Online Appendices: University admission and preferred field of study

Online Appendix A: Admission Thresholds Plots for Covariates

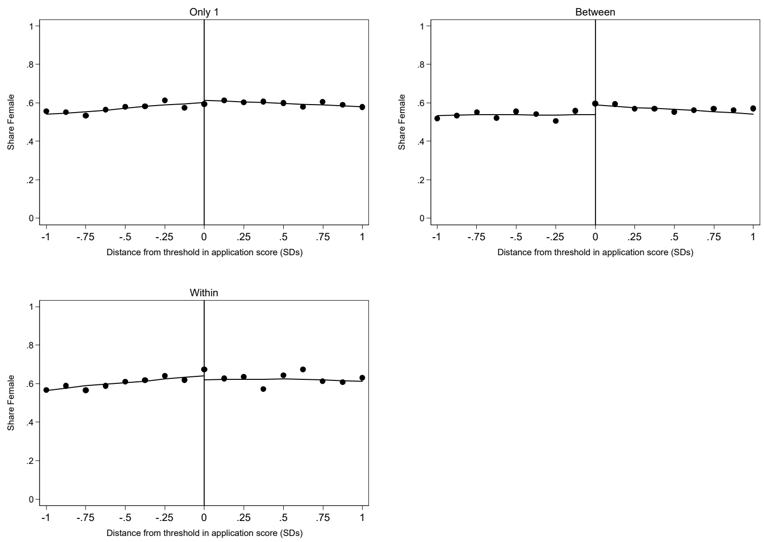


FIGURE A1: ADMISSION THRESHOLDS BY SEX

"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

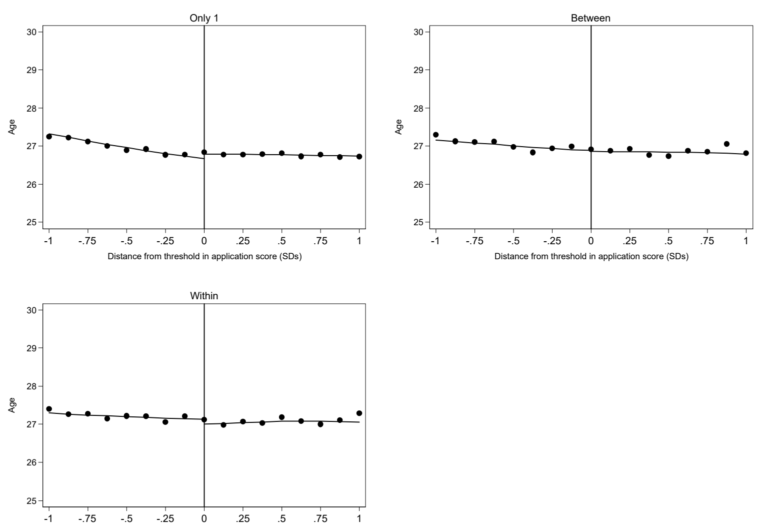


FIGURE A2: ADMISSION THRESHOLDS BY AGE

"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

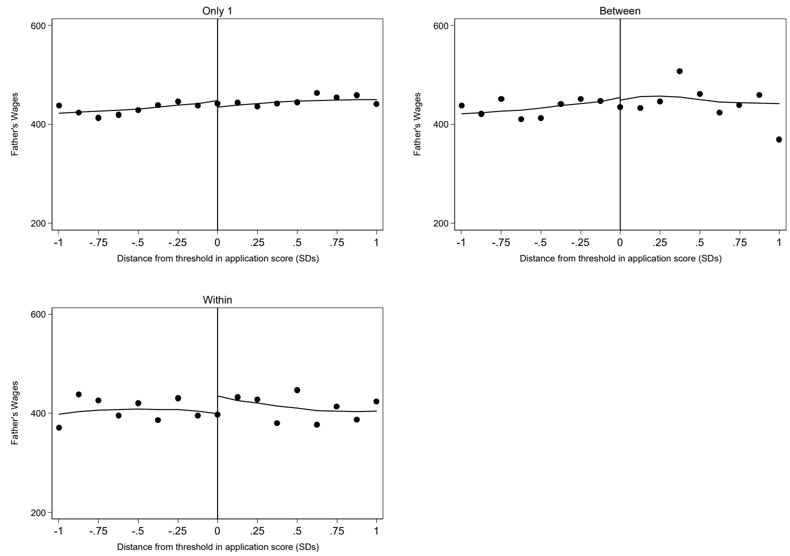


FIGURE A3: ADMISSION THRESHOLDS BY EARNINGS OF FATHER WHEN THE APPLICANT IS AGE 16

"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

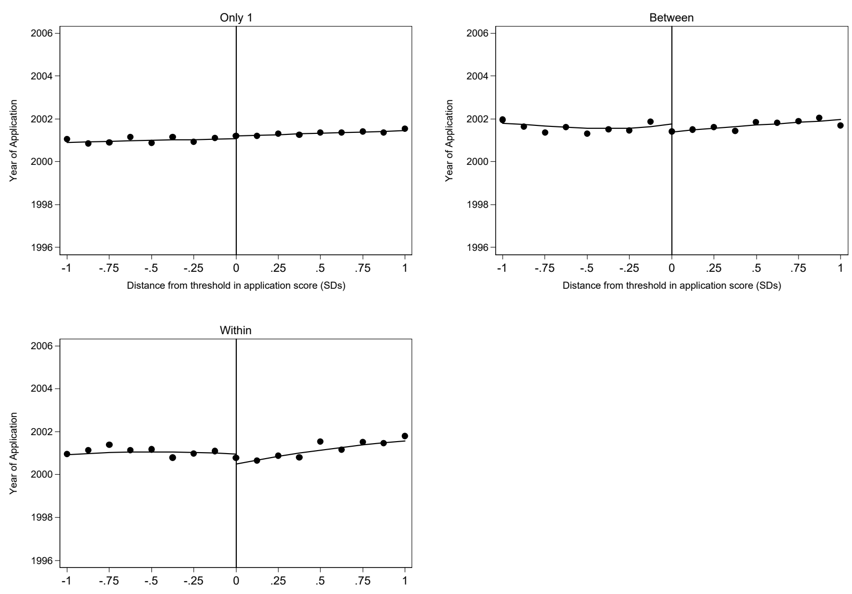


FIGURE A4: ADMISSION THRESHOLDS BY YEAR OF APPLICATION

"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

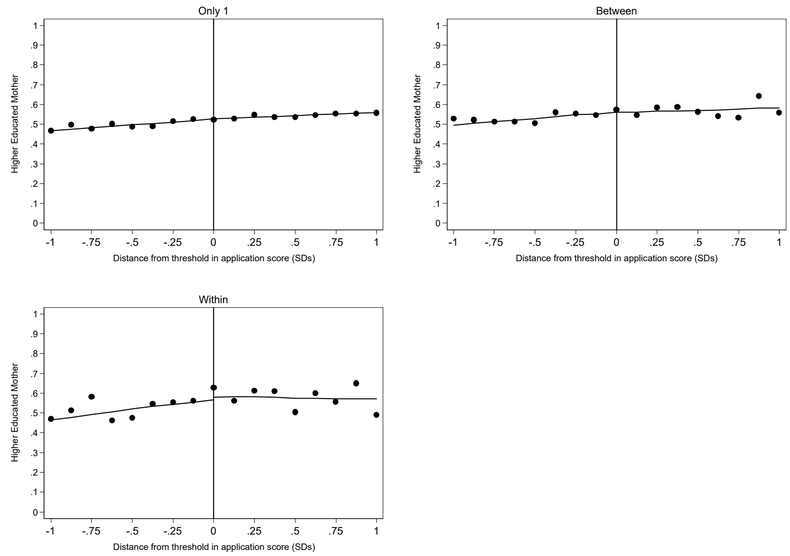


FIGURE A5: ADMISSION THRESHOLDS BY WHETHER MOTHER HAS A HIGHER EDUCATION WHEN THE APPLICANT IS AGE 16
"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

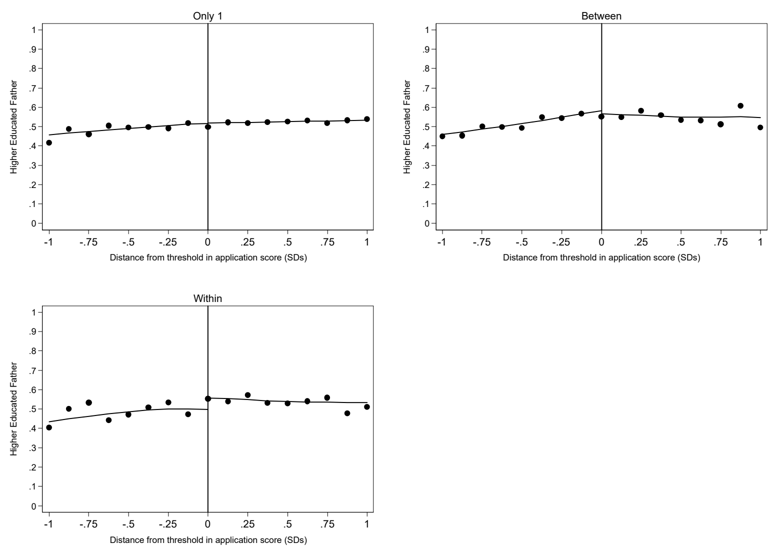


FIGURE A6: ADMISSION THRESHOLDS BY WHETHER FATHER HAS A HIGHER EDUCATION WHEN THE APPLICANT IS AGE 16
"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

Online Appendix B: Additional Results

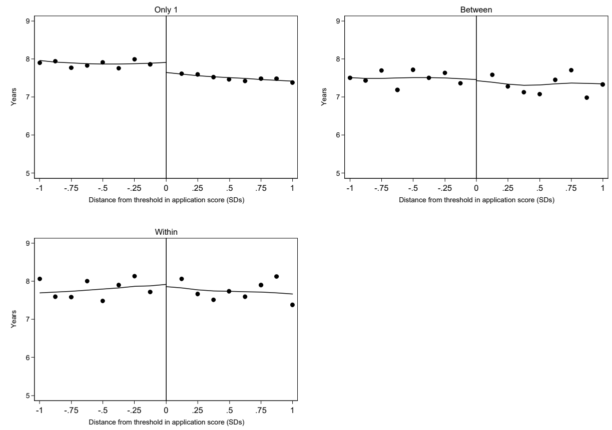


FIGURE B1: ADMISSION THRESHOLDS AND TIME TO GRADUATION

"Only 1" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

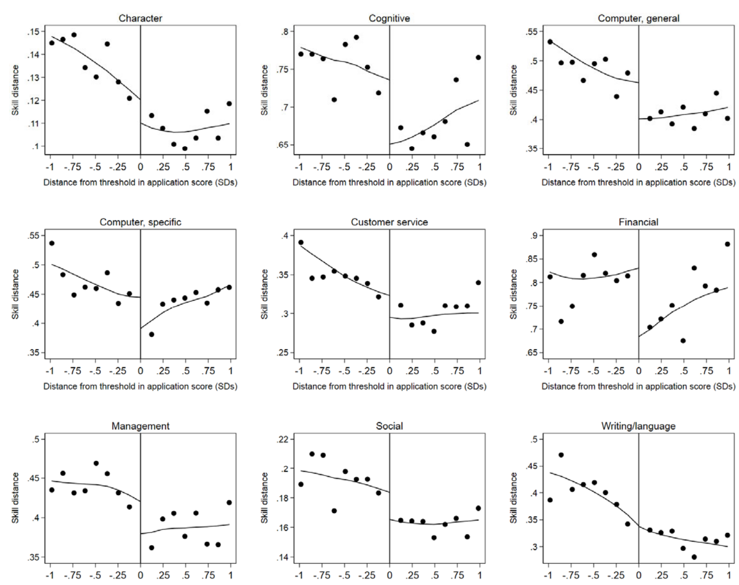


FIGURE B2: ADMISSION THRESHOLDS AND SKILL DISTANCE, THOSE ON THE MARGIN BETWEEN TWO DIFFERENT BROAD FIELDS, *BETWEEN* TYPE

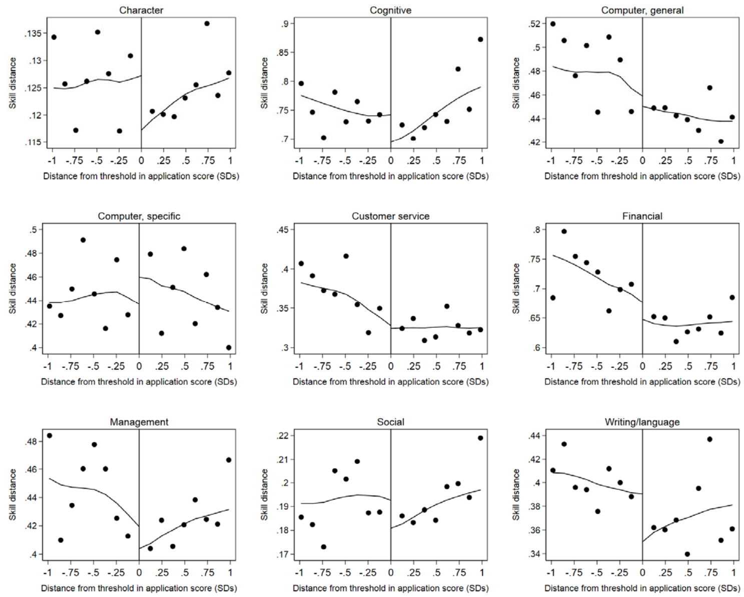


FIGURE B3: ADMISSION THRESHOLDS AND SKILL DISTANCE, THOSE ON THE MARGIN BETWEEN TWO DIFFERENT BROAD FIELDS, *WITHIN* TYPE

TABLE B1: MULTIPLE SPECIFICATIONS

	(1)	(2)	(3)	(4)	(5)
(A)					
1(Application Score > Cutoff)	19.00***	21.36***	21.73***	29.71***	29.72***
	(4.26)	(3.76)	(3.64)	(4.63)	(4.61)
Observations	282,632	282,632	282,632	282,632	282,632
Individuals	43838	43838	43838	43838	43838
Clusters	50	50	50	50	50
(B)					
Only One * 1(Application Score>Cutoff)	21.10***	24.07***	24.34***	32.51***	32.70***
	(4.80)	(4.68)	(4.57)	(4.82)	(4.79)
Within * 1(Application Score>Cutoff)	-2.45	-0.51	-0.08	8.15	7.74
	(7.92)	(7.59)	(7.12)	(7.18)	(7.39)
Between * 1(Application Score>Cutoff)	25.59***	25.82***	26.21***	34.64***	34.12***
	(7.22)	(6.06)	(6.28)	(8.10)	(8.09)
Observations	282,632	282,310	282,310	282,310	282,310
Individuals	43838	43838	43838	43838	43838
Clusters	50	50	50	50	50
Preferred and second-best education indicators	YES	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES
Different slopes	NO	NO	YES	YES	YES
Quadratic terms	NO	NO	NO	YES	YES
Preferred and second-best institution indicators	NO	NO	NO	NO	YES

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields. The set of control variables includes sex, a quadratic in age, father's earnings at applicant age 16, an indicator for whether father's earnings are missing, calendar year indicators, indicators for year of application, and indicators for *Within* and *Between* type. All regressions include the function of the application score indicated in the table. Standard errors, clustered at the six-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE B2: MULTIPLE SPECIFICATIONS

	(1)	(2)	(3)	(4)	(5)
Between * 1(Application Score>Cutoff)*					
Humanities	-11.76	-11.17	-10.92	-1.85	-1.99
	(10.94)	(8.81)	(8.30)	(9.39)	(9.22)
Science	7.99	10.49	10.68	19.61	12.40
	(39.55)	(37.86)	(37.70)	(37.84)	(38.70)
Social Sciences	20.00*	20.48**	20.73**	29.88***	29.32***
	(10.21)	(8.93)	(9.01)	(10.44)	(9.91)
Business	18.01	33.03***	33.29***	42.78***	44.87***
	(12.48)	(10.34)	(9.86)	(11.43)	(11.41)
Law	48.63***	56.12***	56.27***	65.20***	64.80***
	(5.52)	(6.04)	(5.80)	(7.51)	(7.54)
Technology	69.67***	58.33***	58.33***	67.89***	66.99***
	(13.83)	(11.39)	(11.38)	(12.01)	(12.61)
Life Sciences	-3.52	-13.53	-12.99	-3.55	-4.29
	(12.28)	(9.79)	(9.70)	(11.46)	(11.79)
Medicine	46.31***	33.35***	33.61***	42.90***	42.97***
	(7.72)	(8.33)	(8.22)	(9.07)	(9.11)
Within * 1(Application Score>Cutoff)*					
Humanities	-3.41	-2.12	-1.93	7.08	5.90
	(10.04)	(9.39)	(9.16)	(9.44)	(9.45)
Science	-17.27	-12.98	-12.54	-3.59	-2.36
	(14.92)	(13.14)	(12.80)	(12.25)	(12.28)
Social Sciences	-5.16	5.41	5.79	14.70	14.80
	(12.91)	(11.28)	(10.51)	(10.80)	(11.43)
Technology	87.82***	65.69**	65.83**	75.01***	68.47**
	(28.65)	(27.08)	(27.03)	(26.43)	(26.73)
Life Sciences	4.55	-11.38	-10.58	-1.46	2.62
	(16.51)	(19.51)	(19.94)	(19.50)	(17.57)
Medicine	-2.57	-25.14	-25.05	-16.54	-15.07
	(21.76)	(17.28)	(17.13)	(17.04)	(17.76)
Only One * 1(Application Score>Cutoff)					
Humanities	-17.38	-11.14	-11.01	-2.18	-2.51
	(11.80)	(11.08)	(10.83)	(10.55)	(10.54)
Science	-14.40	-17.09	-16.86	-8.08	-8.19
	(21.14)	(16.10)	(15.67)	(15.11)	(14.88)
Social Sciences	-3.06	8.79	9.06	17.90	17.50
	(13.70)	(13.07)	(12.88)	(12.98)	(12.76)
Business	32.92***	40.11***	40.20***	49.41***	54.96***
	(10.08)	(8.93)	(8.74)	(7.97)	(7.96)
Law	74.78***	75.77***	75.83***	84.55***	84.02***
	(9.82)	(8.97)	(8.83)	(7.88)	(7.66)
Technology	60.75**	50.52**	50.44**	59.78***	60.60***
	(24.76)	(18.88)	(18.97)	(18.45)	(18.28)
Life Sciences	36.03**	38.71***	39.21***	48.50***	49.50***
	(16.18)	(13.11)	(12.77)	(12.34)	(11.90)
Medicine	47.47***	42.55***	42.77***	51.80***	51.36***
	(13.50)	(12.54)	(12.45)	(11.96)	(11.87)

Observations	282,632	282,632	282,632	282,632	282,632
Preferred and second-best education indicators	YES	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES
Different slopes	NO	NO	YES	YES	YES
Quadratic terms	NO	NO	NO	YES	YES
Preferred and second-best institution indicators	NO	NO	NO	NO	YES
Clusters	50	50	50	50	50

TABLE B3: STANDARD ERRORS CLUSTERED ON THE RUNNING VARIABLE

	(1)	(2)	(3)	(4)	(5)
Only One * 1(Application Score>Cutoff)	21.10***	24.07***	24.34***	32.51***	32.70***
	(3.32)	(2.98)	(3.10)	(5.88)	(5.72)
Within * 1(Application Score>Cutoff)	-2.45	-0.51	-0.08	8.15	7.74
	(6.76)	(5.32)	(5.58)	(8.07)	(7.90)
Between * 1(Application Score>Cutoff)	25.59***	25.82***	26.21***	34.64***	34.12***
	(4.76)	(4.82)	(4.75)	(6.54)	(6.48)
Observations	282,632	282,632	282,632	282,632	282,632
Individuals	43838	43838	43838	43838	43838
Clusters	32	32	32	32	32
Preferred and second-best education indicators	YES	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES
Different slopes	NO	NO	YES	YES	YES
Quadratic terms	NO	NO	NO	YES	YES
Preferred and second-best institution indicators	NO	NO	NO	NO	YES

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields. The set of control variables includes sex, a quadratic in age, father's earnings at applicant age 16, an indicator for whether father's earnings are missing, calendar year indicators, indicators for year of application, and indicators for *Within* and *Between* type. All regressions include the function of the application score indicated in the table. Standard errors, clustered on the running variable, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B4: Effects of Preferred Degree on Earnings, including those with an application score of 0 in the control group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1(Application Score > Cutoff)	22.08***	20.45***	18.88***	21.13***	18.05***					
	(3.65)	(4.22)	(3.19)	(3.80)	(4.26)					
Only One * 1(Application Score>Cutoff)						23.31***	23.37***	21.32***	24.41***	21.35***
						(4.56)	(4.42)	(4.02)	(3.94)	(4.96)
Within * 1(Application Score>Cutoff)						-14.12	0.73	-1.03	3.4	-3.9
						(10.27)	(8.32)	(7.40)	(7.41)	(9.46)
Between * 1(Application Score>Cutoff)						33.93***	25.11***	23.52***	21.80***	22.46***
						(7.32)	(6.95)	(5.60)	(7.72)	(7.04)
Observations	303,591	303,592	303,593	236,038	154,505	303,591	303,592	303,593	236,038	154,505
Individuals	47033	47034	47035	36,391	23,687	47033	47034	47035	36,391	23,687
Clusters	50	50	50	50	50	50	50	50	50	50
Window	2.0	2.0	2.0	1.0	0.5	2.0	2.0	2.0	1.0	0.5
Preferred and second-best education indicators	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Different slopes	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Quadratic terms	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Preferred and second-best instituion indicators	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO

The set of control variables includes sex, a quadratic in age, father's earnings, an indicator for whether father's earnings are missing, *Within* and *Between* type indicators, calendar year indicators and indicators for year of application. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B5: Effects of Preferred Degree on Earnings, including those with an application score of 0 in the treatment group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1(Application Score > Cutoff)	15.36**	23.55***	17.91***	20.77***	13.55***					
	(5.94)	(3.82)	(3.30)	(3.70)	(3.00)					
Only One * 1(Application Score>Cutoff)						19.93***	26.37***	20.59***	24.36***	17.39***
						(6.37)	(3.86)	(4.08)	(3.66)	(3.85)
Within * 1(Application Score>Cutoff)						-22.15*	3.69	-2.13	3.31	-8.39
						(12.35)	(5.74)	(5.91)	(5.72)	(7.29)
Between * 1(Application Score>Cutoff)						26.93***	27.28***	21.57***	20.73**	16.86**
						(7.75)	(7.89)	(6.38)	(8.70)	(8.37)
Observations	303,591	303,591	303,591	236,038	154,505	303,591	303,591	303,591	236,038	154,505
Individuals	47033	47033	47033	36391	23687	47033	47033	47033	36391	23687
Clusters	50	50	50	50	50	50	50	50	50	50
Window	2.0	2.0	2.0	1.0	0.5	2.0	2.0	2.0	1.0	0.5
Preferred and second-best education indicators	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Different slopes	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Quadratic terms	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Preferred and second-best instituion indicators	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO

The set of control variables includes sex, a quadratic in age, father's earnings, an indicator for whether father's earnings are missing, calendar year indicators and indicators for year of application. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B6: Effects of Preferred Degree on Earnings, including additional parental education variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1(Application Score > Cutoff)	22.66***	29.75***	21.68***	20.77***	13.55***					
	(5.49)	(4.65)	(3.64)	(3.70)	(3.00)					
Only One * 1(Application Score>Cutoff)						25.42***	32.82***	24.37***	24.36***	17.39***
						(6.13)	(4.82)	(4.57)	(3.66)	(3.85)
Within * 1(Application Score>Cutoff)						-17.55	7.37	-0.56	3.31	-8.39
						(12.44)	(7.44)	(7.14)	(5.72)	(7.29)
Between * 1(Application Score>Cutoff)						35.42***	34.11***	26.14***	20.73**	16.86**
						(8.12)	(8.10)	(6.30)	(8.70)	(8.37)
Observations	282,632	282,632	282,632	236,038	154,505	282,632	282,632	282,632	236,038	154,505
Individuals	43838	43838	43838	36391	23687	43838	43838	43838	36391	23687
Clusters	50	50	50	50	50	50	50	50	50	50
Window	2.0	2.0	2.0	1.0	0.5	2.0	2.0	2.0	1.0	0.5
Preferred and second-best education indicators	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Different slopes	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Quadratic terms	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Preferred and second-best institution indicators	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO

The set of control variables includes sex, a quadratic in age, father's earnings, indicators for *Within* and *Between* type, an indicator for whether father's earnings are missing, an indicator for whether the mother had a higher education when the student was 16 years old, whether the mother's education was missing when the student was 16, an indicator for whether the student's father had a higher education when the student was 16, an indicator for whether the father had a missing education, and calendar year indicators and indicators for year of application. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Pooled Results

Table B7 presents the results from estimating a simpler version of equation (1) in which all applicant types are pooled:

$$y_{it} = \beta\mathbb{I}(r_i > 0) + f(r_i) + \alpha x_{it} + \varepsilon_{it}$$

The first column displays the results for the most parsimonious model, one that includes the application score, calendar and application year indicators and is estimated from a sample window of +/- 2 application score points. From the first row of regression coefficients, we see that applicants whose GPA exceeded the GPA admissions requirement for her preferred program will on average realize a highly significant 23,000 DKK annual reward for doing so (about 3,000 USD).

In the second column, we add (narrowly defined) first and next-best subject indicators, while the third column presents the least parsimonious model, also estimated from a sample window of +/- 2 application score points. In column (3), sex, a quadratic in age, earnings of the applicant's father at age 16 and an indicator for whether the earnings of the father are missing are included. Furthermore, we allow the function of the application score, included as a quadratic, to change on either side of zero. In both columns (2) and (3), the effect of crossing the GPA cutoff is positive and significant, and it is between 19,000 and 30,000 DKK. These are non-negligible effects: as a consequence of surpassing the GPA requirement of one's preferred degree, applicants on average realize a bonus approximately equal to about 7%-10% of annual earnings 8 years after application.

Columns (4), (5) and (6) are estimated from a sample window of +/- 2, +/- 1 and +/- 0.5 application score points, respectively. We see that narrowing the estimation window does not substantially affect the estimates. The take-away from Table III is that applicants who meet the GPA required for admission into their preferred program realize a significant 19,000-30,000 DKK reward for doing so.

TABLE B7: EFFECTS OF PREFERRED DEGREE ON EARNINGS

	(1)	(2)	(3)	(4)	(5)	(6)
1(Application Score > Cutoff)	22.66***	19.00***	29.72***	21.73***	26.77***	22.71***
	(5.49)	(4.26)	(4.61)	(3.64)	(4.30)	(3.85)
Observations	282,632	282,632	282,632	282,632	215,079	133,546
Individuals	43838	43.838	43.838	43.838	33.196	20.492
Clusters	50	50	50	50	50	50
Window	2.0	2.0	2.0	2.0	1.0	0.5
Preferred and second-best education indicators	NO	YES	YES	YES	YES	YES
Control variables	NO	NO	YES	YES	YES	YES
Different slopes	NO	NO	YES	YES	YES	YES
Quadratic terms	NO	NO	YES	NO	NO	NO
Preferred and second-best institution indicators	NO	NO	YES	NO	NO	NO

The set of control variables includes sex, a quadratic in age, father's earnings, an indicator for whether father's earnings are missing, calendar year indicators and indicators for year of application. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix C

Additional Institutional Details

The admission system just described is usually referred to as the Quota 1 application system. Some programs also offer slots through Quota 2. To be eligible to apply through Quota 2, the applicant must have collected a sufficient number of points in a point-based system in which non-academic activities, such as work experience, organization and political work, military service, and living abroad, are rewarded. The specific criteria and the share of slots available in Quota 2 are decided at a decentralized level. If a Quota 2 applicant has a higher GPA than the Quota 1 GPA cutoff, she will be admitted through Quota 1. Thus, the benefit of applying through the Quota 2 system is that the high school GPA requirement is lower than the Quota 1 GPA requirement.

As mentioned, if an applicant is not admitted to any of her listed priorities, it is still possible to enroll in programs with vacant slots. In addition, some programs also offer standby slots. Standby slots require a lower GPA cutoff than the Quota 1 slots and offer admittance into the program in the following year.

More than three-quarters of applicants are admitted through Quota 1, which seems to suggest that this is the most relevant cutoff to consider. Nevertheless, our main argument for using the Quota 1 cutoff and not the standby cutoff is that lowering the latter would imply that more students would have to wait for a year before beginning university studies. From a policy perspective, it is clearly more attractive for both society and the individual to admit students in the current year rather than postponing their studies.

The existence of standby slots, the Quota 2 system, and the applicant’s ability to reject an offered slot imply that we do not have a sharp regression discontinuity design, even for enrollment.

However, from a policy point of view, the main question of interest is the effect of changing the GPA cutoffs on earnings.

Skill data

In the following sections, we describe the construction of our datasets with information on skills of applicants. Some of this is also described in the working paper by Jensen (2020). In order to obtain information on skills, we first need consistent occupational codes across for the period in which we consider labor market outcomes, namely 2003-2014. How we obtain consistent occupational codes is described in the first subsection below, and next, we describe our skills data in more detail.

DISCO-codes

DST has adopted 6-digit versions of the International Labour Organization's ISCO88 and ISCO08 occupational codes, namely DISCO88 and DISCO08. The two extra digits are added to provide additional detail. Prior to 2010, all occupation codes in DST's datasets are coded using the 6-digit DISCO88 codes (although for some years, only 4-digit codes are reported). From 2010 and onwards, all occupation codes in DST's datasets are coded using the 6-digit DISCO08 codes. Unfortunately, the (D)ISCO88 and (D)ISCO08 codes do not map consistently one-to-one, one-to-many or many-to-one, and thus, a crosswalk cannot be straightforwardly produced, and crosswalks are not provided by either ILO or DST. Since we are looking at labor market outcomes from 2003-2014, we need consistent occupational codes over this period. Therefore, we produce a revealed crosswalk, using occupational information on people that remain in the same job during the break in occupational codes from December 2009 to January 2010. We aggregate 4-digit DISCO88 and

6-digit DISCO08 codes into 228 mutually exclusive occupational groups. In comparison, there are 150 unique 3-digit and 492 unique 4-digit DISCO88 codes reported in AKM from 2003-2009. Thus, our grouping gives a level of detail somewhere between the 3- and 4-digit level.

Skill datasets

Danish online job vacancy data from 2007-2014 are supplied by the Danish consultancy firm, Højbjerre Brauer Schultz (HBS). These data also include a firm identifier and an occupational code for each job post as well as a posting date. Thus, it is possible to match these data with register data along those dimensions. HBS collects online job vacancy data from numerous Danish online jobs boards, and thus, they believe that their data contains the near universe of publicly accessible Danish online job posts.[32] They remove duplicates and clean the data before machine reading the job posts. HBS extracts the date on which a given job vacancy was posted online, the identification number (CVR-number) of the posting firm, and a 6-digit DISCO-code. If the firm identifier is not listed directly in the job post, HBS imputes it from publicly accessible registers using the firm name and/or address listed in the job post. Importantly, HBS also extract keywords from the raw text in the job post. In many ways, the resulting data is similar to the US job vacancy data supplied by Burning Glass Technologies. In order to be able to match with the register datasets, the vacancy data sample is restricted to include job posts with non-missing firm identifiers and occupational codes. The basis of our skills datasets is 1,928,972 unique job posts with at least one keyword, posted from 2007-2014. When we drop job posts with missing occupation codes, we have 1,232,920 posts, and after dropping those with missing firm identifiers, we are left with 1,020,294

[32] http://www.hbseconomics.dk/wp-content/uploads/2017/09/Eftersp%C3%B8rgslen-efter-sproglige- kompetencer.pdf

job posts. From these 1,020,294 job posts, we derive two datasets with information on skills of university applicants. The first dataset gives us information on individual variation in skills for people who start a new job that was recently posted, and thus, observed in our job vacancy data. Using this data, we can verify how skill usage change across the cut-off for *Between* applicants, but not for *Within* applicants, in t-tests. However, since people do not change jobs very often, we are left with a relatively low number of observations in this dataset, and thus, this dataset does not yield the statistical power we need in regression analyses. Thus, we also construct a dataset with occupation-level information skills and match the occupational information to all people working in a given occupation, and not only people who recently started a new job. More details on these datasets are in available in Table C1.

TABLE C1: SKILLS DATASETS

	Individual-level skills	**Occupation-level skills**
Initial skill data	Obtain data from the first 12 months of new jobs (either new firm identifier or new occupational code) from BFL from 2008-2014, and merge with job posts at the firm*occupation*time-level. We assume that a vacancy is filled in the same month it is posted or maximum 4 months later. This gives a 5 months matching window. Merge onto KOT-sample.	Collapse skills data from 2007-2014 at the occupation-level. Obtain occupation codes at individual-level from AKM and merge these and occupational-level skills onto KOT-sample.
For analyses, *all years* after KOT	Keep only if GPA falls within of 2.0 application score points (i.e. standardized GPA) around cut-off.	Keep only if GPA falls within of 2.0 application score points (i.e. standardized GPA) around cut-off.
For *calculation of mean skill usage of graduates* within narrow fields	Keep only graduates of master's programs Keep only first observed job after graduation (and drop if this is 8 years or more after graduation)	Keep only graduates of master's programs Keep only if job is observed 8 years after application.

Skill categorization

In order to extract skill requirements from the job vacancy data, we initially follow the method of Deming and Kahn (2018). They map a selection of keywords into skills categories. For example, the keyword "teamwork" is indicative of a job requiring social skills. The nine skill categories, which we use, can be seen in Figure II . Unlike Deming and Kahn (2018) who only map a selection of keywords into skill categories, we assign all keywords either a skill category or a noise tag. This is done as follows: 1) The most frequent keywords (approx. 2000) are assigned a skill category or noise tag manually. These words amount to the vast majority of keyword-observations. 2) Using online dictionary APIs each word's synonyms are obtained. Each word's synonyms are assigned the same category. 3) Using online dictionary APIs each word's definitions are obtained. 4) Using the definition of the words, the remaining non- categorized words are assigned a category using machine-learning methods. The machine learning methods are described in more detail here.

The training set consists of both the more than 2000 manually categorized words and their categorized synonyms. In order to categories the remaining words, the dictionary definition of each keyword obtained from two dictionaries, one Danish dictionary and one English dictionary. To use the English dictionary, the keywords are translated beforehand. Although the translation step may seem tedious, it involves some regularization of the keywords, which again helps when looking up definitions of the words. Next, the classification exercise is undertaken.

Two approaches to the classification problem is repeated for both Danish and English versions of the keywords' definitions. The first approach is a one-step categorization, where each keyword is assigned one of 10 categories, i.e. either one of the nine skills or a noise tag. A Random Forest Predictor is used for this exercise. The second approach is a two-step categorization. In the first step, each keyword is classified as either noise or non-noise. In the second step each non-noise word is assigned to one of the nine skill categories. For both steps a Random Forest Predictor is applied.

Thus, four predicted categorizations are available for each keyword that was not a part of the training set: a one-step and a two-step version for both the Danish and English definitions. If predictions from all four approaches agree on a category, the keyword is assigned to this category. The same step is undertaken if predictions from three out of four approaches agree. Some words' definitions are only available in either the Danish or English dictionary. These words are categorized if the two approaches in the same language agree and if the probability of the predicted class is relatively high. For the few words that have not been categorized after these steps, English predictions with very high probabilities are considered and assigned to keywords. The predictions based on the English definitions are typically more reliable due to longer definitions of the keywords. If keywords are not categorized after this procedure, they are assigned a noise tag.

Skill measures

In the following two subsections, we describe how we derive the skill measures for the datasets with individual- and occupation-level information on skills respectively.

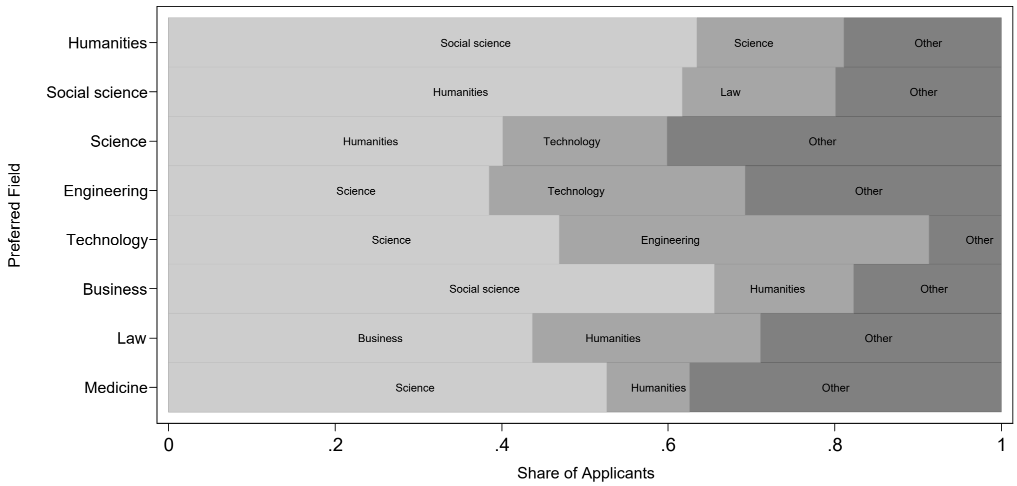
Individual-level skills

In the individual-level data, we match an individual who starts a new job in a given firm*occupation cell with job posts that have occurred within the same firm*occupation cell in same month the individual starts the job or maximum 4 months prior. An individual may therefore be matched with one or more job posts. We calculate the fraction of words indicative of a certain skill across the matched job post(s). We interpret these skill fractions as intensive measures of skill usage of workers. Thus, we are left with intensive measures of skills usage that vary at the individual level. Next, we "normalize" the skill measures by dividing them by the average skill usage across all individuals. We do this because certain skills are rare, e.g. specific computer skills, and others are very common, e.g. character skills. The "normalization" makes the measures more comparable. Since we want to know more about the (dis)similarities of the skill usage of applicants that are just above/below the cut-off of their preferred choice of BA program, we calculate the distances between the average Master's graduate of a narrow field and a given applicant in that field as follows: 1) We consider the first observed job of each graduate of a Master's degree in a given narrow field, no more than 7 years after application, and calculate their average skills use based on the skills measure derived above; 2) We calculate the absolute distances between these averages and the skills usage of the applicant who has listed the corresponding narrow field BA program as their preferred choice.

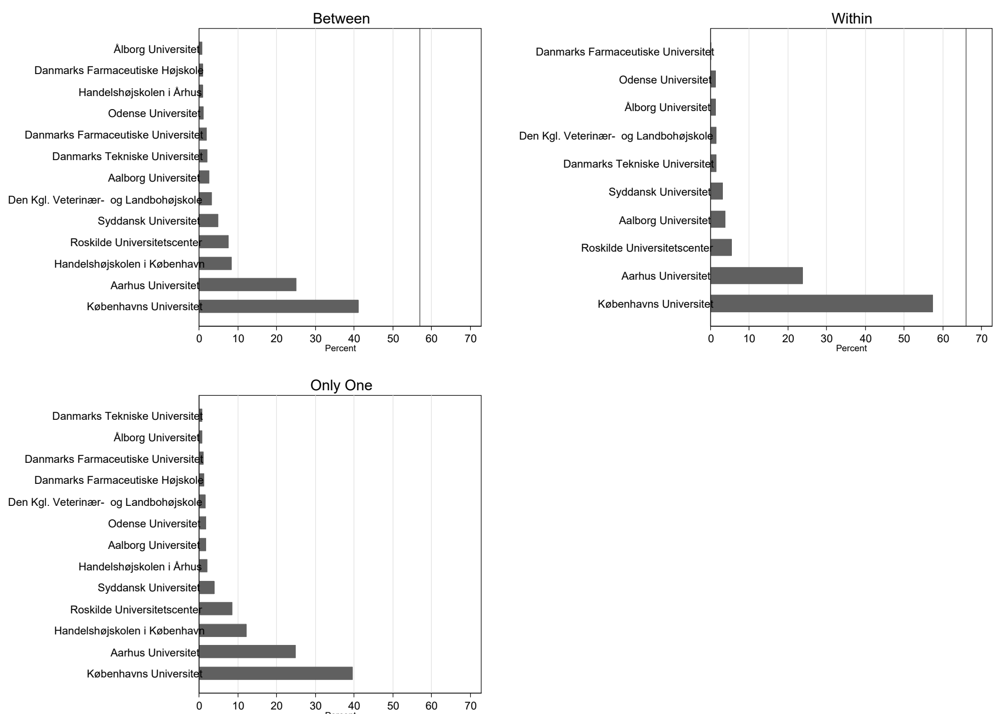
Occupation-level skills

For each job post, we calculate the fraction of words indicative of a certain skill. After calculating the fraction of words indicative of a certain skill for each job post, we average these fractions within our 228 occupational groups. Thus, we are left with intensive measures of skills usage that vary at the occupation level. We merge these skills measures onto our estimation sample after converting DISCO88/DISCO08 codes into our 228 occupational groups. Finally, we also "normalize" these skill measures by dividing them by the average skill usage across all occupations. Again, we calculate the distances between the average Master's graduate of a narrow field and a given applicant as follows: 1) We consider all graduates of a Master's degree in a given narrow field 8 years after application, and calculate their average skills use based on the skills measure derived above; 2) We calculate the absolute distances between these averages and the skills usage of the applicant who has listed the corresponding narrow field BA program as their preferred choice.

Online Appendix D: Additional descriptive information, results and data cleaning



F IGURE D1: MOST COMMON NEXT-BEST FIELDS BY PREFERRED FIELDS FOR BETWEEN APPLICANTS



F IGURE D2: MOST PREFERREDINSITITUTIONS BY TYPE

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

Results by sex

O4 presents the effects of surpassing the GPA admission requirement in one's preferred broad field broken out by the sex of the applicant. The same general patterns observed earlier are present for both sexes: male and female *Within* applicants realize no benefits from surpassing the GPA requirement of their preferred field, whereas *Between* and *Only One* applicants receive sizable and significant benefits for doing so. Among *Only One* applicants, women receive an added 9%-11% of their average annual earnings from exceeding the GPA cutoff required for admittance in their preferred degree while men receive an additional 6%-11%. Among *Between* applicants, men benefit more from surpassing the GPA requirement necessary for admittance into one's preferred degree: they realize a benefit from 10%-14% of their average earnings opposed to women who only receive 6%-7%. Figure D3 in Online Appendix plots the estimate effects on earnings for each year after application, by sex. There is no substantial variation over time and the effects generally remain significant for the *Between* and *Only One* applicants.

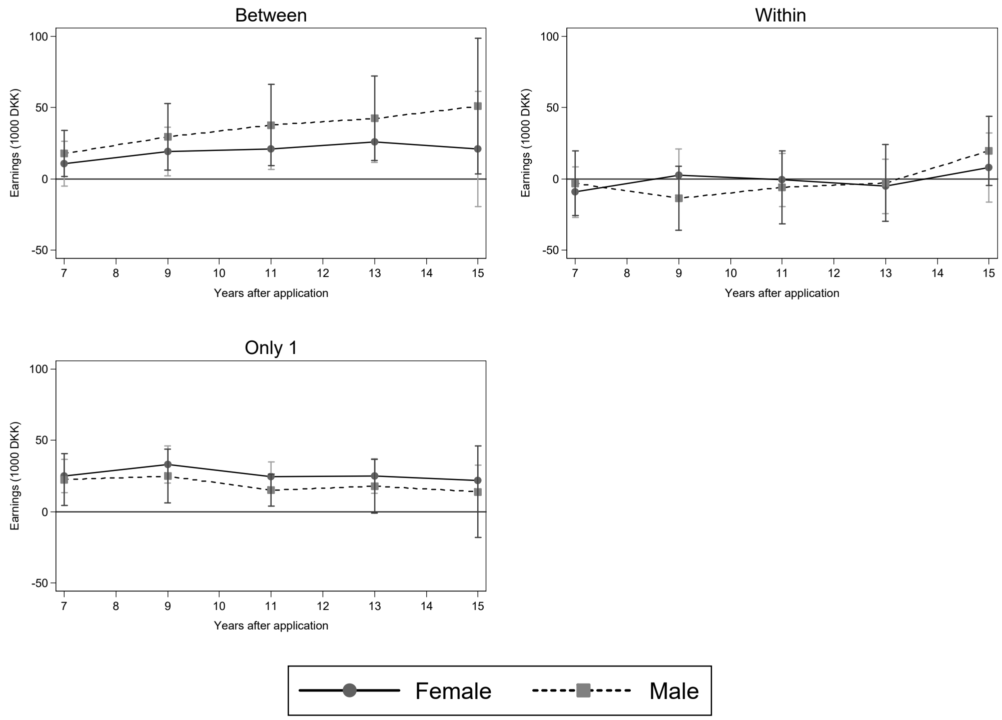


FIGURE D3: ESTIMATED PAYOFFS TO PREFERRED DEGREE OVER TIME (DKK YEAR), BY GENDER

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields.

TABLE D2: EFFECTS OF PREFERRED DEGREE ON EARNINGS, BY SEX

	(1)	(2)	(3)	(4)	(5)
(A) Women					
Only One * 1(Application Score>Cutoff)	24.84***	28.92***	26.31***	29.67***	29.96***
	(4.91)	(7.53)	(5.09)	(6.41)	(7.16)
Within * 1(Application Score>Cutoff)	-1.79	0.81	-1.24	4.40	3.06
	(8.61)	(8.83)	(8.04)	(8.09)	(12.20)
Between * 1(Application Score>Cutoff)	19.64**	19.94**	18.23**	16.10*	17.56**
	(7.81)	(8.87)	(7.22)	(8.80)	(7.42)
Observations	163,535	163,535	163,535	126,330	79,571
Individuals	25,280	25,280	25,280	19441	12149
Clusters	50	50	50	49	47
(B) Men					
Only One * 1(Application Score>Cutoff)	19.04***	36.07***	22.78***	30.62***	18.86**
	(5.57)	(8.77)	(5.85)	(7.30)	(8.35)
Within * 1(Application Score>Cutoff)	-1.86	14.46	1.69	9.95	-12.73
	(11.67)	(11.95)	(10.85)	(12.40)	(12.97)
Between * 1(Application Score>Cutoff)	36.21***	45.91***	33.00***	36.33**	34.34**
	(10.36)	(15.23)	(9.81)	(16.22)	(14.31)
Observations	119,097	119,097	119,097	88,749	53,975
Individuals	18,558	18,558	18,558	13755	8343
Clusters	50	50	50	50	49
Window	2,0	2,0	2,0	1,0	0,5
Preferred and second-best education indicators	YES	YES	YES	YES	YES
Control variables	NO	YES	YES	YES	YES
Different slopes	NO	YES	YES	YES	YES
Quadratic terms	NO	YES	NO	NO	NO
Preferred and second-best institution indicators	NO	YES	NO	NO	NO

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields. The set of control variables includes sex, a quadratic in age, father's earnings at applicant age 16, an indicator for whether father's earnings are missing, calendar year indicators, indicators for year of application, and indicators for *Within* and *Between* type. All regressions include the function of the application score indicated in the table. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE D3: MAIN RESULTS DROPPING VARIOUS FIELDS

	(1)	(2)	(3)
	Baseline	No Humanities	No Law and No Business
Only One * 1(Application Score>Cutoff)	21.10***	31.87***	21.69***
	(4.80)	(4.44)	(5.50)
Within * 1(Application Score>Cutoff)	-2.45	2.03	7.82
	(7.92)	(10.90)	(7.71)
Between * 1(Application Score>Cutoff)	25.59***	28.50***	18.38***
	(7.22)	(7.83)	(6.34)
Observations	282,632	217,709	235,249
Preferred and second-best education indicators	YES	YES	YES
Control variables	YES	YES	YES
Different slopes	YES	YES	YES
Quadratic terms	YES	YES	YES
Preferred and second-best institution indicators	YES	YES	YES
Clusters	50	28	48

"Only One" refers to applicants who applied for one study program. "Between" refers to applicants whose preferred and next-best fields are in different broad fields. "Within" refers to those applicants whose preferred and second-best fields are within the same broad fields. The set of control variables includes sex, a quadratic in age, father's earnings at applicant age 16, an indicator for whether father's earnings are missing, calendar year indicators, indicators for year of application, and indicators for *Within* and *Between* type. All regressions include the function of the application score indicated in the table. Standard errors, clustered at the 6-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Data Cleaning

TABLE D4: BASIC CLEANING

	Drop	Individual-Application Year-Preferences	Individual-Application Years	Individuals
1	Raw, 1993-2006	1,776,163	857,297	592,272
2	Drop observation with empty/numeric pnr	1,690,091	823,069	561,153
3	Drop observations with KOT priority errors	1,667,904	814,447	555,833
4	Drop those who can't be matched to education registries (educ spells)	1,653,365	806,760	548,937
5	Drop years before 1996 (after flagging first year applied)	1,247,414	626,346	442,624
6	Drop individuals not on Fainv	1,245,366	625,498	441,898
7	Keep those whose age at application is between the ages of 17 and 25	1,004,869	487,973	347,999
8	Drop folks who do not appear on BEF (which goes from 2008-2013)	1,004,471	487,788	347,839
9	Drop immigrants (ie_type==2)	932,676	459,164	326,682
10	Keep first time applicants	603,215	302,672	302,672
11	Drop individuals with no HS GPA	522,310	259,152	259,152
12	Drop those had a KOT application year before graduation year	497,978	246,739	246,739

TABLE D5: SAMPLE SELECTION

A	B	C	D	E	F	G
	Drop	**Observation Type in column D**	**Observations**	**Individual**	**Individuals with Multiple Preferences**	**Individuals with Only One Preference**
	After Basic Cleaning	**Individual-Raw Preferences**	**497,978**	**246,739**	**130,024**	**116,715**
1	Dropping those who only have preferences for KOT>=30000 or other fields that we don't consider	Individual-Raw Preferences	270,097	126,758	71,018	55,740
2	Aggregating at the 6-digit level	Individual-Aggregated Preferences	221,752	126,758	57,273	69,485
3	Dropping those with a non-binding cut-off in most preferred broad field	Individual-Aggregated Preferences	169,209	91,762	45,883	45,879
	Drops made on those with multiple preferences					
4a	Dropping those who are most interested in High KOT before (i.e. before preferred and next-best)	--	--	--	33,177	--
4b	Dropping those whose next-best field is for a program we are not interest in (High KOT)	--	--	--	24,937	--
4c	Drop people whose GPA never exceed a threshold or who have local priorities for HIGH KOT	--	--	--	19,908	--
4d	Drops individuals whose preferred and next-best have non-descending GPA cutoffs	--	--	--	15,129	--
4e	Again need to drop those who have a high KOT preference before their preferred and next bet. Did this for KOTS that appeared before ANY other GPA in the preference ranking. But we need to drop folks who have low KOT preferences, followed by high KOT preferences, followed by their preferred and next-best	--	--	--	15,079	--
4f	For those who have preferred field of 3 and next-best of 4, we need that the GPA cutoffs of 1&2 be higher than the cutoff of 3 and 4, but we don't care if 1 is less than 2	--	--	--	14,226	--
	Drops made to those with just one preference					
5	Dropping those who have a non-binding cutoff or only apply for high KOT	--	--	--	--	41,644
6	Bringing sample together after drops 4 & 5	Individual-Aggregated Preferences	80,079	55,870	14,226	41,644
7	Dropping preferences other than preferred and next-best. Bringing together those with one preference (one record per individual) and those with multiple preference (2 records per individual)	Individual-Aggregated Preferences	70,096	55,870	14,226	41,644