ONLINE APPENDIX

FOR

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

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Justine Hastings
Brown University and NBER
justine_hastings@brown.edu

Christopher Neilson
New York University
cneilson@stern.nyu.edu

Seth Zimmerman
Princeton University
sethz@princeton.edu

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1 Postsecondary Educational Options in Chile, 1980-2011

1.1 Characteristics of Accepted Students and College Applications

Table A.I.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 score for admitted students). It also shows the fraction of degrees by the eight broad fields of interest.

Table A.I.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 1982 through 2000 we do not have full ranked choices but instead have only digitized admission, waitlist and score data from hard copy records).[1] Column 2 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 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% matriculate to that choice.

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

Table A.I.I Descriptive Information for Institutions

Universities	Ave. Score	% selective	Bus.	Art/Arch.	Educ	SS	Medicine	Sci/Tech	Hum.	Law	N
UNIVERSIDAD DE CHILE	695.84	97.60%	8.33%	20.20%	0.31%	7.79%	18.65%	31.50%	4.73%	8.51%	104,434
PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE	680.38	82.40%	5.33%	11.90%	16.90%	4.63%	7.03%	32.10%	9.34%	12.78%	101,244
UNIVERSIDAD DE SANTIAGO DE CHILE	647.69	77.83%	16.21%	3.00%	6.86%	0.00%	3.33%	64.03%	1.40%	5.19%	84,740
PONTIFICIA UNIVERSIDAD CATOLICA DE VALPARAISO	639.96	68.08%	8.14%	4.71%	22.28%	6.74%	0.96%	50.70%	1.24%	5.24%	65,629
UNIVERSIDAD DE CONCEPCION	627.9	55.85%	8.94%	2.74%	16.74%	4.06%	14.42%	44.67%	1.47%	6.95%	98,148
UNIVERSIDAD DE VALPARAISO	619.88	50.50%	16.65%	15.04%	3.21%	5.99%	19.70%	21.88%	0.00%	17.54%	41,752
UNIVERSIDAD TECNOLOGICA METROPOLITANA	615.48	41.78%	18.66%	11.19%	0.00%	0.00%	0.00%	64.73%	2.22%	3.21%	26,299
UNIVERSIDAD DE TALCA	614.42	44.24%	26.04%	3.93%	7.22%	7.16%	13.97%	39.66%	0.00%	2.03%	24,537
UNIVERSIDAD TECNICA FEDERICO SANTA MARIA	612.74	44.04%	2.52%	1.14%	0.00%	0.00%	0.00%	96.34%	0.00%	0.00%	50,401
UNIVERSIDAD AUSTRAL DE CHILE	608.93	40.90%	11.75%	1.65%	8.95%	3.56%	14.99%	52.26%	0.45%	6.39%	42,517
UNIVERSIDAD DE LA FRONTERA	608.46	41.61%	7.10%	0.00%	14.29%	0.00%	18.90%	43.79%	0.00%	15.91%	37,144
UNIVERSIDAD METROPOLITANA DE CIENCIAS DE LA EDUCACION	603.64	32.79%	0.00%	0.00%	98.69%	0.00%	1.31%	0.00%	0.00%	0.00%	30,487
UNIVERSIDAD CATOLICA DEL NORTE	594.46	29.22%	15.94%	6.21%	3.43%	6.96%	3.06%	56.40%	0.64%	7.37%	30,747
UNIVERSIDAD DEL BIO-BIO	593.55	28.02%	10.21%	8.51%	10.15%	0.00%	4.10%	65.44%	0.00%	1.58%	44,169
UNIVERSIDAD CATOLICA DEL MAULE	586.75	24.17%	0.31%	3.36%	11.50%	6.99%	10.95%	49.95%	0.00%	16.94%	12,250
UNIVERSIDAD DE LA SERENA	576.33	13.30%	7.00%	5.06%	35.72%	0.00%	1.86%	44.99%	1.04%	4.35%	38,357
UNIVERSIDAD CATOLICA DE LA SANTISIMA CONCEPCION	568.34	9.46%	23.31%	0.00%	22.42%	11.12%	9.36%	31.50%	0.32%	1.98%	19,997
UNIVERSIDAD DE ANTOFAGASTA	566.04	16.59%	2.29%	4.13%	10.78%	4.23%	22.10%	50.02%	0.00%	6.45%	27,472
UNIVERSIDAD DE TARAPACA	562.28	13.72%	16.05%	0.00%	11.72%	4.40%	10.87%	47.98%	1.49%	7.51%	28,376
UNIVERSIDAD DE PLAYA ANCHA	560.69	7.63%	0.00%	10.48%	63.27%	0.00%	3.16%	10.98%	7.99%	4.12%	34,220
UNIVERSIDAD DE MAGALLANES	550.11	2.36%	14.53%	0.97%	18.40%	2.39%	11.90%	46.30%	0.00%	5.52%	11,124
UNIVERSIDAD CATOLICA DE TEMUCO	547.87	6.80%	0.11%	0.00%	30.71%	10.78%	0.00%	53.49%	4.91%	0.00%	17,247
UNIVERSIDAD ARTURO PRAT	541.29	2.14%	25.99%	3.51%	12.69%	7.55%	6.46%	35.99%	2.12%	5.68%	22,677
UNIVERSIDAD DE ATACAMA	540.19	1.04%	0.00%	0.00%	22.69%	8.77%	0.00%	65.14%	3.09%	0.31%	13,707
UNIVERSIDAD DE LOS LAGOS	529.15	0.04%	14.15%	12.57%	33.39%	0.00%	0.82%	27.14%	0.00%	11.92%	14,603
Professional Institutes											
ACADEMIA SUPERIOR DE CIENCIAS PEDAGOGICAS DE SANTIAGO	641.96	88.51%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3,960
INSTITUTO PROFESIONAL DE SANTIAGO	641.54	79.90%	12.79%	11.37%	0.00%	0.00%	0.00%	65.85%	4.93%	5.06%	13,500
ACADEMIA SUPERIOR DE CIENCIAS DE VALPARAISO	590.89	16.00%	0.00%	0.00%	97.91%	0.00%	0.00%	0.00%	2.09%	0.00%	4,645
INSTITUTO PROFESIONAL DE CHILLAN	575.89	8.52%	10.06%	6.61%	71.28%	0.00%	12.06%	0.00%	0.00%	0.00%	4,345
INSTITUTO PROFESIONAL DE VALDIVIA	562.26	0.52%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	3,489
INSTITUTO PREFESIONAL DE IQUIQUE	556.50	0.77%	21.59%	0.00%	35.23%	0.00%	0.00%	43.18%	0.00%	0.00%	1,940
INSTITUTO PROFESIONAL DE OSORNO	541.38	0.49%	8.07%	0.00%	60.29%	0.00%	0.00%	19.86%	0.00%	11.79%	10,905

Notes: Ave. score is the average entrance exam score of admittees from 1982 through 2006. Selective is defined as being above the degree-level median for average admission cutoff across the sample. Source: Authors' calculations from administrative data.

TABLE A.I.II

DESCRIPTIVE STATISTICS ON APPLICATIONS AND CHOICES

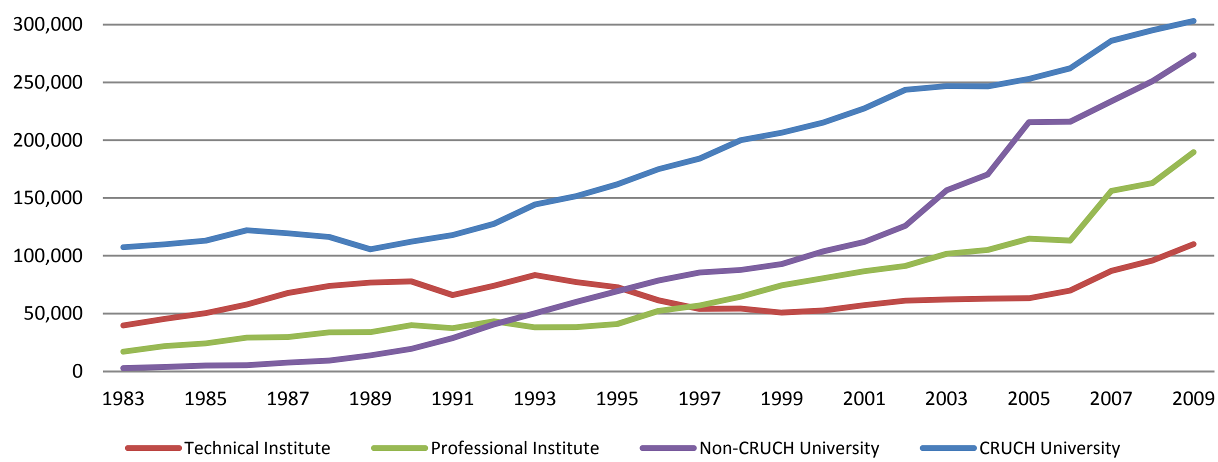
(1) Year	(2) # Choices (SD)	(3) PSU Dist. from 1st Choice Cutoff	(4) PSU Dist, from Last Choice Cutoff	(5) Ave. # Dif. Narrow Fields Listed	(6) Ave. # of Dif. Areas Listed	(7) Ave. # of Dif. Institutions Listed	(8) # of Dif. Selectivity Tiers Listed	(9) Percent Accepted at 1st Choice	(10) Ave. Rank of 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.

1.2 Total Enrollment by College Type

This section describes how total enrollment by each college type evolves over time using data from Rolando (2010).[2] Figures A.I.I and A.I.II show graphically how enrollment in each type of institution varies over time in terms of total enrollment and share of total enrollment, respectively. While enrollment in professional institutes and technical institutes (offering professional/vocational and technical degrees) remained relatively steady until 2005, enrollment in private non-CRUCH universities expanded steadily starting in the early 1990s. In 1985, CRUCH enrollment was 96% of all university enrollment. By 1995 it was 70%, and by 2005 it was 54%. Figure A.I.III shows CRUCH enrollment as a fraction of all university enrollment.

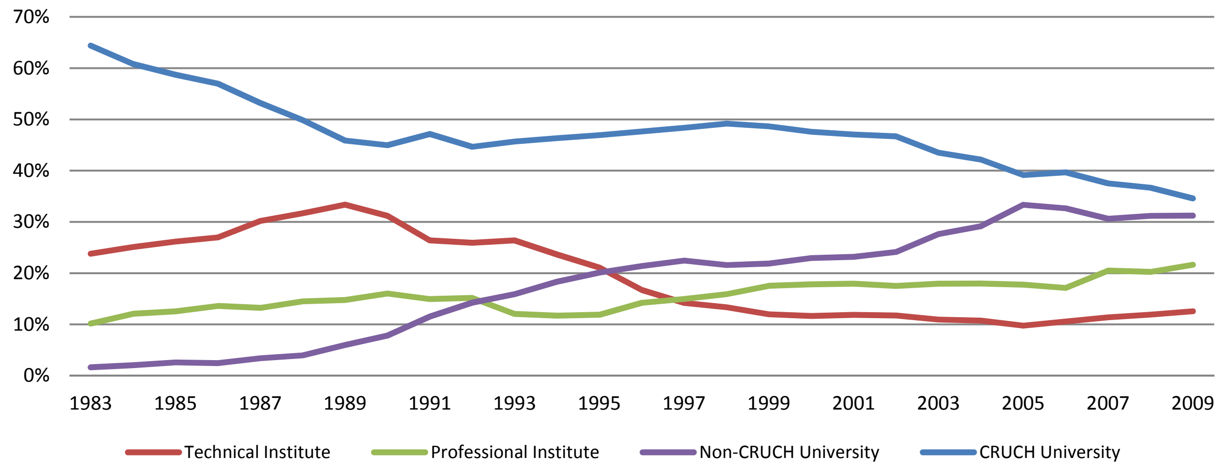
FIGURE A.I.I
Enrollment by Institution Type over Time (1983-2009)



Note: Uses data from Rolando (2010) on aggregate college enrollment from 1983-2009 by type of college.

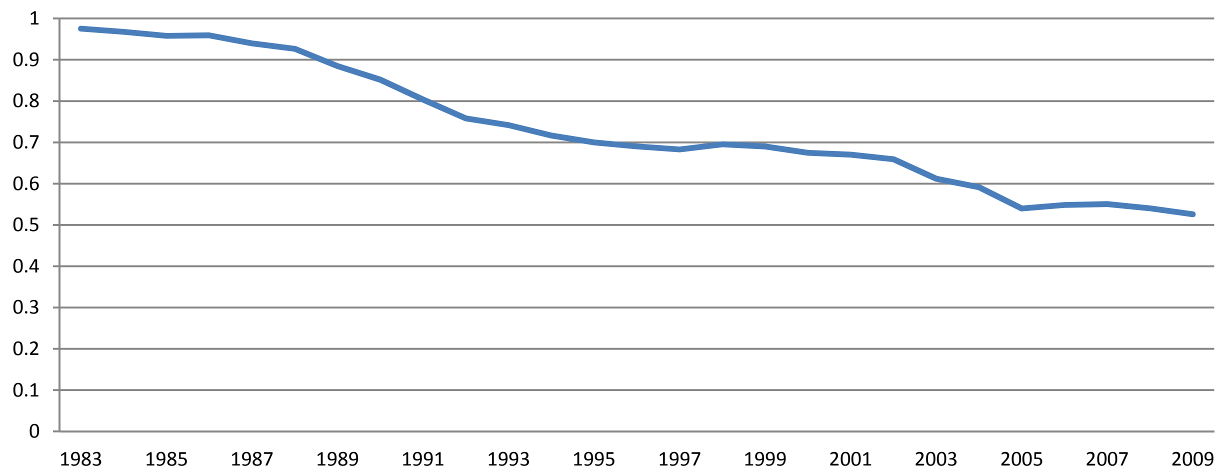
[2] We thank Rodrigo Rolando for his generous help and support in providing us with the underlying data from his report.

FIGURE A.I.II
Percentage of All Enrollment by Institution Type over Time (1983-2009)



Note: Uses data from Rolando (2010) on aggregate college enrollment from 1983-2009 by type of college.

FIGURE A.I.III
CRUCH Enrollment as a Fraction of all University Enrollment (1983-2009)



Note: Uses data from Rolando (2010) on aggregate college enrollment from 1983-2009 by type of college.

1.3 Outside Options for Those Admitted to Non-Selective CRUCH Options

Tables A.I.III through A.I.V show where students in our marginal regression discontinuity sample who were not admitted to any marginal CRUCH degree enrolled. We show same-year enrollment and enrollment within two years of initial application. While the set of available postsecondary options is clearly different in the 2000s than in the 1980s and 1990s, these statistics are still informative. We focus our discussion on data from the year 2000; data from 2001-2006 are presented as well.

Table A.I.III shows that 21 percent of students initially rejected from selective CRUCH options enroll in a selective CRUCH choice off of a waitlist, and approximately 26 percent of students end up re-applying and being admitted to a CRUCH option within two years after their original application. 16% enroll in a private non-CRUCH university within two years. Private university enrollment grows sharply from 15.7% in for the 2000 entering cohort to 31.2% for the 2006 cohort. During that time, private non-CRUCH university enrollment share grew from 33% to 46% of university enrollment, closely matching this increase. This suggests that for most of our sample, when private universities were a small share of overall university enrollment, this outside option share was likely also small. 4 to 6% of students enroll in a professional or technical degree outside of CRUCH, and 24% enroll in no postsecondary institution within two years. This number fell from 23.7% in 2000 and 3.3% in 2006 as students substituted into private universities.

Table A.I.III. Outside Options for Those Not Admitted to Selective CRUCH Option

	(1)	(2)	(3)	(4)	(5)	(6)
Application Year	CRUCH Admit	Enrolled in CRUCH off Wait List	Enrolled in non-CRUCH Univ.	Enrolled in Prof. or Tech. Inst.	Enrolled Nowhere	N
Same Year as Application						
2000	8.30%	20.60%	10.70%	3.70%	56.60%	10,325
2001	9.40%	16.70%	13.80%	4.30%	55.70%	15,444
2002	7.10%	13.90%	16.20%	4.70%	57.90%	14,564
2003	9.40%	13.70%	21.00%	5.80%	49.80%	11,429
2004	18.20%	12.60%	25.80%	3.80%	39.10%	4,708
2005	18.60%	9.30%	18.80%	4.80%	48.50%	13,102
2006	25.10%	9.50%	24.00%	4.20%	37.00%	15,235
Within Two Years of Application						
2000	29.10%	25.80%	15.70%	5.70%	23.70%	10,325
2001	32.00%	20.30%	17.30%	7.00%	23.20%	15,444
2002	31.80%	17.80%	23.10%	7.40%	19.70%	14,564
2003	26.70%	16.30%	27.60%	8.20%	21.00%	11,429
2004	33.70%	14.40%	28.90%	5.60%	17.00%	4,708
2005	39.10%	15.20%	30.70%	9.20%	5.70%	13,102
2006	41.70%	14.90%	31.20%	8.80%	3.30%	15,235

Notes: Sample is at the year-student-application level and is all of those that were not admitted to a selective CRUCH degree and were in our marginal RD sample. Column 1 is based on administrative data of CRUCH application results and does not include being admitted from a wait-list. Columns 2-5 are based on administrative enrollment records for all postsecondary institutions. Within two years of application includes the application year and the following two years, for a total of up to three application cycles. These statistics are for where the student was first admitted or enrolled if they enrolled in multiple types of institutions during those three years

Tables A.I.IV and A.I.V present the same statistics broken down by student socioeconomic status (SES) (coming from Poverty A, B, or C high schools vs. Poverty D or E schools), and by the selectivity of the target degree in our regression-discontinuity sample. Overall, high-SES students are more likely to go to a private university. Low-SES students are more likely to enroll in a technical or professional. Students applying to more-selective CRUCH degrees are more likely to go to a private university, less likely to enroll in a technical or professional institute, and are less likely to enroll in no postsecondary education.

Table A.I.IV Outside Options for Those Not Admitted to Selective CRUCH Option by Socioeconomic Status

Application Year	(1) CRUCH Admit	(2) Enrolled CRUCH off Wait-List	(3) Enrolled in non-CRUCH Univ.	(4) Enrolled in Prof. or Tech. Inst.	(5) Enrolled Nowhere	(6) N
Panel A: Same Year as Application						
Low Socioeconomic Status						
2000	9.4%	22.2%	7.2%	5.0%	56.3%	5,162
2001	10.1%	17.4%	8.8%	5.1%	58.6%	7,770
2002	7.4%	14.1%	11.8%	5.9%	60.8%	6,909
2003	10.6%	13.2%	14.7%	7.8%	53.5%	5,632
2004	21.2%	15.7%	15.6%	4.9%	42.5%	2,421
2005	22.2%	10.4%	11.5%	6.5%	49.3%	7,197
2006	28.5%	10.8%	16.8%	5.3%	38.4%	8,724
High Socioeconomic Status						
2000	7.0%	16.0%	17.8%	2.0%	57.1%	3,201
2001	7.3%	15.9%	24.4%	3.0%	49.1%	4,712
2002	5.9%	12.6%	26.5%	2.9%	52.0%	4,410
2003	7.0%	12.9%	32.6%	2.9%	44.3%	3,457
2004	14.9%	8.1%	38.9%	2.4%	34.9%	1,908
2005	13.8%	7.6%	28.7%	2.6%	47.2%	5,239
2006	19.9%	7.7%	34.7%	2.7%	34.8%	5,981
Panel B: Within Two Years of Application						
Low Socioeconomic Status						
2000	32.3%	26.3%	10.0%	7.5%	23.9%	5,162
2001	33.6%	20.3%	12.3%	8.8%	25.0%	7,770
2002	33.6%	18.5%	17.0%	9.4%	21.5%	6,909
2003	30.3%	15.9%	19.1%	11.3%	23.3%	5,632
2004	37.4%	17.6%	18.5%	7.6%	18.8%	2,421
2005	43.6%	15.5%	20.7%	12.5%	7.5%	7,197
2006	45.1%	15.8%	23.4%	11.2%	4.1%	8,724
High Socioeconomic Status						
2000	26.9%	23.2%	26.6%	2.9%	20.3%	3,201
2001	29.0%	20.9%	28.2%	4.0%	17.6%	4,712
2002	28.2%	16.3%	37.1%	3.9%	14.3%	4,410
2003	23.9%	15.0%	42.5%	3.7%	14.7%	3,457
2004	30.2%	9.6%	42.8%	3.1%	13.8%	1,908
2005	33.5%	14.3%	44.7%	4.9%	2.5%	5,239
2006	36.3%	13.6%	42.8%	5.3%	1.9%	5,981

Notes: Sample is at the year-student-application level and is all of those that were not admitted to a selective CRUCH degree and were in our marginal RD sample. Column 1 is based on administrative data of CRUCH application results and does not include being admitted from a wait-list. Columns 2-5 are based on administrative enrollment records for all postsecondary institutions. Within two years of application includes the application year and the following two years, for a total of up to three application cycles. The statistics are for where the student was first admitted or enrolled if they enrolled in multiple types of institutions during those three years. Socioeconomic status is determined by high school graduated from. The Chilean Ministry of Education categorizes high schools into five categories by the poverty level of their student body. For our purposes, we categorized low socioeconomic status students as those that graduated from a high school in one of the three highest-poverty level categories, and high socioeconomic status students came from one of the two lowest-poverty level categories.

Table A.I.V Outside Options for Those Not Admitted to Selective CRUCH Option by Application Selectivity

Application Year	(1) CRUCH Admit	(2) Enrolled CRUCH off Wait-List	(3) Enrolled in non-CRUCH Univ.	(4) Enrolled in Prof. or Tech. Inst.	(5) Enrolled Nowhere	(6) N
Panel A: Same Year as Application						
Application to Less Selective Career						
2000	7.3%	22.1%	9.1%	5.0%	56.5%	6,640
2001	9.2%	15.0%	9.3%	6.0%	60.4%	9,678
2002	7.1%	13.2%	12.1%	6.3%	61.3%	9,558
2003	9.7%	13.0%	17.1%	7.6%	52.5%	8,029
2004	19.4%	16.2%	18.6%	5.5%	40.0%	2,894
2005	21.6%	10.1%	13.4%	6.5%	48.2%	6,918
2006	28.4%	10.7%	18.8%	5.5%	36.3%	8,724
Application to More Selective Career						
2000	11.7%	16.3%	14.3%	1.0%	56.5%	3,185
2001	10.6%	17.1%	22.8%	1.3%	48.0%	5,134
2002	7.2%	14.7%	24.4%	1.8%	51.8%	4,936
2003	8.8%	14.2%	30.9%	1.7%	43.8%	3,313
2004	16.4%	6.9%	37.2%	1.1%	37.5%	1,814
2005	15.3%	8.4%	24.9%	2.9%	48.4%	6,074
2006	21.2%	8.1%	31.1%	2.3%	37.2%	6,381
Panel B: Within Two Years of Application						
Application to Less Selective Career						
2000	28.9%	24.5%	12.4%	7.5%	26.8%	6,640
2001	32.1%	16.8%	13.1%	9.8%	28.2%	9,678
2002	31.4%	17.4%	17.7%	10.0%	23.5%	9,558
2003	26.9%	16.2%	22.0%	10.6%	24.2%	8,029
2004	33.6%	18.0%	21.9%	8.0%	18.1%	2,894
2005	39.4%	15.4%	24.8%	12.7%	7.6%	6,918
2006	42.0%	15.5%	26.3%	11.9%	4.2%	8,724
Application to More Selective Career						
2000	31.6%	24.9%	22.9%	2.0%	18.5%	3,185
2001	33.5%	23.2%	25.7%	2.3%	15.0%	5,134
2002	32.9%	18.1%	33.9%	2.6%	12.5%	4,936
2003	26.8%	15.5%	41.5%	2.6%	13.4%	3,313
2004	33.8%	8.6%	40.2%	1.7%	15.3%	1,814
2005	39.3%	14.2%	37.5%	5.4%	3.5%	6,074
2006	41.8%	13.3%	38.0%	4.7%	2.1%	6,381

Notes: Sample is at the year-student-application level and is all of those that were not admitted to a selective CRUCH degree and were in our marginal RD sample. Column 1 is based on administrative data of CRUCH application results and does not include being admitted from a wait-list. Columns 2-5 are based on administrative enrollment records for all postsecondary institutions. Within two years of application includes the application year and the following two years, for a total of up to three application cycles. The statistics are for where the student was first admitted or enrolled if they enrolled in multiple types of institutions during those three years. Selectivity of careers is determined by the average cutoff scores for admittance and more detail on how this was determined is available in Section 5.4.

Table A.I.VI shows the fraction of applicants in our marginal regression-discontinuity sample who were not admitted to a CRUCH degree with a binding admissions cutoff (Binding-cutoff), but were admitted to a non-selective CRUCH degree that year. Table A.I.VII shows the fraction of rejected applicants in our marginal regression-discontinuity sample who were admitted to a CRUCH degree within two years of initial application. These statistics are similar to those presented in Table A.I.IV, but focus on admission, not matriculation, and use data for the older cohorts in the 1980s and 1990s. Matriculation data is not available for these students.

Finally, Table A.I.VIII describes the characteristics of CRUCH degrees with binding admissions cutoffs relative to the full sample. We refer to these degrees as "inside option." Degrees with no binding admissions thresholds are referred to as "outside option" degrees. The inside option degrees are very similar to the full sample of degrees, but have slightly higher-scoring applicants. Consequently, the 10% of the sample admitted to "outside option" CRUCH degrees are admitted to degrees with a substantially lower scoring student body population. Degrees with no binding admissions thresholds tend to admit lower-scoring students and also to be located in remote areas where demand is low (for example Universidad de Magallanes, which located outside of Punta Arenas in the Chilean Antarctic).

Table A.I.VI. How many not admitted to binding-cutoff CRUCH option accepted to CRUCH career in same year?

		Selectivity of Target Application		Area of Target Application							
Application Year	All	Less Sel.	More Sel.	Bus.	Art/Arch.	Educ.	Soc. Sci.	Health	Sci/Tech	Hum.	Law
1982	33.9%	24.5%	46.3%	45.1%	48.3%	24.1%	69.4%	41.5%	39.4%	23.1%	33.8%
1983	14.8%	6.9%	23.2%	17.6%	37.0%	13.8%	19.8%	13.7%	13.3%	24.2%	30.1%
1984	16.6%	8.3%	34.4%	19.2%	35.9%	19.1%	46.1%	22.0%	12.1%	31.9%	26.1%
1985	17.0%	12.1%	24.9%	15.4%	38.7%	15.6%	15.1%	19.4%	16.3%	25.5%	20.0%
1986	23.2%	12.5%	36.1%	22.6%	36.5%	32.1%	21.1%	27.2%	18.0%	44.3%	27.2%
1987	13.2%	7.8%	20.0%	8.3%	23.0%	22.0%	12.8%	16.9%	10.0%	7.1%	32.1%
1988	21.6%	15.1%	26.6%	17.3%	30.1%	28.5%	14.0%	21.5%	20.8%	32.1%	25.3%
1989	31.2%	20.6%	42.6%	24.0%	50.0%	41.7%	31.4%	24.1%	28.1%	48.5%	47.7%
1990	25.1%	22.4%	27.6%	18.7%	30.6%	38.2%	23.1%	27.7%	18.0%	30.5%	40.4%
1991	23.0%	21.7%	25.0%	23.1%	24.0%	27.6%	28.2%	20.5%	20.2%	23.2%	27.4%
1992	17.2%	15.7%	18.5%	24.4%	26.3%	17.7%	15.9%	12.3%	15.2%	13.2%	23.1%
1993	19.1%	14.4%	25.4%	26.4%	22.6%	21.8%	13.8%	27.7%	16.4%	20.3%	22.0%
1994	20.2%	19.0%	22.6%	23.1%	26.6%	20.4%	12.8%	29.1%	17.6%	9.1%	24.3%
1995	13.9%	13.8%	14.2%	17.6%	11.4%	6.1%	15.8%	19.4%	15.1%	4.9%	11.2%
1996	14.1%	12.2%	15.6%	8.2%	12.4%	4.8%	12.5%	23.3%	18.8%	13.1%	8.8%
1997	7.5%	6.2%	9.3%	10.2%	7.6%	3.4%	6.3%	7.0%	9.4%	1.3%	5.0%
1998	11.0%	8.3%	15.7%	16.9%	13.0%	7.3%	11.5%	11.1%	12.2%	0.8%	11.6%
1999	5.2%	3.9%	7.0%	5.5%	6.6%	4.3%	2.1%	7.0%	5.6%	3.7%	4.3%

Notes: Sample is at the year-student-application level and is all of those that were not admitted to a selective CRUCH degree and were in our marginal RD sample. Selectivity of careers is determined by the average scores for admitted students. See section 5.4 for more detail.

TABLE A.I.VII

How many of those not admitted to a Binding-RD CRUCH option are accepted to any CRUCH career within two years?

		Selectivity of Target Application		Area of Target Application						
Application Year	All	Less Sel.	More Sel.	Art/Arc.	Business	Educ.	Health	Hum.	SS/Law	Sci./Tec.
1985	44.2%	39.6%	58.8%	57.1%	38.2%	40.4%	63.0%	57.9%	48.4%	43.9%
1986	45.3%	41.1%	55.6%	52.8%	38.4%	56.5%	60.9%	54.6%	47.3%	39.1%
1987	40.3%	35.5%	50.6%	46.4%	31.1%	48.1%	52.5%	41.0%	45.8%	37.9%
1988	42.5%	42.5%	42.5%	50.9%	32.0%	53.8%	47.5%	47.4%	40.4%	41.3%
1989	48.6%	44.8%	54.7%	65.3%	33.4%	63.4%	55.5%	73.7%	60.1%	44.5%
1990	49.4%	47.2%	52.7%	56.5%	36.5%	51.4%	59.5%	54.5%	57.0%	47.9%
1991	46.0%	44.1%	49.4%	51.7%	43.3%	46.8%	49.3%	49.5%	50.0%	44.5%
1992	44.1%	41.3%	48.0%	40.4%	39.5%	37.9%	53.1%	43.2%	44.8%	46.1%
1993	40.5%	38.7%	45.0%	45.8%	32.1%	38.4%	51.6%	33.7%	41.9%	40.7%
1994	41.8%	41.6%	42.3%	49.8%	34.6%	45.7%	50.7%		46.2%	38.2%
1995	36.1%	33.9%	38.9%	23.4%	30.4%	25.8%	46.1%	13.9%	38.9%	41.2%
1996	34.9%	33.3%	36.3%	31.2%	27.4%	20.1%	43.9%	38.6%	32.5%	42.0%
1997	31.4%	30.0%	33.2%	29.4%	27.1%	20.4%	39.6%	27.7%	28.6%	34.9%
1998	27.7%	25.3%	31.4%	24.4%	24.9%	21.3%	38.5%	21.8%	24.6%	29.3%
1999	30.3%	28.8%	32.8%	28.9%	29.9%	23.8%	42.7%	25.1%	27.4%	31.4%

Notes: Sample is at the year-student-application level and is all of those that were not admitted to a selective CRUCH degree and were in our marginal RD sample. Selectivity of careers is determined by the average scores for admitted students. See section 5.4 for more detail. Includes the application year and the following two years, for a total of up to three application cycles.

Table A.I.VIII Description of Inside Option CRUCH Degrees

	Full sample			Inside Option Degrees		
	N programs	N Applications	Mean Accepted Score	N programs	N Applications	Mean Accepted Score
Pooled	1,931	2,382,656	623	1,103	2,102,360	628
By Area:						
Business	135	204,886	625	80	188,179	630
Art/Architecture	84	137,514	650	49	121,756	652
Education	364	402,361	576	212	338,848	579
Social Science	31	92,453	661	25	90,990	663
Health	132	309,723	670	102	294,949	673
Science/Technology	785	893,453	621	462	797,655	623
Humanities	59	56,011	621	32	51,112	626
Law	112	180,978	640	70	159,858	645

Notes: Data are at application level. Full sample includes all CRUCH degrees in the 1985-2006 application cohorts. Inside Option degrees are those for which we are able to estimate threshold-crossing effects. Mean accepted scores are the average of math and language test scores for accepted students

2 Centralized CRUCH Applications, Scoring, and Admissions

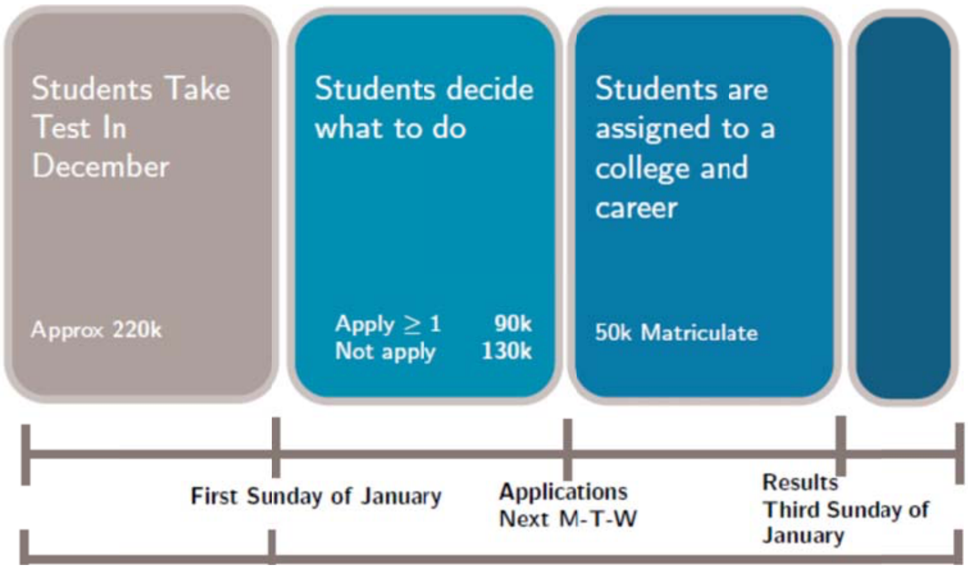
2.1 Background

CRUCH applications have been centrally processed since the early 1970s. Applicants are required to take a national standardized exam. Up until 2003, this exam was called the Academic Aptitude Test, or PAA, (*Prueba de Aptitud Académica*). The PAA test was discontinued after 2003 and replaced with the University Selection Test, or PSU (*Prueba de Selección Universitaria)*. To the best of our knowledge, the application process has otherwise been unchanged.

Prospective students sign up for the PSU during the academic year, and everyone must take the test on the same day in December. There is only one chance to take the test each year. Scores are then posted in newspapers and online. A week after scores are published, prospective students have three days to submit their college applications using these scores. Figure A.II.I shows the timeline of college admissions. The college application consists of a list of one to eight college and major combinations. Students are then assigned to college and major combinations according to their composite scores, in order of the highest to lowest scoring applicants, until all spots are filled. Notice that this method does not maximize first choice assignment; the slots are allocated to the students with the highest composite score who have indicated they want to attend.

FIGURE A.II.I

Example Timeline from Application Year 2008



Students' composite scores are calculated as a weighted average of their different test scores (math, language, history, and specific tests such as physics, path, etc.) and their GPA. This composite score varies across college and major combinations, as every college and major can choose its own combination of weights.

The applications consist of a list of options and a composite score for each of these options. The composite score depends on the students' test scores and the weights given to each of these scores by each college and major combination.

For example, take a student who scores 500 on math, 400 on verbal and has a GPA that gives him 700 points. The student then applies to College A – Major A, College B – Major A and College A, Major B. For each option, the way the scores are weighted is different so that the student has three composite scores, one for each application option.

FIGURE A.II.II

Examples of Composite Score Weighting Differences

		Weights			
Option	College –Major	Math	Verbal	GPA	Composite Score
1	College A - Major A	0.4	0.4	0.2	500
2	College B - Major A	0.3	0.3	0.4	550
3	College A - Major B	0.2	0.4	0.4	540
4	.				
5	.				
6	.				
7	.				
8	.				

The assignment mechanism can be described as follows:

1. Take every student’s first option and assign them to that option.
2. Rank the students by their composite score and drop students that are ranked below the allotted spots for that option.
3. Take all students who did not get into their first option. Assign them to their second option and rank the students by composite score, dropping the students who are ranked below the allotted spots. Note that some that were assigned in the first round may now be dropped.
4. Take all students who have not yet been assigned, or were dropped in the previous round, and assign them to their next listed preference. Rank the students by composite score at each option, again dropping the students who are ranked below the allotted spots. Note that once again, some students who were previously assigned are dropped because other students who ranked the option lower in their preferences have higher scores and still want to go there.
5. Repeat step 4 until all students’ options have been exhausted.

The results of this process are published in newspapers in the form of acceptance and wait lists. These lists are ordered by "composite score" and their relative spot on the list is noted. Students who are not accepted, but put on a wait list, are possibly accepted to one of their less preferred options.

3 Digitization Process for Historic Student Data

3.1 Historic Entrance Exam and CRUCH Admissions

We partnered with several government agencies to compile and digitize the data used in several research projects related to the higher education system in Chile. Prior to this work, detailed administrative databases for tertiary education outcomes were available only for the last five to ten years.. We developed longer time series by collecting and digitizing information from public and private records available from different stakeholders in the higher education system in Chile.

The data compilation efforts used in this particular project focused on recreating administrative databases of the college applications process. In Chile, students planning on applying to institutions of higher education take a college admissions test which is administered by an institution called DEMRE.[3] This institution is run by CRUCH. The admissions test score is then used in a centralized admissions process to determine the allocation of students to majors and institutions among CRUCH. This admissions process is based solely on observable test scores and grades (see Section 2 for more detail on the application process). Digital administrative data on college applications was available from 2001 onward. Records of test scores beginning in 1980 were available in DEMRE archives, but only in hard copy. We assembled college application results from newspaper publications contained in a restricted archive within the Biblioteca Nacional, the Chilean equivalent of the Library of Congress.

[3] *Departamento de Evaluación, Medición y Registro Educacional*, or Department of Educational Evaluation, Measurement, and Registration, DEMRE is responsible for the development and construction of evaluation mechanisms to measure the abilities of students who have graduated from high school. This institution is in charge of implementing the college application and selection process in Chile. www.demre.cl

3.2 Entrance Exam Data from 1980-2000

Test score results are kept in large books at DEMRE. These books are the sole reference for old test score results. An individual's test score prior to 1989 can be found by looking in two different books. One contains a reference number and personal information such as ID number (RUT), name, sex, year of graduation, region, school code, etc. The second contains information such as the reference number (same as in the first book), test scores and high school GPA. We used the reference numbers to link information from each source to individual characteristics, and, critically, test scores.

Each year of data consisted of approximately 10-12 books with 300-400 pages each. Over several months, our team of four to eight researchers photographed each page and created digital copies of the books. We photographed the books because DEMRE deemed scanning them to be impossible based on their large size as well as their fragile state. The images were then sent to a data entry firm which captured the data in two different spreadsheets based on the type of book (scores vs. individual characteristics). To validate the data entry, the spreadsheet immediately verified RUT numbers using a formula based on the digits used in the RUT.

Once the data had been entered, we merged the two sources of data together by the identification number (RUT). Some observations were lost because the person did not have a RUT associated with their score. In a second round of data collection, we collected another set of images for all the data that was not merging and entered it again. The process required approximately 63.8 million keystrokes and is described in Table A.III.I below. Figures A.III.I through A.III.III provide examples of each record type, with personal data obscured.

TABLE A.III.I
Number of Typed Observations

Year	Score Data	Valid Score Data	RUT Data	Valid RUT Data	Total	Merge Rate
1980	120,525	110,859	120,373	91,235	109,542	90%
1981	127,048	117,403	126,769	108,312	117,514	92%
1982	114,840	109,109	114,504	103,101	108,415	94%
1983	124,007	119,171	123,779	116,157	119,521	95%
1984	127,205	122,192	127,019	121,024	120,166	92%
1985	127,953	121,263	127,763	123,071	123,859	96%
1986	131,931	125,799	131,922	126,471	128,646	97%
1987	118,725	114,950	118,308	116,479	113,546	93%
1988	115,492	110,925	115,165	112,197	110,583	94%

Note: Validation of information was possible for RUT data due to the internal consistency check provided by the RUT number. The validation of score data was done by requiring test scores in both math and reading. Merge rates are calculated with validated observation by joining score data and RUT data by the unique registration number.

TABLE A.III.II
Number of Valid RUT Observations

Year	Total N with RUT	Percent Male	Just Graduated High School
1980	81,104	53%	65%
1981	99,231	53%	66%
1982	94,882	53%	70%
1983	109,294	52%	67%
1984	111,371	50%	63%
1985	114,816	51%	60%
1986	119,089	51%	59%
1987	109,095	50%	59%
1988	105,550	50%	60%

FIGURE A.III.I

Examples of Newspaper Publication of Test Scores

FIGURE A.III.II

Example Page from “Score” Books of Administrative Data From DEMRE

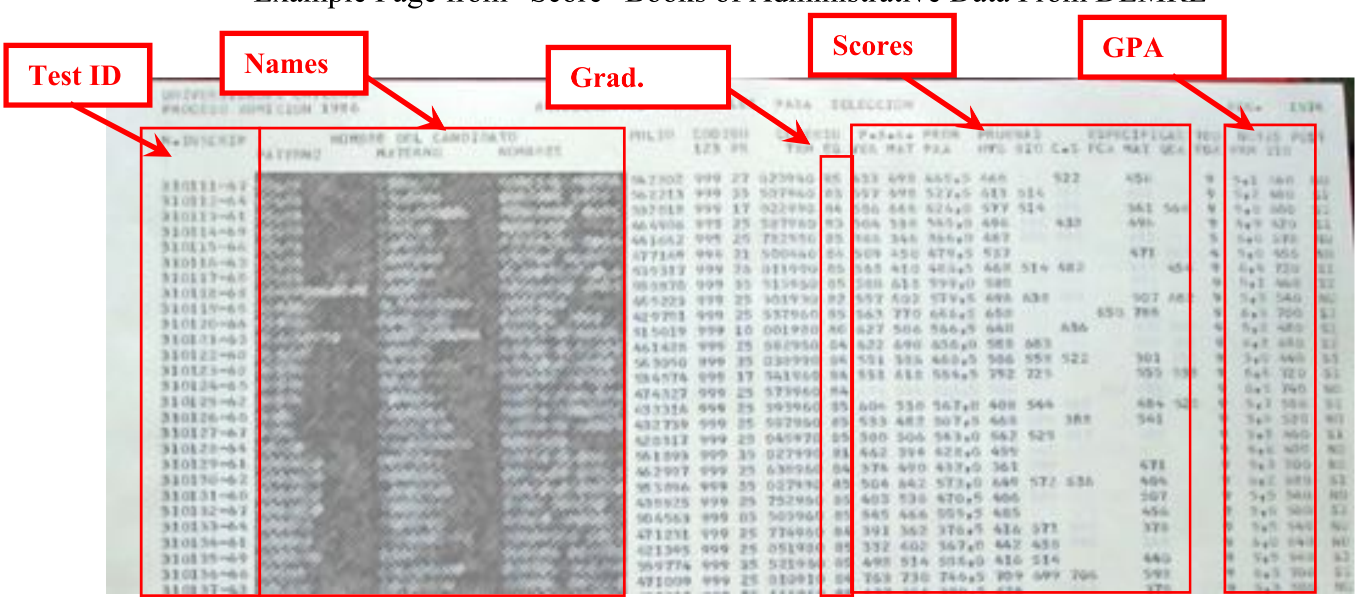


Figure A.III.III

Example of "RUT" Books from Administrative Records From DEMRE

Note: Personal information intentionally blurred.

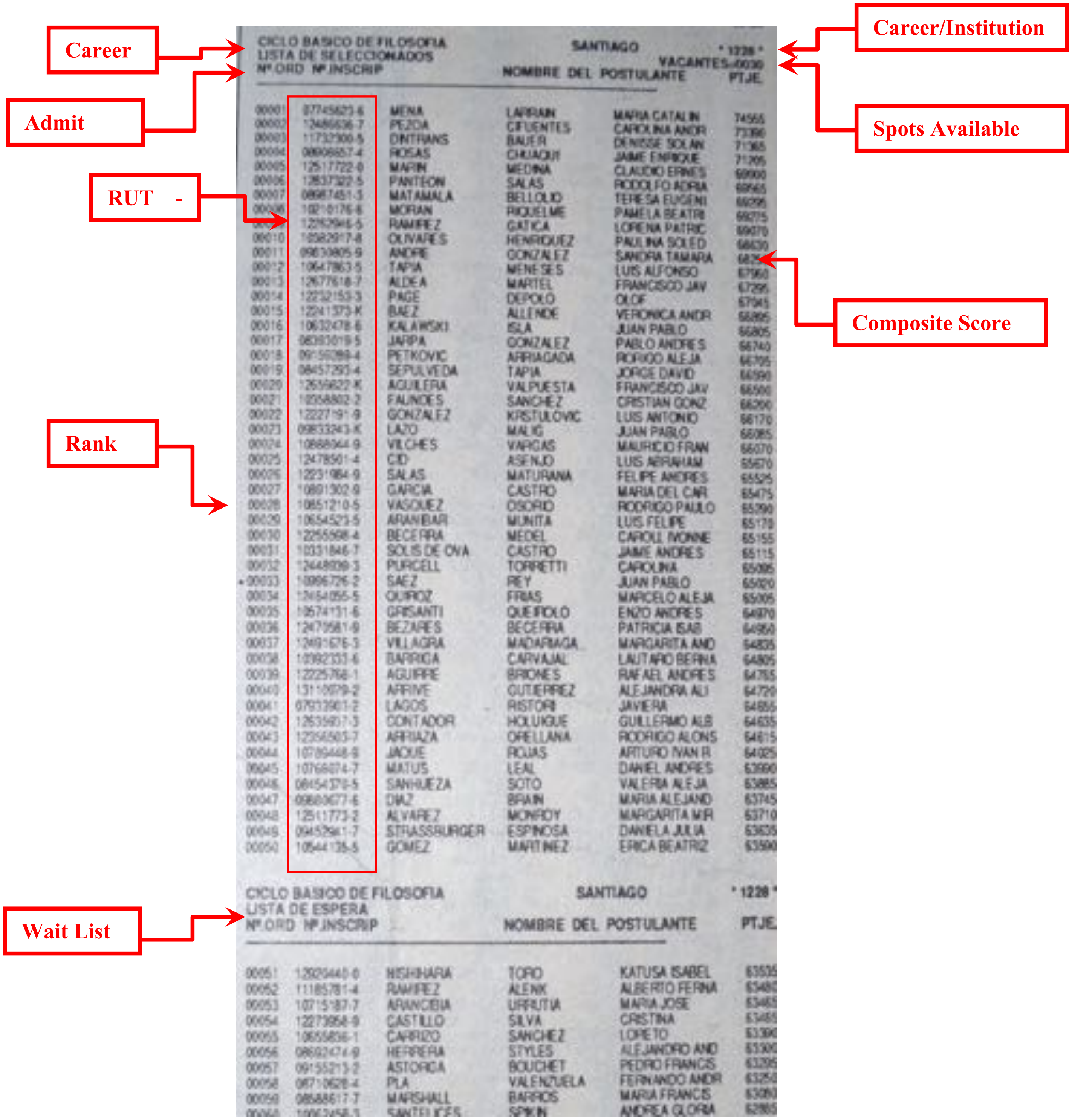
3.3 College Applications and Results Data 1982-2000

Data on college admissions was not available in digital format and no administrative source of written record exists as it is not used for any reference purposes. However, we were able to find newspaper publications of these lists for the years 1982 to 2000 at the National Library (*Biblioteca Nacional)*. Our team photographed each acceptance list and waitlist. These images were then sent for data entry.

From 1989 onward, newspapers published the individuals' RUTs and names. Before 1989 however, newspapers published the Test ID instead of the RUT. It was therefore necessary to also capture the Test ID and then to merge that using the typed and merged data for Test ID and RUT described in the previous section. This process required 19.3 million keystrokes. Figures A.III.IV and A.III.V present examples of newspaper records.

FIGURE A.III.IV

Example of Results Published In Newspaper from 1992 (Post-1989 Format)



CICLO BASICO DE FILOSOFIA SANTIAGO * 1228 *
LISTA DE SELECCIONADOS VACANTES-0030

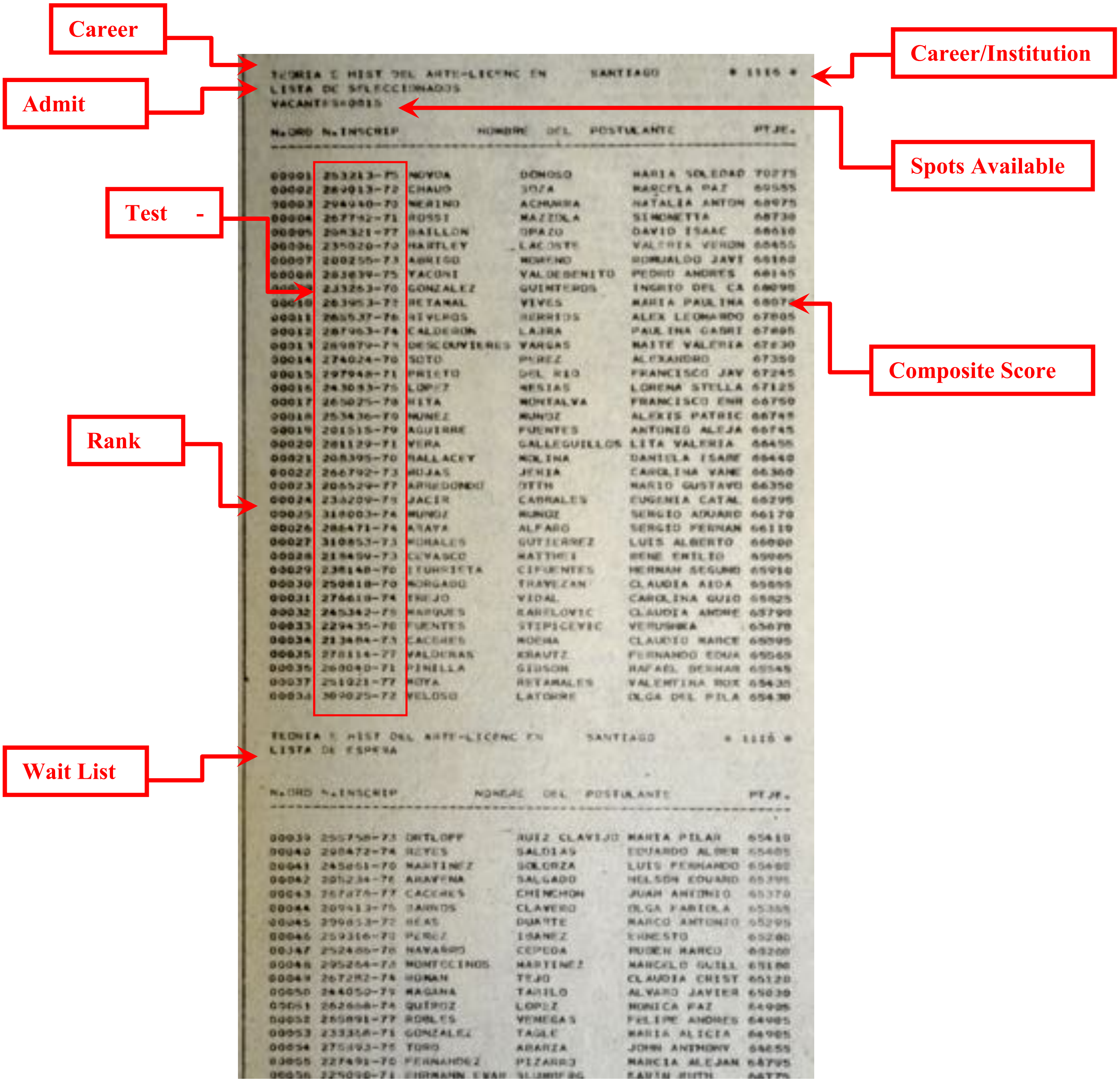
Nº ORD	Nº INSCRIP	NOMBRE DEL POSTULANTE			PTJE.
00001	07745623-6	MENA	LARRAIN	MARIA CATALIN	74555
00002	12486636-7	PEZOA	CIFUENTES	CAROLINA ANDR	73390
00003	11732300-5	DINTRANS	BAUER	DENISSE SOLAN	71365
00004	08906657-4	ROSAS	CHUAQUI	JAIME ENRIQUE	71295
00005	12517722-0	MARIN	MEDINA	CLAUDIO ERNES	69900
00006	12837322-5	PANTEON	SALAS	RODOLFO ADRIA	69565
00007	08987451-3	MATAMALA	BELLOLIO	TERESA EUGENI	69295
00008	10218176-6	MORAN	RIQUELME	PAMELA BEATRI	69275
00009	12262946-5	RAMIREZ	GATICA	LORENA PATRIC	69070
00010	10582917-8	OLIVARES	HENRIQUEZ	PAULINA SOLED	68630
00011	09830805-9	ANDRE	GONZALEZ	SANDRA TAMARA	682[illegible]
00012	10647863-5	TAPIA	MENESES	LUIS ALFONSO	67960
00013	12677618-7	ALDEA	MARTEL	FRANCISCO JAV	67295
00014	12232153-3	PAGE	DEPOLO	OLOF	67045
00015	12241373-K	BAEZ	ALLENDE	VERONICA ANDR	66895
00016	10632478-6	KALAWSKI	ISLA	JUAN PABLO	66805
00017	08393019-5	JARPA	GONZALEZ	PABLO ANDRES	66740
00018	09156089-4	PETKOVIC	ARRIAGADA	RODRIGO ALEJA	66705
00019	08457293-4	SEPULVEDA	TAPIA	JORGE DAVID	66590
00020	12659622-K	AGUILERA	VALPUESTA	FRANCISCO JAV	66500
00021	10358802-2	FAUNDES	SANCHEZ	CRISTIAN GONZ	66290
00022	12227191-9	GONZALEZ	KRSTULOVIC	LUIS ANTONIO	66170
00023	09833243-K	LAZO	MALIG	JUAN PABLO	66085
00024	10888044-9	VILCHES	VARGAS	MAURICIO FRAN	66070
00025	12478501-4	CID	ASENJO	LUIS ABRAHAM	65670
00026	12231984-9	SALAS	MATURANA	FELIPE ANDRES	65525
00027	10891302-9	GARCIA	CASTRO	MARIA DEL CAR	65475
00028	10851210-5	VASQUEZ	OSORIO	RODRIGO PAULO	65390
00029	10654523-5	ARANIBAR	MUNITA	LUIS FELIPE	65170
00030	12255598-4	BECERRA	MEDEL	CAROLL IVONNE	65155
00031	10331846-7	SOLIS DE OVA	CASTRO	JAIME ANDRES	65115
00032	12448939-3	PURCELL	TORRETTI	CAROLINA	65095
• 00033	10996726-2	SAEZ	REY	JUAN PABLO	65020
00034	12454055-5	QUIROZ	FRIAS	MARCELO ALEJA	65005
00035	10574131-6	GRISANTI	QUEIROLO	ENZO ANDRES	64970
00036	12479581-9	BEZARES	BECERRA	PATRICIA ISAB	64950
00037	12491676-3	VILLAGRA	MADARIAGA	MARGARITA AND	64835
00038	10992333-6	BARRIGA	CARVAJAL	LAUTARO BERNA	64805
00039	12225768-1	AGUIRRE	BRIONES	RAFAEL ANDRES	64755
00040	13110979-2	ARRIVE	GUTIERREZ	ALEJANDRA ALI	64720
00041	07933901-2	LAGOS	RISTORI	JAVIERA	64655
00042	12535907-3	CONTADOR	HOLUIGUE	GUILLERMO ALB	64635
00043	12356503-7	ARRIAZA	ORELLANA	RODRIGO ALONS	64615
00044	10789448-8	JACUE	ROJAS	ARTURO IVAN R	64025
00045	10766074-7	MATUS	LEAL	DANIEL ANDRES	63990
00046	08454370-5	SANHUEZA	SOTO	VALERIA ALEJA	63885
00047	09880677-6	DIAZ	BRAIN	MARIA ALEJAND	63745
00048	12511773-2	ALVAREZ	MONROY	MARGARITA MIR	63710
00049	09452941-7	STRASSBURGER	ESPINOSA	DANIELA JULIA	63635
00050	10544135-5	GOMEZ	MARTINEZ	ERICA BEATRIZ	63590

CICLO BASICO DE FILOSOFIA SANTIAGO * 1228 *
LISTA DE ESPERA

Nº ORD	Nº INSCRIP	NOMBRE DEL POSTULANTE			PTJE.
00051	12925440-0	NISHIHARA	TORO	KATUSA ISABEL	6353[illegible]
00052	11185781-4	RAMIREZ	ALENIK	ALBERTO FERNA	6348[illegible]
00053	10715187-7	ARANCIBIA	URRUTIA	MARIA JOSE	6346[illegible]
00054	12273958-9	CASTILLO	SILVA	CRISTINA	6346[illegible]
00055	10655836-1	CARRIZO	SANCHEZ	LORETO	6339[illegible]
00056	08692474-9	HERRERA	STYLES	ALEJANDRO AND	6330[illegible]
00057	09155213-2	ASTORCA	BOUCHET	PEDRO FRANCIS	6329[illegible]
00058	08710628-4	PLA	VALENZUELA	FERNANDO ANDR	6325[illegible]
00059	08588617-7	MARSHALL	BARROS	MARIA FRANCIS	630[illegible]
000[illegible]	[illegible]	SANTELICES	SPIKIN	ANDREA GLORIA	628[illegible]

FIGURE A.III.V

Example of Results Published in Newspaper from 1985 (Pre-1989 Format)



TEORIA E HIST DEL ARTE-LICENC EN SANTIAGO * 1116 *
LISTA DE SELECCIONADOS
VACANTES=0015

N.ORD	N.INSCRIP	NOMBRE	DEL	POSTULANTE	PTJE.
00001	253213-75	NOVOA	DONOSO	MARIA SOLEDAD	70275
00002	289013-72	CHAUD	SOZA	MARCELA PAZ	69555
00003	294940-70	MERINO	ACHURRA	NATALIA ANTON	68975
00004	267742-71	ROSSI	MAZZOLA	SIMONETTA	68730
00005	298321-77	BAILLON	OPAZO	DAVID ISAAC	68610
00006	235020-72	HARTLEY	LACOSTE	VALERIA VERON	68455
00007	200255-73	ABRIGO	MORENO	ROMUALDO JAVI	68160
00008	283039-75	YACONI	VALDEBENITO	PEDRO ANDRES	68145
00009	233263-70	GONZALEZ	QUINTEROS	INGRID DEL CA	68090
00010	283953-77	BETANAL	VIVES	MARIA PAULINA	68070
00011	265537-76	RIVEROS	BERRIOS	ALEX LEONARDO	67805
00012	287963-74	CALDERON	LAJRA	PAULINA GABRI	67805
00013	289879-75	DESCOUVIERES	VARGAS	MAITE VALERIA	67630
00014	274024-70	SOTO	PEREZ	ALEXANDRO	67350
00015	297948-71	PRIETO	DEL RIO	FRANCISCO JAV	67245
00016	243093-75	LOPEZ	MESIAS	LORENA STELLA	67125
00017	265025-78	MITA	MONTALVA	FRANCISCO ENR	66750
00018	253436-70	MUNEZ	MUNOZ	ALEXIS PATRIC	66745
00019	201515-79	AGUIRRE	FUENTES	ANTONIO ALEJA	66745
00020	281129-71	VERA	GALLEGUILLOS	LITA VALERIA	66455
00021	208395-70	BALLACEY	MOLINA	DANIELA ISABE	66440
00022	266792-73	ROJAS	JEMIA	CAROLINA VANE	66360
00023	205529-77	ARREDONDO	OTTH	MARIO GUSTAVO	66350
00024	234209-75	JACIR	CABRALES	EUGENIA CATAL	66295
00025	318003-74	MUNOZ	MUNOZ	SERGIO ADUARD	66170
00026	288471-74	ARAYA	ALFARO	SERGIO FERNAN	66110
00027	310853-73	MORALES	GUTIERREZ	LUIS ALBERTO	66000
00028	219459-73	CESVASCO	MATTHEI	RENE EMILIO	65985
00029	238140-70	ITURRIETA	CIFUENTES	HERNAN SEGUND	65910
00030	250818-70	MORGADO	TRAVEZAN	CLAUDIA AIDA	65855
00031	276610-74	TREJO	VIDAL	CAROLINA GUIO	65825
00032	245342-75	MARQUES	KARELOVIC	CLAUDIA ANDRE	65790
00033	229435-70	FUENTES	STIPICEVIC	VERUSHKA	65670
00034	213484-73	CACERES	MOENA	CLAUDIO MARCE	65595
00035	278114-77	VALDERAS	KRAUTZ	FERNANDO EDUA	65565
00036	260040-71	PINILLA	GIBSON	RAFAEL BERNAR	65545
00037	251021-77	MOYA	RETAMALES	VALENTINA ROX	65435
00038	309025-72	VELOSO	LATORRE	OLGA DEL PILA	65430

TEORIA E HIST DEL ARTE-LICENC EN SANTIAGO * 1116 *
LISTA DE ESPERA

N.ORD	N.INSCRIP	NOMBRE	DEL	POSTULANTE	PTJE.
00039	255758-73	ORTLOFF	RUIZ CLAVIJO	MARIA PILAR	65410
00040	290472-74	REYES	SALDIAS	EDUARDO ALBER	65405
00041	245651-70	MARTINEZ	SOLORZA	LUIS FERNANDO	65400
00042	205234-76	ARAVENA	SALGADO	NELSON EDUARD	65395
00043	267876-77	CACERES	CHINCHON	JUAN ANTONIO	65370
00044	209413-75	BARROS	CLAVERO	OLGA FABIOLA	65355
00045	299853-72	BEAS	DUARTE	MARCO ANTONIO	65295
00046	259316-70	PEREZ	IBANEZ	ERNESTO	65200
00047	252486-78	NAVARRO	CEPEDA	RUBEN MARCO	65200
00048	295264-73	MONTECINOS	MARTINEZ	MARCELO GUILL	65180
00049	267282-74	ROMAN	TEJO	CLAUDIA CRIST	65120
00050	244050-75	MAGANA	TAPILO	ALVARO JAVIER	65030
00051	262668-74	QUIROZ	LOPEZ	MONICA PAZ	64905
00052	265891-77	ROBLES	VENEGAS	FELIPE ANDRES	64905
00053	233358-71	GONZALEZ	TAGLE	MARIA ALICIA	64905
00054	275493-75	TORO	ABARZA	JOHN ANTHONY	64855
00055	227491-70	FERNANDEZ	PIZARRO	MARCIA ALEJAN	64795
00056	225090-71	EHRMANN EVAR	SLUMBERG	KARIN RUTH	64775

Newspapers publish only those students who have been admitted or waitlisted. Thus, not all students who participated in the process are listed. The same applicant may also appear on several lists. If an applicant is waitlisted on his preferred option, he will appear again on his next option should he be accepted or waitlisted there as well. The person can appear for each of his preferences until one of them is accepted. Table A.III.III below shows the number of unique individuals that appear in the data by year (first column) and also the number of unique application results that have been typed each year (second column).

TABLE A.III.III
Typed Application Results Data

Year	Individuals	Applications (N)
1982	39,077	69,232
1983	40,388	69,287
1984	38,996	68,804
1985	35,145	61,573
1986	37,578	66,292
1987	33,190	60,170
1988	33,480	59,430
1989	32,427	53,452
1990	40,843	68,209
1991	42,573	70,835
1992	46,126	74,842
1993	45,842	74,501
1994	44,708	70,261
1995	45,930	68,979
1996	48,601	73,274
1997	52,551	82,318
1998	52,428	82,337
1999	53,686	81,283
2000	58,119	90,829

TABLE A.III.IV

The 25 CRUCH Universities

Universidad de Chile
Pontificia Universidad Católica de Chile
Universidad de Concepción
Pontificia Universidad Católica de Valparaíso
Universidad Técnica Federico Santa María
Universidad de Santiago de Chile
Universidad Austral de Chile
Universidad Católica del Norte
Universidad de Valparaíso
Universidad de Antofagasta
Universidad de La Serena
Universidad del Bío-Bío
Universidad de La Frontera
Universidad de Magallanes
Universidad de Talca
Universidad de Atacama
Universidad de Tarapacá
Universidad Arturo Prat
Universidad Metropolitana de Ciencias de la Educación
Universidad de Playa Ancha de Ciencias de la Educación
Universidad Tecnológica Metropolitana
Universidad de Los Lagos
Universidad Católica del Maule
Universidad Católica de la Santísima Concepción
Universidad Católica de Temuco

4 Constructing Labor Earnings from Tax Records

The main source of earnings data comes from the Chilean income tax summary Form F22. This form summarizes different sources of income including: wages, profits from investments, pensions, and other sources of income. Some individuals have not filed an F22 form because their only source of income is from wages and their taxes are thus paid directly to the Chilean Internal Revenue Service (*Servicio de Impuestos Internos*) (SII)[4] from their employer. If this is the case, they have no need to file an F22 form and their income data comes from the Form F1887. This form shows monthly wages after discounts for pensions and health insurance.[5]

Labor income comes from three main sources. The first is wages paid to employees with a contract that has no specified end date. An example would be a secretary working for large firm. This data comes from the F1887 form and appears on the F22 form (if filed) on line 9, box 161 together with pension income.[6] The second type of labor income is from "*honorarios*" which are specific short-term contracts for a specified time frame or task. An example of this would be a freelance journalist. This data comes from form F1879 and on the F22 appears in boxes 461 and 545. The sum of these boxes after deductions is presented on line 6 and box 110 together with income deriving from directorships which is also from form F1879 and F22 in box 479. The third type of income is that derived from a group of professionals providing services ("*participación en sociedades de profesionales*"). An example would be a group of doctors who get together to form a small clinic. This income is reported directly on form F22 in box 617 and is included in line 6 and box 110 with other *honorarios* and income from directorships.

Total income adds income derived from investments, dividends, pensions, and other sources to labor income. These can be found on lines 1, 2, 4, and 7, and boxes 104, 105, 108, and

[4] 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.

[5] If an individual made less than 13.5 UTM, he would be exempt from income tax, and prior to 2006, would be reported in a group, making it impossible to identify the individual. From 2006 onward, this data is available at the individual level even if the worker is exempt from paying taxes.

[6] If an individual does not require an F22 and in addition voluntarily saves more than the required amount to their private pension fund through their employer, this difference will be deducted from their income reported at this point.

155 of form F22. Tables A.IV.I through A.IV.IV describe the contributions of different types of income to total income.

TABLE A.IV.I.
Labor Earnings Breakdown by Components

	Total Income	% Labor of Total	%Wages of Labor	% Honorarios of Labor	% Prof Assoc of Labor	% Dir of Labor	N
All 6 to 26	10,339,422	95.48%	74.71%	25.13%	0.14%	0.02%	8,419,559
All 6 to 15	7,566,409	96.63%	72.46%	27.43%	0.09%	0.01%	5,567,075
All 16 to 26	15,751,399	93.23%	79.17%	20.56%	0.24%	0.03%	2,852,484
Marg 6 to 26	12,614,541	94.94%	74.65%	25.12%	0.20%	0.02%	2,266,333
Marg 6 to 15	9,470,490	96.23%	71.63%	28.20%	0.15%	0.02%	1,388,620
Marg 16 to 26	17,588,709	92.91%	79.52%	20.16%	0.28%	0.03%	877,713

Note: “All” refers to all individuals in the sample. “Marg” refers to individuals in the marginal RD groups. The numbers are the years since the college application occurred. So “6 to 26” include all cohorts who have at least 6 years since application to those with 26 years since their application.

TABLE A.IV.II
Labor Earnings Breakdown by Components and Area

	Total Income	% Labor of Total	% Wages of Labor	% *Honorarios* of Labor	% Prof Assoc of Labor	% Dir of Labor	N
Business all	12,702,052	95.06%	81.57%	18.30%	0.09%	0.03%	869,231
Art/Arch. all	9,317,878	93.00%	59.58%	40.23%	0.16%	0.03%	472,095
Educ. all	6,818,618	96.57%	79.41%	20.50%	0.07%	0.01%	1308,358
Hum/SS all	9,912,882	95.58%	64.90%	34.84%	0.23%	0.03%	1152,437
Health all	12,140,778	96.30%	69.13%	30.38%	0.48%	0.01%	884,700
Sci/Tech all	10,927,257	95.26%	77.97%	21.95%	0.06%	0.01%	3643,406
Business marg	15,289,348	94.68%	82.14%	17.69%	0.12%	0.04%	307,770
Art/Arch. marg	10,126,178	92.76%	59.22%	40.58%	0.16%	0.04%	120,135
Educ. marg	7,053,931	96.60%	81.33%	18.59%	0.07%	0.01%	194,181
Hum/SS marg	12,146,527	95.11%	63.27%	36.37%	0.32%	0.04%	286,070
Health marg	15,480,201	95.61%	65.95%	33.30%	0.74%	0.01%	294,544
Sci/Tech marg	12,569,221	94.72%	78.99%	20.93%	0.06%	0.02%	1,032,492

Note: "Area" refers to the broad category of study the student was accepted in. "All" refers to all individuals in the sample. "Marg" refers to individuals in the marginal RD groups. The numbers are the years since the college application occurred. So "6 to 26" include all cohorts who have at least six years since application to those with 26 years since their application.

TABLE A.IV.III
Non Labor Earnings Breakdown by Components

	Total Income	% Nonlab of Total	% Cap Gains of Nonlabor	% *Retiros* of Nonlabor	% Dividends of Nonlabor	% Pensions of Nonlabor	Other	N
All 6 to 26	10,339,422	5%	71%	19%	5%	3%	3%	8,419,559
All 6 to 15	7,566,409	3%	77%	15%	3%	2%	2%	5,567,075
All 16 to 26	15,751,399	7%	62%	24%	6%	4%	4%	2,852,484
Marg 6 to 26	12,614,541	5%	68%	21%	6%	2%	3%	2,266,333
Marg 6 to 15	9,470,490	4%	75%	16%	5%	1%	2%	1,388,620
Marg 16 to 26	17,588,709	7%	59%	26%	7%	3%	4%	877,713

Note: "All" refers to all individuals in the sample. "Marg" refers to individuals in the marginal RD groups. The numbers are the years since the college application occurred. So "6 to 26" include all cohorts who have at least six years since application to those with 26 years since their application.

TABLE A.IV.IV
Non Labor Earnings Breakdown by Components and Area

	Total Income	% Nonlabor of Total	% Cap Gains of Nonlabor	% *Retiros* of Nonlabor	% Dividends of Nonlabor	% Pensions of Nonlabor	Other	N
Business all	12,702,052	5%	65%	21%	8%	3%	4%	869,231
Art/Arch. all	9,317,877	7%	68%	23%	5%	2%	2%	472,095
Educ. all	6,818,618	3%	76%	15%	2%	4%	2%	1,308,358
Hum/SS all	9,912,881	4%	75%	15%	5%	2%	2%	1,152,437
Health all	12,140,778	4%	79%	15%	4%	2%	1%	884,700
Sci/Tech all	10,927,257	5%	67%	22%	5%	2%	4%	3,643,406
Business marg	15,289,348	5%	61%	22%	11%	2%	4%	307,770
Art/Arch. marg	10,126,178	7%	67%	23%	6%	1%	2%	120,135
Educ. marg	7,053,931	3%	76%	15%	2%	5%	2%	194,181
Hum/SS marg	12,146,527	5%	73%	17%	6%	2%	2%	286,070
Health marg	15,480,201	4%	76%	17%	5%	1%	1%	294,544
Sci/Tech marg	12,569,221	5%	63%	24%	6%	2%	4%	1,032,492

Note: “Area” refers to the broad category of study the student was accepted in. “All” refers to all individuals in the sample. “Marg” refers to individuals in the marginal RD groups. The numbers are the years since the college application occurred. So “6 to 26” include all cohorts who have at least six years since application to those with 26 years since their application.

5 Construction of Degree Characteristics

5.1 Overview

This section describes our degree categorization system. We divide degree programs into groups based on selectivity, field of study, and course content. We focus on these three degree attributes because they capture important and distinct drivers of heterogeneity in labor market returns. Selectivity, as measured by average peer test scores, may affect the efficiency of human capital investment (e.g., if more selective programs have better teachers or facilities, or if peers with higher skills facilitate learning) or allow students to more effectively leverage a fixed amount of human capital through peer or institutional connections in the labor market. Degree area speaks to the sector of the labor market where students will use the skills and peer connections they acquire in college. Course content plays a large role in determining the types of human capital enrolling students accumulate. Students who take math courses as part of a medical degree and work in the health sector may realize different labor market returns than students who take math courses as part of an economics degree and work in finance.

We focus on broad categories of selectivity, field of study, and course content. We do this with the goal of an analysis that is relatively parsimonious but also allows for interactions between the different degree attributes. Area is divided into eight groups: business, art and architecture, education, social science, law, health, science and technology, and humanities. Selectivity is divided into four groups, based on quartiles of scores for accepted students. . We divide degrees into two groups based on the fraction of required courses that have a vocational focus. Our data indicate that many science and technology degrees are heavy on vocational courses. Health degrees are also likely to include a high proportion of vocational courses, and tend to be quite selective. Humanities, social science, and law degrees tend not to have a vocational focus.

Clearly other categorization strategies are possible. That said, our strategy captures important variation in degree type and earnings outcomes. Within low-selectivity education degrees, the most common degree in the vocational course category focuses on special education, while the most common in the non-vocational course category focuses on science teaching. The former involves courses aimed at the specific challenges inherent in teaching special needs children, while the latter includes both quantitative science courses and qualitative courses on the theory of education. Within the health area, degrees in nursing and medical technology are characterized by vocational courses, whereas students studying to be doctors take non-vocational courses that focus on more abstract quantitative and qualitative reasoning.

The remainder of this section describes the categorization process in detail.

5.2 Area Categories

Mineduc divides degrees into ten broad categories for administrative purposes: agriculture, art and architecture, basic sciences or natural sciences and mathematics, social sciences, juridical sciences or law, humanities, education, technology, health, and business. These categories are based on the International Standard Classification of Education, constructed by UNESCO.

We modify these groups slightly when constructing our area categories, with an eye towards parsimony as well as improved statistical power through the elimination of smaller categories.[7] We make two important changes.

First, we move a set of programs with the Futuro Laboral code "Commercial Engineering" from social science to business. Analysis of course lists indicates that these programs focus on business economics, so we believe the business categorization is more appropriate.

Second, we combine basic science, technology, and agriculture into a broad science and technology category. This broad category contains programs that teach students quantitative-oriented skills with a possible focus on basic research or a specific application, including but not limited to agriculture, manufacturing, and mining or construction (the latter two within the technology sector). Students with degrees within this category may fulfill similar roles within firms. For example, the agriculture category includes programs such as agroindustrial engineering, marine biology and ecology; while the technology category includes degrees such as engineering for construction and the basic science category includes degrees such as biology. Similarly, the technology category includes degrees with a substantial basic science component such as engineering in computation and informatics. The qualifications of the recipient of a

[7] Note that we developed our group categories prior to estimation of our RD results.

degree from one of these programs for a particular job will likely depend as much on course content, which we evaluate separately, as on the field designation of the degree. This is borne out to some extent by empirical data on major/occupation match from the U.S. (Altonji et al. 2012) report that both electrical engineers (a technology program in our scheme) and computer science (a basic science program) are likely to work as computer software engineers once they enter the labor force.

A simple empirical analysis suggests that this grouping does not obscure meaningful heterogeneity. As reported in Table A.V.I, point estimates of earnings effects are positive for each of the three subgroups and not statistically distinguishable. The point estimate for broad science and technology category reflects an average of the three estimates that is weighted towards technology, the largest category but the one with the lowest point estimate.

5.3 Course Categories

We divide degrees into two categories based on the proportion of vocational course requirements. The goal is to differentiate between degrees that teach students job-specific skills versus those that seek to impart more general human capital that may be applicable at many jobs. We assign course groups using the following procedure. First, we obtain lists of required courses for existing degree programs using web search. We then assign each course to one of 11 categories. These categories are listed in Table A.V.II and include categories such as "science," "applied technology," "art/design," and "professional experience." Figure A.V.I gives an example of an online course lists and the associated categorization choices. The distinction between basic science and applied technology is important to make clear. Basic science consists of courses like chemistry, biology, or electrical engineering that have broad applications across different sectors of the economy and fields of study. The applied technology category consists of courses like "refrigeration" or "industrial wood properties" that may draw upon scientific concepts but focus on applications to a particular field.

We observe course requirement data for 57% of the degree programs in our regression discontinuity sample, accounting for 64% of applications. For degrees without course requirement data, we compute predicted values by regressing observed course data on a) a set of dummies for each of the roughly 200 administrative Futuro Laboral degree groupings, b) a set of selectivity quintile dummies based on the average math and reading scores of accepted students at each degree, and c) linear controls in math and reading scores. Note that the Futuro Laboral codes differentiate between degree levels, so we are not assigning course values from professional degrees to technical programs, or vice versa. In practice, these regression imputations are quite similar to what we would obtain simply by taking mean scores within each Futuro Laboral category.

Because degree programs may include electives that contribute to degree length but do not show up on required course lists, we transform course type totals to course type proportions (summing to one within each degree) and then multiply by administrative records of degree duration to obtain final course counts. We assume that within degrees the distribution of elective coursework across course categories is similar to the distribution of required coursework.

We aggregate the 11 course types into quantitative, qualitative, and vocational courses, as shown in Table A.V.II. Vocational courses include both “professional experience” courses such as school-sponsored internships as well as “applied technology” courses in which students learn skills with applications to particular jobs. We assign degrees to the vocational category if they include more than the median proportion of required vocational courses.

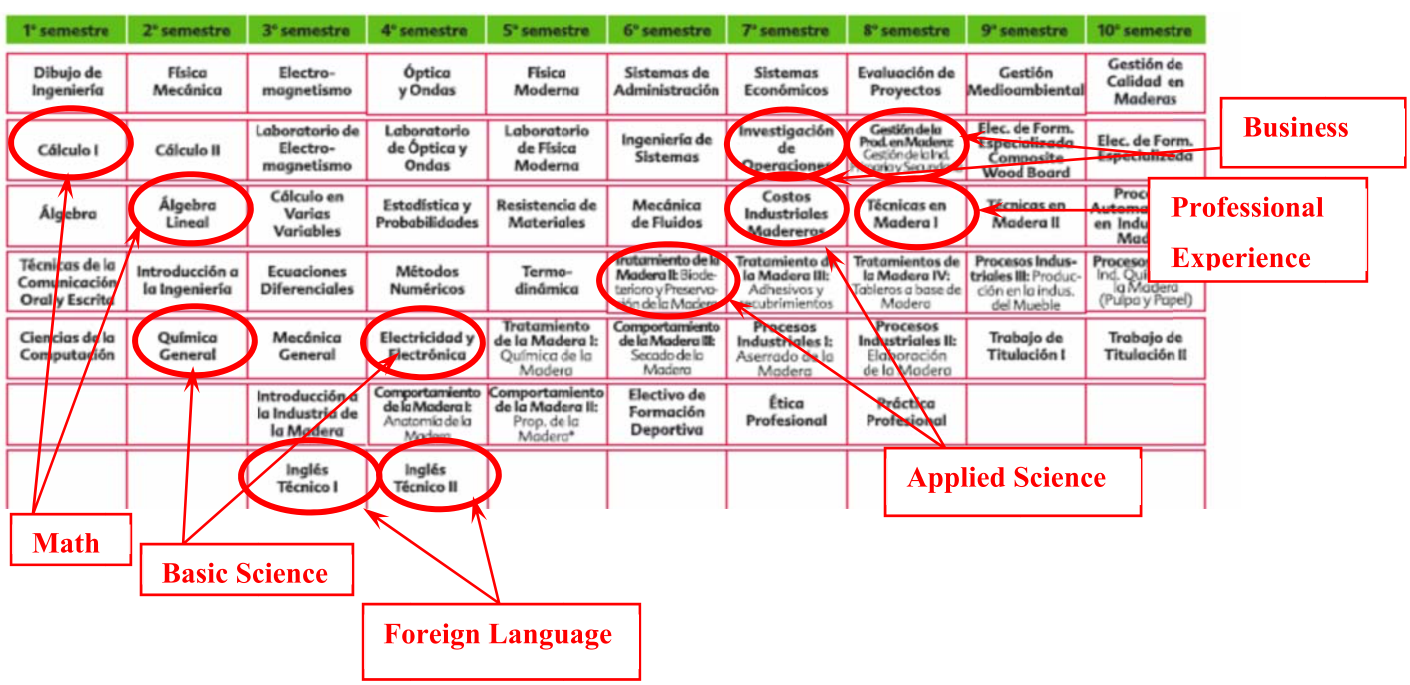
Table A.V.I. RD and Model Estimates by Disaggregated Area

Area	TC	MODEL	N
Business	0.027	0.101	87,387
	(0.028)	(0.114)	
Agriculture	0.057	0.129	60,952
	(0.028)	(0.048)	
Art & Arch.	-0.030	0.014	43,719
	(0.029)	(0.049)	
Basic Science	0.042	0.087	27,708
	(0.039)	(0.054)	
Social Science	0.082	0.161	49,961
	(0.026)	(0.046)	
Law	0.070	0.151	41,372
	(0.044)	(0.069)	
Education	0.015	0.042	105,087
	(0.014)	(0.025)	
Humanities	-0.027	-0.007	15,301
	(0.048)	(0.134)	
Health	0.108	0.256	109,753
	(0.020)	(0.044)	
Technology	0.041	0.120	229,551
	(0.015)	(0.038)	

TABLE A.V.II
Course categories and examples

	Course Categories	Broad grouping	Examples
1	Science	Quant.	Chemistry, Biology
2	Math	Quant.	Algebra, Calculus
3	Computer Science or Programming	Quant.	Introduction to C++, Programming
4	Humanities and Non Economics Social Sciences	Qual.	Psychology, History, Anthropology
5	Law	Qual.	International Law
6	English and other Foreign Languages	Qual.	English, French
7	Econ, Business and Administration	Quant.	Macroeconomics, Accounting
8	Applied Technology	Voc.	Industrial Wood Properties, Refrigeration
9	Education	Qual.	Early Childhood Pedagogy
10	Art/Design	Qual.	Culture and Design, Structures
11	Professional Experience	Voc.	Professional Practice, Clinical Experience

FIGURE A.V.I
Example of Coursework for Engineering Degree in the Timber Industry
(Ingeniería en Industria de la Madera)



5.4 Selectivity Categories

Finally, we classify a degree program as being selective if the average score for accepted applicants in a given year is above the median average score for accepted applicants across all program-years, weighted by the number of applicants. Other degrees are classified as being non-selective. We choose to use a binary selectivity variable rather than a finer designation for reasons of parsimony.

6 Estimation Procedure

6.1 Instrumental Variables Estimates

Due to limitations on the frequency with which we were able to access sensitive tax records within the Chilean tax authority, we constructed our model estimates using a two-step instrumental variables procedure. We document this procedure here because we believe it may be useful for other researchers facing similar access constraints.

Consider the just-identified homogeneous effects model. We can write this model as

$$
\begin{aligned}
Y &= X\theta + e \\
X &= Z\pi + u
\end{aligned}
\tag{1}
$$

where Y is an $N \times 1$ vector of earnings outcomes, X is an $N \times 6P$ matrix of degree-specific intercepts, polynomial terms (four per degree in our core specifications), and endogenous admissions outcomes, and Z is and $N \times 6P$ matrix of degree-specific intercepts, polynomial terms, and threshold-crossing indicators. θ is a vector of length 6P and π is a $6P \times 6P$ matrix. We may also write the reduced form threshold-crossing equation as

$$
Y = Z\Delta + v\,. \tag{2}
$$

where Δ is a vector of length 6P.

When estimating (1), we faced two constraints. First, we were only able to access data on earnings outcomes Y while physically present in SII offices in Chile on a limited number of scheduled days. Second, we had access to limited computing power. Therefore, rather than estimating an IV specification with nearly 800,000 observations and 6,618 (6x1103) regressors, we estimated the model in two steps.

First, we estimated the reduced form coefficients Δ separately for each program. We conducted this step while at SII. Second, we used data on our local servers to construct estimates of the first stage effects π. We then combined these estimates using the indirect least squares estimator $\hat{\theta} = \hat{\pi}^{-1}\hat{\Delta}$. We constructed standard errors using a bootstrap procedure described below. This yielded the estimates of interest with lower computational requirements and allowed us to conduct many specification checks outside of SII and in compliance with their confidentiality restrictions.

Now consider an overidentified model in which we allow for heterogeneous effects by student and degree characteristics. Write the model as in (1), but with X now a $N \times (11P + G)$ matrix (two sets of P intercepts, two sets of 4P polynomial terms, one set of P admissions outcomes, and G heterogeneity terms), and Z now a $N \times 12P$ matrix. $P > G$, so the model is overidentified. We obtain estimates of Δ and π as before, and construct the estimator

$$\hat{\theta} = (\hat{\pi}'\tilde{W}\hat{\pi})^{-1}\hat{\pi}'\tilde{W}\hat{\Delta} \tag{3}$$

where $\tilde{W}$ is a $12P \times 12P$ weight matrix. Note that if we choose $\tilde{W} = (Z'Z)\,\mathrm{W}(Z'Z)$ for some $12P \times 12P$ weight matrix W, $\hat{\theta}$ collapses to the standard IV estimator $\hat{\theta}_{IV} = (X'ZWZ'X)^{-1}X'ZWZ'Y$. We weight by the number of marginal applications. We prefer this to weighting schemes based on estimates of the inverse variance matrix because the variances can be larger for degree programs with larger effects on earnings, and we do not want to systematically down-weight such degrees.

6.2 Inference

We compute standard errors using a clustered wild bootstrap-se procedure (Cameron et al. 2008, Davidson and Mackinnon 2010). We prefer the wild bootstrap to other common bootstraps in this application for several reasons. Standard pairs bootstraps risk sampling out certain degree programs entirely for at least some bootstrap replications, which can lead to identification problems. We cannot stratify at the degree level because nearly all of our clusters (individuals) span multiple degrees (when an individual is a marginal reject at one degree and a marginal accept at another). Residual bootstraps can only be implemented when clusters are all the same size, which they are not. In addition, they impose a homoscedasticity assumption.

Unlike these residual bootstraps, the wild bootstrap permits heteroscedasticity across clusters and can be applied to data in which clusters have different sizes. We choose a bootstrap-se rather than a bootstrap-t procedure (see Cameron et al. 2008) because our two-step estimation procedure makes it difficult for us to compute t-statistics at each bootstrap iteration.

We compute standard errors using 400 bootstrap replications. The bootstrap is clustered at the student level. We conduct the bootstrap resampling using Rademacher weights. We impose the null hypothesis that all program effects are zero when resampling.

The bootstrap procedure yields estimates of the variance-covariance matrices for $\hat{\Delta}$ and $\hat{\theta}$. The summary statistics we present are linear combinations of these values.

7 Specification Checks for Main Earnings Results

7.1 Robustness checks

We perform several specification checks for our main threshold-crossing effects. Table A.VII.I presents the impact on earnings of crossing the threshold under the alternative assumptions listed in each row. The robustness checks are as follows:

(1) Narrow Window: This specification uses a regression discontinuity sample of students whose scores fall within 12.5 points of the cutoff score and linear polynomials in distance from cutoff that differ on the other side of cutoff.

(2) Wide Window: This specification uses a regression discontinuity sample of students whose scores fall within 50 points above the cutoff score and 25 points below the cutoff score.

(3) More Applications: This specification uses a regression discontinuity sample in which more applications are considered "marginal." In our main analysis, we consider applications in which at least 18 rejected applicants have scores within five points of the cutoff. In the More Applications sample, we consider applications in which at least 14 rejected applicants have scores within eight points of the cutoff. In our main sample we are able to obtain threshold-crossing and model estimates for 1,103 out of 1,923 total degrees, accounting for 88.2% of applications (see Table A.I.VIII). In the "More Applications" sample, we estimate effects for 1,188 degrees accounting for 91.3% of applications.

(4) Low Top-code: This specification top-codes all incomes above the 98^{th} percentile.

(5) High Top-code: This specification top-codes all incomes above the 99.5^{th} percentile.

Table A.VII. I
Robustness checks

	Narrow	Wide	More Applications	Low topcode	High topcode
Pooled	0.043***	0.040***	0.041***	0.043***	0.047***
	(0.011)	(0.010)	(0.008)	(0.008)	(0.009)
By selectivity tier of target degree:					
Bottom Quartile	0.020	0.022*	0.014	0.018*	0.021**
	(0.015)	(0.013)	(0.009)	(0.010)	(0.011)
2nd Quartile	0.040**	0.024	0.034***	0.035***	0.038***
	(0.018)	(0.015)	(0.012)	(0.013)	(0.013)
3rd Quartile	0.036	0.025	0.040**	0.035**	0.033**
	(0.024)	(0.019)	(0.016)	(0.015)	(0.017)
Top Quartile	0.075***	0.091***	0.083***	0.086***	0.096***
	(0.028)	(0.026)	(0.021)	(0.019)	(0.022)
By field of target degree:					
Business	0.024	-0.001	0.029	0.020	0.032
	(0.034)	(0.030)	(0.024)	(0.025)	(0.030)
Art/Arch.	-0.033	-0.015	-0.039	-0.031	-0.028
	(0.042)	(0.035)	(0.025)	(0.028)	(0.030)
Educ.	0.002	0.005	0.008	0.016	0.014
	(0.020)	(0.017)	(0.013)	(0.013)	(0.014)
Law	0.079	0.084*	0.071*	0.063	0.078*
	(0.059)	(0.051)	(0.040)	(0.041)	(0.045)
Health	0.085***	0.096***	0.106***	0.108***	0.107***
	(0.027)	(0.024)	(0.021)	(0.020)	(0.020)
Sci/Tech	0.050***	0.047***	0.039***	0.041***	0.046***
	(0.017)	(0.015)	(0.012)	(0.012)	(0.013)
Humanities	-0.011	-0.003	-0.013	-0.030	-0.026
	(0.063)	(0.055)	(0.045)	(0.046)	(0.050)
Social Science	0.082**	0.067**	0.084***	0.083***	0.083***
	(0.039)	(0.028)	(0.023)	(0.024)	(0.026)
N	497,614	905,848	930,649	796,724	796,724

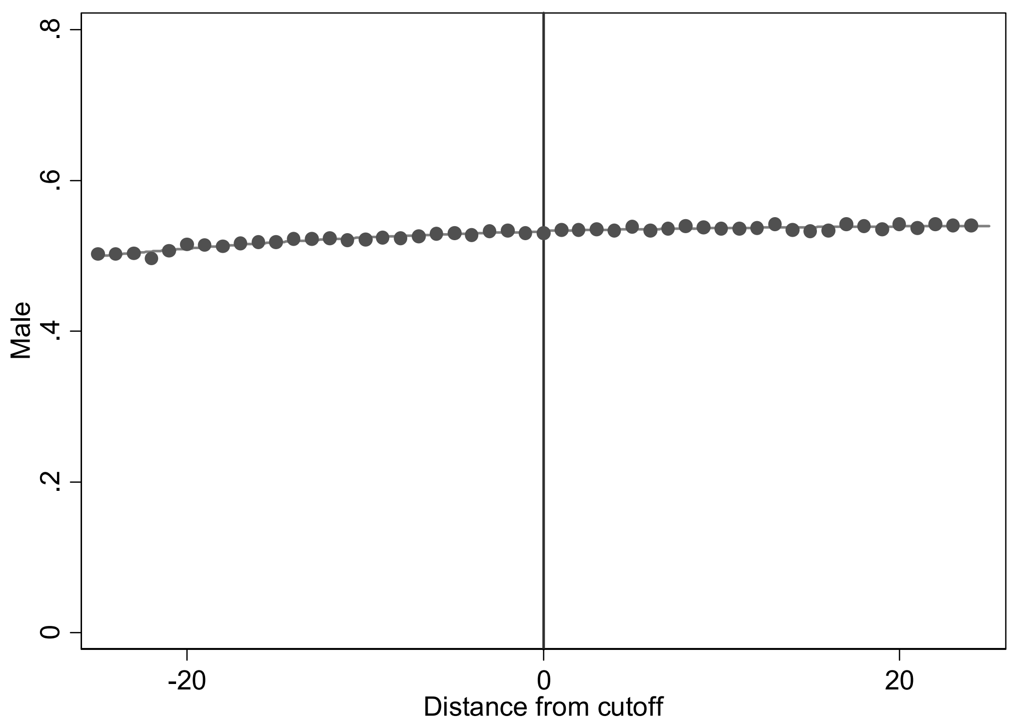
Notes: Significance levels: 1%***, 5%** and 10%*. Means of threshold-crossing effect estimates from equation (3) by degree type. Narrow window is a local linear regression using a 12.5 point window above and below the cutoff score. Wide window uses a window of 50 points above the cutoff and 25 points below the cutoff. We only use 25 points below because newspaper waitlist records in many cases do not include students with scores more than 25 points below the cutoff. Low topcode denotes all incomes above the 98th percentile. Hi topcode denotes all incomes above the 99.5th percentile.

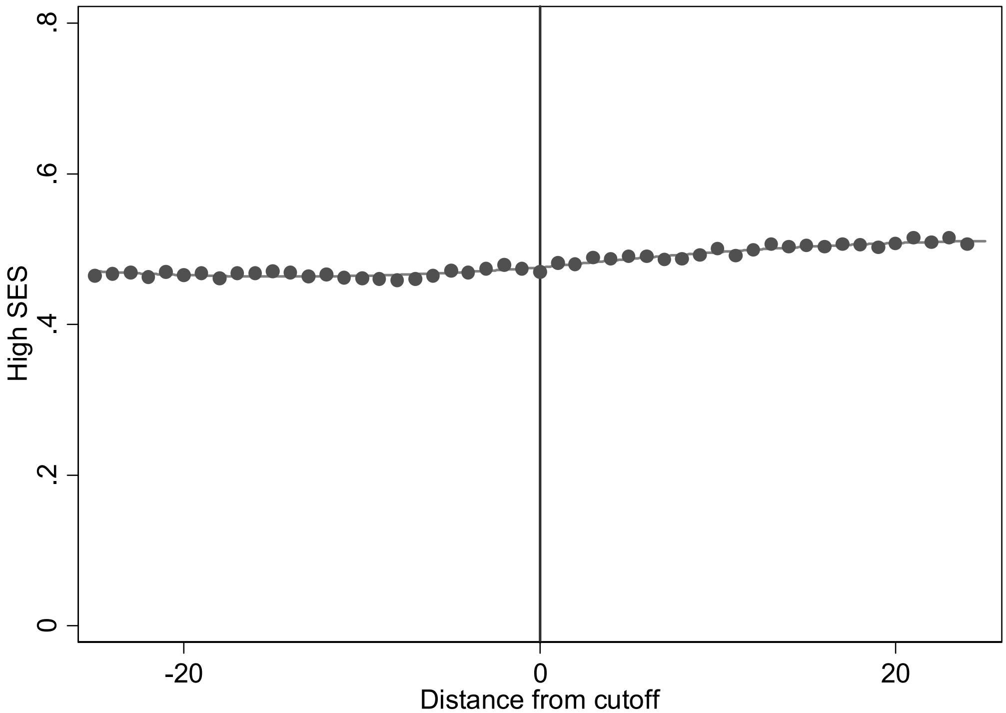
7.2 Additional Regression Discontinuity Graphs

Figure A.VII.I shows regression discontinuity graphs for individual baseline demographic characteristics. Figure A.VII.II shows the effect of threshold-crossing on labor force participation.

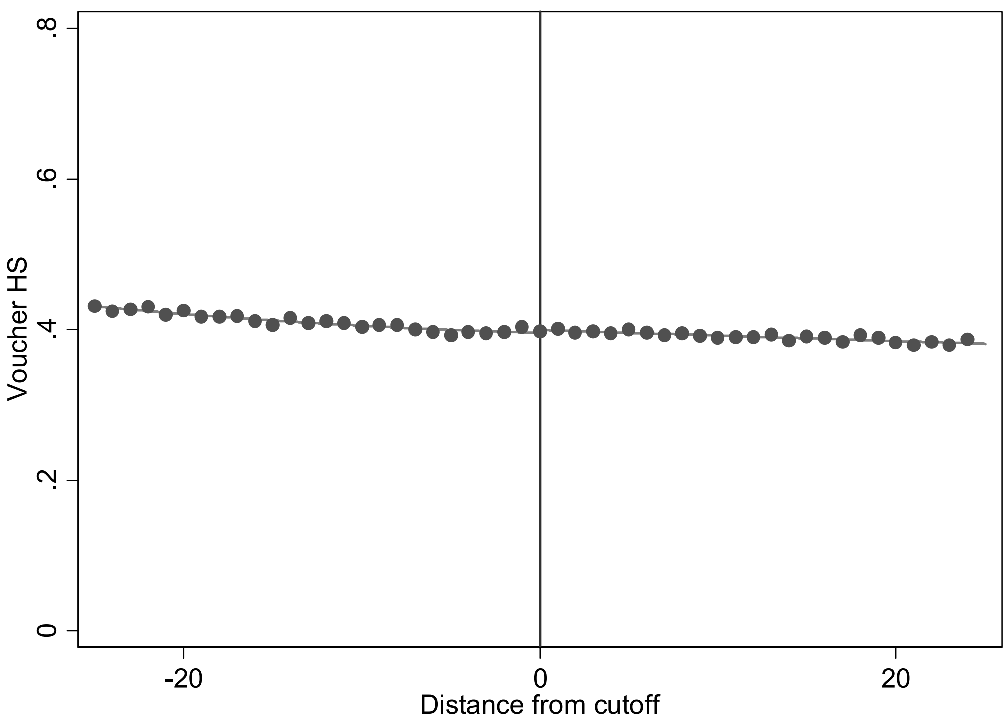
FIGURE A.VII.I

Impact of Threshold-Crossing on Demographics

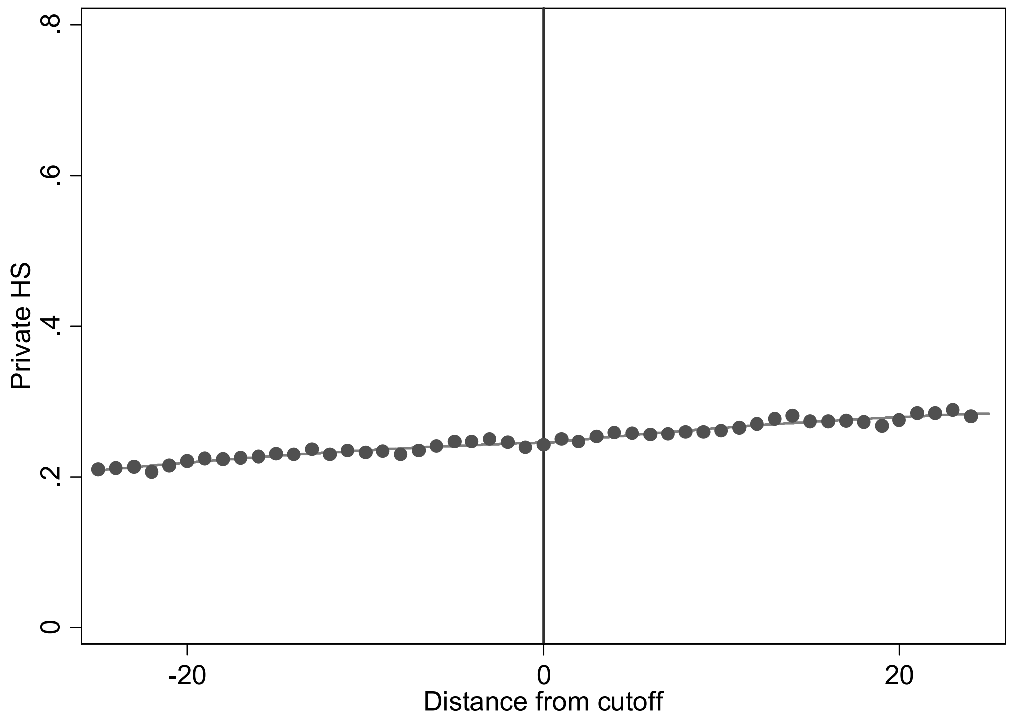




High SES
.8
.6
.4
.2
0
-20
0
20
Distance from cutoff



Voucher HS
.8
.6
.4
.2
0
-20
0
20
Distance from cutoff


Private HS
0
.2
.4
.6
.8
-20
0
20
Distance from cutoff

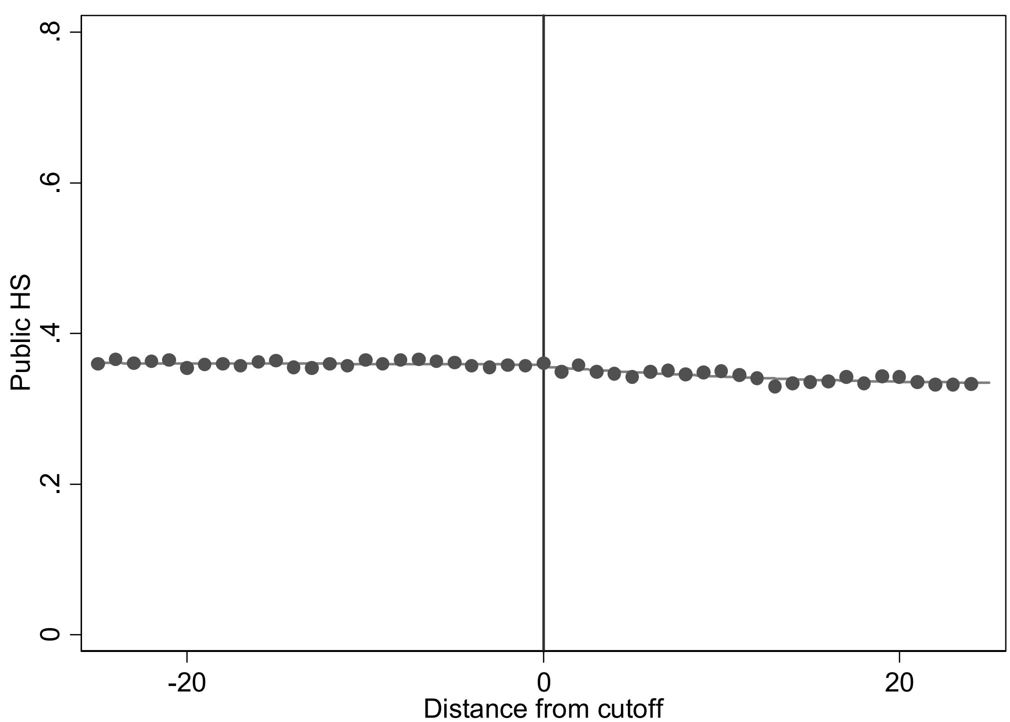
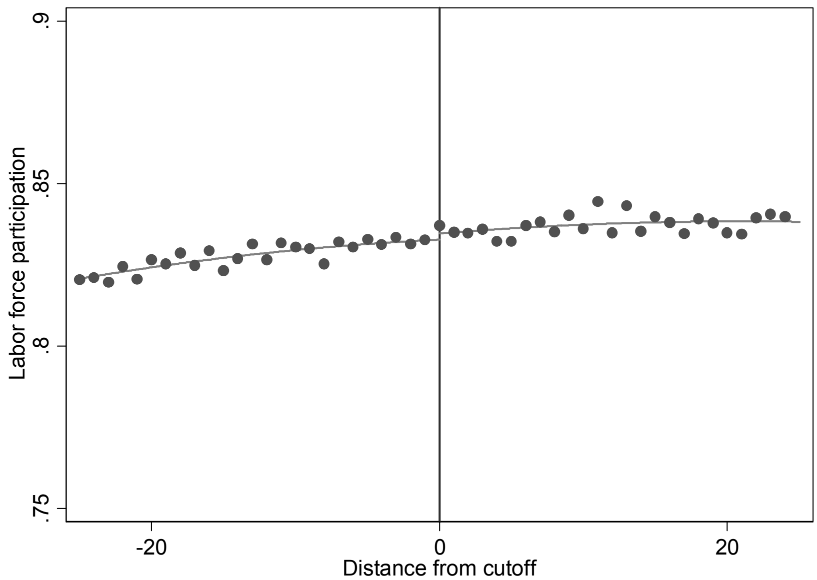

Public HS
0
.2
.4
.6
.8
-20
0
20
Distance from cutoff

FIGURE A.VII.II
Impact of Threshold-Crossing on Labor Force Participation



Notes: Fitted values and means within one bins of a dummy variable for labor force participation by distance relative to the threshold. Sample pools over all marginal applications in the 1982-2006 cohorts. Earnings outcomes reflect averages over annual earnings realized at least six years after the application year.

7.3 Additional heterogeneous effect estimates

Tables. A.VII.II, A.VII.III and A.VII.IV display additional heterogeneous effect estimates by gender, socioeconomic status and comparative advantage in subject areas (respectively).

Table A.VII.II: threshold crossing effects by SES

	High SES		Low SES	
Bottom Quartile	0.031		0.011	
	(0.030)		(0.012)	
2nd Quartile	0.027		0.034**	
	(0.028)		(0.016)	
3rd Quartile	0.018		0.030	
	(0.028)		(0.021)	
Top Quartile	0.076***		0.050	
	(0.027)		(0.037)	
	Low Sel	High Sel	Low Sel	High Sel
Business	0.001	0.098	-0.025	-0.033
	(0.070)	(0.070)	(0.036)	(0.071)
Art/Arch.	-0.103	-0.065	-0.007	0.042
	(0.080)	(0.050)	(0.050)	(0.057)
Education	0.047	-0.038	0.022	0.029
	(0.046)	(0.091)	(0.016)	(0.058)
Law	-0.113	0.050	0.001	0.031
	(0.110)	(0.076)	(0.059)	(0.077)
Health	-0.097	0.095***	0.149***	0.117***
	(0.065)	(0.034)	(0.044)	(0.034)
Sci/Tech	0.028	0.036	0.016	0.017
	(0.037)	(0.033)	(0.017)	(0.028)
Humanities	-0.045	-0.086	-0.030	0.177
	(0.104)	(0.109)	(0.044)	(0.137)
Soc. Sci.	0.142	0.106**	-0.008	0.103**
	(0.092)	(0.052)	(0.033)	(0.048)

Notes: Significance at 1%***, 5%** and 10%*. Means of threshold-crossing estimates from equation (1) by degree type, with separate specifications for high- and low-SES students. allowing for heterogeneous effects by student SES. Selectivity tier is defined by quartiles of average cutoff values across the 1982-2006 period. 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 A.VII.III Threshold-crossing effects and model estimates by gender

	Threshold-crossing		Model estimates	
	Male	Female	Male	Female
Pooled	0.050***	0.038***	0.117***	0.103***
	(0.013)	(0.009)	(0.031)	(0.023)
By Selectivity:				
Bottom Quartile	0.018	0.021*	0.03	0.048**
	(0.017)	(0.012)	(0.028)	(0.019)
2nd Quartile	0.046**	0.023	0.078**	0.057**
	(0.021)	(0.015)	(0.033)	(0.024)
3rd Quartile	0.029	0.039**	0.111**	0.092***
	(0.027)	(0.018)	(0.045)	(0.031)
Top Quartile	0.101***	0.068***	0.245***	0.213***
	(0.032)	(0.024)	(0.059)	(0.046)
By Area:				
Business	0.022	0.021	0.1	0.104*
	(0.044)	(0.031)	(0.073)	(0.054)
Art/Arch.	-0.044	-0.009	0.006	0.026
	(0.042)	(0.035)	(0.062)	(0.055)
Education	0.031	0.006	0.065	0.033
	(0.034)	(0.014)	(0.046)	(0.022)
Law	0.038	0.133**	0.14	0.186**
	(0.062)	(0.057)	(0.094)	(0.084)
Health	0.170***	0.071***	0.344***	0.184***
	(0.042)	(0.020)	(0.078)	(0.038)
Sci/Tech	0.045***	0.036**	0.096***	0.096***
	(0.017)	(0.018)	(0.036)	(0.033)
Humanities	-0.001	-0.041	0.037	-0.066
	(0.095)	(0.049)	(0.126)	(0.068)
Soc. Sci.	0.079	0.071**	0.164**	0.158***
	(0.048)	(0.028)	(0.066)	(0.045)

Notes: Significance at 1%***, 5%** and 10%*. Means of threshold-crossing estimates from equation (1) and model estimates from equation (4) by degree type. We compute threshold-crossing estimates separately for men and women, and for heterogeneous model estimates by gender as described in section 4.2. Selectivity tier is defined by quartiles of average cutoff values across the 1982-2006 period. 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 A.VII.IV Threshold-crossing effects and model estimates by Comparative Advantage

	Threshold-crossing			Model estimates		
	Math	Reading	Neither	Math	Reading	Neither
Pooled	0.044***	0.021	0.049***	0.106***	0.010	0.109***
	(0.016)	(0.014)	(0.011)	(0.039)	(0.027)	(0.026)
By Selectivity:						
Bottom Quartile	-0.002	0.026	0.020	-0.002	-0.026	0.065***
	(0.024)	(0.018)	(0.017)	(0.037)	(0.031)	(0.024)
2nd Quartile	0.048*	0.026	0.037*	0.069	0.011	0.074**
	(0.025)	(0.026)	(0.020)	(0.043)	(0.030)	(0.031)
3rd Quartile	0.054*	0.010	0.032	0.125**	-0.013	0.089**
	(0.031)	(0.030)	(0.024)	(0.050)	(0.042)	(0.036)
Top Quartile	0.071*	0.017	0.100***	0.217***	0.089	0.197***
	(0.040)	(0.041)	(0.028)	(0.069)	(0.066)	(0.051)
By Area:						
Business	0.062	0.038	0.001	0.165**	-0.019	0.047
	(0.048)	(0.093)	(0.041)	(0.079)	(0.088)	(0.063)
Art/Arch.	-0.093	0.001	-0.015	-0.057	-0.029	0.014
	(0.057)	(0.053)	(0.040)	(0.087)	(0.074)	(0.064)
Education	0.034	0.010	0.011	-0.019	-0.007	0.047
	(0.046)	(0.020)	(0.022)	(0.065)	(0.030)	(0.034)
Law	0.269*	0.048	0.073	0.385*	0.079	0.136
	(0.160)	(0.058)	(0.071)	(0.220)	(0.083)	(0.107)
Health	0.096**	0.084**	0.119***	0.187**	0.085	0.242***
	(0.040)	(0.039)	(0.025)	(0.075)	(0.072)	(0.049)
Sci/Tech	0.037*	0.010	0.047**	0.086**	-0.049	0.098***
	(0.022)	(0.032)	(0.019)	(0.043)	(0.050)	(0.034)
Humanities	-0.200	-0.023	-0.015	0.067	-0.012	0.045
	(0.252)	(0.051)	(0.081)	(0.284)	(0.071)	(0.100)
Soc. Sci.	0.053	0.026	0.062	0.297*	0.071	0.117*
	(0.106)	(0.034)	(0.045)	(0.153)	(0.047)	(0.067)

Notes: Significance at 1%***, 5%** and 10%*. Means of threshold-crossing estimates from equation (1) and model estimates from equation (4) by degree type. We compute threshold-crossing estimates separately by skill group, and for heterogeneous model estimates by skill group as described in section 4.2. Selectivity tier is defined by quartiles of average cutoff values across the 1982-2006 period. 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.

7.4 Model Robustness Tests

Table A.VII.V presents estimates of the homogeneous effects model using a subset of the alternate samples described in Appendix Section 7.1. In addition, we present model estimates that allow for students who differ on observable characteristics to have unrestricted comparative advantage in each degree program. This contrasts with our main estimates, which restrict comparative advantage to depend on observable degree program characteristics. Standard errors become very large when allowing for unrestricted comparative advantage and weighting by sample size. We therefore present estimates that weight by the inverse variance of the degree-specific effect estimates. For comparison, we also present inverse variance weighted estimates of the homogenous effects model. Variance-weighted estimates are similar across the homogeneous effects and unrestricted comparative advantage models, suggesting that the restrictions on heterogeneity we impose in our main estimation are not critical to our findings. Variance-weighted estimates are qualitatively similar to but generally smaller than sample-weighted estimates, because observations with large but noisily estimated effects are downweighted. We prefer the sample-weighted estimates in our main analysis because they reflect average effects based on the distribution of marginal students across degrees rather than on properties of effect estimates.

Table A.VII.V Model Robustness Checks

	Homogeneous Effects	Wide	Narrow	More Applications	Homogeneous effect Variance weighted	Unrestricted Comp Adv.: Gender	Unrestricted Comp Adv.: Skill	Unrestricted Comp Adv.: SES
Pooled	0.121***	0.122*	0.138***	0.107***	0.068***	0.057**	0.051***	0.039**
	(0.033)	(0.063)	(0.048)	(0.040)	(0.014)	(0.026)	(0.012)	(0.015)
By selectivity tier of target degree:								
	0.047*	0.048*	0.045*	0.031	0.047***	0.042***	0.036***	0.021*
	(0.021)	(0.026)	(0.025)	(0.076)	(0.013)	(0.014)	(0.012)	(0.013)
	0.084***	0.072	0.101**	0.072**	0.061***	0.059*	0.039**	0.044**
	(0.027)	(0.049)	(0.042)	(0.036)	(0.020)	(0.031)	(0.017)	(0.022)
	0.113**	0.101	0.148*	0.116***	0.088***	0.099	0.071***	0.077**
	(0.061)	(0.118)	(0.084)	(0.033)	(0.026)	(0.068)	(0.022)	(0.031)
	0.242***	0.268***	0.261***	0.228***	0.175***	0.133	0.149***	0.09
	(0.053)	(0.092)	(0.085)	(0.044)	(0.040)	(0.146)	(0.039)	(0.076)
By field of target degree:								
Business	0.101	0.095	0.135**	0.103*	0.048	0.060	0.029	0.009
	(0.114)	(0.092)	(0.062)	(0.057)	(0.032)	(0.044)	(0.026)	(0.032)
Art/Arch.	0.014	0.047	0.037	-0.001	0.034	0.038	-0.003	0.010
	(0.049)	(0.054)	(0.067)	(0.037)	(0.030)	(0.054)	(0.028)	(0.039)
Educ.	0.042*	0.016	0.029	0.030	0.047***	0.044**	0.030*	0.041**
	(0.025)	(0.080)	(0.055)	(0.096)	(0.016)	(0.020)	(0.015)	(0.017)
Law	0.151**	0.198*	0.222**	0.139**	0.064	0.019	0.022	0.032
	(0.069)	(0.118)	(0.099)	(0.060)	(0.044)	(0.086)	(0.045)	(0.051)
Health	0.256***	0.253***	0.248***	0.237***	0.167***	0.144***	0.151***	0.15***
	(0.044)	(0.062)	(0.074)	(0.053)	(0.030)	(0.056)	(0.031)	(0.036)
Sci/Tech	0.119***	0.130**	0.142***	0.104***	0.065***	0.053**	0.056***	0.023
	(0.034)	(0.057)	(0.046)	(0.037)	(0.020)	(0.025)	(0.018)	(0.021)
Humanities	-0.007	-0.051	-0.006	0.020	0.033	0.010	0.034	0.023
	(0.134)	(0.536)	(0.368)	(0.063)	(0.034)	(0.041)	(0.036)	(0.038)
Social Science	0.161***	0.134	0.182**	0.148***	0.088***	0.060	0.045*	0.069**
	(0.046)	(0.082)	(0.085)	(0.036)	(0.028)	(0.048)	(0.025)	(0.032)
N	796,724	905,848	497,614	921,107		766,462	754,396	664,331

Notes: Significance at 1%***, 5%** and 10%*. Alternate estimates of models from equation (4). “Homogeneous Effects” column is repeated from Table VI. “Wide,” “Narrow,” and “More Applications” columns reflect estimate of the homogeneous effects model from equation (4) in the listed sample. The “Homogeneous effects, Variance Weighted” column reflects estimates of the Homogeneous Effects model weighting by inverse variance of degree-specific effect estimator. The “Unrestricted Comp. Ad.” Columns contain inverse-variance weighted estimates of equation (4) that allow for unrestricted degree effects degree program X student characteristic group, for the listed characteristic.

7.5 Effects by Selectivity and Course Content

Table A.VII.VI. Threshold Crossing & Model Estimates by Course Content

	Threshold-Crossing	Model Estimate
Low Selectivity		
Vocational	0.011	0.044**
	(0.013)	(0.021)
Core curriculum	0.038***	0.071***
	(0.012)	(0.020)
High Selectivity		
Vocational	0.058***	0.151***
	(0.018)	(0.049)
Core curriculum	0.068***	0.194***
	(0.018)	(0.058)

N=773,487. Significance: 1%*** 5%** 10%*. Threshold-crossing and model estimates by selectivity and course content. Degree programs are designated as “vocational” or “core curriculum” if they are above- or below-median in the fraction of required career-focused courses, respectively. Model estimates are from homogeneous effects model. Standard errors computing using wild-bootstrap procedure (Cameron et al. 2008, Davidson and MacKinnon 2010).

8 Impact of Threshold-Crossing on Postsecondary Education Completion

Figures A.VIII.I and A.VIII.II plot the pooled impact of threshold-crossing on degree completion using the same specification as Figure 2 in the main text. We examine the impact of threshold-crossing on two measures of degree completion: 1) completing at least half of a degree and 2) graduating.

Table A.VIII.I shows the impact of threshold-crossing on degree completion using the same specification as the final column of Table 2 (reproduced here as the first column for comparison). We examine the impact of threshold-crossing on two measures of degree completion: 1) completing at least half of a degree and 2) graduating.

Tables A.VIII.II, A.VIII.III, and A.VIII.IV show the impact of threshold-crossing on matriculation, 50% or more of a degree completed, and graduation respectively. They use the same regression framework as Table 3 in the main text, which examined the impact of threshold-crossing on acceptance to degrees of different types. However, they use data from the 2000-2005 application cohorts only as those are the years for which we have acceptance, matriculation and graduation data for threshold-crossers.

FIGURE A.VIII.I
Impact of Threshold-crossing on Completing
at Least Half of the Degree

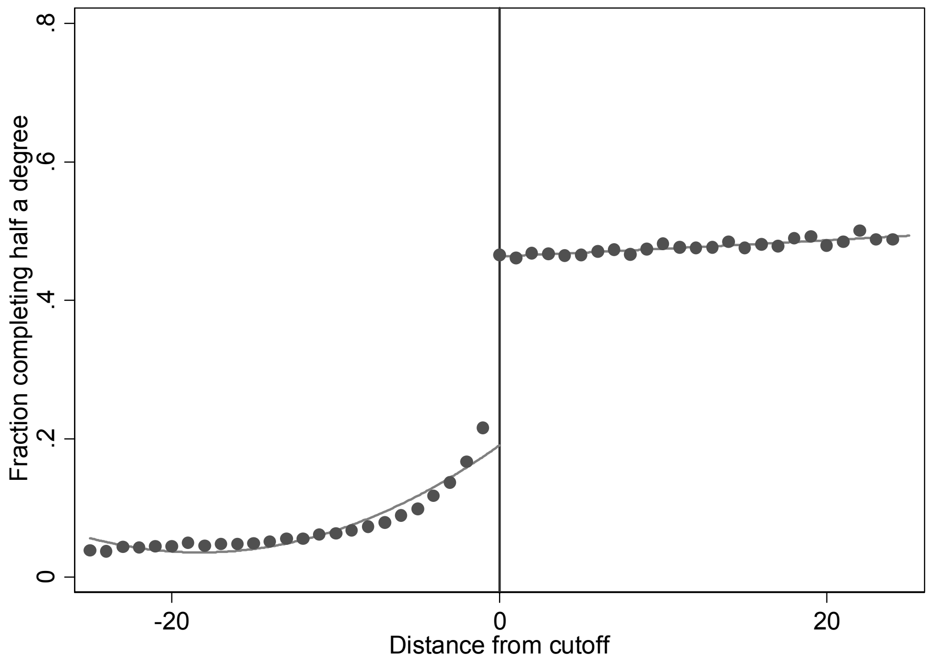


FIGURE A.VIII.II
Impact of Threshold-crossing on Graduation

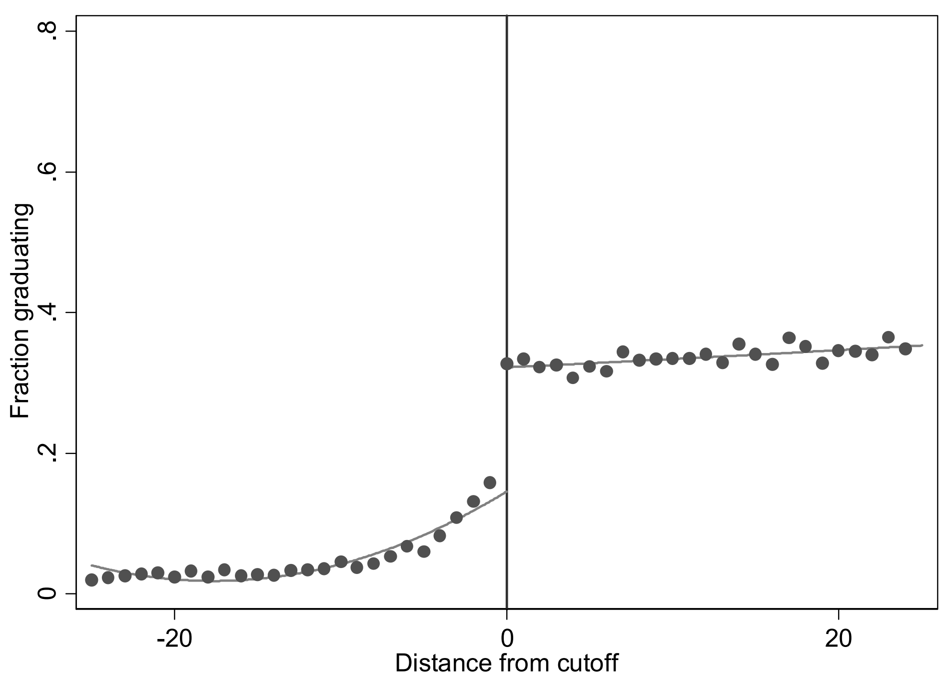


Table A.VIII.I Impact of Threshold-crossing on Degree Outcomes

	(1) Matriculation	(2) 50% Completion	(3) Graduation
Pooled	0.499***	0.281***	0.183***
	(0.003)	(0.004)	(0.007)
By Area:			
Business	0.518***	0.304***	0.197***
	(0.011)	(0.012)	(0.023)
Art/Arch.	0.389***	0.235***	0.154***
	(0.015)	(0.017)	(0.025)
Education	0.425***	0.282***	0.213***
	(0.010)	(0.010)	(0.018)
Law	0.636***	0.359***	0.093***
	(0.013)	(0.016)	(0.017)
Health	0.485***	0.354***	0.273***
	(0.008)	(0.009)	(0.019)
Sci/Tech	0.532***	0.203***	0.081***
	(0.006)	(0.006)	(0.011)
Humanities	0.537***	0.267***	0.260***
	(0.020)	(0.022)	(0.029)
Soc. Sci.	0.490***	0.321***	0.284***
	(0.012)	(0.013)	(0.025)
JOINT TEST	0.000***	0.000***	0.000***
By Selectivity:			
Less Sel.	0.414***	0.220***	0.127***
	(0.005)	(0.005)	(0.011)
More Sel.	0.574***	0.335***	0.220***
	(0.004)	(0.005)	(0.009)
JOINT TEST	0.000***	0.000***	0.000***
By coursework:			
Core Curriculum	0.494***	0.291***	0.209***
	(0.005)	(0.005)	(0.010)
Vocational	0.514***	0.273***	0.159***
	(0.005)	(0.006)	(0.010)
JOINT TEST	0.000***	0.000***	0.000***
N applications	469,791	399,616	93,972
N students	288,515	255,699	71,219

Notes: Significance at 1%***, 5%** and 10%*. Matriculation and 50% completion is for 2000-2010 cohorts, graduation is for 2000-2005 cohorts. N refers to pooled specifications. 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.

Table A.VIII.II Below-threshold Same-year Enrollment Outcomes

	All	High Sel	Low Sel	Bus.	Art/Arch.	Educ.	Soc. Sci.	Health	Sci./Tech.	Humanities	Law	N
All	0.640	0.347	0.286	0.053	0.028	0.081	0.023	0.114	0.251	0.018	0.053	116,573
High Sel	0.709	0.617	0.086	0.060	0.034	0.030	0.032	0.191	0.262	0.015	0.070	70,198
Low Sel	0.558	0.020	0.530	0.045	0.021	0.144	0.012	0.022	0.240	0.022	0.032	46,375
Business	0.651	0.347	0.299	0.466	0.003	0.012	0.004	0.001	0.122	0.006	0.031	9,145
Art/Arch.	0.594	0.348	0.240	0.021	0.407	0.028	0.002	0.002	0.078	0.009	0.039	6,840
Educ.	0.544	0.050	0.488	0.008	0.007	0.436	0.006	0.003	0.034	0.018	0.025	16,679
Soc. Sci.	0.669	0.420	0.236	0.019	0.012	0.029	0.374	0.009	0.021	0.041	0.129	6,464
Health	0.739	0.628	0.108	0.003	0.006	0.011	0.002	0.610	0.090	0.001	0.009	23,888
Sci./Tech.	0.659	0.327	0.325	0.028	0.004	0.015	0.001	0.010	0.584	0.002	0.005	35,830
Humanities	0.582	0.213	0.348	0.006	0.025	0.154	0.005	0.001	0.011	0.289	0.066	3,899
Law	0.580	0.374	0.197	0.023	0.025	0.052	0.016	0.008	0.039	0.021	0.379	11,181

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

Table A.VIII.III Below-threshold Probability of Completing 50% of Degree

	All	High Sel	Low Sel	Bus.	Art/Arch.	Educ.	Soc. Sci.	Health	Sci./Tech.	Humanities	Law	N
All	0.456	0.286	0.168	0.034	0.016	0.081	0.020	0.167	0.079	0.010	0.045	73,332
High Sel	0.522	0.471	0.050	0.030	0.021	0.021	0.029	0.270	0.085	0.008	0.055	46,734
Low Sel	0.364	0.026	0.336	0.040	0.009	0.166	0.007	0.022	0.070	0.012	0.032	26,598
Bus.	0.452	0.216	0.241	0.367	0.004	0.013	0.004	0.003	0.042	0.004	0.016	5,305
Art/Arch.	0.411	0.264	0.142	0.016	0.311	0.029	-0.001	0.000	0.024	0.011	0.022	3,119
Educ.	0.425	0.049	0.377	0.005	0.002	0.378	0.000	0.005	0.006	0.012	0.017	12,269
Soc. Sci.	0.422	0.324	0.098	0.000	0.006	0.018	0.280	0.011	-0.001	0.018	0.087	4,623
Health	0.617	0.568	0.049	0.002	0.001	0.004	0.002	0.580	0.023	0.001	0.004	23,168
Sci./Tech.	0.327	0.174	0.152	0.015	0.004	0.008	0.001	0.013	0.276	0.001	0.005	15,577
Humanities	0.353	0.171	0.164	0.003	0.021	0.089	0.016	0.002	0.002	0.157	0.044	2,421
Law	0.469	0.301	0.157	0.011	0.006	0.039	0.015	0.011	0.011	0.006	0.362	6,501

Notes: Results from regressions of the form of equation (3) where the dependent variable is an indicator if the applicant applied completed 50% of a degree of the type indicated in the column heading as a result of not crossing the threshold into a degree of type indicated in the row label. Thus it is the probability of completing 50% of a degree of type indicated in column heading for people who just missed the threshold of admission to a degree of type indicated in the row label. Less-selective and more-selective are defined as degrees with below- or above-median average admission cutoff-score over the 1985-2005 sample

Table A.VIII.IV Below-threshold Probability of Graduation Outcomes

	All	High Sel	Low Sel	Bus.	Art/Arch.	Educ.	Soc. Sci.	Health	Sci./Tech.	Humanities	Law	N
All	0.332	0.231	0.098	0.028	0.020	0.073	0.010	0.117	0.028	0.013	0.041	20,662
High Sel	0.364	0.333	0.027	0.026	0.026	0.027	0.015	0.167	0.035	0.015	0.048	13,685
Low Sel	0.262	0.013	0.250	0.030	0.005	0.169	0.000	0.010	0.013	0.008	0.025	6,977
Bus.	0.355	0.213	0.153	0.311	0.003	0.009	-0.001	0.003	0.020	0.001	0.009	2,168
Art/Arch.	0.272	0.229	0.043	0.004	0.209	0.018	0.000	0.002	0.018	0.009	0.012	1,557
Educ.	0.366	0.058	0.309	0.000	0.001	0.342	0.000	0.000	0.003	0.012	0.008	3,713
Soc. Sci.	0.154	0.126	0.026	-0.004	0.003	0.011	0.079	0.003	-0.001	0.008	0.053	2,552
Health	0.559	0.535	0.025	0.002	0.001	0.005	0.000	0.533	0.012	0.000	0.007	3,889
Sci./Tech.	0.171	0.127	0.044	0.009	0.008	0.004	0.000	0.013	0.134	0.000	0.002	3,415
Humanities	0.293	0.216	0.053	0.000	0.012	0.039	0.007	0.000	-0.002	0.162	0.051	1,076
Law	0.333	0.233	0.075	0.008	0.000	0.032	0.004	0.012	0.006	0.004	0.244	2,130

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