001	0.001	0.384***
	(27,927.0)	(0.012)	(0.012)	(0.014)	(0.015)	(0.015)	(0.015)
Education	-8,561.6	-0.011	0.010	-0.002	0.012	-0.012	0.422***
	(11,323.3)	(0.007)	(0.009)	(0.005)	(0.009)	(0.009)	(0.009)
Law/Soc.sci.	11,252.6	-0.010	-0.016**	0.009	0.012	-0.012	0.524***
	(18,007.7)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.009)
Health	14,256.3	-0.003	-0.007	0.002	0.005	-0.005	0.475***
	(15,378.7)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Science/Tech	-3,618.1	0.002	0.001	-0.004	-0.003	0.003	0.526***
	(9,999.9)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Humanities	799.5	-0.005	-0.018	0.009	0.011	-0.011	0.570***
	(37,985.0)	(0.019)	(0.020)	(0.018)	(0.023)	(0.023)	(0.019)
JOINT TEST	0.938	0.258	0.527	0.782	0.711	0.711	0.000***
By selectivity:							
Less selective	9,885.5	-0.008*	-0.006	0.005*	0.006	-0.006	0.408***
	(6,737.9)	(0.004)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)
More selective	-5,845.7	0.003	0.001	-0.005	0.001	-0.001	0.568***
	(9,205.4)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
JOINT TEST	0.279	0.144	0.488	0.136	0.515	0.515	0.000***
By coursework:							
Core-curric.	5,449.0	-0.003	-0.003	0.000	0.005	-0.005	0.491***
	(8,918.7)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Vocational	2,969.5	0.000	-0.002	0.001	0.006	-0.006	0.497***
	(8,505.3)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
JOINT TEST	0.781	0.774	0.708	0.981	0.356	0.356	0.000***
N applications	646,204	974,500	694,664	694,915	694,915	609,266	512,164
N students	376,701	573,298	400,934	401,077	401,077	352,973	306,085

Notes: +HS type and SES based on 1998-2005 cohorts. ++Matriculation based on 2000-2010 cohorts. Gender based on all cohorts. N refers to pooled specifications. Significance at 1%***, 5%** and 10%*. Baseline characteristics index is the portion of earnings predicted by baseline characteristics in an OLS regression of labor market earnings that also controls for polynomials in score and cohort and experience effects. Baseline characteristics include gender and indicators for type of high school (municipal vs. private). Results from estimates of equation (3) within group described in row for the dependent variables given in the column. Data are at the person-application level and include 1998-2005 cohorts only due to current unavailability of high-school of graduation records before 1998.

TABLE V

BELOW-THRESHOLD SAME-YEAR ACCEPTANCE OUTCOMES

	Below-threshold probability of same-year acceptance in:										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Applied to a career in:	Bus.	Art/Arch.	Educ.	Law/SS	Health	Sci/Tech	Hum.	Less Sel.	More Sel.	Outside	N
Bus.	0.334	0.018	0.037	0.053	0.004	0.245	0.006	0.286	0.413	0.301	79,569
Art/Architecture	0.038	0.264	0.046	0.039	0.007	0.246	0.013	0.210	0.449	0.341	36,874
Education	0.019	0.011	0.277	0.020	0.006	0.090	0.017	0.356	0.088	0.555	79,546
Law/Social-science	0.060	0.026	0.069	0.399	0.014	0.092	0.048	0.212	0.505	0.283	83,122
Health	0.015	0.011	0.038	0.045	0.466	0.177	0.004	0.138	0.620	0.243	90,694
Science/Tech.	0.041	0.014	0.037	0.012	0.018	0.502	0.004	0.305	0.326	0.369	281,766
Humanities	0.011	0.037	0.146	0.093	0.002	0.078	0.215	0.181	0.402	0.417	13,255
Less-Selective	0.046	0.010	0.109	0.025	0.009	0.266	0.007	0.454	0.023	0.523	268,301
More-Selective	0.083	0.039	0.049	0.098	0.129	0.334	0.021	0.142	0.613	0.245	406,763

Notes: Results from regressions of the form of equation (3), where the dependent variable is an indicator if the applicant was admitted to a degree of the type indicated in the column heading as a result of *not* crossing the threshold into a degree of the type indicated in the row label. Thus it is the probability of being admitted to a degree of the type indicated in column heading for people who just missed the threshold of admission to a degree of the type indicated in the row label. Less-selective and more-selective are defined as degrees with below- or above-median average admission cutoff-scores over the 1985-2005 sample

TABLE VI

THRESHOLD-CROSSING AND COMPARATIVE ADVANTAGE MODEL ESTIMATES

(1)	(2) Threshold-crossing	(3) Homogeneous effects	(4) Comparative Adv. Math	(5) Comparative Adv. Lang.	(6) OLS
Pooled	0.029***	0.065***	0.058**	0.039	0.219***
	(0.008)	(0.024)	(0.025)	(0.050)	(0.003)
By selectivity tier of target degree:					
Tier 1 - (<550)	0.009	0.025	0.027	0.001	-0.023***
	(0.013)	(0.018)	(0.022)	(0.033)	(0.003)
Tier 2 - [550,600)	-0.002	0.001	0.001	-0.028	-0.031***
	(0.012)	(0.023)	(0.023)	(0.040)	(0.003)
Tier 3 - [600,650)	0.030**	0.050	0.047*	0.023	0.105***
	(0.015)	(0.033)	(0.027)	(0.052)	(0.004)
Tier 4 - [650, 675)	0.041*	0.098**	0.081*	0.058	0.353***
	(0.022)	(0.043)	(0.045)	(0.137)	(0.006)
Tier 5 - (≥675)	0.092***	0.228***	0.203***	0.227**	1.012***
	(0.030)	(0.063)	(0.071)	(0.124)	(0.010)
N	675,064	675,064	664,118	664,311	1,057,990

Notes: Significance at 1%***, 5%** and 10%*. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that φ=0. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. OLS uses all students on admit and waitlist, controlling for year of application dummies, degree of application dummies and cubic functions of math and language entrance exam scores. Selectivity tier is defined by whether or not the average cutoff for a degree falls inside of the row label specified range. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.

TABLE VII

RETURNS BY AREA OF STUDY, THRESHOLD CROSSING AND COMPARATIVE ADVANTAGE MODELS

	(1) Threshold-crossing	(2) Homogeneous effects	(3) Comparative Adv. Math	(4) Comparative Adv. Lang.	(5) OLS
Field of target degree					
Business	0.034	0.087*	0.065	0.076	0.429***
	(0.028)	(0.051)	(0.047)	(0.068)	(0.003)
Art/Architect.	-0.075***	-0.106*	-0.103**	-0.085	-0.122***
	(0.031)	(0.056)	(0.042)	(0.066)	(0.007)
Education	0.007	0.015	0.021	-0.009	-0.118***
	(0.013)	(0.022)	(0.024)	(0.033)	(0.003)
Law/Soc.-sci.	0.076***	0.122***	0.128**	0.096	0.229***
	(0.025)	(0.044)	(0.050)	(0.066)	(0.006)
Health	0.076***	0.184***	0.173***	0.156	0.587***
	(0.023)	(0.048)	(0.048)	(0.264)	(0.007)
Science/Tech	0.020*	0.046	0.035	0.011	0.196***
	(0.012)	(0.031)	(0.029)	(0.060)	(0.004)
Humanities	-0.045	-0.064	-0.080	-0.140*	-0.038***
	(0.050)	(0.088)	(0.073)	(0.078)	(0.009)
N	664,826	664,826	653,976	649,468	1,057,990

Notes: Significance at 1%***, 5%** and 10%*. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that φ=0. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. OLS uses all students on admit and waitlist, controlling for year of application dummies, degree of application dummies and cubic functions of math and language entrance exam scores. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.

TABLE VIII

RETURNS BY FIELD AND SELECTIVITY, THRESHOLD-CROSSING AND COMPARATIVE ADVANTAGE MODELS

	Less-Selective			More-Selective		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Field	Threshold-crossing	Homogeneous Effects	OLS	Threshold-crossing	Homogeneous Effects	OLS
Business	0.012	0.018	0.027***	0.054	0.148*	0.668***
	(0.033)	(0.046)	(0.006)	(0.044)	(0.082)	(0.010)
Art/Architect.	-0.025	-0.049	-0.153***	-0.087**	-0.121*	-0.107***
	(0.046)	(0.058)	(0.008)	(0.038)	(0.067)	(0.008)
Education	0.012	0.023	-0.122***	-0.021	-0.027	-0.104***
	(0.013)	(0.020)	(0.003)	(0.045)	(0.069)	(0.008)
Law/Social-science	0.023	0.036	-0.002	0.099***	0.159***	0.303***
	(0.027)	(0.040)	(0.006)	(0.033)	(0.057)	(0.008)
Health	0.090**	0.134**	0.114***	0.074***	0.191***	0.665***
	(0.040)	(0.057)	(0.009)	(0.025)	(0.052)	(0.008)
Science/Technology	-0.003	0.001	-0.011***	0.044**	0.091*	0.355***
	(0.012)	(0.052)	(0.003)	(0.020)	(0.052)	(0.005)
Humanities	0.017	0.038	-0.045***	-0.083	-0.126	-0.034***
	(0.044)	(0.052)	(0.008)	(0.076)	(0.140)	(0.013)
N	260,479			399,555		

Notes: Significance at 1%***, 5%** and 10%*. Less-selective and more-selective are defined as degrees with below- or above-median average admission cutoff-score over the 1985-2005 sample. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that $\varphi=0$. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. OLS uses all students on admit and waitlist, controlling for year of application dummies, degree of application dummies and cubic functions of math and language entrance exam scores. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.

TABLE IX

RETURNS BY SELECTIVITY AND COURSE REQUIREMENTS, HOMOGENEOUS EFFECTS MODEL

	Less-Selective		More-Selective	
	(1) Vocational	(2) Core Curriculum	(3) Vocational	(4) Core Curriculum
Threshold-crossing	0.007	0.012	0.025	0.066***
	(0.011)	(0.012)	(0.018)	(0.016)
Homogeneous Effects	0.010	0.027	0.067	0.141***
	(0.022)	(0.020)	(0.042)	(0.038)
Comparative Adv. - Math	0.011	0.020	0.056	0.128***
	(0.022)	(0.024)	(0.041)	(0.041)
Comparative Adv. - Lang	-0.015	-0.003	0.040	0.118
	(0.039)	(0.044)	(0.084)	(0.081)
OLS	-0.066***	0.019***	0.449***	0.327***
	(0.003)	(0.003)	(0.006)	(0.005)
N	248,161		402,088	

Notes: Significance at 1%***, 5%** and 10%*. Less-selective and more-selective are defined as degrees with below- or above-median average admission cutoff-score over the 1985-2005 sample. Vocational versus core-curriculum are defined as above versus below median in vocational course requirements for the degree as of 2012 website listings. Online Appendix Section V outlines the categorization process. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that $\varphi=0$. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. OLS uses all students on admit and waitlist, controlling for year of application dummies, degree of application dummies and cubic functions of math and language entrance exam scores. Selectivity tier is defined by whether or not the average cutoff for a degree falls inside of the row label specified range. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.

TABLE X

RETURNS BY SELECTIVITY AND SOCIO-ECONOMIC STATUS, THRESHOLD-CROSSING AND HOMOGENEOUS EFFECTS MODELS

	Pooled SES sample		High-SES high school		Low-SES high school	
	(1)	(2)	(3)	(4)	(5)	(6)
	Threshold-crossing	Homog. Effects	Threshold-crossing	Homog. Effects	Threshold-crossing	Homog. Effects
Pooled	0.006	0.028	0.007	0.034	0.004	0.020
	(0.007)	(0.019)	(0.012)	(0.028)	(0.007)	(0.018)
By selectivity tier of target degree:						
Tier 1 - (<550)	0.002	-0.002	0.014	0.049*	-0.002	-0.017
	(0.010)	(0.015)	(0.030)	(0.029)	(0.012)	(0.015)
Tier 2 - [550,600)	-0.002	0.000	0.023	0.020	-0.014	-0.010
	(0.010)	(0.016)	(0.021)	(0.027)	(0.011)	(0.017)
Tier 3 - [600,650)	0.009	0.028	-0.003	0.021	0.022	0.034
	(0.013)	(0.025)	(0.018)	(0.030)	(0.017)	(0.027)
Tier 4 - [650, 675)	0.016	0.054	0.017	0.044	0.013	0.077**
	(0.018)	(0.033)	(0.021)	(0.036)	(0.027)	(0.038)
Tier 5 - (≥675)	-0.004	0.053	-0.009	0.042	0.025	0.123*
	(0.026)	(0.053)	(0.030)	(0.055)	(0.057)	(0.063)
N	307,923		164,994		142,929	

Notes: Significance at 1%***, 5%** and 10%*. Current sample from 1998-2005 cohorts only as high-school of graduation records for 1985-1997 are still being added to database. High-SES high school defined as one with 2000-2008 Mineduc poverty rating of D or E. Low-SES is rating A, B or C. Threshold-crossing estimates from equation (3). Homogeneous effects model estimates from equation (4) with restriction that $\varphi=0$. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. OLS uses all students on admit and waitlist, controlling for year of application dummies, degree of application dummies and cubic functions of math and language entrance exam scores. Selectivity tier is defined by whether or not the average cutoff for a degree falls inside of the row label specified range. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.

TABLE XI
TUITION VS. EARNINGS COMPARISON

	Estimated Earnings Gains (% of an ave. annual salary, Homogeneous Effects Model)	Tuition (years of an ave. annual salary)
Field:		
Business	0.087*	1.24
Art/Architecture	-0.106*	1.42
Education	0.015	0.85
Law/Social-science	0.122***	1.31
Health	0.184***	1.74
Science/Technology	0.046*	1.25
Humanities	-0.064	1.02
Selectivity Tier:		
Tier 1	0.025	0.93
Tier 2	0.001	1.09
Tier 3	0.050	1.33
Tier 4	0.098**	1.52
Tier 5	0.228**	2.22

Notes: Significance at 1%***, 5%** and 10%*. Homogeneous effects model estimates from equation (4) with restriction that $\varphi=0$. Comparative advantage models from equation (4) with φ a vector of field-and-selectivity indicators fully interacted with an indicator if the student has above median math or language scores, respectively. Tuition data from Mineduc degree-level matriculation and semester fees in 2011 summed up over the expected time to degree completion. Standard errors computed using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010). Online Appendix Sections VI and VII provide further details on estimation.