Determinants of Causal Returns to Postsecondary Education in Chile: What's Luck Got to do with it?

by

Justine Hastings
Brown University and NBER
justine.hastings@brown.edu

Christopher Neilson
Yale University
christopher.neilson@yale.edu

Seth Zimmerman
Yale University
seth.zimmerman@yale.edu

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1. Introduction

Understanding the causal returns to college education is central to designing effective postsecondary education policy. A substantial literature has documented the rising returns to college education, and its implications for rising inequality in income, consumption, and well-being (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). This fact spurred apush in the 1990's and early 2000's to expand subsidization of student loans for postsecondary degrees, with the US student Loan Reform Act in 1993 followed by the College Cost Reduction and Access Act (CRAA) in 2007 both aiming to increase access to postsecondary education. State-level merit-based higher education subsidies also expanded rapidly over the period (Dynarski, 2004).

The recent student loan crisis in the US and abroad has brought renewed focus on loan policy and the causes and determinants of the college wage premium. In particular, the college wage premium identified in panel data may not apply to marginal students induced to postsecondary degree completion by loan programs, or excluded from postsecondary education by supply constraints (Zimmerman, 2012). Moreover, returns to college education may not only vary with student characteristics but also with degree characteristics like field of study (Altonji et. al 2012) or type of institution (e.g. elite versus non-elite as examined in Dale & Krueger 2002; 2011, or for profit versus not-for-profit as in Deming, Katz & Goldin 2012). Differences in returns to degrees and type of institution could be driven by heterogeneity in the amount or types of skill accumulated during the degree program and the extent to which accumulated skills are in undersupply in the labor market (Autor, Levy & Murnane 2003; Acemoglu & Autor 2010). Understanding causal effects of college attendance on earnings and the drivers of heterogeneity in those effects is a crucial component of designing successful loan and education policy, though causal evidence on which to base policy decisions is hard to find (Altonji et. al 2012).

This paper provides new evidence on the determinants of returns to college education using a unique and extensive database constructed from high school, college and tax return records for 26 cohorts of high school graduates in Chile. The data and research design allow us to tease apart the labor-market returns to field of study, degree selectivity, and postsecondary curriculum for students coming from different socio-economic backgrounds. Examining these questions in the Chilean context provides several benefits. First, to our knowledge this is the first data base that has linked administrative data from high school, college entrance exam, college choice, college admission and matriculation, and tax return data for a population of students across multiple cohorts. Second, while the postsecondary education system in Chile is similar

in many ways to that in the US, the majority of admissions are centralized and score-based (Bertrand et al. 2009). This provides thousands of regression discontinuities in the admission process which we exploit to estimate labor market returns along several dimensions.

In Chile, students apply to a career (major/degree) and a university simultaneously (e.g. Civil Engineering at UC Berkeley; similar to application processes in countries like England, Italy and the Netherlands). Students apply using a central application system, ranking up to eight institution-degree choices. Students are ranked by a score composite of standardized tests and GPA, and ordered. Their choices are evaluated in rank order of the student and in rank order of choices within student, placing each student in the best option with available admission slots given their score-rank. This admission process generates hundreds of sharp discontinuities each year in the form of admissions score cutoffs that cannot be precisely predicted by applicants. Because students apply to institutions of different tiers and careers in different fields of concentration, these regression discontinuities provide random variation in quality of institution attended, field of study, and accumulation of particular skills (which we measure by categorizing core requirements for the institution-career chosen).

In partnership with the Chilean Ministry of Education (MINEDUC) and several other agencies, we constructed from hard copy or electronic copy high school, entrance exam, college choice, admissions and matriculation data for cohorts of admissions test takers beginning in 1985 and extending through the present. We were then able to link these data to labor market earnings from tax records from 2006-2011 (accessed securely within the tax authority), providing labor market returns from 1 year post-graduation among the youngest cohorts to 26 years post-graduation among the oldest cohorts. Links to high school records allow us to examine heterogeneous impacts of threshold crossing by measures of socio-economic status by field of study and selectivity of the chosen degree.

Our analysis reveals several interesting patterns. We find that earnings gains associated with college admission are heterogeneous by degree area. Students who cross the admissions threshold when applying to a health degree realize annual earnings gains equal to 8.5 percent of average post-college earnings for students in our data relative to students just below the threshold. Business, Science, and Humanities/Law/Social science applicants also realize earnings gains from admission, while applicants to Education and Art degrees realize zero gains or even losses. These gains are concentrated amongst students applying to high-selectivity programs and programs that perform well on empirical measures of degree-specific labor market value-added. Students admitted to degrees with substantial pre-professional coursework (which consists of internship experience or applied science courses aimed at particular labor market applications) realize earnings returns that are close to zero. By contrast, students admitted to

degrees in which the coursework has a quantitative focus realize earnings gains equal to between 8 and 9 percent of the average salary.

Our findings suggest that frictions exist in the markets that match students to postsecondary degrees. Constraints on the supply of high-return degrees (see Bound and Turner, 2007) may push students into programs with lower economic returns at many margins. Admitting the marginal applicant to a high-return program by lowering the score cutoff a small amount likely represents a policy change with a positive social return. At the same time, we observe excess demand for degrees that lead to zero or, in some cases, large and negative earnings returns for admitted students. This could be because these degrees offer high non-pecuniary compensation that is valued by all students, or because some students have very strong tastes for the coursework or careers associated with these degrees. That said, Hastings et al. (2012) present evidence suggesting that students may base college choices on beliefs about economic returns that are systematically biased and uniformed. The existence of oversubscribed degrees with zero or negative returns thus suggests two possible avenues for welfare-improving policy intervention. First, if information aggregation is a public good, policymakers supply centralized ranking and earnings information to guide to provide students with accurate information needed before making life-long decisions. Second, loan policy could be used to provide additional supply-side incentives to ease frictions in supply of high-return degrees (Hastings et al. 2012).

2. Background on Chilean education system

There are several features of the Chilean education system that are important for this analysis.

First, Chile has a universal voucher system, which requires all students at private-non-voucher, private-voucher, and municipal (public) schools to participate in standardized testing in eleventh grade (the SIMCE in math and language tests) and report enrollments and progress centrally to the Ministry of Education.[1] This allows us to construct high school graduation records for most cohorts for the universe of high school students (hard copy from 1995-2001, and electronically thereafter). It provides a proxy for socio-economic status through high-school socio-economic status categorization done by MINEDUC (A through E, where E is most economically disadvantaged), and through high school type (public, private, or voucher), which is highly correlated with school SES.

[1] See Hsei & Urquiola 2003 and Gallego 2004 for more details on the Chilean high school system.

Second, all students take a standardized test for college admission. This test was called the PAA until 2002 (taken for the 2003 college entering year), and the PSU after 2002. It is constructed and administered by the central testing authority, DEMRE, which is under the authority of the Council of Rectors of Universities of Chile (CRUCH). Together with high school grades, which are submitted to DEMRE and converted to a standardized score, this universal entrance exam is the primary component for postsecondary admissions, scholarships, and student loan eligibility. Online Appendix, Section 1 describes the scoring system in detail. An entrance exam is given for language and for mathematics. Scores range from a minimum of 150 to a maximum of 850. A minimum score of 450 is required for admission to a CRUCH institution. The distribution is standardized so that the mean and median are 500.

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

Table 1 lists these universities and the interquartile range of entrance exam scores of graduating classes from 1995 to 2012 as well as their overall share of college graduates. There is a wide selectivity range within the CRUCH universities, and the relative selectivity is fairly constant over time for top- versus bottom-ranked schools. In the 80's and 90's CRUCH Universities made up over 80% of all University degree granting institutions by students graduating.[2] Over time, there has been entry by new Universities, typically serving lower-scoring students.[3]

Figure 1 shows the fraction of high school graduates taking the college entrance exam in Chile from 1995 through 2011, and the fraction of students who scored above the minimum score to apply to CRUCH. Overall, entrance exam taking has been increasing over time in Chile, though it has persistently been higher in Chile than in the US, if we consider the SAT an analogous college entrance exam.

[2] Rolando et al. (2010), MINEDUC report on aggregate trends in postsecondary education provides similar statistics for the 1980's.
[3] Hastings, Neilson & Zimmerman (2012b) 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.

Application to CRUCH is centralized; students submit one application with up to eight choices for institution and career.[4] Unlike the US, but similar to many other postsecondary education systems in Europe, a choice is an institution and a career. Most degrees are licenciatura (licenture) degrees which take an average of 5 years to complete. These degrees are similar to a combined bachelor's and 1 year master's degree. Professional degrees are also offered in more recent years by for-profit Professional Institutes. These are 3-4 year degrees, similar to a combination of two year degree with professional training. CRUCH institutions also offer 2 to 3 year technical degrees, as do the newer for-profit Professional Institutes and Technical Institutes. These are similar to an Associate of Art, or a technical degree from a two year college in the US.

Students apply with some knowledge of where they might be admitted. Institution-degrees currently post statistics such as interquartile range of PSU scores for admittees on their websites to aid students with gauging their likelihood of admission, and students can look up cutoff scores from past years in publicly available sources, including the newspaper. Students know that they are ranked based on a scoring system driven predominantly by their PAA/PSU score and high school grades, but face two sources of uncertainty. First, the weights used to convert PAA/PSU scores and grades into the single admissions score are not widely available. Second, and more importantly, the cutoff score fluctuates year to year as the number of available spots and the profile of the other applicants changes. Even if students can predict their own admissions score perfectly, marginal students will be unable to predict their admissions outcome, since the cutoff score is only known ex post.

Table 2 shows summary statistics from CRUCH applicants for years 2001-2011, years for which we have full preference rankings from electronic records. For 1985 to 2000, we do not have full ranked choices but instead digitized admission, waitlist and score data from hard records (to our knowledge, full applications in these earlier years do not exist in any form). Column 1 shows the mean and standard deviation of choices listed (1 is the min and 8 is the max). Students on average do not list a full set of eight, but list on average 4-5 choices. On average their first choice school is one they could get into with some probability based on historic admissions; on average their own PSU score is slightly higher than the cutoff for their year of admission. They are on average more comfortably over the cutoff score for their last choice school, indicating that students apply for reach options on their first choice and safer options for their lower-ranked choices. On average there is a lot of variation in the careers, areas of study and universities a student lists in their application. Out of their average 4-5 choices, they list 3-4 different careers in close

[4] Other systems that use centralized applications include University of California 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

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

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

3. Data

Administrative records on college applicants:

We compiled several databases for this study, often from original hard-copy records. Compiling these data required forging MOUs and coordinating cooperation between several Chilean institutions, the impetus for which was a need for better data-driven policy response to the student loan debt crisis in Chile.

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

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

For the years 1995, 1998, 2000 through 2011 we have data on graduates from each postsecondary degree-granting institution in Chile. For 2000 through 2011 we have data on matriculation on a semester-by-semester basis for all degree-granting institutions.

These data combined give us a panel of college applicants and graduates from 1985 through 2010 – twenty-six cohorts of students.. We have cutoffs for admissions and scores used for admissions to each CRUCH University and career over that time period We also have high school of graduation and handful of demographic variables for a subset of years beginning in late 1990s.

We match these data to individual tax records at the Chilean tax authority in compliance with privacy laws in Chile. Over 99% of individuals in our data have matches in the tax records. The tax records are available for tax years 2005 to 2011, and include all labor earnings. Online Appendix Section 3 describes the tax records in Chile in detail and explains how we construct labor earnings. All values are reported in 2011 pesos.

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

Institution and Career characteristics:

We construct several measures of institution and career characteristics. First, careers come with administrative categorizations by CINE category (UNESCO Normalized International Classification of Education). There are ten categories: Agriculture, Art and Architecture, Basic Science, Business

Administration, Education, Health, Humanities, Law, Social Science, and Technology. We group these ten categories into six categories in most specifications to facilitate parsimony in our exposition and to improve statistical power.[5] These five areas are Agriculture, Technology and Basic Science; Education; Health; Business and Administration; Humanities, Social Science and Law; and Art and Architecture. In addition to these broad categories, MINEDUC categorizes careers into 191 narrow majors. Within these categories, a major is essentially the same, but may have a slightly different name at different universities. For instance, the "Social work" code includes degrees titled "Social work", "Social service", and "Social service with a degree in social work". We will use this very detailed career categorization in some specifications. Online Appendix Section 5 details these field categorizations and provides further helpful examples.

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

Third, we construct measures of selectivity and "value-added" for institution-CINE-area and institution-career level aggregation levels. We define selectivity using the average entrance exam score of students admitted. We define "value-added" as the fixed effect for the category of interest (institution-CINE or institution-career) from a regression of earnings on a cubic function of math and reading exams, , cohort fixed effects, a second-degree polynomial in experience, application year fixed effects, and category fixed effects for students accepted. Online Appendix Section 5 describes the value-added regression and sample in detail.

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

We combine each of the data sets above to arrive at our estimation sample. Online Appendix Section 7 provides details on how this sample is constructed. Table 3 compares characteristics of the full sample with our current estimation sample and the sample of students near the score cutoff for admission to each institution-career in each application year. Column 1 shows summary statistics for all applications. Column 2 shows summary statistics for the marginal sample of applications – those within 25 points of the cutoff for each institution-career-year combination where we observe excess demand, defined as a minimum of 15 applications in the five points below the cutoff score . Column 3 shows summary statistics for students on the margin for which we have all data. We currently lose approximately 10% of our data due to either missing CINE-UNESCO classification or missing course requirement data. We are currently working to fill these in where possible. On average our marginal sample has higher entrance exam scores, are more likely to be applying to a degree in the Business area classification, and less likely to be applying to a degree in the Education area. They are slightly more likely to be applying to high-selectivity degrees, since low selectivity ones may not have marginal students in many years. Their degrees are more likely to be rigorous in quantitative and qualitative requirements.

Marginal applicants are more slightly more likely to be male, and significantly more likely to come from private schools, which serve on average wealthier families and enroll/produce higher-scoring students.

For the 2011 tax year, labor earnings for our marginal group is slightly higher than that of the total applicant population. If we convert Chilean pesos to USD using OECD Purchasing Power Parity for 2011, this results in an average income of $24,449 per person in 2011. Positive earnings probability per person is high at 85.6%.

4. Model and Empirical Framework

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

Using data at the student-application-outcome year level, we estimate equations of the form

(1)

$$Y_{ijpt} = \beta + \delta Z_{ijp} + f(d_{ijp}) + \varepsilon_{it}$$

Where: Y_{ijpt} is total earnings in outcome year *t* for individual *i* who applies to program *j* in application process (application year) *p*; d_{ijp} is the difference between the admissions score assigned to application *ijp* and the cutoff score for admission in application *jp*. $Z_{ijp} = 1[d_{ijp} \geq 0]$ is an indicator variable equal to one if application *ijp* is accepted (is above the cutoff score); $f(d_{ijp})$ is a smooth function of the score difference. ε_{it} is an error term; note that it varies at the student-outcome year level.

We estimate these equations separately within subgroups defined by the characteristics of program *j* and the elapsed time since the year of application, *E=t-j*. Specifically, we obtain estimates within groups defined by program area, program selectivity, program course content, and the interactions between these categories. For each category, we estimate separate equations for four categories of E: E between 1 and 5, E between 6 and 26, E between 6 and 15, and E between 16 and 26. The goal of the estimation strategy is to understand how program attributes affect earnings during the period of college attendance, and after the period of college attendance when we expect the student to be in the labor force. In some specifications we split the post-college labor force period in two groups so that we can assess the degree to which the returns to admission change over time.

We estimate equation 1 using a local polynomial regression in the neighborhood of the cutoff value. We focus on a specification that uses data within 25 points on either side of the cutoff and approximates the function $f(d_{ijp})$ with second-order polynomials that are different above and below the cutoff value. To assess the robustness of our results, we also present estimates for two other bandwidth/polynomial combinations. The first is a tight window that uses an 8 point interval on either side and a linear approximation of the $f(d_{ijp})$ function. The second is a wider specification that extends the above-cutoff window to 50 points and uses cubic polynomials above and below the threshold. We don't extend the below-cutoff window because few students with scores more than 25 points below the cutoff value apply. Results for these specifications are in Online Appendix 9.

Note that in this specification, individuals who appear in multiple marginal applications may function as both treated students (in the application to which they are accepted) and control students (in the applications where they are rejected). To account for this, we allow for arbitrary correlation between error terms at the individual level (as opposed to the application level) when computing standard errors and conducting hypothesis tests. This also allows for possible correlations within individuals over time; which could be important if persistent shocks affect the earnings process.

Second, as discussed in Abdulkadiroglu et al. 2012, the presence of multiple application cutoffs could raise concerns about discontinuities in the conditional mean function at points other than the cutoff value, for example if many or all students applying to one program also apply to another with a very close cutoff score. This is much less likely to be a problem in our setting than in the Boston magnet school application process in Abdulkadiroglu et al 2012 for two reasons. First, students have the option to choose from over a thousand institution-degree combinations, and their preferences across these programs are heterogeneous as evident in summary statistics tables describing choices. For comparison, Abdulkadiroglu et al. focus on an application process to only three programs with a fairly distinct hierarchy in terms of desirability. Second, as described earlier, each institution-degree combination has a different scoring system. Accordingly, our data show no indication of discontinuities in matriculation or earnings functions over the windows we use.

5. Results

We start by measuring the Intent to Treat (ITT) impact of threshold crossing in the application process on labor market earnings by key application and applicant characteristics. These results reflect earnings returns to an offer of admission for a student at the admissions margin. We are interested in measuring the wage premium associated with different career fields versus skills acquired during study: to what extend to wages vary with field (e.g. health versus education) or acquired skill (e.g. quantitative versus professional)? We are also interested in measuring to what extent returns vary with selectivity of the peer group versus measures of value-added of the institution: are more selective peers or higher educational inputs stronger determinants of wage returns? Furthermore, we care about the extent to which returns to fields, skills, selective peers or higher educational inputs vary with the socio-economic backgrounds of students.

If the regression discontinuity design is valid, observable and unobservable characteristics of students are the same on both sides of the discontinuity, implying that on average, personal preferences, skills, and expected personal returns to particular courses of study, which all unobservable to the econometrician, are on average the same between those crossing and just missing thresholds for admissions.

We start by establishing the validity of the regression discontinuity approach in the pooled sample and by each cut of the data we examine in our results section.

5.1 Validation of RD Design

Threshold crossing does not coincide with a change in the conditional mean of baseline characteristics. Baseline characteristics are gender and high-school type (voucher, public or private). We also consider an index which is the portion of earnings predicted by these baseline characteristics in an OLS regression of labor market earnings that also controls for polynomials in score and cohort and experience effects. Figure 4 graphs balance of the baseline characteristics pooled and for each of our application characteristic categories of interest. Table 4 shows the corresponding regression results from equation (1) where baseline characteristics instead of wages are the dependent variables. We conclude that baseline characteristics are balanced above and below the threshold. Figure 5 plots the density of score in 2 point bins around the cutoff, verifying that there is continuous density in the running variable across the cutoff.

5.2 Treatment size and impact

Figure 6 plots matriculation into the target institution-degree against distance from the cutoff score from applications from 2004 to 2010. Recall that we currently only have matriculation files for 2004 through 2011 and are currently building the data back to 2000. Overall, threshold crossing causes a 54.2 percentage point increase in enrolling in the target degree. This is less than 100 percentage points because students may 1) opt not to enroll to pursue alternative plans or try again next year for a higher ranked choice or 2) be pulled off the waitlist, which is visible among score bins just to the left of the cutoff. This implies that the ITT results of the impact of admission on labor market outcomes are approximately half the size of the effects of matriculation on labor market outcomes. Table 5 shows the impact of threshold crossing on matriculation by our institution-degree characteristics of interest. Business and Science/Tech degrees have the highest causal impact of admission on matriculation. Art and Education are the lowest. Degrees with high-concentration in Professional courses, and high Quantitative+Qualitative concentrations have higher matriculation rates. Highly selective institutions have higher matriculation rates as a result of admission, which may be because they are higher ranked choices on average. Online Appendix Section 7 shows the coefficients on threshold crossing for all combinations of these categorical variables.

These differences will be important to keep in mind when interpreting the ITT results. In section 5.3, we present specification checks including two-sample-two-stage least squares (2S2SLS) estimates of effect of matriculating in degrees with characteristics *c* on labor market earnings. We find similar differences

across institution-degree classifications as we do in the ITT results, implying that differences in the causal impact of admission on matriculation across categories of interest are not the primary determinants of differential impacts on labor market outcomes.

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

Table 6 shows the impact of threshold crossing in an application to a degree of the type given by the row label on the probability of being admitted to a degree of the type indicated in the column label. The category Any shows the increased probability of being admitted to any degree – in other words, it is the probability that someone just below the threshold gets admitted to no alternative degree. This is largest for Education degrees, which tend to be the least selective and for which students appear to select fewer alternatives. For business degrees, crossing the threshold increases the probability of getting accepted to a business degree by 63%, implying that those just below the threshold are being accepted to business degrees 37% of the time, to Art degrees 1.9% of the time, to Education degrees 2.8% of the time, to Humanities/social-sciences degrees 6.4% of the time, to health degrees next to never, and to Science/Tech degrees 24.3% of the time. The remaining 26.9% are not accepted to any degree. From this table we can also see that the most likely alternate field is the same as the target field, but in general far from 1. This means we can interpret our RD estimates as the impact of increasing the probability of being admitted to a business degree, relative to a weighted average of the other degrees, with the most likely being no-admission or Science-technology.

5.4 Impact on labor market outcomes

Table 7 presents our key results. We present earnings effects as percentages of mean full sample earnings, equal to 8.13 million pesos. Overall, gaining admission to a target degree increases labor market earnings by 4.0%. These earnings gains are concentrated by field among Business, Humanities, Health and Science and Technology. In particular, just getting into a health degree increases earnings by 8.5% relative to getting into the mix of alternates described in Table 6. One way to look at this is that individuals who got

into a health degree were very lucky in that they experienced large earnings gains even though on average they had the same schooling and field-of-study preferences as those who did not cross the threshold and therefore had a 52.5% lower change of being admitted to a health program.

In contrast, just making it into a high-selectivity program has a significant 4.2% impact on earnings. However, looking at columns 2 and 3, we see that almost all of the gains to field accrue to those also crossing the threshold into high-selectivity degrees.

Splitting degrees by course content, we see that most gains to skills interact with field of study. For example, following art degrees with a focus on professional practice leads to a negative impact on earnings of 13.2% relative to just missing admission. Among Humanities and Social Sciences, we see that professional degree focus does increase earnings by 10.2%. Heavy quantitative focus in Education lowers earnings by 16.4%, while it raises earnings in Health, Science and Technology, and Business fields substantially. Interestingly, Business degrees that focus both on quantitative and qualitative skills result in the largest gains to earnings.

Overall, conditional on preferences and choices, field of study and skills from core coursework have a significant causal impact on labor market outcomes. Degree selectivitydoes as well. However, this could also be selectivity of individual or peers rather than a causal impact of the institution.

We next estimate value-added for each institution-field combination. Our goal is to know if selectivity matters for labor market outcomes or if an observational measure of institution-field productivity better predicts causal returns to admission. We are also interested in how this varies by students' SES. To do this, we focus on earnings for the sample of applicants in 1998 and later, for which we currently have full demographic and high-school type constructed (we are currently completing the data construction for these variables back to 1980). We test between these two categorizations of quality among students coming from public, voucher and private schools as a measure of socio-economic background.

Table 8 shows the results. Overall, the pooled earnings gains for the 1998 and later cohorts are lower but significant at 2.4%. These gains come primarily from Public school students, and the point estimates are similar for voucher and private school students. Gains to high value added institution-degrees are 5.1% and near zero for low-value added schools. This gain drops in magnitude to 2.9% in the 1998 and later sample. Of that, gains are similar in magnitude across high school type, though only marginally significant among public school students.

Looking at the cross-combinations of selectivity and value added, we see that high selectivity and high value added has the largest impact on earnings – 5.4% and 3.0% in the full and recent samples

respectively. Gains again are really similar across high school groups. Negative outcomes accrue to those going to selective schools with low value added.

Overall these results suggest that selectivity and value-added are important determinants of labor market outcomes, and accrue to those with varying socio-economic backgrounds conditional on admission above the cutoff score. We don't find evidence that highly selective schools on either dimension are less beneficial to those coming from lower socio-economic backgrounds. Though we have more pushing to do on this front with added measures of socio-economic status and earlier years of data.

5.5 Further interpretations and specification checks

5.5.1 Two-sample 2SLS estimates

The above ITT estimates show the effect of threshold crossing on earnings by key characteristics of the institution-degree. As stated earlier, some differences could be caused by differences in matriculation as a result of admission. In addition the ITT is evaluated at the mean treatment size – the mean increase in probability of acceptance to an institution-degree of type *c*. This mean treatment size is always less than one, and the extent to which it is less than one varies with *c*'s characteristics. As stated earlier, matriculations do not exist prior to 2000, and we currently have matriculation data from 2004 to 2010 cohorts cleaned, checked and usable. We can use the 2004-2010 cohort sample to estimate the first-stage impact of threshold crossing on matriculation into target institution-degrees and into institution-degrees of different characteristics *c*, thus allowing us to examine the local average treatment effect of matriculating in to a target degree and the impact of moving into one degree versus any other degree.

Tables 9 and 10 show the 2S2SLS impact of matriculation into a target degree and into a degree of characteristic *c* on expected earnings. The results are considerable in magnitude and significance. Overall, crossing the threshold into a business degree rather than an alternative field would have resulted in 27.4% higher earnings; Art and Architecture results in earnings losses of 29.3% versus other fields. The best field to have causally entered was Health with a 14.4% gain in earnings. High selectivity fields increase earnings by 15.6% however this is not substantially different than low-selectivity gains. Returns to quantitative course concentrations are the highest; either coupled with high qualitative emphasis or alone. Returns to these institution-degrees with high quantitative requirements are close to 21.6 to 23.2 % over fields with other emphasis.

In results reported in Online Appendix 8, we test the robustness of our findings to various alternative specifications. We consider wider and narrower bandwidths, coupled with changes in polynomial degrees. We consider alternate definitions of the level of excess demand required to qualify for the marginal sample, as well as alternate thresholds for earnings topcoding. Our results are robust to each of these changes. We also examine the effects of threshold-crossing on labor market participation and labor market earnings conditional on participation. We find that our results are driven by labor market earnings conditional on participation as opposed to changes in participation.

6. Conclusion

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

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

Our findings suggest that frictions exist in the markets that match students to postsecondary degrees. Constraints on the supply of high-return degrees (see Bound and Turner, 2007) may push students into programs with lower economic returns at many margins. Admitting the marginal applicant to a high-return program by lowering the score cutoff a small amount likely represents a policy change with a positive social return. At the same time, we observe excess demand for degrees that lead to zero or, in some cases, large and negative earnings returns for admitted students. This could be because these degrees offer high non-pecuniary compensation that is valued by all students, or because some students have very strong tastes for the coursework or careers associated with these degrees. That said, Hastings et al. (2012) present evidence suggesting that students may base college choices on beliefs about economic returns that are systematically biased and uniformed. The existence of oversubscribed degrees with zero or negative returns thus suggests two possible avenues for welfare-improving policy intervention. First, if information aggregation is a public good, policymakers supply centralized ranking and earnings

information to guide to provide students with accurate information needed before making life-long decisions. Second, loan policy could be used to provide additional supply-side incentives to ease frictions in supply of high-return degrees (Hastings et al. 2012).

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TABLE 1: DESCRIPTIVE STATISTICS ON UNIVERSITIES IN CHILE

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

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

TABLE 2: DESCIRPTIVE STATISTICS ON APPLICATIONS AND CHOICES

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

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

TABLE 3: APPLICATION CHARACTERISTICS, SAMPLE MEANS

Application Characteristics	Full sample	Marginal	Marginal and Complete Data
Application Characteristics			
Math score	595	637	638
Read score	583	612	613
Accepted	0.395	0.41	0.406
Business	0.089	0.126	0.126
Art/Arch.	0.057	0.055	0.058
Education	0.159	0.096	0.103
Hum./Law/SS	0.158	0.151	0.145
Health	0.166	0.167	0.18
Sci/Tech	0.37	0.406	0.388
Low Sel.	0.50	0.353	0.337
High Sel.	0.50	0.647	0.663
Prof. Courses	0.477	0.484	0.498
Quant. Courses	0.105	0.106	0.107
Qual. Courses	0.292	0.244	0.238
Quant+Qual Co.	0.126	0.165	0.158
Applicant Characteristics			
Male	0.491	0.524	0.518
Public HS	0.381	0.334	0.336
Voucher HS	0.442	0.398	0.403
Private HS	0.177	0.267	0.261
Post-college market outcomes, 2011 tax year, 6 to 26 years post application			
Non-zero earnings	0.837	0.856	0.853
Earnings (mil.pesos)	8.13	10.4	10.6
Earnings (USD)	$19,113	$24,449	$24,920
N apps	3,094,827	685,425	608,398
N students	1,118,574	438,932	399,490

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

TABLE 4: BALANCE OF BASELINE CHARACTERISTICS IN RD DESIGN

	Index	Male	Public HS	Private HS	Voucher HS
Pooled	6818	0.001	-0.006	0.003	0.004
	(7169.00)	(0.00)	(0.00)	(0.00)	(0.00)
Within Area:					
Business	-417	-0.004	-0.006	0	0.006
	(22251.00)	(0.01)	(0.01)	(0.01)	(0.01)
Art/Arch.	1745	-0.004	-0.02	-0.002	0.022
	(32272.00)	(0.02)	(0.02)	(0.02)	(0.02)
Education	-14600	-0.003	0.004	-0.007	0.004
	(14663.00)	(0.01)	(0.01)	(0.01)	(0.01)
Humanities	-28	-0.017	-0.009	0.003	0.006
	(18668.00)	(0.01)	(0.01)	(0.01)	(0.01)
Health	14695	0.004	-0.014	0.005	0.009
	(16953.00)	(0.01)	(0.01)	(0.01)	(0.01)
Sci/Tech	-1929	0.004	0.002	-0.002	0
	(11575.00)	(0.01)	(0.01)	(0.01)	(0.01)
Joint P-value:	*0.939*	*0.767*	*0.472*	*0.953*	*0.779*
By Sel. Group:					
Low Sel	646	-0.005	-0.007	0	0.008
	(8399.00)	(0.01)	(0.01)	(0.00)	(0.01)
High Sel	1137	0.003	-0.002	-0.001	0.003
	(9764.00)	(0.01)	(0.01)	(0.01)	(0.01)
Joint P-value	*0.99*	*0.692*	*0.472*	*0.989*	*0.443*
By Course Content:					
Professional	4627	0.003	0.002	0.002	-0.004
	(10211.00)	(0.01)	(0.01)	(0.01)	(0.01)
Quantitative	-2.50E+04	-0.001	-0.009	-0.017	0.026*
	(21739.00)	(0.01)	(0.01)	(0.01)	(0.01)
Qualitative	4678	-0.004	-0.011	0.002	0.009
	(13886.00)	(0.01)	(0.01)	(0.01)	(0.01)
Quant+Qual	26142	0.004	-0.014	0.012	0.002
	(18768.00)	(0.01)	(0.01)	(0.01)	(0.01)
Joint P-value	*0.649*	*0.944*	*0.422*	*0.488*	*0.092+*
Full interaction:					
Joint P-value	*0.7037*	*0.3801*	*0.3297*	*0.9253*	*0.426*
N apps	443,672	443,690	443,564	443,704	443,704
N students	282,211	282,222	282,142	282,236	282,236

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

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

	Coefficient	St. Error	N
Business	0.542***	(0.01)	30,232
Art/Arch.	0.389***	(0.02)	13,411
Educ.	0.431***	(0.02)	25,925
Hum/SS	0.577***	(0.01)	45,943
Health	0.499***	(0.01)	56,002
Sci/Tech	0.608***	(0.01)	84,920
Prof.	0.583***	(0.01)	110,579
Quant	0.445***	(0.01)	32,882
Qual	0.509***	(0.01)	72,297
Quant+Qual.	0.570***	(0.01)	44,913
Low Sel.	0.463***	(0.01)	109,455
Hi Sel.	0.600***	(0.01)	152,059

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

TABLE 6: EFFECTS OF THRESHOLD-CROSSING ON ACCEPTANCE OUTCOMES

Target	Any	Business	Art/Arch	Educ	Hum/SS	Health	Sci/Tech	N
Business	0.269***	0.630***	-0.019***	-0.028***	-0.064***	-0.005***	-0.243***	85,320
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	
Art/Arch.	0.287***	-0.037***	0.668***	-0.048***	-0.061***	-0.006***	-0.227***	36,993
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	
Educ.	0.437***	-0.022***	-0.010***	0.629***	-0.060***	-0.009***	-0.089***	65,404
	(0.007)	(0.002)	(0.002)	(0.007)	(0.003)	(0.001)	(0.004)	
Hum/SS	0.253***	-0.056***	-0.031***	-0.090***	0.520***	-0.011***	-0.075***	101,987
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	
Health	0.192***	-0.012***	-0.009***	-0.035***	-0.037***	0.475***	-0.189***	112,788
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	
Sci/Tech	0.297***	-0.045***	-0.013***	-0.038***	-0.015***	-0.017***	0.429***	275,765
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Target app:	Prof	Quant	Qual	Quant+Qual	Low Sel	Hi Sel	N
Prof.	0.499***	-0.069***	-0.069***	-0.069***	0.056***	0.230***	328,158
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	
Quant	-0.359***	0.801***	-0.078***	-0.117***	-0.011	0.256***	72,032
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	
Qual	-0.179***	-0.021***	0.559***	-0.040***	0.092***	0.222***	165,579
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	
Quant+Qual	-0.268***	-0.159***	-0.075***	0.717***	0	0.214***	111,674
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	
Low Sel.	0.231***	0.032***	0.145***	0.037***	0.453***	-0.022***	243,640
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	
Hi Sel.	0.061***	0.013***	0.046***	0.078***	-0.157***	0.353***	446,170
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	

Notes: +0.1, *0.05, **0.01, ***0.001; Estimates of equation (1) in the sample defined by the row variable with dependent variables as given in the column names. Data are at the person-application level and include 1985-2010 cohorts. Dummy variables are equal to one if a person is accepted at a program of a given type, and zero otherwise.

TABLE 7: EFFECTS OF THRESHOLD-CROSSING ON POST-COLLEGE EARNINGS

	Pooled	Low Sel	Hi Sel	Prof	Quant	Qual	Quant+Qual
Pooled	0.040***	0.016	0.042***	0.014	0.079**	0.047**	0.091***
	(0.009)	(0.012)	(0.011)	(0.012)	(0.029)	(0.017)	(0.025)
Within Area:							
Business	0.050+	0.043	0.068*	0.028	0.123	-0.010	0.088*
	(0.026)	(0.037)	(0.033)	(0.037)	(0.082)	(0.075)	(0.041)
Art/Arch.	-0.032	0.08	-0.055	-0.132**	N/A	0.013	N/A
	(0.035)	(0.093)	(0.036)	(0.050)		(0.045)	
Education	-0.004	0.007	-0.018	-0.082+	N/A	0.047*	-0.164**
	(0.019)	(0.019)	(0.051)	(0.049)		(0.022)	(0.060)
Humanities	0.061*	0.004	0.072*	0.102*	N/A	0.051+	N/A
	(0.024)	(0.035)	(0.028)	(0.049)		(0.027)	
Health	0.085***	0.019	0.095***	0.028	0.079	N/A	0.168***
	(0.025)	(0.062)	(0.025)	0.03	(0.050)		(0.043)
Sci/Tech	0.030*	0.012	0.028	0.008	0.082*	0.012	0.111*
	(0.013)	(0.018)	(0.018)	(0.015)	(0.036)	(0.069)	(0.052)
By Sel. Group							
Low	0.016	0.016	N/A	0.01	0.076	0.028	-0.027
	(0.012)	(0.012)		(0.016)	(0.054)	(0.019)	(0.045)
High	0.042***	N/A	0.042***	0.007	0.086**	0.049*	0.121***
	(0.011)		(0.011)	(0.016)	(0.032)	(0.024)	(0.028)

Notes: +0.1, *0.05, **0.01, ***0.001; Estimates of equation (1) for experience levels 6-26. Includes cohorts 1985-2005. Rows and columns define analysis sample. Results in the "Pooled" row (column) are from pooled estimates within samples defined by the column (row). Results where neither the column nor row is "pooled" are obtained by estimating separate regressions within each area-selectivity-course cell, then aggregating up to the two-way interaction using weights defined by sample proportions. For instance, to get the business-low selectivity cell, we estimate separate RDs for each course category within the business-selectivity group, then compute a linear combination of those estimates in which the weights are the sample proportions (summing to one)

TABLE 8: COMPARING EARNINGS EFFECTS BY SELECTIVITY AND VALUE-ADDED CATEGORIES

	All	All post-1998	Public	Voucher	Private
Full sample	0.040***	0.024**	0.030*	0.018	0.026
	(0.009)	(0.009)	(0.013)	(0.013)	(0.018)
	2,621,433	998,338	349,601	330,646	315,517
Low VA	0.002	0.004	0.007	0.016	-0.026
	(0.012)	(0.010)	(0.013)	(0.015)	(0.030)
	837,085	322,056	142,259	119,358	59,522
Hi VA	0.051***	0.029*	0.032+	0.024	0.032
	(0.011)	(0.011)	(0.018)	(0.018)	(0.021)
	1,784,348	676,282	207,342	211,288	255,995
Low Sel	0.016	0.020+	0.018	0.014	0.046
	(0.012)	(0.010)	(0.014)	(0.016)	(0.035)
	843,701	323,711	156,986	126,753	39,101
Hi Sel	0.042***	0.023*	0.032+	0.024	0.016
	(0.011)	(0.011)	(0.019)	(0.019)	(0.020)
	1,777,732	674,627	192,615	203,893	276,416
Low Sel/Low VA	0.011	0.018+	0.013	0.028+	0.012
	(0.013)	(0.011)	(0.014)	(0.017)	(0.039)
	557,931	221,345	110,000	84,841	25,869
Low Sel/Hi VA	0.023	0.020	0.026	-0.015	0.098
	(0.023)	(0.021)	(0.031)	(0.033)	(0.067)
	285,770	102,366	46,986	41,912	13,232
Hi Sel/Low VA	-0.028	-0.032	-0.02	-0.019	-0.063
	(0.024)	(0.021)	(0.030)	(0.030)	(0.044)
	279,154	100,711	32,259	34,517	33,653
Hi sel/Hi VA	0.054***	0.030*	0.031	0.035+	0.027
	(0.012)	(0.013)	(0.021)	(0.021)	(0.021)
	1,498,578	573,916	160,356	169,376	242,763

Notes: +0.1, *0.05, **0.01, ***0.001; Estimates of equation (1) for experience levels 6-26. Includes cohorts 1985-2005. We compute separate estimates within samples defined by rows and column labels. Data high school type is available from 1998-2005 only. Selectivity estimates are based on scores of accepted students, while value-added estimates are based on OLS regressions of earnings on control variables and program fixed effects for accepted students. See text. Sample size N is on the last row within each sample.

TABLE 9: 2S2SLS ESTIMATES OF EFFECT OF
MATRICULATION INTO TARGET CAREER ON EARNINGS

Pooled	0.072***		
	(0.000)		
Business	0.092+	Low Sel.	0.034
	(0.076)		(0.140)
Art/Arch.	-0.075	High Sel.	0.069***
	(0.404)		(0.000)
Education	-0.008	Professional	0.024
	(0.892)		(0.216)
Humanities	0.102*	Quantitative	0.169***
	(0.016)		(0.000)
Health	0.163***	Qualitative	0.088**
	(0.000)		(0.004)
Sci/Tech	0.049*	Quant+Qual	0.158***
	(0.012)		(0.000)
FS N	929,875		
RF N	2,621,433		

Notes: +0.1, *0.05, **0.01, ***0.001; Results from TS2SLS regressions. Reduced form regressions are taken from the "Pooled" column of Table 8; these include the 1985-2005 cohorts. First stage regressions are computed using data form 2004-2010 cohorts. Bootstrapped P-values are in parentheses; they allow for clustering at the level of the individual. "Matriculate at target" is a dummy equal to one if a student attends the target program. "Target area" is a dummy equal to one if a student attends any program with the same area as the target area. "Target sel or higher" is a dummy equal to one if a student attends a program that falls in the same (or higher) binary selectivity category as the target. "Target course type" is a dummy equal to one if a student attends a program in the same course content category as the target. [1] p-values not available for these columns at present.

TABLE 10: 2S2SLS ESTIMATES OF EFFECTS OF MATRICULATION INTO TYPES OF CAREERS ON EARNINGS

Pooled	0.151***		
Business	0.144+	Low Sel.	0.090
Art/Arch.	-0.139	High Sel.	0.156***
Education	-0.017	Professional	0.047
Humanities	0.196*	Quantitative	0.232***
Health	0.340***	Qualitative	0.179**
Sci/Tech	0.127*	Quant+Qual	0.216***
FS N	929,875		
RF N	2,621,433		

Notes: +0.1, *0.05, **0.01, ***0.001; Results from TS2SLS regressions. Reduced form regressions are taken from the "Pooled" column of Table 8; these include the 1985-2005 cohorts. First stage regressions are computed using data form 2004-2010 cohorts. Bootstrapped P-values are in parentheses; they allow for clustering at the level of the individual. "Matriculate at target" is a dummy equal to one if a student attends the target program. "Target area" is a dummy equal to one if a student attends any program with the same area as the target area. "Target sel or higher" is a dummy equal to one if a student attends a program that falls in the same (or higher) binary selectivity category as the target. "Target course type" is a dummy equal ot one if a student attends a program in the same course content category as the target. [1] p-values not available for these columns at present.

FIGURE 1: TRENDS IN COLLEGE ENTRANCE EXAM TAKING, CHILE AND US

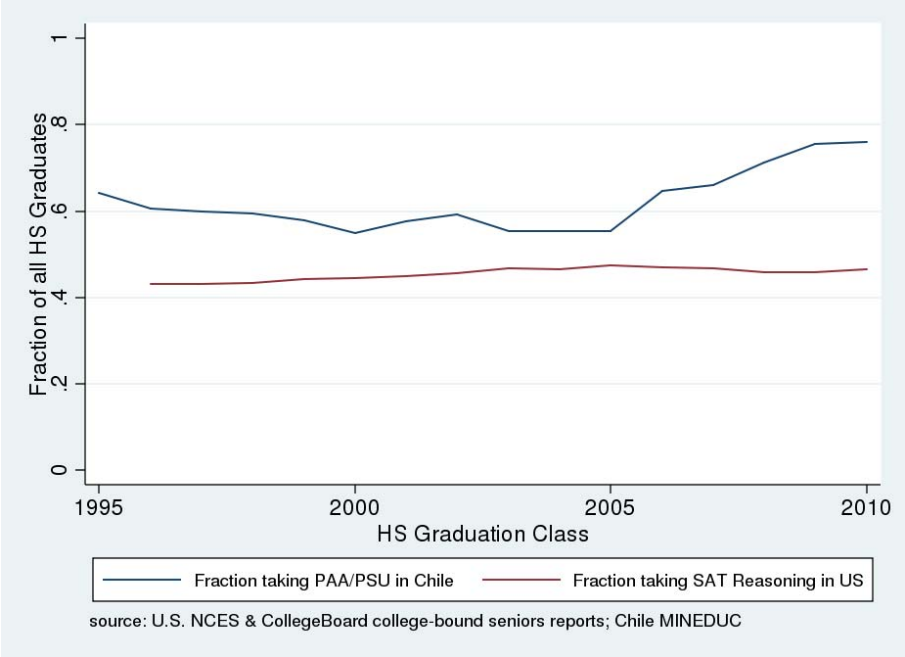


FIGURE 2: ENTRANCE EXAM SCORE DISTRIBUTION BY HIGH SCHOOL TYPE

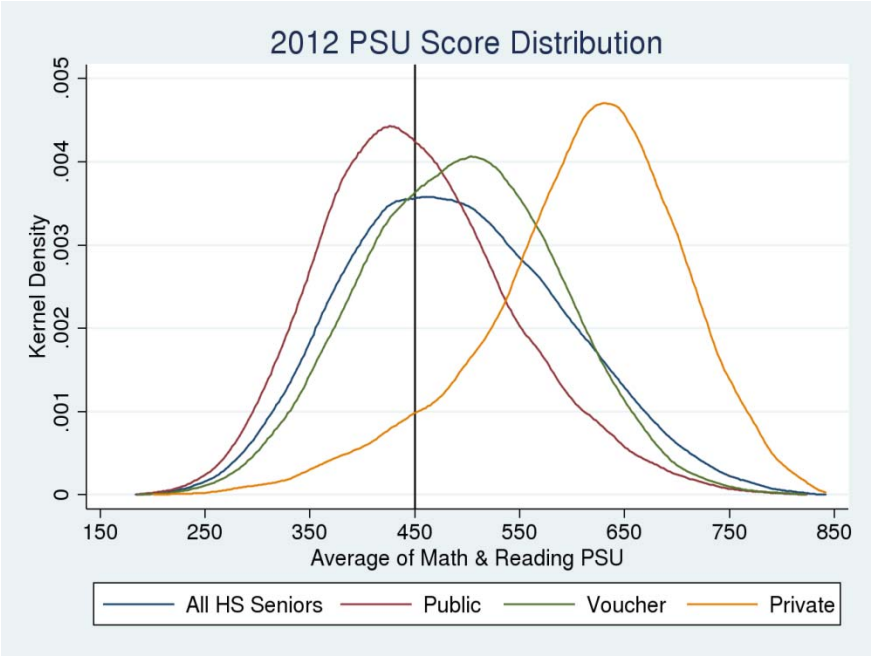


FIGURE 3: VARIATION IN MEAN ENTRANCE EXAM SCORES OF ACCEPTED COHORTS BY SELECTIVITY

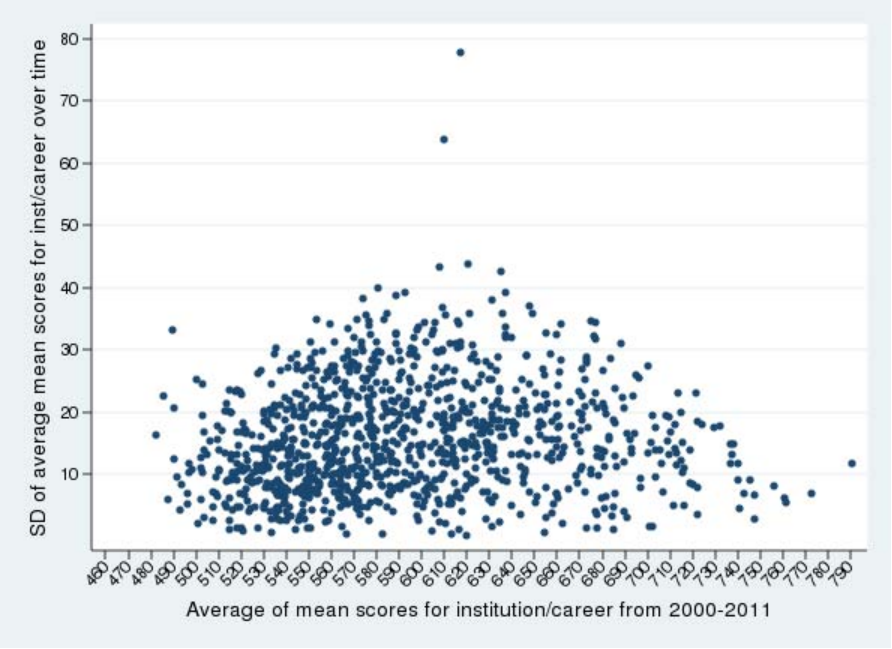
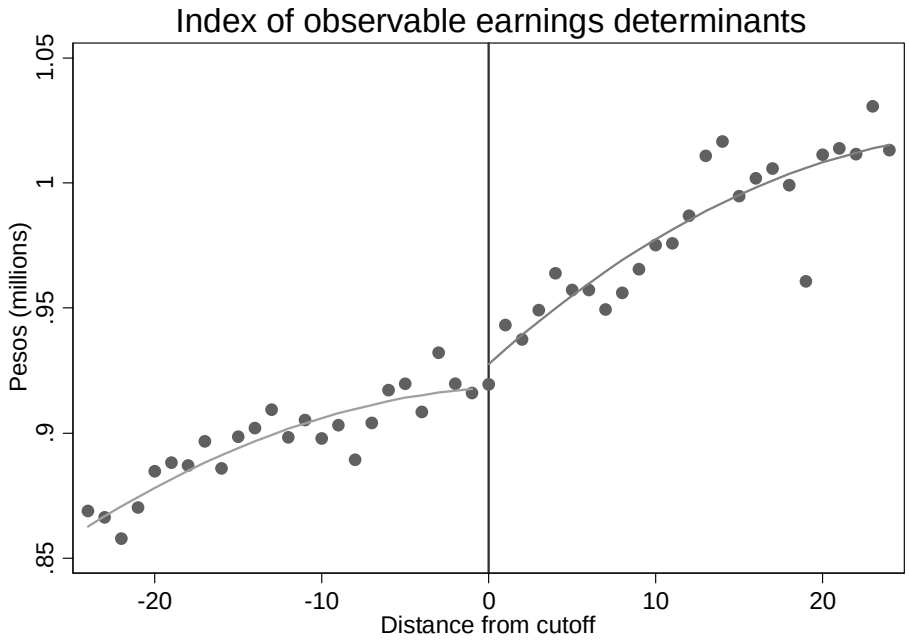
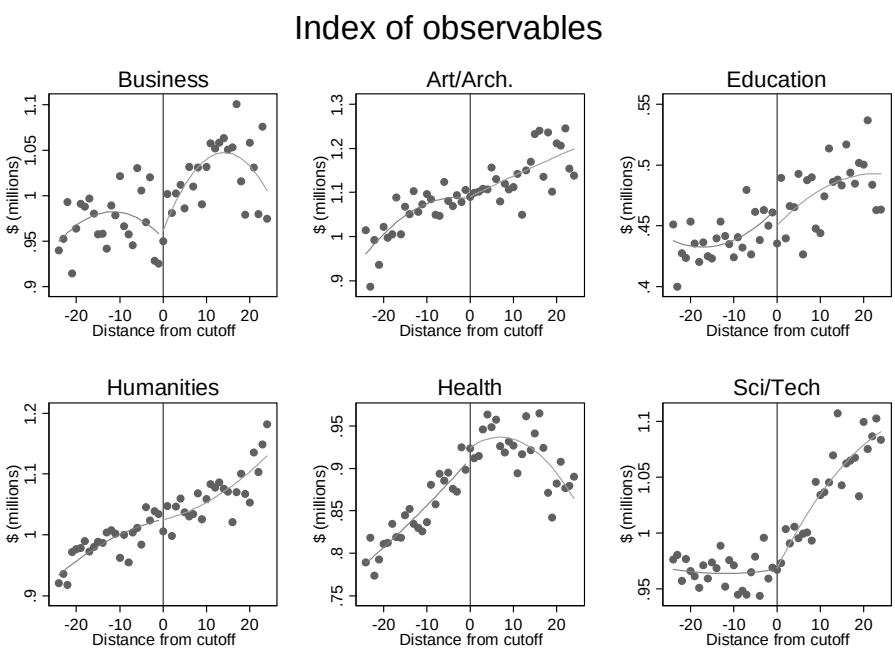


FIGURE 4: CONDITIONAL MEAN OF INDEX OF STUDENT DEMOGRAPHICS (1 POINT SCORE BINS)

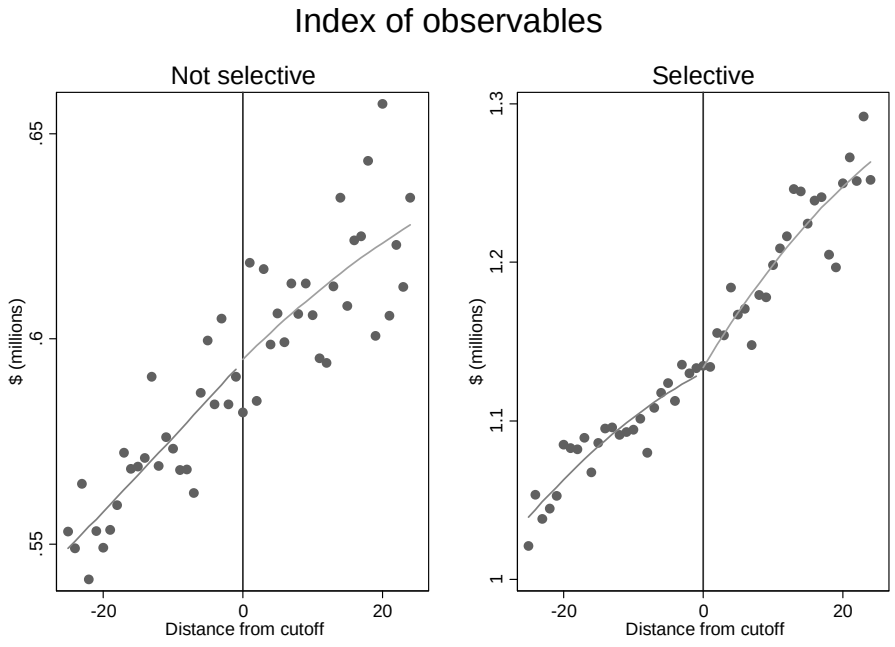
4.A. Pooled sample:



4.B. By Area:



4.C. By Selectivity:



4.D. By course category:

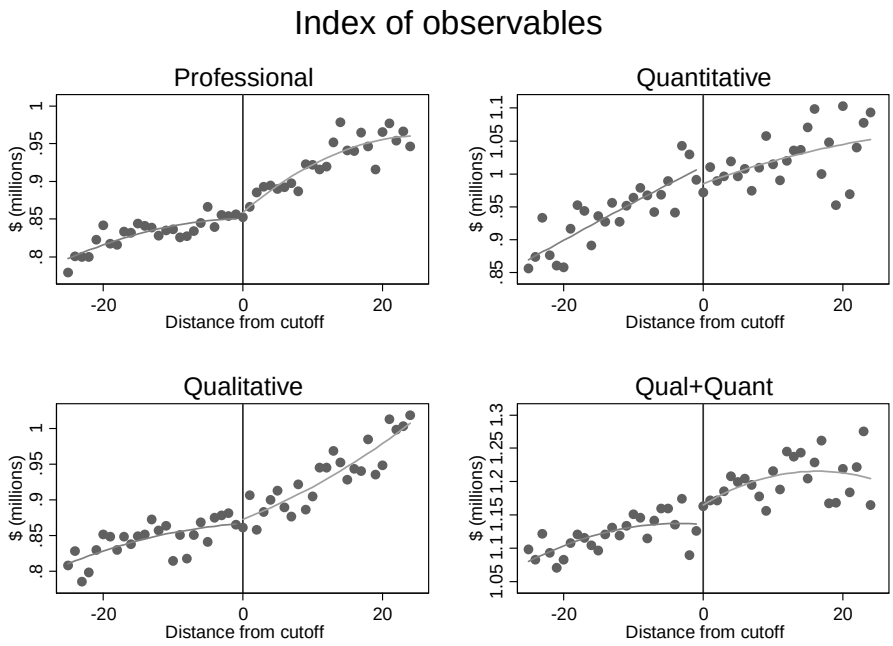


FIGURE 5: DENSITY OF RUNNING VARIABLE (2 POINT BINS)

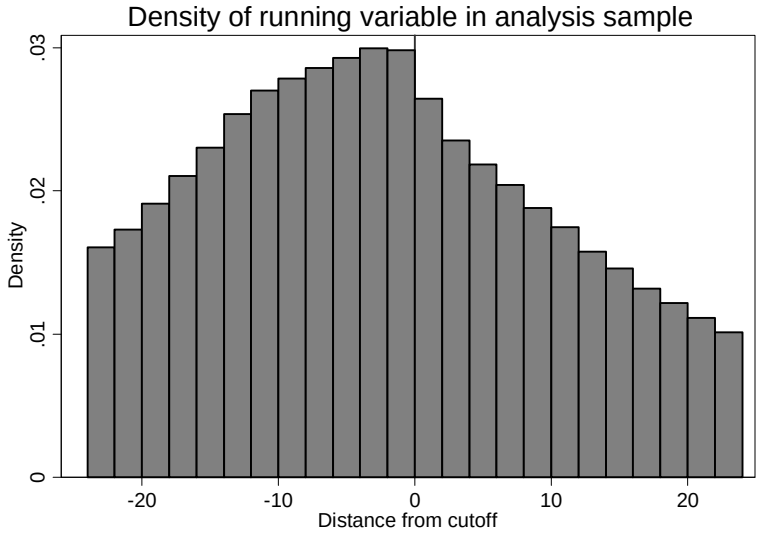
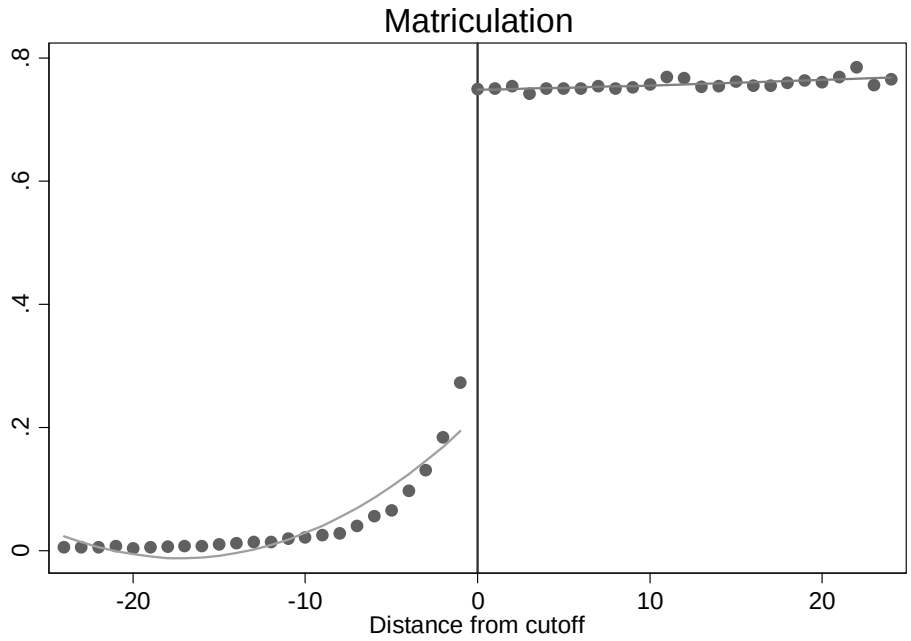
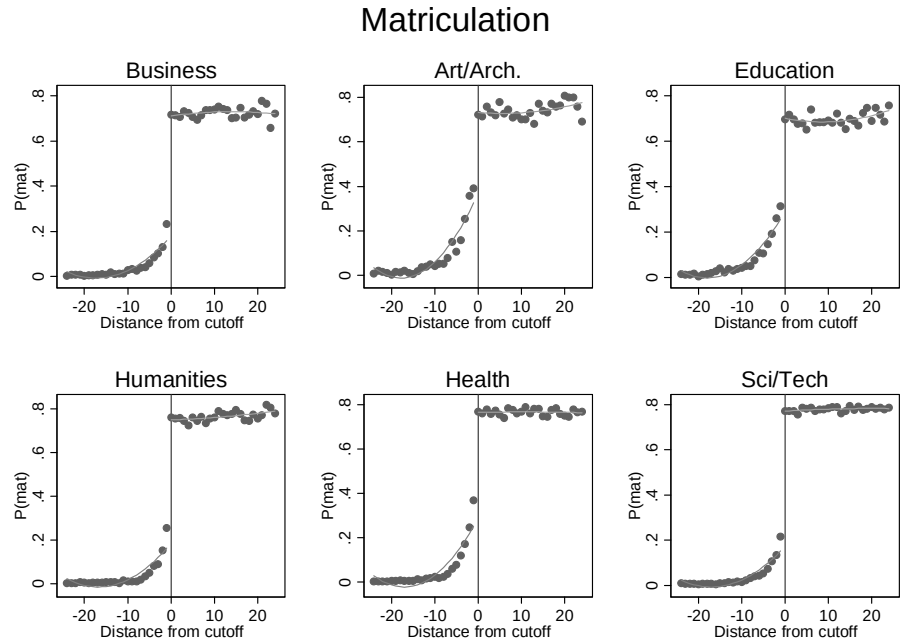


FIGURE 6: MATRICULATION BY POSITION RELATIVE TO CUTOFF (1 POINT SCORE BINS)

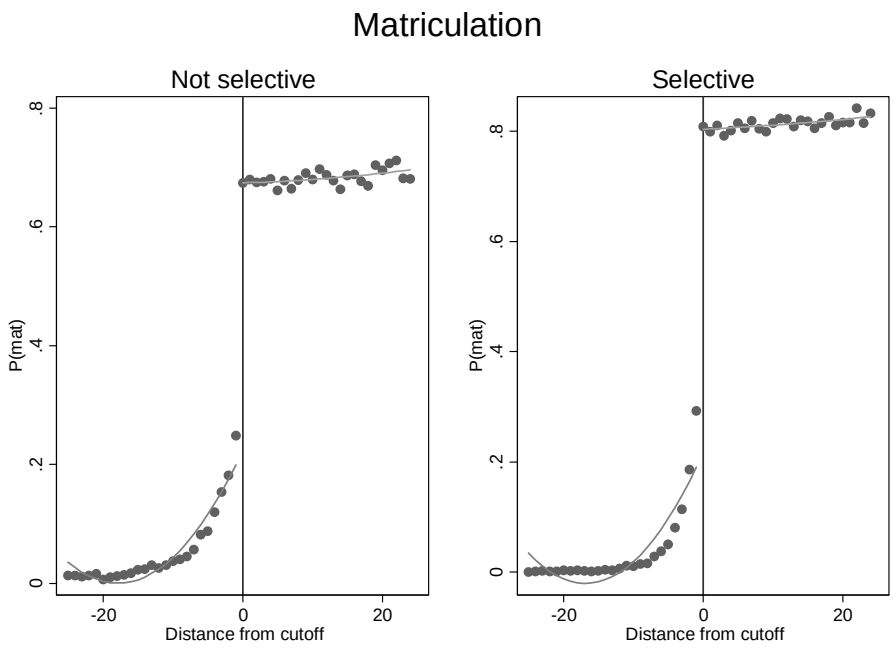
6.1. Pooled:



6.2. By Area:



6.3. By Selectivity:



6.4. By Course category:

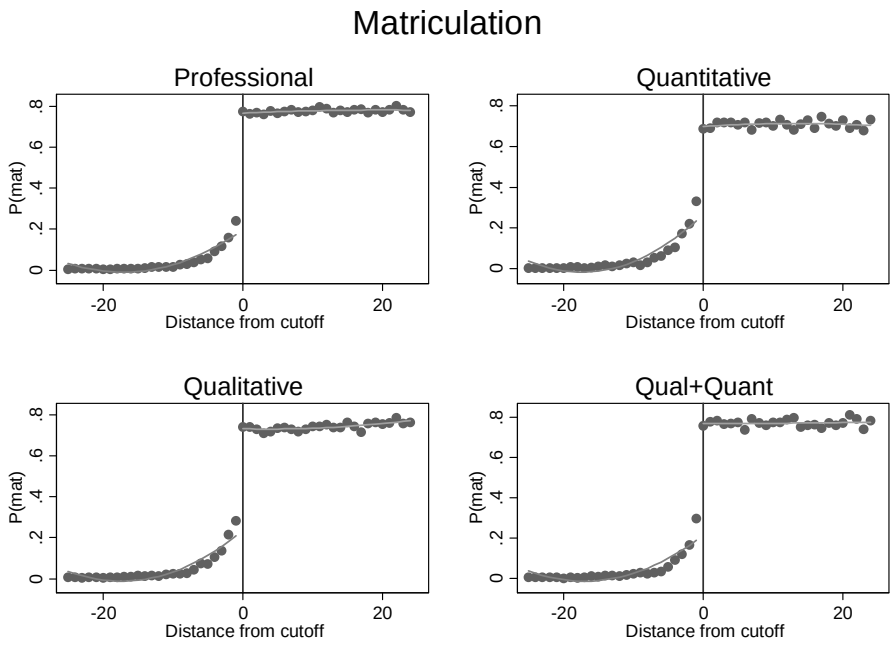
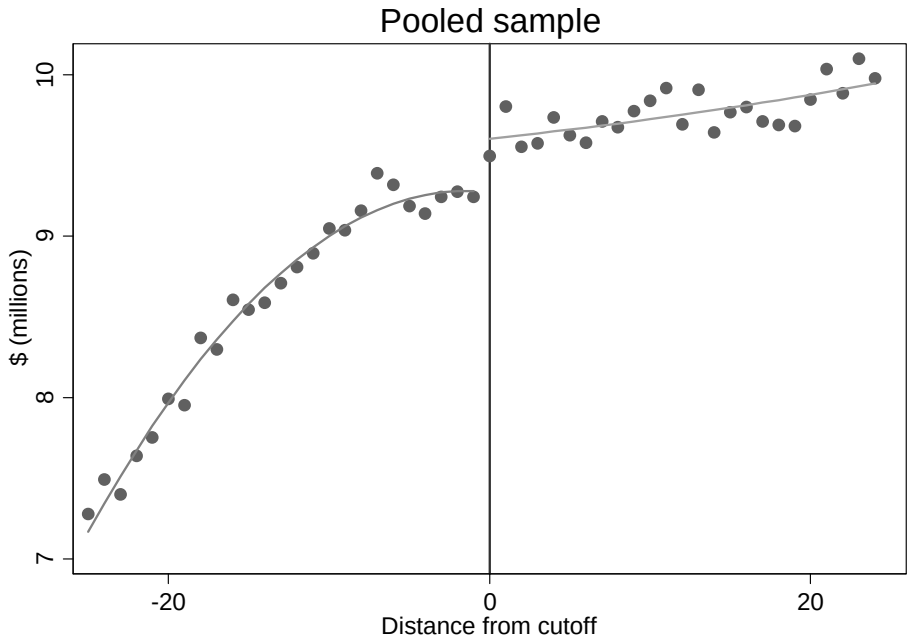
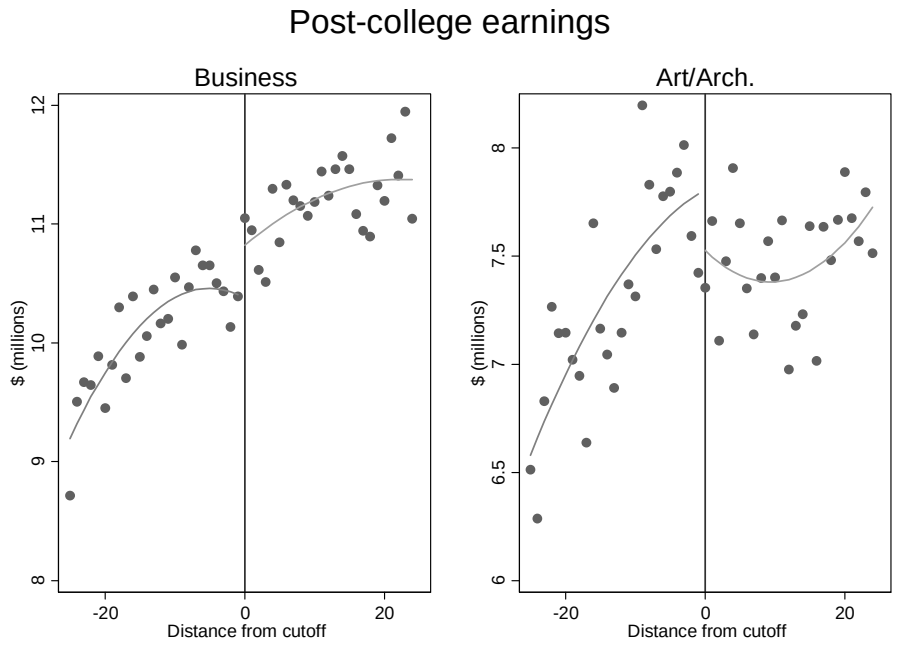


FIGURE 8: POST-COLLEGE EARNINGS BY POSITION RELATIVE TO CUTOFF

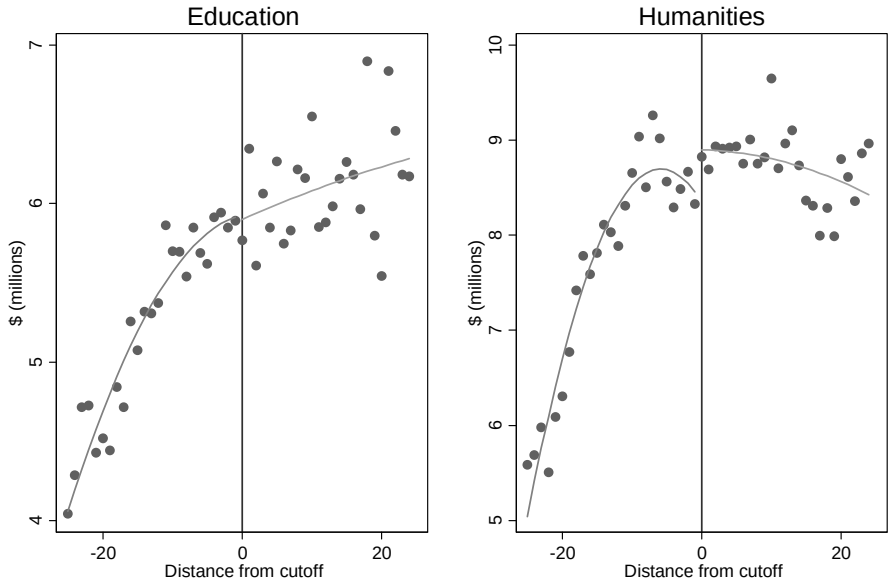
8.A. Pooled sample:



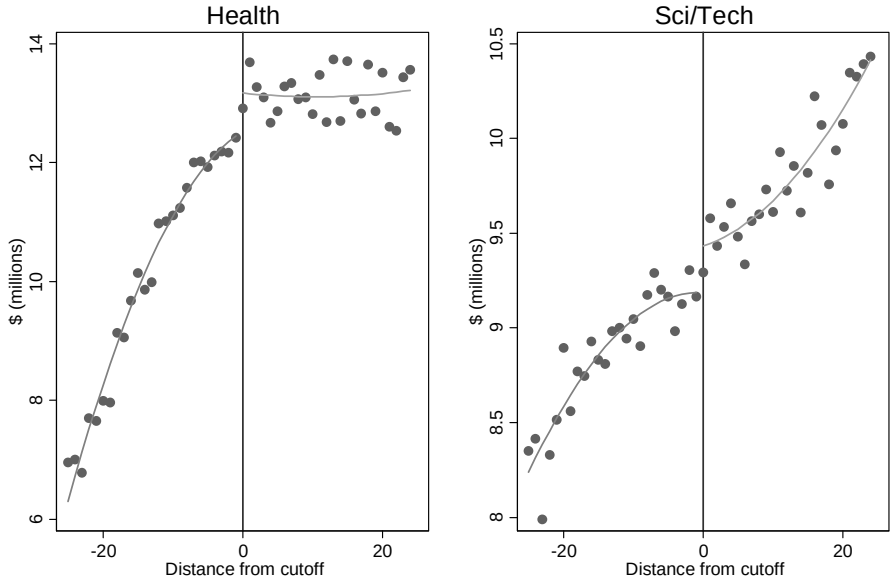
8.B. By Area:



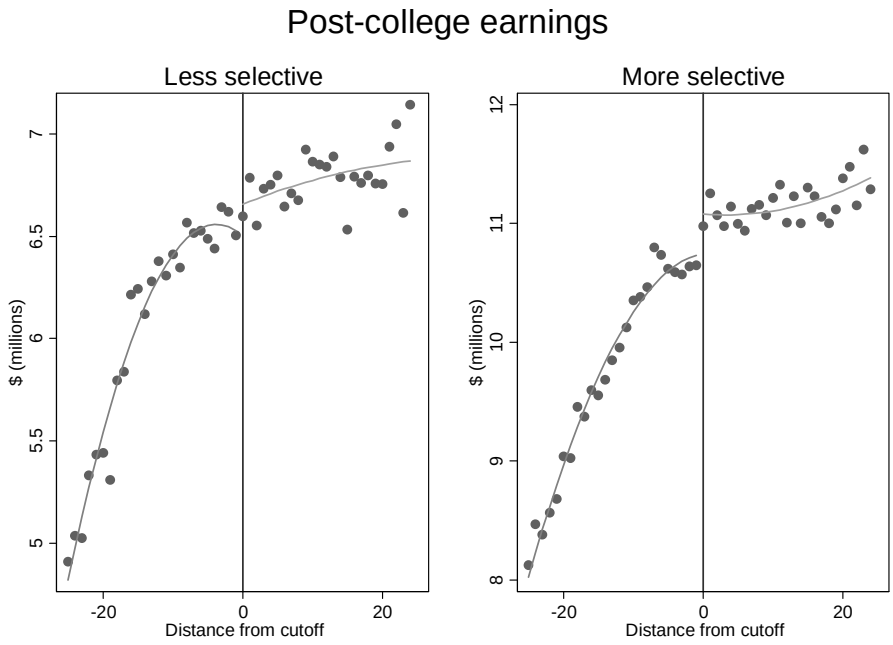
Post-college earnings



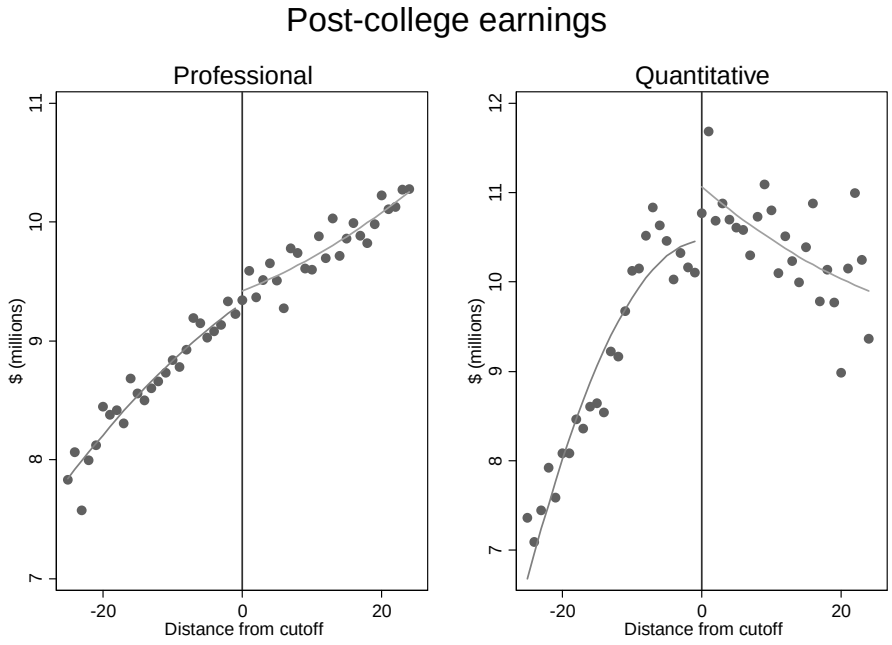
Post-college earnings

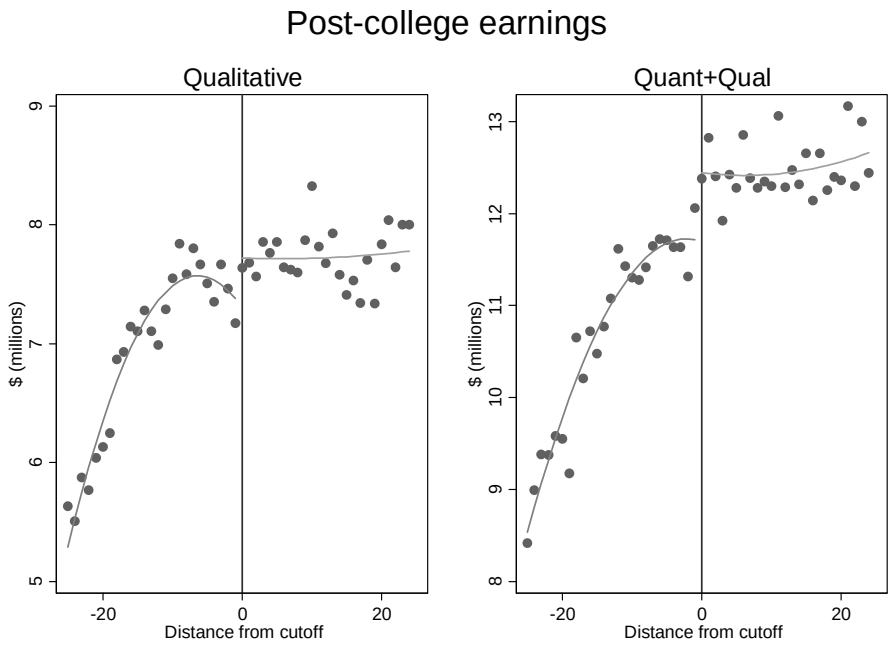


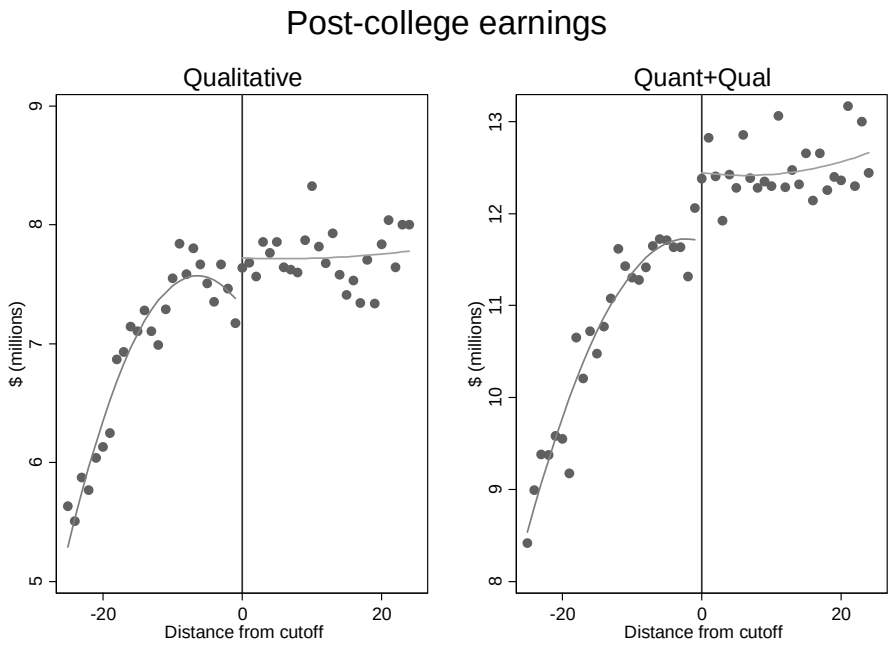
8.C.By selectivity:



8.D. By course type:




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


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