University admission and preferred field of study

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Using discontinuities from the Danish college enrollment system, we find that students who are marginally accepted into their preferred program in a broad field that is different from their next-best choice (e.g., business rather than science) experience significant and long-lasting rewards for doing so. In contrast, students whose preferred and next-best program lie within the same broad field do not. Exploiting data from online job postings, we find that the estimated effects on skill usage similarly vary according to the degree of similarity between preferred and next-best choices, consistent with what the Roy model predicts.

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1. Introduction

In this paper, we ask whether exceeding the admission requirements of one's preferred field has an effect on one's future earnings and subsequent skill usage and next, whether this effect is a function of the similarity of the applicant's preferred and next-best alternatives. If programs within the same broad field tend to reward similar skills, Roy (1951) predicts that individuals whose preferred and next-best fields lie within the same broad field ought to realize smaller earnings gains relative to those whose preferred and next-best fields are in two different broad fields. We find evidence that supports this conjecture.

Using data provided by the Danish centralized college enrollment system, we use a regression discontinuity design to estimate these effects. Prospective students rank up to eight programs and are admitted into the highest ranked program for which they are qualified according to whether their high school grade point average (GPA) exceeds the program's GPA admission criteria. Programs are restricted when there are fewer available slots than applicants for the program. Therefore, at the time of application, the admission cutoffs are not known.

Using information on the applicants' ranking of programs, we compare those who are on the margin between two broad fields (e.g., social sciences, sciences, humanities) with applicants whose preferred and next-best field lie within the *same* broad field (e.g., archaeology and history). We can visually confirm and cleanly estimate the causal effects on subsequent earnings and skill usage of just exceeding the GPA threshold of one's preferred degree. Only for applicants whose next-best field of study lies in a *different* broad field do we detect significant effects on earnings, confirming the predictions of the Roy model.

Recently, Kirkeboen et al. (2016) and Hastings et al. (2013) have used college admission data from Norway and Chile, respectively, to examine whether students sort into fields of study based on comparative advantage.[1] Hastings et al. (2013) find small earnings gains from being

[1] See Altonji et al. (2016) for a thorough discussion of Hastings et al. (2013) and Kirkeboen et al. (2016).

admitted to one's preferred field of study, but do not find strong support for students sorting in to fields of study by comparative advantage. In fact, Hastings et al. (2013) find that a significant share of prospective students sort into programs with zero or negative returns. In contrast, Kirkeboen et al. (2016) find that students, on average, have considerably larger future earnings in their preferred field of study and that students sort according to comparative advantage. Our results help to reconcile these different findings.[2]

When we follow Kirkeboen et al. (2016) and distinguish between each student's preferred and next-best broad fields and only consider applicants whose preferred and next-best programs lie in *different* broad fields, we also find fairly large earnings gains from being admitted to one's preferred field. However, when we consider students whose preferred and next-best fields lie within the *same* broad field, we do not find significant earnings gains from admission. The analysis of Hastings et al. (2013) includes both types of applicants, and therefore based only on this difference in inclusion criteria, their earnings effects ought to be smaller than those found by Kirkeboen et al. (2016).

We also contribute to the literature in the following four ways. First, we examine how admission into one's preferred fields affects subsequent skills use. To do so, we use Danish online job posting data. Largely following Deming and Kahn (2018), we identify keywords indicative of nine different skill categories in each job ad. We then construct measures of skills intensity for each category at the job-level. We find that the effect of being admitted to one's preferred field on skills used in subsequent jobs is a function of the similarity of the preferred and next best alternative: those on the margin between two different broad fields realize larger effects on their skill sets than do those on the margin between two fields within the same broad field. This result does not rule out competing explanations of education earnings premiums such

[2] Another cause for the divergence stems from the fact that Hastings et al. (2013) estimate the intent to treat, that is, the effect of marginally exceeding university admission requirements, whereas Kirkeboen et al. (2016) estimate the effect of completing a degree into which one was marginally admitted.

as signaling, but it does provide a basis for the exploration of sorting based on comparative advantage. In other words, if we did not find any effects on skill usage, a story based on comparative advantage would have little support.

Second, we are able to provide evidence that being admitted to one's preferred program, in itself, does not generate long lasting motivation effects that affect earnings.[3] The psychology literature suggests that individuals' passion and motivation affect their academic performance (Stoeber et al., 2011). If such effects are long lasting, being admitted into one's preferred program should yield significant positive effects on earnings regardless of the next-best alternative.[4] This is not what we find, rather, we find that those on the margin between two fields within the same broad field realize no rewards for admission to their preferred program.

Third, we also consider the effects of admission on students who only list one program at the time of application. More than half of students in Denmark only list one program in their application. We find that for these applicants, not exceeding the GPA requirement necessary for admittance translates into significant temporary earnings losses, mainly because of a delay in enrollment. The effect on total earnings within 15 years of enrollment for those applicants who just exceed the admission threshold is large, positive, and significant.

Fourth, given our longer observation window we are able to document that the earnings gains from being admitted to one's preferred field relative to a next best alternative in another broad field persists for at least 15 years after application. We also find no short or long term admission effects for those who preferred and next best field lie in the same broad field.

Overall, we find that a marginal loosening of the GPA requirements, on average, will increase the subsequent labor market earnings by allowing more students to begin studying earlier and improve the allocation of students across fields. We consider a simple cost-benefit

[3] See, for instance (Stoeber et al., 2011) who suggest such motivation effects.

[4] Only this absolute notion of motivation allows for it to be meaningfully differentiated in concept from as comparative advantage.

analysis using the three groups of applicants according to the similarity of the first and next-best preferred programs and find that the benefits outweigh the costs for a marginal loosening of the GPA requirements.[5] An additional policy implication of our results is that students should be encouraged to apply to several programs within their preferred broad field to increase the probability of immediate acceptance.[6]

The literature using a regression discontinuity design to study the effect of post-secondary education generally finds significant positive effects on graduation of being admitted into one's preferred field. However, the evidence is mixed concerning the findings on earnings. For example, Öckert (2010) finds low or no earnings effects for Sweden, whereas studies examining the effect of being admitted to higher-quality institutions find substantial effects for the U.S. (Hoekstra, 2009), for Columbia (Saavedra, 2008), and Italy (Anelli, 2016).

Whereas other studies have focused on just those applicants whose preferred and next-best fields lie in different broad fields (Kirkeboen et al., 2016) or pooled all applicants together (e.g., Hastings et al., 2013; Heinesen, 2018; Öckert, 2010; & Humlum et al., 2017), we believe our categorization of applicants according to the similarity of the preferred and next-best alternatives is novel to the literature.

Two recent studies use the regression discontinuity design in the Danish college enrollment system. Humlum et al. (2014) estimate the causal effects of exceeding the admission requirements of one's first-choice program on the timing of university enrollment, educational outcomes, and how these factors relate to family formation. They find that threshold-crossing increases the speed with which students enroll in and complete university, enter the labor market, and begin a family.[7] Heinesen (2018) studies the effect of crossing the standby

[5] For this cost-benefit analysis, we use earnings to capture the benefits of studying a program and measure the costs as based on the fixed rates the universities are paid when an additional student graduates. These fixed rates differ between fields of studies.

[6] Note that we do not suggest that a university admission policy should directly target applicant types as this would induce the strategic behavior of applicants, if, say, the chance of admission in the preferred program is higher when the preferred and next-best programs are in different broad fields.

[7] Their results agree with our finding that those applicants who apply to only one field and exceed the GPA requirement for admittance into that program are able to complete their programs earlier.

admission threshold (i.e., the threshold for admission in the following year rather than the main admission threshold that allows for enrollment in the current year) of one's first-choice program on completion and earnings. While he finds no robust effects of exceeding the standby GPA requirement on earnings 11 years after application, he does find an increase in the probability of completing a master's degree in that subject.[8]

The paper is organized as follows. In section 2, we discuss the institutional details of higher education in Denmark. In section 3, we consider the econometric framework employed in this paper. We describe the data in section 4 and provide simple descriptive statistics. In the following section, we provide graphical checks of the research design, while we present our results in section 6. Section 7 concludes the paper.

2. Institutional Details

In Denmark, children must attend compulsory schooling for 9 years, usually from the age of 7 to 16. After completing compulsory schooling, more than half of a cohort completes a 3-year high school program, a precondition for admittance into a university or professional bachelor's degree program. Studying in Denmark is comparatively cheap: University programs are publicly provided and are free of charge. In addition, the government provides generous student grants and optional student loans with favorable terms. The vast majority of university students study a two-year master's degree immediately after their bachelor's degree.

Danish students make their choice of study program when they apply for admission to university. A program identifies a field (e.g., economics) and an institution (e.g., University of Copenhagen) combination. All applications to university programs are handled by a centralized admission system. Once an applicant has been admitted to a program, generally speaking, the only way for her to change her program is to apply through the centralized application system

[8] Heinesen (2018) also briefly considers the effect of crossing the immediate admission GPA cutoff for admission to one's first-choice program and finds significant earnings effects in the sample closest to ours. See the bottom of Table D.1 in his online appendix and note that his estimates are reported in year 2000 DKK.

in the following year. However, if she would like to change to a program that has vacant slots, she may do so in the current year without reapplying.

During the period we are studying, universities determined the maximum number of students who could be admitted into each program.[9] The number of available slots in a program is determined prior to the period of application. Some programs also have a course-specific admission requirement, which naturally is determined prior to the period of application.[10]

If, after the application deadline, the number of applications exceeds the number of available slots, admission to a program is restricted and only applicants whose high school GPA exceeds a cutoff will be admitted. Programs with fewer applicants than available slots will have open admission; i.e., no GPA cutoff. About half of all programs have a GPA admission restriction. In practice, this cutoff is the binding constraint facing the vast majority of applicants who are not admitted to a program.

An applicant may list up to eight preferences in her application each year. If her GPA exceeds the GPA cutoff for her first-choice program, she is admitted and will not be considered for lower priorities. If she does not meet the GPA requirement for her first choice, she will be considered for her second-choice program. This process will continue down her preference rankings until she is admitted to one of her listed programs or receives no offer of admittance. In this way, the best students will be offered their preferred education. The application system is strategy-proof such that students' ranking of fields truthfully reflects their preferences.

The GPA admission requirement changes from year to year, mainly due to variation in applicant pools and, to a lesser extent, because of changes in the number of available slots. As a consequence, applicants do not know the exact GPA cutoff when applying. In particular, an

[9] There a few exceptions to this practice. A small number of university programs have a maximum number of students set at a central level. For example, as medicine involves mandatory practice, universities cannot determine the size of the incoming class. Beginning in 2014, a centralized system determines the maximum number of students per program based on projections of the labor demand for each field.

[10] An example of a course-specific admission requirement is that the applicant has passed high-level (A-level) math in high school.

applicant with a high school GPA close to the previous year's GPA requirement will not be able to predict whether or not she will be accepted.[11]

There are two mechanisms in place which allow admission for students with lower GPAs (see Online Appendix C for more details). Students admitted through these mechanisms a make up less than a quarter of the admitted students. These two mechanisms, and the applicant's ability to reject an offered slot imply that we do not have a sharp regression discontinuity design, even for enrollment.

3. Econometric Specification

Does the similarity of an applicant's preferred and next-best fields affect the earnings consequences of meeting one's preferred degree admission requirement? To answer this question, we classify applicants into three types: those who apply to *only one* field; those whose preferred and next-best fields belong to two different broad fields, that is, are on the margin of acceptance *between* two different fields (e.g., have a preferred broad field of Social Science and a next-best broad field of Medicine); and those applicants who are on the margin of acceptance between two fields *within* a broad field (e.g., have a preferred narrow field of Anthropology and next-best narrow field of Sociology, both of which lie within the broad field of Social Science). *Between* applicants are the subject of Kirkeboen et al. (2016), but, as discussed in the data section, comprise only about a quarter of the Danish applicant pool.

We will estimate the causal effect of exceeding the primary GPA requirement of one's preferred field of study (hereafter cutoff) on earnings and skills:

$$(1) \qquad y_{it} = \sum_{j \in O,W,B} \left[\beta_j \mathbb{I}(\, r_i > 0) * \mathbb{I}(\, type = j) \right] + f(r_i) + \alpha x_{it} + \varepsilon_{it}$$

where y_{it} is individual i's earnings in year t, and r_i is the difference between an individual's high school GPA and the GPA cutoff of her preferred program, normalized by the standard

[11] Humlum et al. (2018) provide a valuable discussion of time variation in the Danish admission requirements. They demonstrate a high degree of time variation during the application years that we consider.

deviation of GPA. The index j corresponds to the applicant type: applicants who list only one program are denoted by O, those whose preferred and next-best fields are within the same broad field are denoted as W, those who are on the margin between two different broad fields are denoted by B. Our interest lies in estimating the β_j, the intention to treat effect (ITT) of admittance into one's preferred program, for each applicant type rather than pooling these effects as is often done in the literature.[12] $\mathbb{I}(r_i > 0)$ is an indicator function taking the value of one if an individual's GPA exceeds the cutoff of the preferred program.

We estimate various specifications of $f(r_i)$ including linear, quadratic, and an interaction between $f(r_i)$ and $\mathbb{I}(r_i > 0)$. Finally, we control for a set of predetermined variables, x_{it} including sex, the earnings of the applicant's father at age 16, an indicator for whether or not the father's earnings is missing, age, age squared. Also included in x_{it} are a set of calendar year indicators, a set of application year indicators, a set of preferred narrow field indicators, a set of next-best narrow field indicators, a set of preferred institution indicators and a set of next-best institution indicators as well as indicators for applicant type.

As long as the requirements of a (fuzzy) regression discontinuity design are met in the Danish application process, applicants are locally "as good as randomly assigned" to being above or below admission cutoffs within a narrow enough window of the application score. Subject to an appropriately specified running variable (application score), we can interpret any discontinuous jumps in earnings as the effect of meeting the GPA admissions requirement.

Our running variable is discrete. Thus, we have applicants with an application score of zero. Whether such individuals are considered as passing the admission criteria or not varies at the program level and is not observable to us. To address this issue we drop applicants whose application score is zero prior to estimation, that is, we employ the so-called "donut-RD"

[12] For the estimated ITT effects in the pooled case, please see Table B7 in Online Appendix.

estimator as used by Barreca, et al. (2011).[13] In the case of a discrete running variable, Lee and Card (2008) recommend clustering the standard error on the discrete values of the running variable. Earnings may also be correlated within program type. Following Heinesen (2018) and Humlum et al. (2017), we cluster on preferred program in the earnings regressions as this appears to be more conservative in the earnings regressions.[14]

After carefully examining evidence that the requirements for the regression discontinuity design are met in the Danish enrollment system, we estimate equation (1) with OLS using standardized application score windows of 2, 1 and 0.5.

The average effect on earnings, over individuals and time, of meeting one's preferred GPA requirement is captured by the β's. We would also like to understand how these effects evolve over time. To do so, we will also estimate equation (1) for each year after application, starting with 7 years after application.

4. Data and Descriptive Statistics

4.1 Data

4.1.1 Coordinated Enrollment System and Danish Register Data

Fundamental to our analysis is the availability of detailed information on student preferences over programs of study at time of application, where program identifies a field (e.g. economics) and institution (e.g. University of Copenhagen) combination. The Coordinated Enrollment System (CES), by which all college applications are processed, has provided this data from 1993 to 2014 for all applicants along with each applicant's personal identifier, a key by which additional register data can be merged. Statistics Denmark maintains several high quality administrative registers that cover virtually the entire population of Denmark. Demographic characteristics are taken from the population registers which are available from

[13] Tables B4 and B5 in the Online Appendix present the results when those whose application score is zero are included either as controls or as treated. Estimated earnings effects remain significant and positive, but the estimates are dampened due to the measurement error.

[14] Estimation results from using the running variable to cluster standard errors are presented in Online Appendix Table B3..

1980 onward. Earnings and income histories are taken from the income registers which are available from 1980-2014 and high school GPA is taken from the education registers.

All estimations contain (some function of) an applicant's standardized GPA score, calculated as the difference between her GPA and the GPA admission requirement for her preferred degree normalized by the standard deviation of GPA scores, referred to as her application score. Unfortunately, GPA is recorded to the first decimal place only, and in this sense, our running variable is discrete.

Our measure of total earnings includes wages and self-employment income, and mandatory pension contributions. Monetary figures are shown in 1000s of 2015 DKK.[15] We consider the effects on earnings 7 years after application and beyond.

We use pre-determined demographic variables to verify the validity of the regression discontinuity design as well as to increase power in our estimations: sex, paternal earnings measure defined when the applicant was 16, and an indicator if paternal earnings are missing.

4.1.2 Job Posting Data

Danish online job vacancy data from 2007-2014 are supplied by the Danish consultancy firm, Højbjerre Brauer Schultz (HBS). 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.[16] Most job posting have a firm identifier that can be linked with the Danish register data and a 6-digit occupational code.[17] The data contains raw keywords from the job post.

In order to be able to match with the register datasets, only job posts with non-missing firm identifiers and occupational codes are considered.[18] Largely following Deming and Kahn

[15] An approximate exchange rate of 1USD to 6.5DKK can be used.

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

[17] If the firm identifier is not listed directly in the job post, HBS imputes it from publicly accessible registers using the firm name and address listed in the job post. Occupation is imputed from the job title. See Online Appendix C for more detail.

[18] Please see the Online Appendix C for a detailed description of the skills data, the construction of skill variables and the creation of the skills estimation dataset.

(2018), we map a selection of keywords into nine skill categories: character, cognitive, computer (general), computer (specific), customer service, financial, management, social, writing/language. For example, a job posting containing the raw keyword "teamwork" would be a job posting that requires social skill. We similarly assign the top 2000 or so most frequent keywords (corresponding to the vast majority of keyword observations) to one of the nine skill categories or a noise category. We then use this as a training sample with which to use supervised machine learning methods to assign the remaining keywords. Once all keywords have been assigned a category, we calculate the fraction of non-noise words indicative of a certain skill for each job post. To ease interpretation, all skill measures are normalized by the average usage of each skill in the job posting data**.**

To understand how skills on the job are shaped by just exceeding the admission threshold of one's preferred degree, we first look at those individuals in our estimation sample that we can match at the firm-occupation level with a job posting. We are able to match about 45% of the individuals and almost 14% of the observations in our estimation sample from 2008-2014.

Unlike earnings, there is no natural way to rank a skill mix. Since we want to study whether skills change when crossing the admission threshold, we calculate the distance between an individual's skill use and a relevant benchmark of skill use in their preferred narrow field, henceforth "skill distance". The benchmark that we consider is the average skill use of those who have completed a master's degree in particular narrow field. We calculate such a distance for each skill category (analytic, social, etc.). These skill distance measures will reveal how threshold crossing affects skills, and to what extent this is a function of the degree of similarity between preferred and next best field. If skill sets within a broad field are more similar as compared to skills across broad fields, we expect to see larger reductions in skill distances as a result of threshold crossing for *Between* applicants when compared to *Within* applicants.

As we are only able to match a relatively small fraction of job spells at the individual level, we next impute skills by assigning skill usages to individuals based on the average skill usage in the occupation in which they work and again compute skill distances relative to the benchmark.[19] Using these methods, we are able to assign skill to about 94% of individuals and about 82% of yearly observations.

4.2 Preferred and Next-best Fields

As in Kirkeboen et al. (2016), we use the notion of *preferred field,* defined from the local course ranking around an applicant's GPA rather than the first-choice field (i.e. the field which is given first priority). Changing the focus from preferred field to first-choice field (as well as implied sample selection criteria discussed below) does not significantly alter our results, a consequence of the fact that the vast majority of Danish applicants list few programs.

From the *program* level priority ranking we aggregate preferences to the narrow *field* level and assign the minimum GPA requirement. For example, if an individual applies to the University of Copenhagen's Sociology program with GPA admission requirement of 9.0 and Aarhus University's Sociology program with GPA admission requirement of 8.7 these two individual preferences would be aggregated to a narrow field of Sociology with minimum GPA requirement 8.7. This aggregation is performed in the same way as in Kirkeboen et al. (2016) except that we aggregate at 50 rather narrow definitions of field (e.g. Sociology) whereas Kirkeboen et al. (2016) aggregate at a rather broad definition of field (e.g. Social Sciences).

4.3 Sample Selection

We consider Danish first-time applicants aged 17-25 with non-missing high school GPAs who applied to CES between 1996 and 2006.[20] We use the years 1993-1995 to determine

[19] There are 228 occupational groups. We calculate average skill use for each skill category for each of the 228 occupations. All those working in an occupation are then assigned the average skills for that occupation.

[20] We remove immigrants as information on GPA or other demographics are not available, i.e. earnings of parents at age 16. See Table D4 for a detailed description of the basic cleaning performed.

whether individuals in 1996 and later are indeed first-time applicants. We do not consider applicants after 2006 because of a large change that was made to the Danish grade scale. We focus on applicants whose preferred and next-best fields are for university programs.[21]

Following Kirkeboen et al.'s (2016) construction of an estimation sample suitable for regression discontinuity analysis in this context, we drop applicants whose most preferred field does not have a GPA requirement for admission. *Between* and *Within* applicants whose preferred and next-best fields have non-descending GPA admission thresholds are also dropped, as are those whose GPA never exceeds any an admission threshold.

We remove individuals who completed a master's degree in less than 4 years after being admitted to a bachelor (3.4% of individuals) and observations with negative earnings or with earnings above the 97.5$^{\text{th}}$ percentile.[22] For most of the analysis, we use an estimation window of 2.0 application score points (i.e. standardized GPA), but also show results with a narrower window of 1.0 and 0.5. As a donut regression discontinuity estimator is used, applicants with an application score of 0 are dropped, but results are robust to including these individuals, see Tables B4 and B5 in Online Appendix B.

4.4 Descriptive Statistics

About half of all individuals who applied through CES between 1996 and 2006 listed just one preferred program, about 22% listed two programs and 17% listed three programs. Less than 6% listed four or more programs despite the ability to list up to eight. Aggregating preferences and imposing some basic cleaning, the share of individuals applying to one field increases to almost 60%. The share of individuals who are on the margin between two different (same) broad fields is about 26% (16%).

[21] There are 13 institutions at the university level. See Online Appendix Figure D2.

[22] If one complete a master's degree in less than 4 years it is likely that the student was admitted previously, or equivalently, that the student has studied a similar field in another country.

Panel (A) of Table I presents descriptive statistics, by type of applicant, calculated from the *main estimation sample*. Comparing these columns with the equivalent figures for the *full sample* in panel (B) reveals that the two samples are rather similar, i.e. earnings 8 years after application are effectively identical, though the estimation sample is perhaps positively selected: applicants in the estimation sample tend to have higher application scores, slightly more educated parents with higher earning fathers.

Comparing summary statistics across applicant type in the first six columns of panel (A) reveals noticeable differences. We see that almost 75% of the individuals in the *estimation sample* are single program applicants, as opposed to the 60% of the dataset before imposing sample selection criterion; this is primarily driven by the fact that *Between* and *Within* applicants whose preferred and next-best fields have non-descending GPA admission thresholds are dropped. Relative to *Only One* or *Between* applicants, *Within* applicants make approximately 50,000 DKK less 8 years after application, are more likely to be women, and have fathers who tend to earn less. Whereas one in two *Between* and *Within* applicants will be offered their first priority and 10% will receive no offer at all, 65% of *Only One* applicants will be offered their first (and only) priority.

Columns (3) and (4) in Panel (A), describing *Between* applicants, is the sub-sample that most closely mimics the sample used by Kirkeboen et al. (2016). Our estimation sample contains almost 7,000 *Between* applicants, noticeably less than the 50,000 used in Kirkeboen et al. (2016). There are three main reasons for this difference in sample size. First, we focus on university educations, more than halving our sample, whereas Kirkeboen et al. (2016) includes non-university educations. Second, on average, Danish applicants list fewer preferences relative to Norwegians. Third, many STEM programs have no admission requirements and are consequently dropped from our analysis.

Immediately noticeable from Figure I is the large concentration of *Within* applicants, approximately 60%, who have Humanities as a preferred field in the full sample. Although this share drops in the estimation sample, still more than 50% of *Within* applicants have a preferred field of Humanities. The large share of *Within* applicants with preferences for Humanities reconciles well with the lower subsequent earnings displayed for these applicants in Table I.

The estimation sample contains larger shares of applicants with preferred fields of Social Science, Medicine and Law and lower shares of applicants with preferred fields of Science, Technology and Engineering.[23] As we drop, for instance, applicants who have a preferred field with no GPA admission criteria this change in distribution is expected: STEM fields are more likely to have non-binding admission requirement whereas Law, Medicine and Social Science generally have the toughest admission requirements. Online Appendix Table D3 contains estimation results from our main specification excluding humanities, and various other fields. Reassuringly, the results do not change substantially.

As discussed earlier, we will also consider the effects of threshold crossing on various measures of skill usage. Figure II presents statistics of the normalized skill usage, defined at the occupational level, for each skill category by applicant type. Bars depict mean values whereas dots show standard deviations. Mean values above (below) 1 indicate that the skill usage is higher (lower) than that found in the entire job posting dataset. For instance, the individuals in our estimation dataset have much higher levels of cognitive skill levels in their jobs, a finding that makes sense given that we are selecting those who apply for university education. Interestingly, despite the different distribution by broad field type shown in Figure I, the skill distribution look relatively stable across applicant type.

5. Graphical Illustration of Research Design

Our identification strategy relies on the discontinuity at the GPA admission giving us exogenous variation. Before proceeding to the estimation results, we will examine the graphical

[23] Also, notice that broad fields of Business or Law each consist of only one narrow field.

evidence to verify the validity of the research design and to provide a sense of the effects we expect to see. We used the naturally occurring (discrete) values of the application score rather than collapsing the data further into broader bins. The application score is the standardized difference between an applicant's GPA and the GPA cutoff, see data section. All figures include a local linear regression line estimated on either side of 0 using a triangular kernel and a bandwidth of 1. As discussed in the estimation section, we dropped applicants whose GPA was equal to the admission requirement.

Figure III plots the share of applicants who are offered admission (in the current year) and complete their preferred field against their application score for each applicant type. There is a clear and large discontinuous jump in the share of applicants who receive an offer below and above 0, regardless of type. Applicants with application scores above 0 almost always receive an offer. Those whose application score falls below the required GPA admission threshold are much less likely to receive an offer. As discussed previously, the positive admission probability to the left of the cutoff results from the existence of alternate admission mechanisms, see Online Appendix C for more detail.

The size of the discontinuous jump decreases when we look at the share of applicants completing their preferred degree, but it remains strong in the case of *Between* and *Within* applicants. *Only One* applicants are clearly more committed to studying a particular program and are likely to seek admission to this program in a subsequent year if not admitted immediately. Interestingly, the share of applicants above 0 who complete their degrees is more or less constant with respect to the application score, regardless of type, implying that one's application score is predictive of degree completion almost only through its effect on admittance.

Regression discontinuity design is only valid if individuals have imprecise control over their application score relative to the GPA cutoff of their preferred program. If we detect discontinuities in the density of the application score, we may suspect that applicants are sorting, placing the validity of the identification strategy in question. Figure IV displays the log density of application scores by type, and there is no evidence of bunching at the GPA cutoff. Verifying that covariates behave well around the application threshold can provide additional evidence that the treatment is locally randomized. Online Appendix A contains plots analogous to Figure III for our control variables. No significant discontinuities are detected.

Figure V plots the pooled average earnings by applicant type for years 7–18 after application. The interpretation of this effect is somewhat difficult: It is the average effect over all observable years after graduation and across all program types. Rather than determining the precise magnitude of the effect, here we seek to verify a non-negligible discontinuous jump in earnings, acknowledging that the magnitude is likely to change once we control for factors such as specific program indicators and year of application indicators. The figure does show jumps in average earnings for applicants whose application score exceeds the admission criteria. For *Only One* and *Between* applicants, we see a jump in earnings of almost 50,000 DKK per year, or around 8,000 USD. In contrast, *Within* applicants experience a very small reward for meeting the admission criteria. The takeaway from Figure V is that we should expect to see similar rewards for exceeding admission criteria for both *Only One* and *Between* applicants, but small (if any) rewards accruing to *Within* applicants.

Next, we look at the effects of threshold crossing on skill formation for those applicants on the margin between two different broad fields and for those on the margin between two fields within the same broad field.[24] Specifically, we compare the intensity of skills usage of the applicant to the average skills usage of graduates with the same preferred narrow field. If

[24] For the skills data, we are focusing on *Between* and *Within* applicants. For *Only One* applicants, we find that the skills distance decreases at the cutoff for three out of the nine skills when using all observations from 7 years after application and beyond. However, when only using observations from 8 years after application and beyond, we only find one significant effect. This reflects that persons just applying to one program usually re-apply in the following year if not admitted. Thus, differences in skills for *Only One* applicants should be expected to be very temporary.

admission has an effect on skills usage in subsequent jobs, this distance should be reduced in a discontinuous manner at the GPA cutoff of the preferred field.

If we only use job spells which can be linked to an online job ad, we have too few observations to graphically show the effect of threshold crossing. However, we can use simple t-tests on the difference in skill distances just above and below the admission threshold for each skill category. For this exercise, we use a window of 1.0 standard deviation of the GPA score.

Table II shows these differences in skill distances along with the t-statistics in parentheses. Columns (1) and (2) present these results for *Between* and *Within* applicants, respectively. Considering first column (1), we see that crossing the admission threshold for one's preferred degree on average reduces the distance between an individuals' subsequent skills use in a job and the average skill use for graduates with the same preferred degree. This decrease in distance is present in all nine skill categories. In six of these nine skill categories the reduction in skill distance is significant. The magnitudes of these differences range from a bit more than 5% of a standard deviation in the case of cognitive and financial skills to more than 15% of a standard deviation in the case of the remaining significant skill differences.[25]

The second column of Table II shows the equivalent t-test for the *Within* applicants. We see that just one of the nine skill category t-tests are significant and negative. Moreover, the absolute value of the differences are generally much smaller for *Within* applicants when compared to *Between* applicants. This simple exercise suggests that skills used in subsequent jobs are affected by admission into one's preferred field, and that these skills vary more across broad fields than within broad fields.

Since we only have individual skills measures for a small share of our estimation sample, we focus on the measure of skills defined at the occupation level for the rest of the analysis. Figures B2 & B3 in Online Appendix B plot the pooled average skill usages for each of the

[25] See Figure II for the standard deviations of each skill level

nine skill categories for *Between* and *Within* applicants respectively, for years 7–18 after application. Clear non-negligible discontinuous drops in skill distances are present for *Between* applicants in all categories except Character and Writing/language. The analogous plots for *Within* applicants are much noisier and suggest no effect of threshold crossing.

6. Results

6.1 Results pooled over years

Table III presents the results from estimating equation (1). The effects of marginally surpassing the GPA requirement of one's preferred field are quite robust to the particular specification used. *Between* applicants realize gains of about 25,000-35,000 DKK per year on average or from 8%-11% of annual earnings 8 years after application. Likewise, the average benefit of threshold crossing of *Only One* applicants is 7%-11% of annual earnings. On the contrary, *Within* applicants see effectively zero and insignificant effects of surpassing the GPA requirement of their preferred degree.

6.2 Results by year after application

The results presented thus far consider the effects on average earnings 7 years and beyond. To understand how these effects evolve over time, we estimate equations (1) for each year, starting 7 years after application, these results are shown in Figure VI. In addition, we estimate a regression that includes a quadratic in actual work experience.[26] Although experience is likely endogenous, we include it only to explore the degree to which our results are sensitive to time differences in the timing of labor market entry.

Figure VI reveals that the rewards realized by *Between* applicants are not just concentrated early in the work life. In fact, these applicants receive a rather constant, and predominantly significant, bonus that hovers around 25,000 DKK per year, from 7-16 years after application. This is true regardless of whether or not experience is included. *Within*

[26] The experience variable has been created by using a worker's historical mandatory payment to the supplementary pension scheme, ATP.

applicants see no statistically significant effects, again regardless of whether or not experience is included. The time profile of effects for *Only One* applicants reveals substantial time variation. The positive threshold crossing effects for these applicants is clearly concentrated early: a large downward trend in the annual bonuses to threshold crossing is evident. The level of the effects also drops early in the profile once experience is included. These facts reconcile well with *Only One* applicants realizing gains to threshold crossing that are due to entering the labor market earlier. In Online Appendix Figure B1, we explore this possibility further by plotting the running variable against the number of years to MA graduation, measured from the application year, for each applicant type. No discontinuities are detected for the *Between* or *Within* applicants, but a clear and significant discontinuous drop of about a quarter of a year is present at the admission threshold for *Only One* applicants.

6.3 Comparative Advantage

In this section, we investigate the degree to which comparative advantage can explain our main result that individuals whose preferred and next-best fields lie in different broad fields generally obtain higher earnings, whereas applicants whose preferred and next-best fields lie within the same broad field generally do not. In other words, to what extent can our main results be explained by individuals preferring fields in which they have a comparative advantage?

We try to answer this question in three ways. First, we examine if skills play a role in generating earnings differences between fields. If the hypothesis of comparative advantage is true, we would expect to observe larger skill differences across broad fields in which we also observe larger differences in earnings. Second, following Kirkeboen et al. (2016), we examine whether it is the case that students obtain higher earnings in their preferred broad field by essentially comparing the effect of threshold-crossing for applicants with preferred field of j and next-best field k with the threshold-crossing of applicants with the preferred and next-best field interchanged, i.e. preferred field k and next-best field j. With this analysis, we want to rule out that the only reason that students obtain higher earnings in preferred fields is that there is a common ranking of broad fields in terms of income, which applies for all prospective students. Third, it is possible that being admitted to one's preferred field leads to a motivation effect that increases performance. However, if there is such a general motivation effect, we would also expect to find earnings gains resulting from being admitted into one's preferred degrees for *Within* applicants.

We begin by exploring the degree to which the skill sets are causally affected by how similar one's preferred and next best degrees are. If we see that skill sets are more distinct across broad fields as compared to fields within a broad field, the potential for a comparative advantage explanation is clearer. For this analysis, we first assign skill usages to individuals based on the average skill usage in the occupation in which they work. We then compare these to benchmark skill usages defined from those who completed an education in the same narrow field as the applicant's preferred narrow field. Specifically, for each skill categories, we calculate the distance between the individual's skill use and the benchmark skill use, henceforth "skill distance".

We then use this skill distance as a dependent variable for each of the nine skill categories in regressions similar to equation (2). Table V displays the results of these estimations. Negative coefficients imply that the effect of surpassing the GPA requirement for admission leads to a skill set that is closer to the skill set used by individuals who have graduated in the same narrow field. In six of the nine skill regressions, the effect of threshold crossing for *Between* applicants on skill distance is significant and negative. The magnitudes of these effects are between 6% and 10% of the standard deviations in the corresponding skill distance. For instance, as shown in column (1), *Between* applicants who just exceed the admission threshold of their preferred field reduce the distance between their cognitive skill usage and the average cognitive skill usage of those who graduated in their preferred field by 0.07, or about 8% of a standard deviation in the cognitive skill measure.[27] *Within* applicants generally see zero effects from just exceeding the admission threshold. Only in one of the nine skill categories, financial, are significant effects found. Our regression-based findings confirm both our earlier descriptive results presented in Table II with individual jobs that could be matched to job ads and the graphical results in the Online Appendix Figures B2 and B3, which use the skill distances imputed at the occupational level.

Next, Figure VII displays the results of estimating the effects on skill usage separately for each year, analogous to Figure V. We can see from Figure VII that the effects on skill usage are generally negative, stable and persistent at least to 15 years for *Between* applicants. As expected, no effects are present for *Within* applicants. These results suggest that earnings differences between broad fields could be due to differences in subsequent jobs' skill content. Such an interpretation is necessary for our results to imply that prospective students sort into broad field according to comparative advantage. However, our skills results alone do not rule out a pure signaling story. In principle, graduation in a field may merely signal that graduates are productive and, hence, open the doors to better paid jobs requiring a particular set of skills. This could be the case without studies in a particular field leading to certain sets of skills.

Next, following Kirkeboen et al. (2016) we examine if the earnings gains across broad fields are simply due to students tending to prefer high-paying broad fields. The starting point is Sattinger's (1978, 1993) definition of comparative advantage: person 1 has comparative advantage over person 2 in field j, while person 2 has comparative advantage over person 1 in field k if the following inequality is true

$$\text{(2)} \qquad \frac{y_1^j}{y_2^j} > \frac{y_1^k}{y_2^k} \Leftrightarrow \left(logy_1^j - logy_1^k\right) - \left(logy_2^j - logy_2^k\right) > 0$$

where y_i^j denotes the productivity – or in our case earnings – for individual i in field j. By

[27] See Figure II for standard deviations

estimating log earnings equations we can estimate the differences in log earnings in equation (2).[28] Denoting β_{jk} as the return to crossing the GPA requirement of the preferred field j ($d_1 = j$) when the individual's next-best field is k ($d_2 = k$), we estimate the following regression:

$$(3) \quad logy_{it} = \sum_{j,k \in B, j \neq k} \left[\beta_{jk} \mathbb{I}(r_i > 0) * \mathbb{I}(d_1 = j) * \mathbb{I}(d_2 = k)\right] + \sum_{l,m \in W, l \neq m} [\beta_{lm} \mathbb{I}(r_i > 0) * \mathbb{I}(d_1 = l) * \mathbb{I}(d_2 = m)]$$

$$+\beta_O \mathbb{I}(r_i > 0) * \mathbb{I}(type = O) + f(r_i) + \alpha x_{it} + \varepsilon_{it}$$

where the first summation has all the combinations of different preferred and next-best broad fields (B is the set of *Between* applicants) and the second summation include all the combinations of different preferred and next-best narrow fields within each broad field (W is the set of *Within* applicants). Because we do not decompose the effect of crossing the GPA threshold for applicants with only one preferred narrow field, we capture their effect by β_O. As in the main regressions, we include narrow field dummies for preferred and next-best fields, year dummies and dummies for year of admission, indicators if an applicant is a *Within* or *Between* applicant, as well as a few socioeconomic controls.

Figure VIII, analogous to Figure XII in Kirkeboen et al. (2016), shows the distribution of the estimated relative differences $\mathrm{E}\left(logy^j - logy^k | d_1 = j, d_2 = k\right) - \mathrm{E}\left(logy^j - logy^k | d_1 = k, d_2 = j\right)$ weighted by the number of persons with the combinations of either field j preferred over field k or field k preferred over field j. The distribution of pairwise relative differences of *Between* field estimates stochastically dominates the distribution of relative differences of *Within* field estimates. This result is intuitive as we would expect that comparative advantage would be smaller within a broad field than across broad fields. Perhaps surprising is the fact that more mass lies below zero than above for *Within* applicants. In fact, as much as 95% of the

[28] We perform this test in the OLS setting, not in the IV setting of Kirkeboen et al. (2016).

relative differences of *Between* estimates are positive whereas this is only true for 44% of the relative differences of *Within* estimates.

As in Kirkeboen et al. (2016), we conclude that *Between* field applicants tend to sort into fields in which they have a comparative advantage as the Roy model predicts. However, for the choice of program within a broad field, non-pecuniary benefits seem to play a larger role than pecuniary benefits. We cannot completely rule out sizable comparative advantage within broad fields. However, the distribution of relative differences within broad fields and the insignificant skills results within a field suggest that broad fields tend to reward similar skills and that comparative advantage tends to be small within a broad.

Our finding that less than half of the pairwise relative differences of *Within* estimates are positive suggests that there is not just a general long-lasting positive effect of being admitted to one's preferred field. Hence, based on the *Within* applicants, we do not seem to find evidence of a general positive effect due to enhanced passion and motivation (see Stoeber et al., 2011). To the extent that there is a general motivation effect, we would expect that effect to be present for both *Within* and *Between* applicants. As the effect for *Within* applicants is insignificant, we conclude that comparative advantage is driving our causal earnings estimates for *Between* applicants. We must note that a motivation effect that is specific to the combination of preferred and second-best choices cannot be ruled out. However, in this case, a motivation effect so defined and a comparative advantage effect are observationally equivalent and arguably the same conceptually.

6.4 Results by broad field

We would like to verify that the results are general and are not just driven by one or two broad fields. To examine this, we estimate the effects of threshold crossing separately for each broad field and applicant type. We will estimate:

$$(4)\ y_{it} = \sum_j \sum_k \left[\beta_{jk} \mathbb{I}(\, r_i > 0) * \mathbb{I}(\, type = j) * \mathbb{I}(\, field = k)\right] + f(r_i) + \alpha x_{it} + \varepsilon_{it}$$

where j indexes applicant type *(Only One*, *Within* or *Between)* and k indexes broad field type (Humanities, Science, Social Science, Technology, Life Sciences, Medicine, Business, Law). As Kirkeboen et al. (2016) discuss, the distribution of next-best fields is likely to be different between the two fields, implying that estimated effects of broad fields from equation (4) should not be used to understand the earnings effects of one broad field relative to another. Nonetheless, the intention to treat parameters, i.e. the βs, are informative for policy decisions, such as marginally expanding or contracting degree programs because the relevant counterfactual is the actual distribution of second-best fields.

Table V presents the results for one representative specification. Turning first to the effects for *Between* applicants shown in column 1, we see insignificant, and sometimes negative, effects on future earning from exceeding the GPA requirement if one's preferred broad field is Humanities, Science or Life Science. The effects of threshold crossing in all other broad fields are positive and significant, ranging from about 20,000 DKK (about 3,000 USD) in the case of those whose preferred field is Social Science to more than 50,000 DKK (about 8,000 USD) for those whose preferred field is Law or Technology.

A similar pattern is seen for the *Only One* applicants except that the estimated earnings effects for those applicants whose preferred field was Social Science is halved and insignificant and those whose preferred field was Life Science now realize positive and significant effects. Otherwise, the effects by broad field are generally larger for the *Only One* applicant group relative to the *Between* group, notably so for those applicants whose preferred field is Law: they receive a more than 75,000 DKK benefit for threshold crossing. Finally, with the exception of Technology, no *Within* applicant realized significant positive gains on future earnings from threshold crossing on average.

6.5 Robustness Checks

In order to further examine the validity of our estimation strategy, we estimate the equivalent of equation (1)

$$(5) \qquad y_{it} = \sum_{j\in O,W,B}[\beta_j \, \mathbb{I}(\, r_i > p) * \mathbb{I}(\, type = j)] \; + f(\, r_i \,) + \alpha \, x_{it} + \varepsilon_{it}$$

separately for different values of p. In the estimation above, p was always set to 0, the true admission cutoff. If our estimation strategy is sound, we expect to see the largest effects when p is zero and that the effects die away as we look at pseudo cutoffs farther from zero. Figure IX plots the estimated effects from equation (5) for values of p between -0.5 and 0.5 for both the *Between* and *Only One* applicants. Reassuringly, we do indeed see this pattern.[29]

6.6 Present Value and Costs of Studying

Understanding the effect of marginally decreasing the GPA admission requirements on student lifetime earnings vis-à-vis the cost of reshuffling applicants across programs is central to any redesign of the college admission process. Although data limitations prevent us from considering lifetime earnings, we can consider the effects on total earnings up to 15 years after application. Table VI presents the results of estimating equation (1) using a simple sum of annual earnings over different post-application time periods as the dependent variable. For instance, in column (1) we see the effects of just exceeding the GPA requirement for one's preferred degree on the total amount earned from the year of application to 6 years afterward.[30] In this column, we see that *Within* and *Between* applicants who just exceed the admission criteria for their preferred degree realize no significant gains from doing so within 6 years of application. On the other hand, those who applied to one field and marginally surpassed the admission requirements for that field earned significantly less (50,000 DKK) during the first 6

[29] *Within* coefficients are not shown as no significant effects were detected at $p = 0$.

[30] For this exercise, we use balanced samples. For instance, for column (4) labeled "0–10," individuals were only included in the estimation if earnings were not missing for each of the years from 0 through 10 after application.

years after application. The intuition here is clear: Those applicants who were not admitted to their preferred field postponed becoming a student and worked in the meantime.

Turning to column (2), we see that effects change when we consider the sum of earnings 7-10 years after application, by which point the majority of students have completed their education. Considering first *Only One,* we see that those who exceed the admission threshold now realize approximately 130,000 DKK more during these 4 years, no doubt at least in part reflecting their earlier entry into the labor market. These gains are temporary: Total earnings in years 11 through 15, shown in column (3), are not significantly different from zero for those who just exceeded the admission threshold relative to those who fell short. Columns (4) and (5) present the effects on total earnings from the year of application to 10 and 15 years after application, respectively. Despite their foregone earnings while in school, *Only One* applicants still realize a significant 175,000 DKK (a bit more than 25,000 USD) bonus to their total earnings within the first 15 years of application. This bonus is non-negligible: It is close to 60% of their average earnings 8 years after application.

Focusing now on the second row of Table VI, we see that *Within* applicants realize no significant effects from surpassing the admission requirements of their preferred field, regardless of the time horizon. This finding contrasts sharply with the effects realized by *Between* applicants shown in the third column of Table VI. Those *Between* applicants who just exceed the admission requirement for their preferred degree are significantly rewarded, receiving almost 100,000 DKK more within 7-10 years after application and 125,000 DKK more within 11-15 years after application. The total gains within the first 15 years after application that equals approximately 280,000 DKK, or 45,000 USD, close to an entire year's worth of earnings.

If the marginal cost of reallocating applicants into their preferred fields is less than the marginal benefit of doing so, policymakers ought to marginally lower admission criteria. Our best estimate of the marginal benefit of exceeding the admission requirement of one's preferred degree is provided in column (5) of Table VI. Of course, this measure captures only the pecuniary effects. In reality, the benefits received by applicants who meet the admission requirement of their preferred degree may be higher (lower) if they also enjoy more (less) nonpecuniary benefits from pursuing their preferred degree.

As discussed earlier, the benefits received by *Only One* applicants mainly stem from earlier enrollment. The small discontinuity for this applicant type shown in Figure III suggests that individuals who are not accepted in the first year of application reapply for the same program in the following year, implying that the marginal cost of admitting slightly more individuals immediately ought to be close to zero. Similarly, *Within* applicants affected by a marginal loosening of the GPA admission requirement would be reallocated to another narrow field within the same broad area. As narrow fields within the same broad discipline tend to have similar per student costs, the relevant marginal-cost measure of these applicants is also zero.

The possibility of a non-zero marginal cost comes into play when considering a marginal loosening of GPA requirements for *Between* applicants. Several scenarios are possible. First, if there is a symmetrical reallocation of the applicants across broad fields, then the aggregate marginal cost would remain zero. To the extent that this is not true, we can place some bounds on the level of the marginal cost. Generally speaking, the most expensive students to educate are those in Science and Medicine, whereas the least expensive students to educate are those in Social Science and Humanities. The cost of shifting a student from Humanities or Social Science to Science or Medicine, an upward bound on the cost of switching any applicant, would be around 250,000 DKK, still less than the marginal benefit at 15 years.[31] Regardless of applicant type, marginally lowering the GPA admission requirements is beneficial.

[31] We calculate the costs using the so-called taximeter funding, which increases at a fixed rate in the number of students. Different rates exist, depending on the field of study. In addition, universities are financed by research funding that is not directly related to the number of students in a field. We thank Fane Groes for sharing this data.

7. Conclusion

In this paper, we have examined the effect of being admitted to one's preferred field of study on future earnings and skill usage and find evidence that some types of students sort based on comparative advantage. Because of this sorting we find that there is a potential for improving the allocation of students across fields by marginally lowering GPA admission requirements. We find that lowering the admission threshold will permit individuals whose preferred and next-best fields are within different broad fields to obtain higher labor market earnings due to a comparative advantage in their preferred field of study. However, we do not find that lowering the admission cutoff will increase earnings for individuals whose preferred and next-best fields are within the same broad field.

Our result that earnings effects vary by applicant type may help explain differences across existing studies. For example, while Hastings et al. (2013) find that a significant share of prospective students sort into programs with zero or negative returns, Kirkeboen et al. (2016) find that students, on average, have considerably larger future earnings in their preferred field of study and that students sort according to comparative advantage. Furthermore, using job posting data, we find evidence supporting that these earning effects reflect that fields within the same broad discipline require similar skills. Consequently, comparative advantage within a broad field, on average, plays only a small role. Lowering the GPA admission thresholds will also allow more individuals who only apply for one field to start their studies immediately and consequently complete their studies earlier.

Our findings imply that a marginal loosening of admission criteria could prove beneficial, but at least for the Danish case, the GPA requirements in Humanities and Science need not be loosened. In addition to this policy recommendation, the small role played by comparative advantage within a broad discipline suggests that prospective students ought to be encouraged to apply to multiple fields within the same broad field rather than just applying to a single narrow field within a particular discipline. The result that comparative advantage generally plays only a small role in fields within the same broad discipline leads to two additional interpretations. First, specialization within a broad field may not be necessary, at least at the start of an individual's university career. On the other hand, perhaps specialization *is* important, but the particular type of specialization an individual selects within a broad field holds less importance. Our results do not allow us to discriminate between these two possible interpretations. To the extent that the former interpretation holds, there may be benefits from increased coordination across courses in different programs within a broad field. A relevant avenue for future research would be to investigate economies of scale within broad fields.

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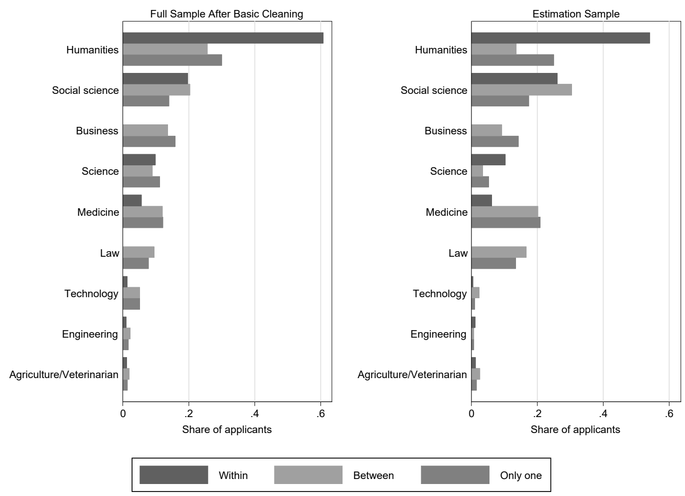

FIGURE I: DISTRIBUTION OF PREFERRED FIELD BY APPLICANT TYPE

"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. The term "preferred" has a different meaning in the two pictures: as the full sample is created prior to the sample selections necessary to define preferred and next-best fields, "preferred" in the full sample actually corresponds to first choice.

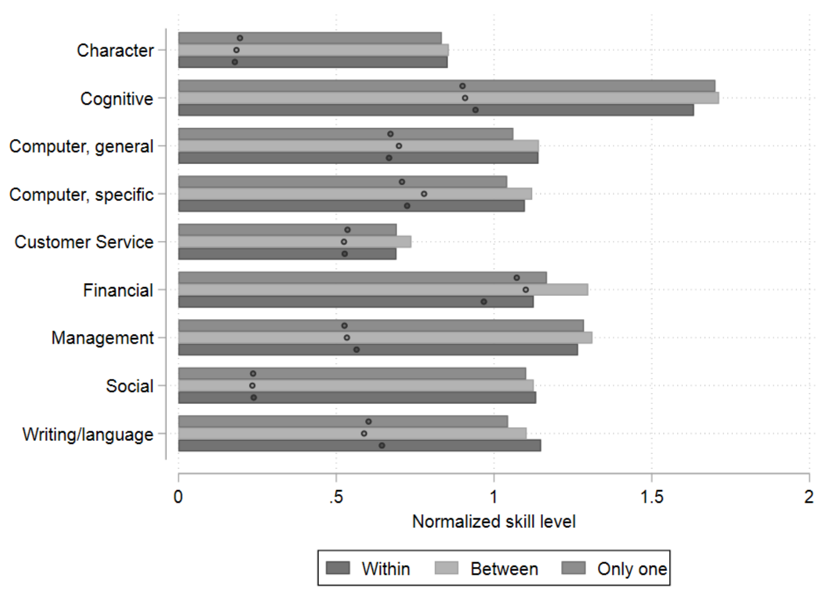

FIGURE II: DISTRIBUTION OF NORMALIZED SKILL LEVEL BY APPLICANT TYPE

Bars correspond to means whereas dots correspond to standard deviations. "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.

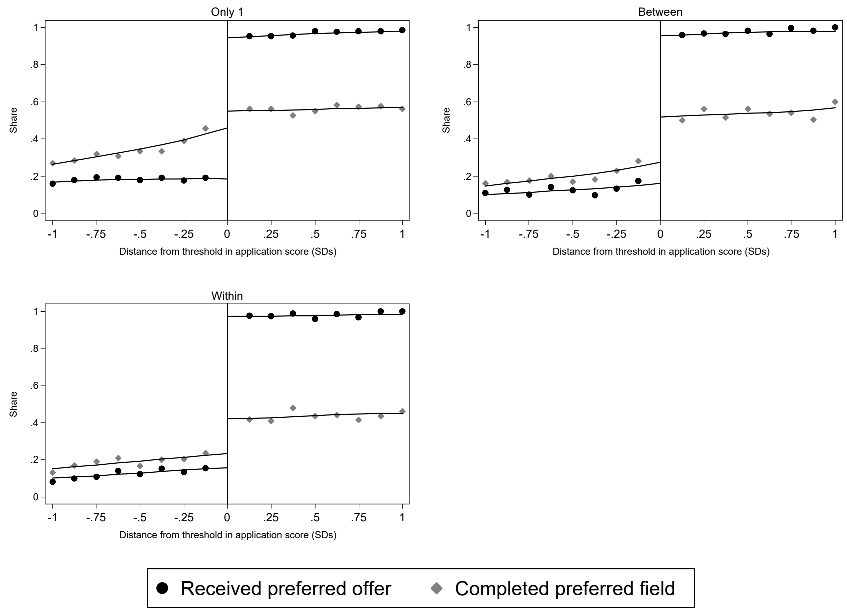

FIGURE III: ADMISSION THRESHOLDS AND PREFERRED FIELD OFFER AND COMPLETION

"Only 1" refers to applicants who applied to one field of study. "Between" refers to applicants whose preferred and next-best fields are in different broad disciplines. "Within" refers to those applicants whose preferred and second-best fields are within the same broad discipline. "Offer" here refers to an offer of admission in the current year.

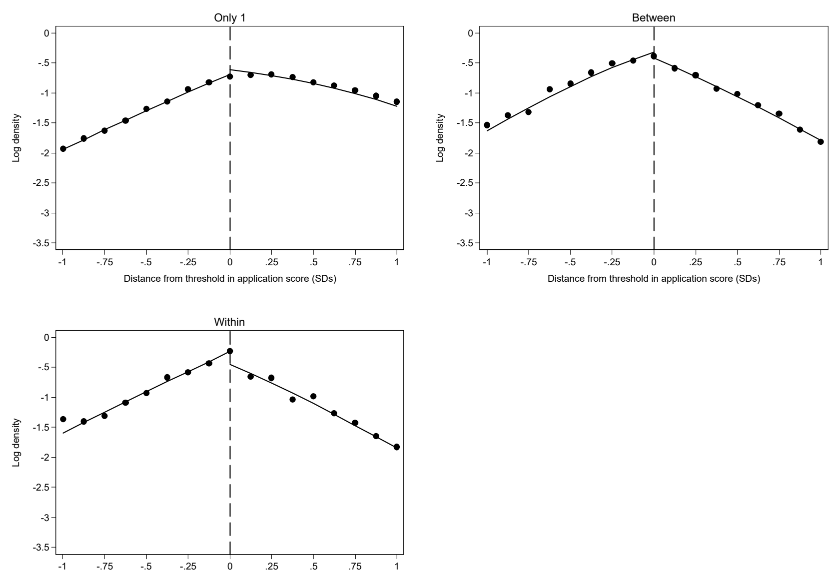

FIGURE IV: BUNCHING CHECK AROUND THE ADMISSIONS CUTOFFS

"Only 1" refers to applicants who applied to one field of study. "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.

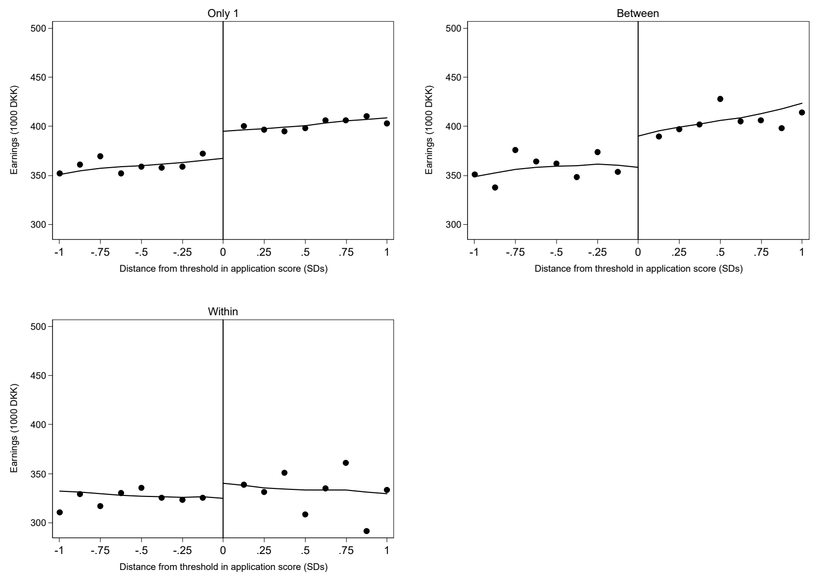

FIGURE V: ADMISSION THRESHOLDS AND AVERAGE POST-GRADUATE EARNINGS

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

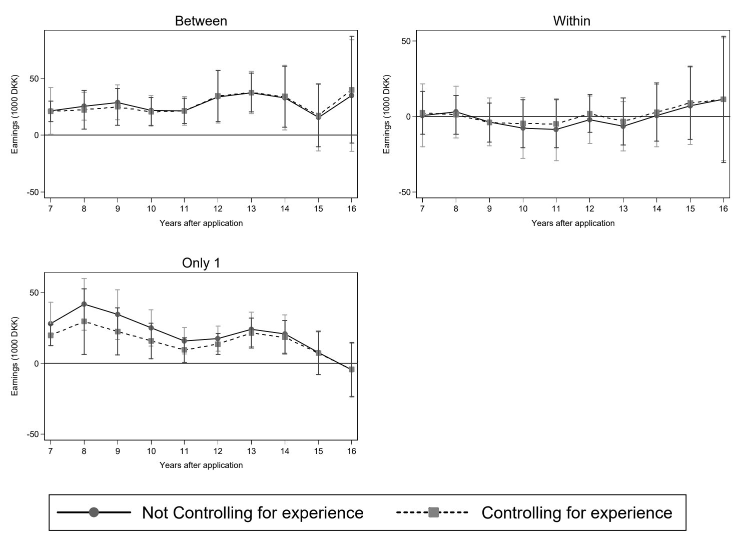

FIGURE VI: ITT PAYOFFS TO PREFERRED DEGREE OVER TIME (DKK YEAR)

"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. This figures plots the results from estimating equation (2) by year.

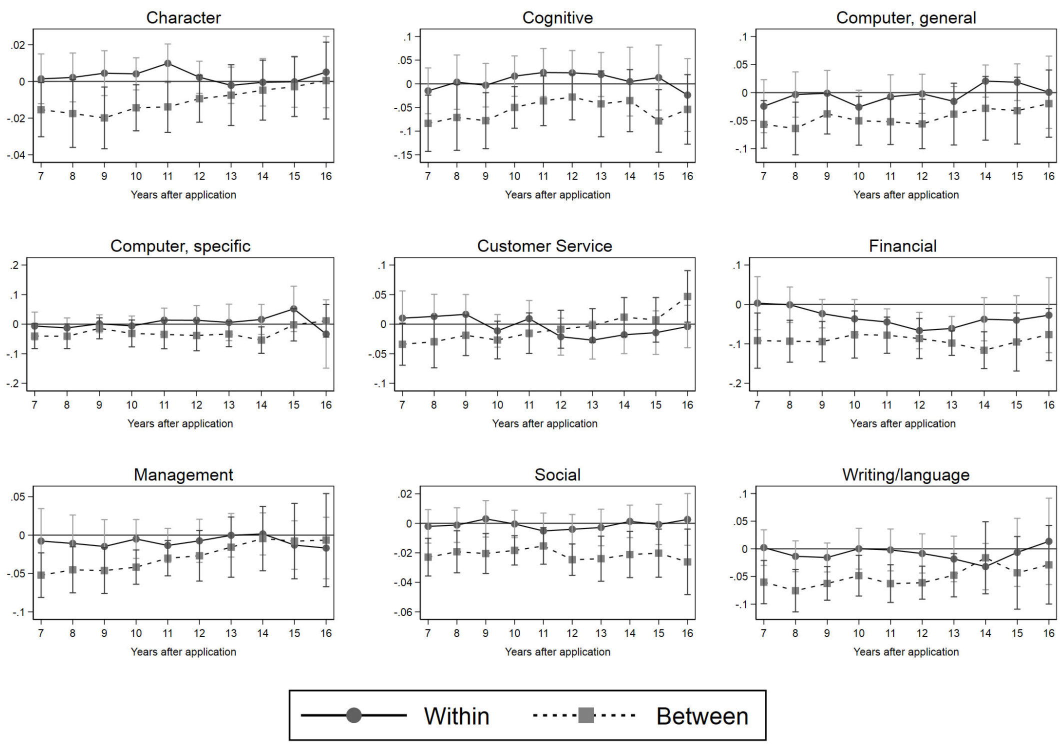

FIGURE VII: ITT SKILL EFFECTS TO PREFERRED DEGREE OVER TIME (DKK YEAR)

"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. This figures plots the results from estimating equation (2) by year.

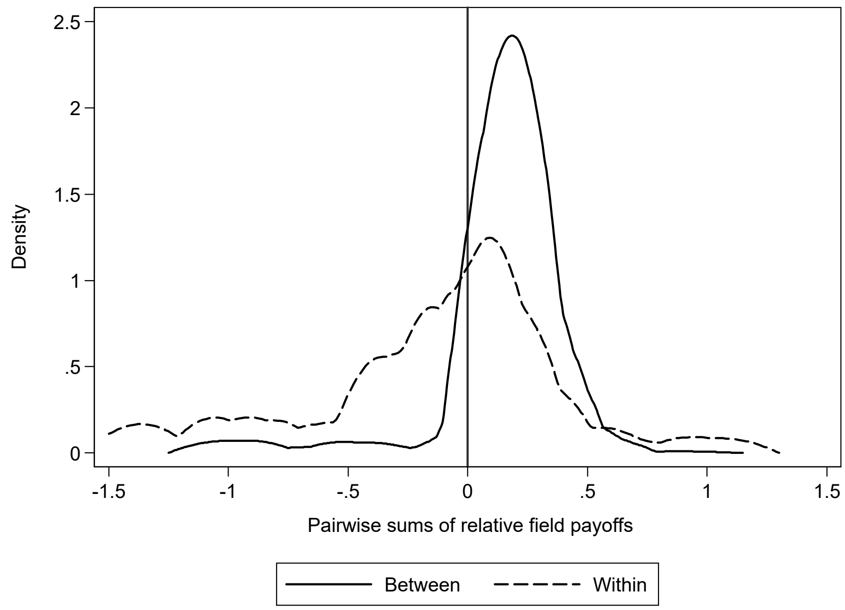

FIGURE VIII: TESTABLE IMPLICATION OF SORTING BASED ON COMPARATIVE ADVANTAGE

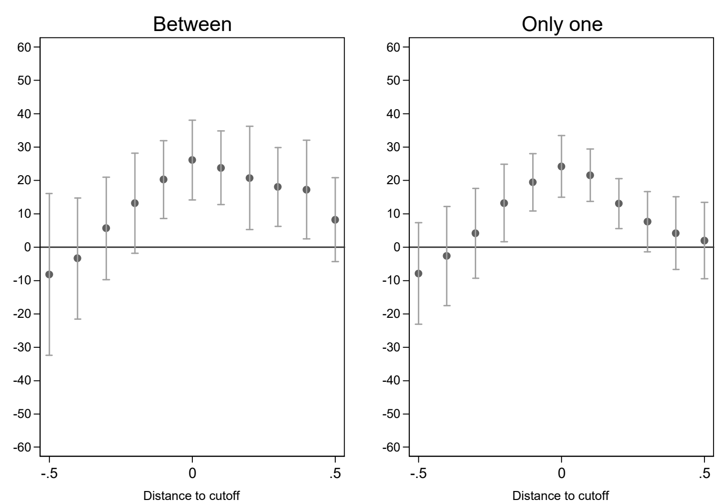

FIGURE IX: ESTIMATED PSEUDO EFFECTS OF PREFERRED DEGREE ON EARNINGS

TABLE I: SUMMARY STATISTICS

	(A) Estimation Sample								(B) Full Sample	
	Only One		Between		Within		All		First time applicants	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age at application	19.82	(1.45)	19.88	(1.39)	20.08	(1.43)	19.85	(1.44)	19.95	(1.47)
Female	0.58		0.55		0.61		0.58		0.55	
Earnings 8 years after application	294.84	(208.42)	299.72	(199.53)	245.01	(181.85)	290.30	(205.06)	294.74	(205.01)
Application Score	0.01	(1.02)	-0.04	(0.94)	-0.04	(0.96)	0.00	(1.00)	-0.34	(1.17)
Mother has higher education	0.51		0.53		0.53		0.52		0.46	
Father has higher education	0.48		0.49		0.47		0.48		0.43	
Father's earnings (1000DKK)	324.41	(277.38)	325.73	(258.11)	294.48	(225.37)	321.45	(269.72)	305.45	(245.72)
Fields ranked	1.00	(0.00)	2.58	(0.92)	2.64	(0.95)	1.41	(0.84)	1.72	(1.03)
Institutions ranked	1.21	(0.52)	1.82	(0.89)	1.72	(0.88)	1.36	(0.68)	1.54	(0.79)
Rank of best offer	1.05	(0.23)	1.63	(0.87)	1.60	(0.83)	1.22	(0.58)	1.23	(0.66)
Offered first priority	0.65		0.50		0.50		0.61		0.69	
Offered second priority	0.02		0.30		0.31		0.09		0.08	
Offered third priority	0.00		0.07		0.07		0.02		0.03	
No offer	0.32		0.10		0.10		0.26		0.18	
Individuals	35078		6971		4984		47033		126758	

The column titled “Only One” refers to applicants who applied for one study field. The column titled “Between” refers to applicants whose preferred and next-best fields are in different broad fields whereas the column titled “Within” refers to those applicants whose preferred and second-best fields are within the same broad fields. About 3% and 6% of mother and father education is missing, respectively. About 5% of father's earnings is missing. Monetary figures shown in 1000s 2015 DKK. The full sample first time applicants sample corresponds to the sample after basic cleaning and the removal of individual who just have preferences for non-university. About 3% of observations don't have earnings in the 8th year after application in the estimation sample: About 17% of observations don't have earnings in the 8th year after application in the full sample of first time applicants mainly because all years are considered (not just more than 7 years after application). Offer refers to not receiving an offer in the current year. The row titled ‘No offer’ in the Table I refers to the percent of individuals who did not receive an offer for admission in the current year. If instead we define ‘No offer’ as not receiving an offer in the current year or in the next year via standby, these numbers become 23%, 3% and 3% for Only One, Between and Within applicants, respectively.

TABLE II: T-TESTS ON SKILL DIFFERENCES

Skill Category	(1) *Between*	(2) *Within*
Character	-0.0350***	-0.0242*
	(-3.18)	(-1.76)
Cognitive	-0.0454**	0.00579
	(-2.38)	(0.26)
Computer, general	-0.0598	-0.0267
	(-1.58)	(-0.69)
Computer, specific	-0.115**	-0.0250
	(-2.18)	(-0.43)
Customer Service	-0.114***	-0.0378
	(-2.91)	(-0.83)
Financial	-0.0772**	0.101**
	(-2.12)	(2.58)
Management	-0.0211	-0.0293
	(-1.28)	(-1.42)
Social	-0.0390***	-0.0171
	(-3.09)	(-1.06)
Writing/language	-0.0527	-0.0844
	(-1.39)	(-1.44)
Observations	2897	1988

t statistics in parentheses. "*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. These differences were calculated from applicants close (a window of 1) to the admission threshold. *** p<0.01, ** p<0.05, * p<0.1

TABLE III: EFFECTS OF PREFERRED DEGREE ON EARNINGS, BY APPLICANT TYPE

	(1)	(1)	(2)	(3)	(4)	(5)
Only One * 1(Application Score>Cutoff)	25.42***	21.10***	32.70***	24.34***	30.39***	26.63***
	(6.13)	(4.80)	(4.79)	(4.57)	(4.38)	(4.92)
Within * 1(Application Score>Cutoff)	-17.55	-2.45	7.74	-0.08	7.33	-3.14
	(12.44)	(7.92)	(7.39)	(7.12)	(6.92)	(9.28)
Between * 1(Application Score>Cutoff)	35.42***	25.59***	34.12***	26.21***	27.03***	27.22***
	(8.12)	(7.22)	(8.09)	(6.28)	(9.02)	(7.95)
Observations	282,632	282,632	282,632	282,632	215,079	133,546
Individuals	43,838	43,838	43,838	43,838	33,196	20,492
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

"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, an indicator for whether father's earnings are missing, calendar year indicators and indicators for year of application. All regressions include application score and indicators for *Within* type and *Between* type. Standard errors, clustered at the 6-digit education level (there are 50), shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE IV: EFFECTS OF PREFERRED DEGREE ON SKILL DISTANCE, BY APPLICANT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Cognitive	Social	Writing, Language	Character	Management	Financial	Computer, general	Computer, Specific	Customer Service
Within*1(Application Score>Cutoff)	-0.01	-0.00	-0.00	0.00	-0.01	-0.05**	-0.00	0.00	0.00
	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)
Between*1(Application Score>Cutoff)	-0.07**	-0.02***	-0.05***	-0.02***	-0.04***	-0.07***	-0.03	-0.02	-0.01
	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)
Observations	61,030	61,030	61,030	61,030	61,030	61,030	61,030	61,030	61,030

"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, an indicator for whether father's earnings are missing, calendar year indicators and indicators for year of application. All regressions include application score and indicators for *Within* type and *Between* type. Standard errors, clustered at the occupation level (there are 196), are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE V: EFFECTS OF PREFERRED DEGREE ON EARNINGS, BY BROAD FIELD

	(1) Between	(2) Only One	(3) Within
Humanities	-10.92	-11.01	-1.93
	(8.30)	(10.83)	(9.16)
Science	10.68	-16.86	-12.54
	(37.70)	(15.67)	(12.80)
Social Sciences	20.73**	9.06	5.79
	(9.01)	(12.88)	(10.51)
Technology	58.33***	50.44**	65.83**
	(11.38)	(18.97)	(27.03)
Life Sciences	-12.99	39.21***	-10.58
	(9.70)	(12.77)	(19.94)
Medicine	33.61***	42.77***	-25.05
	(8.22)	(12.45)	(17.13)
Business	33.29***	40.20***	
	(9.86)	(8.74)	
Law	56.27***	75.83***	
	(5.80)	(8.83)	
Observations	282,632		
Individuals	43.838		

"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. A window of 2.0 is used. All regressions include the function of the application score indicated in the table. Standard errors, clustered at the six-digit education level (50 of them), shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE VI: EFFECTS OF PREFERRED DEGREE ON PRESENT VALUE OF EARNINGS, BY APPLICANT TYPE

	(1) 0-6	(2) 7-10	(3) 11-15	(4) 0-10	(5) 0-15
Only One * 1(Application Score>Cutoff)	-48.36***	131.15***	53.21	87.53***	175.82**
	(9.97)	(22.88)	(40.44)	(27.77)	(84.53)
Within * 1(Application Score>Cutoff)	-5.54	-4.85	7.22	-8.64	50.19
	(19.57)	(32.84)	(49.29)	(46.83)	(95.24)
Between * 1(Application Score>Cutoff)	15.10	97.36***	126.24**	102.83**	282.01***
	(11.30)	(26.85)	(53.11)	(39.95)	(84.22)
Observations	38,868	31,852	12,924	28,690	11,107
Clusters	50	46	40	46	40

"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 included in these regressions includes sex, a quadratic in age at application, father's earnings at applicant age 16, an indicator for whether father's earnings are missing, indicators for year of application, and indicators for *Within* and *Between* type. All regressions include the application score and allow for different slopes on either side of zero. Preferred and second-best education indicators are also included. Standard errors, clustered at the six-digit education level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1