Discussion Papers

Statistics Norway
Research department

No. 725
December 2012

Statistics Norway

Statistisk sentralbyrå

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Abstract:
Expected earnings are considered to influence individuals' choice of education. However, the presence of nonpecuniary attributes and the different choice set available to prospective students make identification of this relationship difficult. This paper employs a conditional logit model on exceptionally rich application data, which are likely to reflect the actual preferences of the applicants, given their individual choice sets. Controlling for several nonpecuniary attributes, average lifetime earnings is shown to strongly influence educational choice. A one-percent earnings increase for a given education increases the number of male applicants by about 5 percent and female applicants by about 2 percent. However, other attributes also matter, in particular earnings risk. Increasing both earnings and risk as they correlate in the cross section has essentially no effect on the number of female applicants. Difference in earnings and risk preferences both contribute to a gender earnings differential. Finally, there is some preference heterogeneity by education chosen.

Keywords: Rank-ordered logit, nested logit, field of study

JEL classification: J24, J31, C25

Acknowledgements: I am grateful to Rolf Aaberge, Kjell Arne Brekke, Christian Brinch, John Dagsvik, Oddbjørn Raaum, Terje Skjerpen and Erik Sørensen, as well as participants at the 34th Annual Meeting of the Norwegian Association of Economists for helpful discussions and comments. The project is funded by the Ministries of Education and Research, Labour, Trade and Industry and Health and Care Services, who have also contributed helpful comments.

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ISSN 0809-733X
Print: Statistics Norway

Sammendrag

Forventet inntekt påvirker sannsynligvis valg av utdanning. Men å beregne denne sammenhengen er krevende, fordi utdanningsvalg også styres av mange andre forhold. Viktige andre forhold er forskjeller i hvilke utdanninger som er tilgjengelige for en søker samt andre kjennetegn ed utdanningene enn gjennomsnittsinntekt etter fullføri. Slike kjenntegn kan være knyttet til selve utdanningene, som varighet, innhold, studiested, medstudenter og krav til innsats, eller til videre utfall senere, som inntektsusikkerhet og arbeidsledighet. I denne artikkelen formulerer jeg en enkel modell, der valg av høyere utdanning beskrives som valg av ”pakker” bestående av et sett av slike kjennetegn. Modellen estimeres på søkedata fra Samordna opptak for årene 2004-2009. Disse er svært omfattende, og gir sannsynligvis et godt bilde av søkernes ønsker, gitt deres muligheter – slik de oppfatter disse selv.

Resultatene viser at forventet inntekt er en viktig motivasjon for utdanningsvalg. En økning i forventet livsløpsinntekt på 1 prosent øker antall mannlige søkere med omtrent 5 prosent og antall kvinnelige søkere med omtrent 2 prosent. Andre forhold har imidlertid også betydning, særlig inntektsusikkerhet, som søkerne prøver å unngå. Utdanninger med høy gjennomsnittsinntekt har gjennomgående også større inntektsusikkerhet, og dette bidrar sterkt til at færre søker høyinntektsutdanninger, særlig for kvinner. At kvinner i gjennomsnitt legger mindre vekt på på inntekt og mer på usikkerhet enn hva menn gjør bidrar sterkt til en inntektsforskjell i favør menn. Det er noen forskjeller i vektleggingen av inntekt mellom søkere til forskjellige utdanninger, men for de fleste utdanninger er det en klart positiv sammenheng.

1 Introduction

There is a long tradition in economics for studying how expected earnings influence choice of education, e.g. Boskin (1974); Berger (1988); Arcidiacono *et al.* (2012); Beffy *et al.* (2012). This question is of great relevance to understand the functioning of the labor market in general as well as to specific policy questions. For example, large and persistent earnings differences exist between fields of education, which in turn influence strongly on gender differences in earnings. Do prospective students respond to this, potentially increasing the supply of fields in high demand, and eventually closing the earnings gaps? Also, if there is a need or desire for an increase in the supply with a given education, say, for more more qualified teachers or for health care professionals as the population ages, it is relevant to know what earnings increase can provide such an increase in students.

However, this literature is still relatively small. One reason may be the problems involved in estimating this relationship. The educational alternatives will also have nonpecuniary attributes, which may both influence choices and be correlated with observed earnings. E.g. Zafar (2009); Arcidiacono *et al.* (2012); Beffy *et al.* (2012); Wiswall and Zafar (2011) find differences in average preferences for fields. Thus, failure to control for these must be expected to give an omitted-variable bias in the estimated significance of earnings for educational choice. Young people tend to choose education similar to their parents (Boudarbat and Montmarquette (2009)), or to get get their parents' approval (Zafar (2009)). Also, comparative advantage and even choice sets vary between prospective students,[1] such that even to the extent that individuals do maximize expected earnings, they will do so subject to constraints that are generally hard to identify for the researcher.

The contribution of this paper is to estimate a simple model for educational choice on unusually rich application data. The application data are arguably informative about the applicants' preferences, and make it possible to - at least partly - overcome the mentioned challenges to identification.

[1] Paglin and Rufolo (1990) find evidence that mathematical ability is an important determinant of college field choice, while Arcidiacono *et al.* (2012) find that self-reported relative skill in all fields matter. Nielsen and Vissing-Jorgensen (2005) argues that it is relevant to control for choice sets in the study of educational choice, while Desposato (2005) argues that choice set selection in general may have a large impact on conditional logit estimates.

The paper specifies a simple model for formation of earnings expectations and choice of education. Choice of higher education is specified as a nested logit model, where the choice of educational alternative (nest) depends on a set of observable attributes of the alternatives, including average earnings. Choice of courses within nests depend on an unobserved random term. The model simplifies to a conditional logit model, where the number of available courses for each alternative enters the modeled utilities.

Most prior studies use either the actual occupation or completed education, i.e. the final outcome of the total process initiated with the application (e.g. Boskin (1974); Berger (1988); Beffy *et al.* (2012)) or data from surveys with relatively few observations (e.g. Arcidiacono *et al.* (2012); Zafar (2009); Wiswall and Zafar (2011)). The Norwegian application data arguably are close to expressing the applicants' true preferences, while also having a large number of observations. As opposed to survey data, the application data are high-stakes. Furthermore, the admission system is, for the most part, strictly meritocratic and give the applicants strong incentives to rank according to their true preferences. There is no scope for strategically manipulating the ranking. While the applicants may take into account the probability of admission, the possibility to rank up to ten courses reduces the applicants' need to apply strategically, as they are very likely to have one of their wishes granted. Also, as the admission process is almost entirely mechanical and approximately the same data are available to the researcher and the applicants, the likely perceived choice sets can be reconstructed for the analysis. The Norwegian system for admission to higher education is very centralized. Thus, almost all applications for almost every kind of higher education is captured by the application data, giving a sample size of more than 40,000 individuals per year for the years 2004-2009. The fact that applicants state not only their most-preferred course, but rank up to ten courses makes it possible to use a rank-ordered logit model to increase the precision of the estimates.

Finally, earnings, earnings risk and several nonpecuniary attributes are all controlled for in the estimations, thus both providing a richer picture of the determinants of educational choice, and reducing the scope for omitted-variable bias in the estimated effect of earnings.

Average lifetime earnings is indeed found to matter for the choice of field and level of education. A one-percent increase in earnings for a given field increases the number of applicants by about 5 percent for men and about 2 percent for women. Controlling for earnings risk has a large impact on the estimated effect of earnings. High-earning educational alternatives carry more risk, and the negative effect of the latter partly offsets the positive effect of the former. This is particularly true for women, who are found to have less of a preference for earnings, and to be more deterred by risk. The total effect of a weaker preference for earnings and more risk aversion contribute strongly to a gender earnings gap in choice of education.

The estimates are mostly stable over time, and not very sensitive to the choice of earnings measure. However, the specification of the choice set has some influence on the results. The applicants do tend to choose educations similar to their parents, but controlling for this has little impact on the estimated preference for earnings.

There is some heterogeneity in preferences. Preferences do not differ much by parental earnings, but younger applicants and women with higher scores from upper secondary show a stronger earnings preference than older applicants and women with lower scores. Finally, there is some heterogeneity by education chosen, indicating that the scope for increasing the number of applicants for an education by increasing earnings may vary between educations.

The paper proceeds as follows: Section 2 presents related literature, Section 3 the institutional setting, Section 4 the model and data and Section 5 the results from the estimation. Section 6 concludes.

2 Related literature

While choice of field is less investigated than choice of level of education, the study of how expected earnings influence choice of educational field, major or occupation has a long tradition in economics, dating back at least to Boskin (1974). Boskin (1974) finds that potential earnings explains a part of the difference in occupational choice for all race and gender groups, while Berger (1988) finds that future earnings streams matter more than initial earnings.

Recent findings are mixed. Montmarquette *et al.* (2002); Boudarbat (2008) find a clear effect of earnings on choice of major. Estimating a dynamic model of major choice, Arcidiacono (2004) finds a clear preference for earnings, but monetary returns explain little of the sorting across majors. Boudarbat and Montmarquette (2009) find a small effect of earnings on choice of field of study, and no effect for some combinations of gender and parental education. Controlling for a range of nonpecuniary attributes, Zafar (2009) finds no clear effect of subjective earnings expectations, but the few observations give little power. Beffy *et al.* (2012) find a statistically significant, but small effect of earnings. Finally, Arcidiacono *et al.* (2012) find sizeable effects of earnings on major choice.

A crucial point in the estimation of the significance of earnings for educational choice is how earnings expectations are formed. Traditionally, economists have been reluctant to collect or use survey data on subjective expectations. Rather, expectations have been assumed to be rational, with individuals acting on the basis of the same earnings function that the researcher estimates, i.e. earnings depend both on educational choice and other characteristics, such as ability. Examples of studies using this approach are Willis and Rosen (1979); Manski and Wise (1983); Boskin (1974); Berger (1988), and more recently Boudarbat (2008). However, as argued by Manski (1993), the facts that such estimations are complicated and that the approach chosen and results obtained vary between studies suggest that this is not necessarily a realistic description of expectation formation.

One possible alternative suggested by Manski (1993) and used e.g. by Rochat and Demeulemeester (2001) and Boudarbat and Montmarquette (2009) is to simply use average earnings for educational groups, unconditional on other characteristics.

Dominitz and Manski (1996); Betts (1996); Zafar (2011) find that students mostly are able to meaningfully assess expected earnings and earning differences between different educations. Following this, Arcidiacono *et al.* (2012); Zafar (2009); Wiswall and Zafar (2011) have studied educational choice, using data on subjective expectations. Wiswall and Zafar (2011) move one step further and provide information to students, measuring how this influences their assessed probabilities of graduating with a given major. While these studies generally find that respondents largely give meaningful responses when questioned about earnings expectations, and may also revise their expectations in a reasonable way when exposed to more information, the analysis of choices is limited by the small sample sizes. The samples are also selective, typically from one specific selective university, making it difficult to assess the relevance of the findings for other groups of students or potential students. Studies investigating subjective expectations often find that these vary considerably, e.g. Dominitz and Manski (1996); Betts (1996); Zafar (2011), thus motivating the use of expectation data. However, these studies give little guidance on how to best model earnings expectations in the absence of expectations data.

Some studies link educational choices and risk. Flyer (1997) finds that the job-match uncertainty implies an option value, valued by the students. Saks and Shore (2005) find that individuals with higher wealth choose riskier careers, suggesting that risk aversion varies between individuals, and that it matters for educational choices. Nielsen and Vissing-Jorgensen (2005) find that risk, in the transitory and in particular permanent income shocks, impacts negatively on the probability that an education is chosen. Also related to risk, Rochat and Demeulemeester (2001) and Montmarquette *et al.* (2002) find that a higher chance of completion matters.

Nonpecuniary attributes in general also matter for educational choice. Arcidiacono *et al.* (2012); Beffy *et al.* (2012); Nielsen and Vissing-Jorgensen (2005) all find that there are differences in average preference between different fields. Zafar (2009) links choice of major to different attributes of the studies and following careers, finding that nonpecuniary attributes explain a large share of the variation in choices.

Finally, comparative advantages are also found to influence the choice of education. Paglin and Rufolo (1990) emphasize the differences between different types of human capital, i.e. verbal and quantitative skills, and find that comparative advantage accounts for male-female differences in occupational choices. Arcidiacono *et al.* (2012) find that perceived comparative advantages across major contribute to explaining major choice.

3 Institutional setting

Following the Bologna process, higher education in Norway is mostly organized in three-year Bachelor and five-year Masters degrees. The higher education sector consists of eight

Some of places at some courses are set aside to different quotas (e.g. students from northern parts of Norway at some institutions), however the bulk of the places and applicants are in the two main quotas: improved grade point average (GPA) and unimproved GPA. In the unimproved GPA quota, applicants compete with admission scores calculated as the GPA they got leaving upper secondary school, i.e. average (original) grades and potentially extra points. Grades range from 1 to 6 (only integer values), grade point is calculated as 10 times average grade (with two decimal places). Extra points are awarded for choosing science subjects (max 4 points) or focusing on subjects in upper secondary (also max 4 points). There are specific rules for some courses, e.g. 2 extra points for women at some male-dominated courses, and medicine has its own implementation of this quota. Improved GPA includes any changes to the grades as the applicants have redone or taken more secondary school subjects after leaving secondary school,[4] the extra points mentioned above and some more for age, education and military service. Medicine and some other courses have separate regulations for extra points.

Qualified applicants are allocated to courses based on their admission scores, with the students with the higher score getting priority in case of a surplus of applicants. Note that this is strictly implemented, irrespective of the applicants' priorities: With two applicant competing for an offered course, the applicant with the higher score will get the offer, even if it is ranked tenth by her and ranked first by the other applicant. Thus, there is no possibility of "gaming" or manipulating the admission system by misreporting preferences.

Applicants only get one offer. This is mechanically chosen by SO as the highest-preferred available. Thus, if an applicant gets offered her second ranked course, courses ranked three and worse are automatically discarded from the application. This gives an obvious incentive to rank the courses in the application according to the applicant's preferences.

While an applicant has every incentive to let the ranking within the (up to) ten ranked courses reflect her preferences, most applicants will have an incentive to be strategic in which ten courses to rank. Even if an applicant may know for certain whether she satisfies the formal qualification requirements for a course, she does not know whether she will be admitted. There are two sources of uncertainty: First, the exact score required to be admitted is unknown at the

[4]A number of students spend much time improving their grades to get competitive courses such as medicine.

time of application, as this will depend on the number and scores of the other applicants, both unknown by the applicant. Also, applicants still in secondary school in April when applying will not know their final grades and GPA, as these are set in May or June. However, minimum admission scores for previous years are available from SO, such that the applicants can make an informed guess when applying. Furthermore, applicants will likely have a good idea about final grades, as these are based on performance throughout the school year. Thus, applicants are likely to judge the probability of admission based on formal requirements, (expectations of) own final grades and previous admission thresholds. To the extent that the final grades expectations are correct, all of these are observable, such that the likely perceived choice sets can be reconstructed.

Finally, it makes little sense for an applicant to rank a course she knows she cannot get admitted to. This has a cost in the form of a lost opportunity to compete for a highly preferred course she may get. However, as the applicant can rank up to ten courses this cost can be low. If an applicant has one or more acceptable courses where she is confident to get an offer, there is little risk in ranking some higher-preferred courses with low probability of admission first.

4 Model and data

Choices of higher education are made from individual-specific choice sets, and are assumed to depend on expected earnings, nonpecuniary attributes and a random term, which are discussed in turn. These cannot be chosen freely, but rather as specific bundles made up by the educational alternatives. Furthermore, while there is some room for heterogeneity in expectations, earnings expectations are proportional to simple measures of average earnings within each education, rather than being functions of individual-specific covariates. Thus, preferences for earnings will be estimated from differences in average earnings between educational alternatives, and not from predicted differences between individuals within the same educational alternative.

While choice of education is an inherently dynamic process, where choices at one stage influences the options and pay-offs at later stages, a static model of choice of higher education will be estimated. Thus, a limitation of the model is that it does not model earlier educational choices, but rather takes the applicants previous qualifications as given. A richer model could include choices through secondary school. This is beyond the scope of this paper.

4.1 Choice of education

There is a total of C different specific courses. These are classified into J different broader educational alternatives (henceforth educations), with each education j consisting of a set C_j of different courses.

As described in Section 3, admission is strongly meritocratic. Thus, each applicant will face an individual-specific choice set, based on her formal qualifications, her admission score, the rankings of the other applicants and their admission scores.[5] While there is uncertainty about the two latter at the time of application, these are still exogenous to an individual applicant, such that they can be summarised in an admission score required to qualify. This uncertainty will be disregarded in the empirical model.

Thus, based on formal qualifications, admission score and the required scores of the different courses, an applicant faces a choice set C_{ij} of courses within education j that she can be admitted to, containing m_{ij} courses. m_{ij} is smaller or equal to total the number of courses in C_j, and may be zero - indicating that the applicant will not be admitted to any course within this education, and hence can not choose this particular education. The total set of educations j available to the applicant, i.e. with $m_{ij} > 0$ is denoted Ω_i. The full choice set for an applicant, including all available courses summed across all educations, denoted C_{i+}, is $\{c|c \in C_{ij}, \forall j\}$. Choice sets are determined by qualifications and admission scores, and will thus differ across individuals.

An applicant has preferences for a range of attributes of the courses. Some of these relate to the careers that follow from choosing a career, such as earnings, earnings risk, unemployment and working time. Other attributes relate to the consumption value and cost of studying, and may include e.g. the effort required to follow a particular course, peer students or the

[5] This is true for a large majority of the applicants. Those applicants who get discretionary treatment are disregarded in the analysis.

geographical location or amenities of the institution.

These preferences are revealed through the ranking of courses in the application. The applicant is assumed to evaluate all courses available to her and choose the most attractive one. Thus, the applicant chooses course c, within education j, with the highest utility U_{icj}, i.e. such that:

$$U_{ijc} = \max_{c' \in C_{ij'}, j' \in \Omega_i} U_{ij'c'} \tag{1}$$

The utility from course c in education j depends on expected earnings, earnings risk and nonpecuniary attributes. In the following we will specify a simple model for average preferences and earnings expectations. The systematic part of the utility function, which depends on attributes observable to the researcher, is denoted V_{ij}. This part does not depend on variables that vary across courses within education. Thus, the systematic part varies across applicants and educational alternatives, but is constant across courses within each education.

Any variation beyond this, e.g. variation between courses within education, variation due to omitted attributes and from heterogeneity in preferences, is modeled as a person course-specific random term, denoted ϵ_{icj}. The two terms are assumed to enter utility additively:

$$U_{icj} = V_{ij} + \epsilon_{icj} \tag{2}$$

The systematic utility function is assumed to depend on the log of expected life-time earnings $\log \mathrm{E}LY_{ij}$,[6] earnings risk expressed by the within-education variance of log earnings ($\sigma^2_{y,j}$) and utility from nonpecuniary variables (X_{ij}):

$$V_{ij} = V(\log \mathrm{E}LY_{ij}, \sigma^2_{y,j}, X_{ij}) \tag{3}$$

Note that expected earnings and nonpecuniary attributes may vary between educations and between individuals within education, while earnings risk is assumed fixed for each education. As noted above, there is no within-education variation in the systematic utility function, such

[6] The same functional form is also used by e.g. Beffy *et al.* (2012) and Nielsen and Vissing-Jorgensen (2005) studying choice of education. Dagvik *et al.* (2006) provide theoretical and empirical support for log income as functional form for the utility of income.

variation enters only through the random term.

The next subsections elaborate on the specification of earnings, nonpecuniary variables and the specification of the random terms, ϵ.

4.2 Expected earnings

The choice of education will depend on the individuals' *expected* earnings. In the current setting, expectations are not observed, and thus must be modeled.

Every individual i has some expected earnings $\mathrm{E}Y_{ija}$ in every education j at every age a. These are assumed to be the product of an individual-education-specific constant term, and an education-specific age-earnings profile:

$$\mathrm{E}Y_{ija} = \alpha_{ij}\beta_{ja} \tag{4}$$

Thus, earnings vary with age and between educations, and the individuals have beliefs about their (age-independent) relative ability or degree of success in each education. For choice of education, the individuals care about their expected lifetime earnings, which is defined by the discounted sum of expected earnings over the age profile:

$$\mathrm{E}LY_{ij} = \sum_a \delta^a \mathrm{E}Y_{ija} \tag{5}$$

Due to the specification (4), expected lifetime earnings can be decomposed into an individual-education-specific factor and an the discounted value of an education-specific earnings-profile:

$$\mathrm{E}LY_{ij} \quad = \quad \alpha_{ij} \sum_a \delta^a \beta_{ja} = \alpha_{ij} \cdot \mu_{LY,j} \tag{6}$$

The first term in (6) is thus the applicant's expectation of own relative earnings potential in a given education, while the second term is the applicant's expected average lifetime earnings for the education.

For the average lifetime earnings, the applicants are assumed to use the population averages. As argued by Manski (1993), it appears more reasonable that young people are able to observe average earnings than to estimate complicated earnings functions. Betts (1996) finds that the single most important source of information on earnings is newspapers and magazines, indicating that the students' knowledge is based on general information.

Thus, applicants are not assumed to have knowledge of a detailed function determining their relative earnings. Rather, expected relative earnings is assumed to be a simple function of information that can be assumed to be available to the applicants: Some unobserved measure of their absolute ability across all educations, their relative ability and the earnings variance within each education. Relative ability is measured as how many standard deviations the applicant's admission score (G) differ from the average of all student admitted within that education: $\tilde{G}_{ij} = (G_{ij} - \bar{G}_j)/\sigma_{G,j}$. With detailed information on admission requirements, it is reasonable that students have a good idea about their relative academic performance. Furthermore, the variance of earnings may matter for the applicants' expectations. In particular, an applicant of high ability may expect a higher return to that ability in a high-variance education. This structure is captured by the following specification of the earnings expectation:

$$\alpha_{ij} = \exp(\alpha_{0i} + \alpha_1 \tilde{G}_{ij} + \alpha_2 \tilde{G}_{ij} \sigma^2_{y,j}) \tag{7}$$

Applicants of average absolute ability and with academic performance equal to the average within a given education are assumed to expect earnings equal to the average within that education. Applicants of higher (lower) ability may expect higher (lower) earnings where their expectation is assumed to increase with $\alpha_1 + \alpha_2 \sigma^2_{y,j}$ for each standard deviation increase in admission points. Thus, we expect $\alpha_1, \alpha_2 \geq 0$.

4.3 Estimation of lifetime earnings and earnings risk

Using a ten-year panel data set (1999-2008) we estimate flexible earnings profiles separately for each of the educations, allowing for individual fixed effects:[7]

$$\log Y_{ijxt} = \alpha_{ij} + \beta_{jx} + \nu_{ijxt} \tag{8}$$

Y_{ijxt} represents the earnings of individual i with education j and x years of experience at time t. Y_{ijxt} is deflated before estimation with a wage index to remove general earnings increase, such that the distribution for every t is similar. The parameter α_{ij} represents the individual fixed effect. β_{jx} is the effect of x years experience, such $\beta_{jx}, \forall x$ yields the earnings profile for education j, and ν_{ijxt} is an iid mean zero disturbance term. The earnings equation (8) is consistent with (4). Earnings vary flexibly between individuals, and flexibly with experience in a way that is shared by all individuals.

Lifetime earnings are calculated for an individual that completes her education at the stipulated age A_j, which is the sum of stipulated duration of the education (S_j) and the school starting age (A). She then starts working and subsequently works and acquire experience every year until retiring when reaching age 67. Thus, at age a she has $x = a - A_j$ years of work experience. Predicted earnings with a given education of length S_j at a given age a is calculated from the average estimated individual-fixed effect of the group, and the estimated earnings profile:

$$\hat{Y}_j(a) = \begin{cases} \exp\left(\hat{\alpha}_{\cdot j} + \hat{\beta}_{j,a-A_j} + \frac{1}{2}\sigma^2_{y,j}\right) & a > A_j \\ Y^0 & a \leq A_j \end{cases} \tag{9}$$

$\hat{\alpha}_{\cdot j}$ is the average of the estimated individual-fixed effect from (8), while $\hat{\beta}_{j,a-A_j}$ is the element of the estimated earnings profile $\hat{\beta}_j$ associated with $a - A_j$ years of experience. Because the log transform is a concave function, by Jensen's inequality, antilog of predicted log earnings underpredicts expected earnings: $\exp(\mathrm{E}\log Y) \leq \mathrm{E}Y$, with equality only when there is no uncertainty in Y. However, as log earnings is approximately normally distributed we correct

[7] The measurement of lifetime earnings is discussed in more detail in Kirkebøen (2010), who also discusses the sensitivity of the measures of lifetime earnings to choice of basic assumptions.

for this bias by adding 1/2 times the residual variance of log earnings, i.e. the sum of the variances of α and ν: $\sigma^2_{y,j} = \sigma^2_{\alpha,j} + \sigma^2_{\nu,j}$. For ages at which an individual is not expected to have completed his education, earnings is assumed to be equal to a small, fixed amount, to reflect earnings while studying.

Expected lifetime earnings for an education group is assessed as the discounted sum of predicted earnings over the life cycle, from graduation from secondary school around age 20 to retirement at 67:

$$\mu_{LY,j} = \sum_{a \in [20,66]} \delta^{a-20} \cdot \hat{Y}_j(a), \tag{10}$$

which is the average earnings measure used in (6).

The variance of log earnings used in (3) and (6) is the same as in (9): $\sigma^2_{y,j} = \sigma^2_{\alpha,j} + \sigma^2_{\nu,j}$. It can be argued that earnings dispersion ($\sigma^2_{\alpha,j}$) and variability ($\sigma^2_{\nu,j}$) have different roles in the determination of expected earnings and choice of education. However, these variances are strongly correlated (coefficient of correlation .89). Thus, this distinction is of little empirical importance. Since earnings dispersion is greater than variability, earnings dispersion is shown to be very strongly correlated with total variance (coefficient of correlation $> .99$).

Earnings is estimated on the basis of data from 1999-2008. We will proceed to estimate educational choices for application data ranging from 2004 to 2009. First, note that these are two different samples. Expected earnings are estimated not by the applicants' future earnings, but by the earnings of other individuals before or around the time of application. These individuals have completed their education and is already in the labour at this time. Furthermore, there is a partial overlap between the two data sources, and the applicants in the earliest years can not possibly have known the earnings in the latest years. This is likely to be of little concern, as the lifetime earnings express very persistent differences. Kirkebøen (2010) find that the correlation between the lifetime earnings based on 1999-2008 data and lifetime earnings based on 1989-1998 data is 0.97.

As educational choices vary significantly with gender, all choice estimations will be done separately by gender. However, it is not a priori clear if earnings should be calculated separately by gender. One question is whether earnings is reported by gender or as an average across gender in channels the applicants have access to, e.g. media. Another question, particularly relevant for young women, is whether older men or women give the more relevant indication of one's own future earnings, given the changes and convergence between genders in labor force participation over the last decades. The main results will be based on pooled earnings estimates, but the sensitivity to this will be investigated in Section 5.

Furthermore, lifetime earnings is a relevant earnings measure in a situation with full information and no borrowing constraints. However, individuals who face credit constrains may be more concerned about early career earnings. Also, the average applicant may have a higher discount rate than that used in the measurement of lifetime earnings. Berger (1988) finds that a measure of earnings over a longer period explains choice of major better than initial earnings. Still, as the earnings measure is arbitrary, the sensitivity to this will be investigated in Section 5.

4.4 Estimation of choice of education

As indicated above, the utility from each course is assumed to depend on log expected lifetime earnings, variance of earnings and a vector of nonpecuniary attributes, as well as unobserved variation captured by the random term. Moreover, let the systematic term be specified as follows:

$$V_{ij} = \gamma \log \mathrm{E} LY_{ij} + \eta \sigma^2_{y,j} + X_{ij} \tag{11}$$

Thus, with a preference for earnings and risk aversion, we expect $\gamma > 0$ and $\eta < 0$.

In order to estimate the effect of earnings, and to predict the change in application patterns following a change in average earnings, it would be preferable to be able to control for the average preference for each education (X_j) with a set of education-specific constants. However, a model with education-specific earnings and education-specifics constants is not identified. Thus, X_{ij} is rather modeled, which increases the scope for omitted-variable bias, but which allows the study of the impact of more attributes on choice of education. X_{ij} is specified as follows:

$$X_{ij} = \zeta_j^{field} + \xi_j^{level} + \phi \tilde{G}_{ij} + F_{ij}\lambda + W_j\psi + C_{ij}\omega \tag{12}$$

Several kinds of nonpecuniary attributes may matter for choice of education, e.g. consumption value of studying and preferences for other career attributes than earnings. As both may vary with field and level of education, we include dummies for field (ζ_j^{field}) and level (ξ_j^{level}) in the specifications of utility. These are assumed additively separable. The interpretation of the coefficients on these dummies will then capture the average preference for the respective fields and levels, irrespective of whether that utility stems from studying or if the utility is from working after graduation.

Status of an education may also be a determinant of choice, see e.g. Zafar (2009). We have no direct data on status. However, earnings probably partly proxy for this, such that this will be part of the estimated earnings effect. The applicant's relative ability ($\tilde{G}_{ij}$) may also partly proxy for status and aspirations. If courses with competent peers are attractive, and applicants aim for high-ability courses, we expect ϕ to be negative.

Students' choice of field have been shown to vary with parental education, see e.g. Boudarbat and Montmarquette (2009); Zafar (2009). As parental education can only influence choices if it is interacted with attributes of the alternatives, we construct in total four variables that measure similarity in field and squared deviation in duration compared to each of the parents' educations (F_{ij}). If applicants want to conform to their parents' educations, we should expect a positive coefficient on similarity in field, and a negative on squared deviation in duration.

Mean and standard deviations of earnings do not fully capture the labor market outcomes associated with an education. To investigate if other attributes influence choices, we control for average time unemployed, average hours of working time per week, and the shares of individuals employed in the public sector and self-employed (W_j).

Finally, comparative advantage may have a role in explaining educational choices. Paglin and Rufolo (1990) find that the level of quantitative skills is important for education choice and earnings. To investigate this relationship, we interact an indicator variable for whether the education is math-intensive with indicator variables for whether the applicant has, respectively, one and two years of elective math in upper secondary (C_{ij}).[8] However, as choice sets largely depend on qualifications in maths and science, they are also likely to capture an element of comparative advantage.

Several of the variables in (12) are education-specific. As with education-specific constant terms, the number of different educations restrict the number of variables in an identified model. With 20 educations, it is necessary to be parsimonious in the specification of X_{ij}. For this reason W_j will be excluded in the main specification, but studied in a sensitivity check.

Inserting for (6), (7) and (12) in (11) yields:

$$\begin{aligned} V_{ij} &= \gamma\left(\alpha_{0i} + (\alpha_1 - \phi)\tilde{G}_{ij} + \alpha_2 \tilde{G}_{ij}\sigma^2_{y,j} + \log \mu_{LY,j}\right) + \eta\sigma^2_{y,j} \\ &\quad + \zeta^{field}_j + \xi^{level}_j + F_{ij}\lambda + W_j\psi + C_{ij} \end{aligned} \tag{13}$$

Note that as relative ability ($\tilde{G}_{ij}$) may both influence earnings expectations and affect utility through a preference for status or competent peers, the estimated sign and magnitude of this coefficient is hard to interpret. However, for the interaction of relative ability and earnings risk ($\tilde{G}_{ij}\sigma^2_{y,j}$) there is no such ambiguity.

For choices, only utility differences matter, not utility levels. Therefore, applicants' characteristics cannot themselves influence choices, as all utility comparisons are done between alternatives, within individuals. Thus, comparing two educations j and j' the individual-specific ability (α_{0i}) cancels out: [9]

$$\begin{aligned} V_{ij} - V_{ij'} &= \gamma\alpha_1(\tilde{G}_{ij} - \tilde{G}_{ij'}) + \gamma\alpha_2(\tilde{G}_{ij}\sigma^2_{y,j} - \tilde{G}_{ij'}\sigma^2_{y,j'}) \\ &\quad + \gamma(\log \mu_{LY,j} - \log \mu_{LY,j'}) + \eta(\sigma^2_{y,j} - \sigma^2_{y,j'}) \\ &\quad + (\zeta^{field}_j - \zeta^{field}_{j'}) + (\xi^{level}_j - \xi^{level}_{j'}) \\ &\quad + (F_{ij} - F_{ij'})\lambda + (W_j - W_{j'})\psi + (C_{ij} - C_{ij'}) \end{aligned} \tag{14}$$

[8] Math-intensive educations are those that mostly consist of courses with formal math requirements: Business educations, science and engineering, architecture as well as medicine and dentistry, veterinary science and pharmacology. Some of these require two years elective math, other one year.

[9] The same would of course happen to any characteristic X_i that does not vary between educations. However, if the effect of an characteristic is allowed to vary between the alternatives, i.e. the characteristic is interacted with a alternative-specific constant term in the utility function, the effect will not cancel out from the utility comparisons (except for a normalization, obtained by omitting the characteristic for one attribute).

Choice of education depends on all systematic differences, as well as the random terms, ϵ_{ijc}. An applicant will choose education j if for some $c \in C_{ij}$

$$V_{ij} + \epsilon_{ijc} \geq V_{ij'} + \epsilon_{ij'c'} \quad \forall \{c' | c' \in C_{ij'}, j'\} \tag{15}$$

The random term in choice models is normally assumed to be iid extreme value, which implies that the choice probabilities have a logit structure. However, in this case, the iid assumption can be questioned for two reasons: First, assuming zero correlations between the random terms appears unreasonable, as some pairs of courses are very different in content and in which careers they qualify for, while other pairs of courses are identical or almost so, for example with the exception of the institution that offer them. Thus, there should be a varying degree of substitutability. Second, the focus of this paper is choice of education among broadly defined alternatives, not the determinants of choice of institution or specific course within education.

The random term is thus assumed to be independent of the systematic utility, and have a generalised extreme value distribution, i.e. cumulative distribution function

$$P(\epsilon_{ijc} \leq \tilde{\epsilon}_{ijc}) = \exp\left(-\sum_{j}\left(\sum_{c \in C_{ij}} \exp(-\tilde{\epsilon}_{ijc}/\rho)\right)^{\rho}\right), \tag{16}$$

which is denoted the nested logit model (see e.g. Train (2003)). Courses are the lowest choice-level alternative, while educations corresponds to nests. The choice of course is decomposed into two choices. Applicants choose education, and course within education. The random terms of two courses ϵ_{ijc} and $\epsilon_{ij'c'}$ are uncorrelated if they belong to different educations, i.e. if $j \neq j'$, but if $j = j'$ the correlation is equal to $1 - \rho^2$.[10] If $\rho = 0$ the random terms are perfectly correlated within each education, indicating that the applicants see no differences between courses within an education. If $\rho = 1$ the random terms are identically and independently distributed across all courses and educations.[11]

[10] In most presentations, including Train (2003), ρ is allowed to vary between educations. In this paper, it will be constant across all educations. While it could be argued that the degree of correlations in the random terms vary between different educations, the relatively large number of educations (20) would significantly increase the number of parameters in the model.

[11] Generalised extreme value random terms means that independence of irrelevant alternatives - that the

The probability of interest is that of i choosing a given education j, i.e. P_{ij}. Furthermore, because there is no variation in V_{ij} for $c \in C_{ij}$, this becomes an standard logit model, adjusted for the number of courses available in the applicant's choice set, m_{ij}:[12]

$$\begin{aligned}
P_{ij}(\Omega_i) &= \frac{\exp(V_{ij} + \rho \log m_{ij})}{\sum_{j'} \exp(V_{ij'} + \rho \log m_{ij'})}, \\
V_{ij} &= (\gamma\alpha_1 + \phi)\tilde{G}_{ij} + \gamma\alpha_2\tilde{G}_{ij}\sigma^2_{y,j} + \gamma LY_j + \eta\sigma^2_{y,j} \qquad (18) \\
&\quad + \zeta_j^{field} + \xi_j^{level} + F_{ij}\lambda + W_j\psi + C_{ij}\omega
\end{aligned}$$

In (18) the α_i's are suppressed as these cancel in comparisons, and the dependency of the probability on the applicant's choice set, Ω_i, is emphasised.

As discussed in Section 3 the applicants do not know m_{ij}. They know whether they have the formal qualifications, but do not know at how many courses they may be admitted. The number m_{ij} depends on their own admission score and those required at the different courses, which in turn depend on the admission scores of the other applicants. The uncertainty in own score is likely to be small. Applicants who are not still in school will know their score, while those still in school are probably able to fairly accurately predict it, based on grades received so far throughout the school year. While the required scores are unknown, last year's required scores are known, and even distributed to the potential applicants, so it seems reasonable that the students calculate m_{ij} based on these. These data are also available for the estimations.

The applicants are assumed to expect unchanging admission requirements. Thus, m_{ij} is calculated as the number of courses an applicant with the same score could have been admitted to the year before. This approach disregards the uncertainty in the admission requirements

likelihood of choosing one alternative over another is independent of any further alternatives, a prominent feature of logit choice models - no longer for the unconditional choice of course. However, it holds for the choice of education, and for the choice of course conditional on education.

[12]Following e.g. Train (2003), the probability of i choosing c within j can be expressed as

$$\begin{aligned}
P_{ijc} &= P_{ic|j} \cdot P_{ij} \\
&= \frac{\delta_{ic} \exp(V_{ic|j})}{\sum_{c' \in C_{ij}} \exp(V_{ic'|j})} \cdot \frac{\exp(V_{ij} + \rho I_{ij})}{\sum_{j'} \exp(V_{ij'} + \rho I_{ij'})}, \quad I_{ij} = \log \sum_{c \in C_{ij}} \exp(V_{ic|j}/\rho), \qquad (17)
\end{aligned}$$

where $\delta_{ic} = 1$ if c is available to i, and zero otherwise. $P_{ic|j}$ is the probability of i choosing c, given that i choose j, and $V_{ic|j}$ is the systematic utility associated with this choice. As there is no variation in systematic utility within education, this can be normalised to zero, such that I_{ij} becomes $\log m_{ij}$. Inserting for I_{ij} in the expression for P_{ij} in (17) yields (18).

(from the applicant's point of view). This is particularly relevant if the difference between the applicant's score and the admission requirement is small. If the applicant just would (not) have been admitted, she thus could fear (hope for) a small change in the requirement, such that it may make sense to apply for a course which she could not get admitted to the previous year. The estimations will therefore for the most part not be restricted to courses with $m_{ij} > 0$. Rather we include courses with $m_{ij} = 0$, but control for the this specifically.[13]

This measure does not capture the distance from the previous year's admission requirement, or the likelihood of making it the next year. However, the m_{ij}'s are highly correlated with the average difference between score and requirement. Also, m_{ij} will mostly be from 10-100, such that if the admission requirements are uncorrelated, the large number of specific courses will mean that increases and decreases in admission requirements will cancel out. However, for some educations m_{ij} is much smaller. Also, if m_{ij} varies systematically, e.g. in response to shifts in aggregate preferences for education, there is more scope for a discrepancy between the applicant's expectations and the choice set inferred from the previous year. Still, it is not clear whether applicants anticipate such complications, or if their perceived probabilities of admission are in line with the modeled probabilities.

Another aspect of an education being available is whether the applicant satisfies the formal admission requirements. In this case there is no uncertainty, such that there is no reason for an applicant to apply for such an education.

The model for educational choice is estimated on unusually rich application data, where each applicant rank up to ten alternatives. Thus, the amount of information is more extensive than in a situation where only the most-preferred choice is known. To fully utilize these data, a rank-ordered logit model is employed. By virtue of the IIA property, excluding any education from the choice set does not alter the ranking of the remaining. Thus, the probability of observing a specific ranking of courses is the probability of having the first choice as the most-preferred from the full choice set, the second choice as the most-preferred in the remaining set excluding the first choice, and so on, i.e. a product of logit probabilities. Both the order and the number of educations ranked will vary between individuals. For an applicant with

[13] In terms of (18), m_{ij} enter as $\log m_{ij}$, such that $m_{ij} = 0$ gives $-\infty$ utility. For the estimations, $\log m_{ij}$ is set to 0 for $m_{ij} = 0$. A dummy variable captures the utility difference between $m_{ij} = 0$ and $m_{ij} = 1$.

a choice set of available educations Ω_i, the probability of having the ranking $R_i = \{j, k, l\}$, which means the applicant has ranked three different educations, and that $j \succ k \succ l \succ$ *all other educations*, is given as:

$$\begin{aligned} P(R_i|\Omega_i) &= P_{ij}(\Omega_i) \cdot P_{ik}(\Omega_{i,-j}) \cdot P_{il}(\Omega_{i,-jk}) \\ &= \frac{\exp(V_{ij} + \rho \log m_{ij})}{\sum_{j'} \exp(V_{ij'} + \rho \log m_{ij'})} \\ &\quad \times \frac{\exp(V_{ik} + \rho \log m_{ik})}{\sum_{j' \neq j} \exp(V_{ij'} + \rho \log m_{ij'})} \\ &\quad \times \frac{\exp(V_{il} + \rho \log m_{il})}{\sum_{j' \neq j,k} \exp(V_{ij'} + \rho \log m_{ij'})} \end{aligned} \tag{19}$$

Each element $P_{ij}(\Omega_i)$ in (19) is the choice probability in (18), with Ω_i being the set of educations available to the applicant, i.e. with $m_{ij} > 0$. $\Omega_{i,-j}$ indicates the set of available educations excluding j, i.e. the educations to be considered as a second choice, when the applicant has already ranked j first, and so on. A likelihood function can then be constructed by multiplying the contributions from each individual, given in (19), such that the log likelihood becomes:

$$ll = \sum_i \log\left(P(R_i|\Omega_i)\right) \tag{20}$$

This can be maximized by standard methods to get the MLE of the coefficients in (18).

4.5 Data description

Application data are gathered from SO's centralized registration of applications, for the years 2004-2009. 20 educations are constructed from about 1300 specific courses at different institutions. Table A.1 in Appendix A lists the different educations, and how these are classified according to field and level.[14]

Table 1 presents descriptive statistics on the attributes of the educations. Labor market attributes - log earnings, variance of log earnings, unemployment, working time and shares

[14] The fields are health and social work, teaching, business and administration, science and engineering, law and social sciences and humanities. Levels are Bachelor, Master and unspecified. While professionally oriented courses have a clear level, broader university studies do not. Students are admitted to a Bachelors course initially, but for most students this is not a final destination, but rather a requirement to enter a Masters course.

Table 1: Descriptive statistics: Educations

	Mean	Std. dev
Lifetime earnings (M NOK)	12.286	3.118
Log lifetime earnings	2.479	0.245
Variance of log earnings	0.157	0.055
Unemployment	0.128	0.065
Hours work/week	32.166	1.447
Share in public sector	0.451	0.240
Share self-employed	0.079	0.107
Requires Math	0.400	0.503
Number of specific courses	58.650	55.198
Share qualifying (at least one course)	0.833	0.304
Share 1st choice	0.050	0.038
Share ranked	0.140	0.107
Observations	20	

working in the public sector and self-employed - are calculated from administrative register data for the years 1999-2008, that cover the entire working-age population.[15] As mentioned, labor market outcomes will be based on data from other cohorts than the cohorts used in the choice estimations. The between-education variance of log lifetime earnings is about .25 log points. The variance of log earnings is highly correlated with log lifetime earnings. Figure A in Appendix A shows a scatterplot for the two variables. Whether the educations require maths, the number of courses in each education and the share of applicants who have either chosen the relevant education as their most-preferred or ranked it in the application is taken from the application data.

As discussed in Section 4, the limited number of educations restricts the possible number of education-specific variables. A main distinction in the admission to higher education is whether the applicant has elective Math subjects from upper secondary, this - and in some cases further science subjects - is a requirement for several educations, but there are no corresponding requirements for other subjects.[16] Also, Paglin and Rufolo (1990) find that quantitative and verbal ability is a relevant dichotomy, with the former being more highly valued in the labor market. Thus, a parsimonious specification for field is whether or not an education requires Math. A more detailed control is the classification of fields and levels in

[15]There is no common classification of courses or clear link from the application data to other administrative registers. The analyses presented thus are based on a custom-made link, emphasizing educations that are well-defined in both data sets. These cover 94 percent of the applications and 77 percent of completed higher educations of 30-year olds in 2008.

[16]I.e., if all of an applicants' elective subjects from upper secondary are within science, she may study science or humanities, while if none of the elective subjects are within science she may not study science.

Table A.1 in Appendix A.

Table 2 presents descriptive characteristics of the applicants in Panel A, and of the applicant-education pairs in Panel B. About 37 percent of the applicants are excluded from the analysis because of missing data on admission score, and another 6 percent because of missing data on parental education. The final sample contains data from 301,678 applicant/year observations.[17] From Table 2 we see that about 60 percent of the applicants are females, and that average age at application is 21 years, but with significant dispersion. The main analysis will be restricted to the applicants who are 23 years or younger, this excludes about a quarter of the applicants. Most of the observations thus excluded are in the mid 20s, however, there is a small share of much older applicants. One motivation for excluding older applicants is that the estimated lifetime earnings are less relevant as the students become older, as the remaining time in the labor market and thus potential return on investment in education will fall. Also, there is a number of applicants of high age, many already with higher education. It is not clear if these have similar preferences as young applicants making decision for a career. However, the exact age cut-off is essentially arbitrary, and the choices of older applicants will be studied separately as a check for heterogeneous preferences.

The average applicant satisfies the formal requirements for almost 17 out of the 20 education. She has a score of 44 points, which means that she can expect to qualify for on average 39 courses within each education. Out of the 10 possible, the average applicant has ranked 5.7 courses, on average within 2.8 different educations. Figure 1 shows the distribution of courses and educations ranked. Almost one in four applicants have ranked the maximum number of courses. The mode of number of educations ranked is one, however, a significant share have ranked more.[18]

Looking at the ranked educations in Panel B, in 87 percent of the cases where an applicant satisfies the formal requirements for qualification, she could have been admitted the previous year. For the ranked educations this share is higher, at 95 percent. Thus, it is uncommon, but not unheard of, that an applicant applies for an education she would not be admitted to

[17]An applicant may have applied in several years.

[18]Obviously, many applicants have ranked several different courses within the same education. However, there is also variation in educations, such that preferences do not seem to be lexicographic, with education dominating.

Table 2: Descriptive statistics: Applicants

Panel A: Individual characteristics

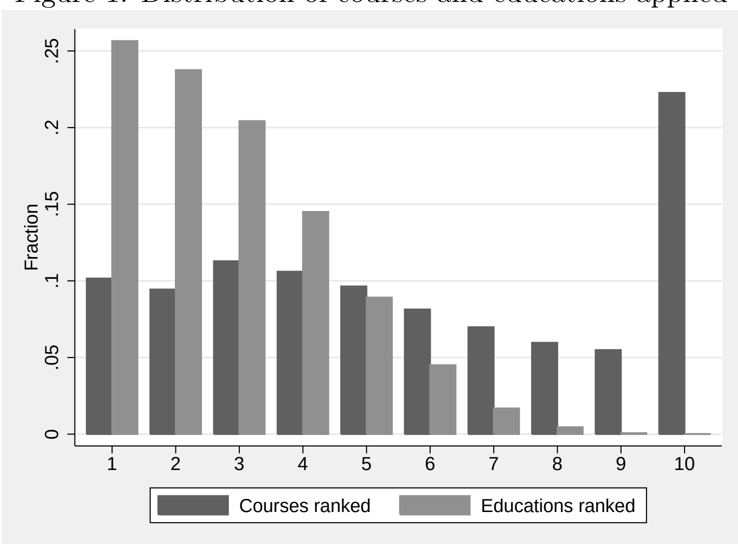
	Mean	Std. dev
Female	0.593	0.491
Age	21.151	2.130
Admission score	44.210	7.506
Educations qualified previous year	16.660	1.754
Courses qualified previous year	39.229	42.255
Number of courses ranked	5.712	3.142
Number of educations ranked	2.803	1.596
Observations	316319	

Panel B: Individual-education match-specific characteristics

	Unranked		Ranked		Total	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Applicant qualifies	0.851	0.356	0.952	0.214	0.869	0.338
Same field as mother	0.134	0.341	0.118	0.322	0.131	0.338
Same field as father	0.093	0.291	0.098	0.298	0.094	0.292
(Length of schooling - mothers length)^2	18.997	40.141	21.228	42.272	19.382	40.525
(Length of schooling - fathers length)^2	17.793	36.860	19.946	38.880	18.165	37.225
Req Math $\cdot$ applicant $\geq$ 2 years Math	0.144	0.351	0.179	0.383	0.150	0.357
Req Math $\cdot$ applicant 3 years Math	0.107	0.309	0.149	0.356	0.114	0.318
Observations	3941038		821440		4762478	

Note: In panel B the sample is restricted to educations where the applicant satisfies the formal requirements for qualification.

Figure 1: Distribution of courses and educations applied



the previous year.

5 Results

Tables 3 and 4 present results from the estimation of (19) for men and women respectively, with the choice probabilities given from (18). For comparison, columns (1) and (2) estimates a (conditional) logit choice model on completed educations, using data for 2009 and a sample of 30-39 year olds.[19] Columns (3) and (4) then presents results for estimations based on the application data, including all educations. Columns (5) and (6) also use application data, but only include education for which the applicant satisfies the formal admission requirements.

For men, in Table 3, there is a positive relationship between log earnings and the number with a given completed education, cf. column (1). This is however not robust to the inclusion of controls for the variance of earnings, for field and level and for similarity with parents' education (column (2)). There is also a positive relationship between log earnings and number of applicants, unconditional on further attributes (column (3)), and a stronger relationship conditional on attributes (column (4)). This relationship becomes even stronger when we restrict the choice set to that likely perceived as the relevant choice set by the applicants, i.e. educations for which the applicant satisfies the formal requirements (columns (5) and (6)). The estimated preference for log earnings in the most credible specification, that one which restricts the choice set and controls for other attributes (column (6)), is quite strong. However, as it may be difficult to gauge the magnitude of the effects in Tables 3 and Table 4, we will for the time being focus on the main patterns. We will discuss the magnitudes of the estimated effects in more detail later, in relation to the estimated valuation of different characteristics and the effect on simulated applications.

Column (6) also shows that earnings risk, measured by the variance of log earnings, is indeed seen as negative. However, applicants of higher relative ability are less risk averse, such that applicants one standard deviation above the education-specific average are indifferent to high variance of log earnings. Relative ability on its own has a negative coefficient, suggesting that the effect of aspirations or the desire for competent peers is stronger than the gain

[19] These are older than the applicants, to allow them to have completed their educations.

Table 3: Preferences for expected earnings and nonpecuniary attributes, men. Different estimation samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	Completed educ.		Applied, all educ.		Applied, formal qual.	
Log lifetime earnings	0.601***	-0.578***	0.194***	2.878***	1.965***	4.868***
	(0.0147)	(0.0541)	(0.00754)	(0.0525)	(0.00960)	(0.0591)
Variance of log earnings		4.209***		3.240***		-2.525***
		(0.288)		(0.140)		(0.150)
Relative ability				-0.469***		-0.743***
				(0.0102)		(0.0112)
Rel ability · var log earn				2.695***		2.488***
				(0.0337)		(0.0367)
Log available courses				0.350***		0.453***
				(0.00354)		(0.00389)
No available courses				-0.104***		-0.234***
				(0.0109)		(0.0118)
Requires Math		0.993***		-2.654***		-1.256***
		(0.0394)		(0.0266)		(0.0296)
Req Math · applicant $\geq$ 2 years Math				0.780***		0.192***
				(0.0124)		(0.0166)
Req Math · applicant 3 years Math				1.099***		0.622***
				(0.0116)		(0.0133)
Field and level dummies		Yes		Yes		Yes
Similarity parental educ.		Yes		Yes		Yes
Log likelihood	-257502.1	-226874.5	-874664.8	-746543.7	-705473.6	-611178.8
Pseudo R^2	0.00317	0.122	0.000376	0.147	0.0288	0.159
No. of observations	1838562	1838562	2189500	2189500	1708767	1708767
No. of individuals	83571	83571	109475	109475	109475	109475

Note: Estimates of coefficients for the choice model (18). Column (1) and (2) are conditional logit estimates for completed education for a sample of 30-39 year olds. Columns (3) to (6) are estimated from the application data, using ranked logit estimation as in (19). Choice sets are all educations in columns (1) to (4), and only educations for which the applicant satisfies the formal qualification requirements in columns (5) and (6). Field and level dummies control for fields and levels as indicated in Table A.1 in Appendix A. Similarity with parental education are two variables reflecting the squared difference in length relative to mother father's education, as well as two variables indicating similarity in field, as shown in Table 2. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

Table 4: Preferences for expected earnings and nonpecuniary attributes, women. Different estimation samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	Completed educ.		Applied, all educ.		Applied, formal qual.	
Log lifetime earnings	-2.155***	-3.017***	-1.627***	-0.117***	-0.134***	2.435***
	(0.0151)	(0.0607)	(0.00659)	(0.0428)	(0.00810)	(0.0511)
Variance of log earnings		-1.375***		-0.996***		-8.897***
		(0.234)		(0.111)		(0.128)
Relative ability				-0.620***		-0.792***
				(0.00726)		(0.00803)
Rel ability · var log earn				3.731***		3.098***
				(0.0280)		(0.0306)
Log available courses				0.160***		0.196***
				(0.00262)		(0.00277)
No available courses				-0.244***		-0.514***
				(0.00889)		(0.0104)
Requires Math		1.549***		-1.741***		-0.698***
		(0.0360)		(0.0203)		(0.0233)
Req Math · applicant $\geq$ 2 years Math				0.845***		0.294***
				(0.0115)		(0.0152)
Req Math · applicant 3 years Math				0.820***		0.532***
				(0.0113)		(0.0127)
Field and level dummies		Yes		Yes		Yes
Similarity parental educ.		Yes		Yes		Yes
Log likelihood	-341524.8	-325654.9	-1377969.0	-1223987.0	-1179925.4	-1062335.0
Pseudo R^2	0.0326	0.0776	0.0233	0.132	0.000117	0.0998
No. of observations	2512774	2512774	3248520	3248520	2397723	2397723
No. of individuals	114217	114217	162426	162426	162426	162426

Note: Estimates of coefficients for the choice model (18). See notes to Table 3.
Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

from performing relatively well. As for the course dimension, an increased number of courses increase the expected utility from an education, as expected. The coefficient of 0.45 suggests a high correlation of unmodeled utility contributions from the specific courses, with a coefficient of correlation of about $1 - 0.45^2 = 0.80$. Having no available courses is negative, as expected. However, this effect is not very large (compared e.g. to the negative preference for Math). This is consistent with the fact that the applicants can rank many courses, and thus need not be very strategic. Math is on average strongly disliked. Even applicants with elective Math from upper secondary avoid Math-intensive educations, although to a lesser extent. However, this need to be seen in relation to the coefficients for fields, which we will return to.

For women, in Table 4, there is a negative relationship between log earnings and the number with a given education (column (1)) and also between log earnings and number of applicants (column (3)). This also holds adding other attributes of the educations (columns (2) and (4)), or restricting the sample to available educations (column (5)). However, the preferred specification, both restricting the sample and adding controls (column (6)) shows a preference for log earnings. This preference is weaker than the one found for men in Table 3. As for the other attributes, women are more risk averse. Risk aversion also decreases more rapidly with relative ability, but women two standard deviation above the education-specific mean score still show risk aversion similar to an average man. Relative ability has a negative coefficient, as for men, and a very similar magnitude. The coefficient on log number of courses suggests a very high correlation of random terms within each education, of about $1 - 0.20^2 = 0.96$. No available courses and Math is negative, as for men.

Tables 5 and 6 investigates how sensitive the results in column (6), Tables 3 and 4 are to specification of the attributes. Column (4) in Tables 5 and 6 is the preferred specification, corresponding to column (6) in Tables 3 and 4. Column (1) in Tables 5 and 6 only control for earnings, corresponding to column (5) in Tables 3 and 4. For men, in Table 5, we see that there is an estimated positive effect of log earnings on number of applicants across all specifications. However, going from a specification with only log earnings (column (1)) to one which also controls for earnings risk (column (2)) strongly increases the estimated preference for earnings. Adding controls for courses, Math, level and field (column (3)) reduces the preference for

Table 5: Sensitivity of estimated preferences for expected earnings and nonpecuniary attributes to specification. Men.

	(1)	(2)	(3)	(4)	(5)	(6)
Log lifetime earnings	1.965***	6.568***	4.781***	4.868***	3.359***	6.687***
	(0.00960)	(0.0285)	(0.0586)	(0.0591)	(0.0504)	(0.0799)
Variance of log earnings		-12.75***	-2.589***	-2.525***		-25.53***
		(0.0906)	(0.151)	(0.150)		(0.325)
Relative ability		-0.114***	-0.738***	-0.743***	-0.532***	-0.444***
		(0.00628)	(0.0112)	(0.0112)	(0.00931)	(0.0123)
Rel ability · var log earn		3.998***	2.441***	2.488***		2.124***
		(0.0306)	(0.0365)	(0.0367)		(0.0377)
Log available courses			0.454***	0.453***	0.527***	0.317***
			(0.00390)	(0.00389)	(0.00330)	(0.00475)
No available courses			-0.267***	-0.234***	-0.350***	-0.506***
			(0.0119)	(0.0118)	(0.0114)	(0.0132)
Requires Math			-1.101***	-1.256***	-0.917***	-0.993***
			(0.0293)	(0.0296)	(0.0286)	(0.0500)
Req Math · applicant $\geq$ 2 years Math			0.182***	0.192***	0.226***	0.359***
			(0.0166)	(0.0166)	(0.0166)	(0.0165)
Req Math · applicant 3 years Math			0.607***	0.622***	0.750***	0.583***
			(0.0133)	(0.0133)	(0.0132)	(0.0134)
Unemployment						-2.083***
						(0.208)
Hours work/week						0.120***
						(0.00726)
Share in public sector						1.907***
						(0.0390)
Share self-employed						10.17***
						(0.111)
Field and level dummies			Yes	Yes	Yes	Yes
Similarity parental educ.				Yes	Yes	Yes
Log likelihood	-705473.6	-681027.0	-614040.8	-611178.8	-613726.2	-606452.6
Pseudo R^2	0.0288	0.0624	0.155	0.159	0.155	0.165
No. of observations	1708767	1708767	1708767	1708767	1708767	1708767
No. of individuals	109475	109475	109475	109475	109475	109475

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Educations for which applicant satisfies formal requirements as in column (5) and (6) Table 3. See notes to Table 3. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

Table 6: Sensitivity of estimated preferences for expected earnings and nonpecuniary attributes to specification. Women.

	(1)	(2)	(3)	(4)	(5)	(6)
Log lifetime earnings	-0.134***	2.546***	2.609***	2.435***	-0.409***	3.193***
	(0.00810)	(0.0273)	(0.0506)	(0.0511)	(0.0473)	(0.0633)
Variance of log earnings		-9.106***	-8.748***	-8.897***		-14.74***
		(0.0892)	(0.129)	(0.128)		(0.320)
Relative ability		-0.501***	-0.732***	-0.792***	-0.555***	-0.698***
		(0.00483)	(0.00795)	(0.00803)	(0.00767)	(0.0100)
Rel ability · var log earn		4.620***	3.237***	3.098***		3.107***
		(0.0254)	(0.0305)	(0.0306)		(0.0309)
Log available courses			0.184***	0.196***	0.308***	0.165***
			(0.00276)	(0.00277)	(0.00263)	(0.00355)
No available courses			-0.547***	-0.514***	-0.555***	-0.600***
			(0.0105)	(0.0104)	(0.00952)	(0.0112)
Requires Math			-0.492***	-0.698***	-0.290***	-0.515***
			(0.0230)	(0.0233)	(0.0227)	(0.0398)
Req Math · applicant $\geq$ 2 years Math			0.276***	0.294***	0.367***	0.344***
			(0.0151)	(0.0152)	(0.0151)	(0.0153)
Req Math · applicant 3 years Math			0.519***	0.532***	0.724***	0.514***
			(0.0127)	(0.0127)	(0.0126)	(0.0128)
Unemployment						-1.161***
						(0.150)
Hours work/week						-0.0313***
						(0.00575)
Share in public sector						0.474***
						(0.0332)
Share self-employed						1.904***
						(0.109)
Field and level dummies			Yes	Yes	Yes	Yes
Similarity parental educ.				Yes	Yes	Yes
Log likelihood	-1179925.4	-1157365.3	-1067050.8	-1062335.0	-1069894.4	-1061766.4
Pseudo R^2	0.000117	0.0192	0.0958	0.0998	0.0934	0.100
No. of observations	2397723	2397723	2397723	2397723	2397723	2397723
No. of individuals	162426	162426	162426	162426	162426	162426

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Educations for which applicant satisfies formal requirements as in column (5) and (6) Tables 3 and 4. See notes to Table 3.

Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

earnings somewhat, while adding interactions for similarity with parents' education has little effect. Removing risk from the main specification (column (5)) reduces the effect of earnings somewhat.

Finally, adding more labor market outcomes increases the estimated preference for earnings, while the estimated risk aversion increases strongly (column (6)). Unemployment is, unsurprisingly, found to be negative. Note however that earnings already controls for effects of unemployment on earnings, such that this estimate can be interpreted as an effect that extends beyond the pure earnings effect. The other three covariates all have positive effects. A preference for long working time is surprising. As for the shares, it is not clear what about the public sector and self-employment that is attractive. Suggestions could be e.g. job security and pension schemes in the public sector, and flexibility for self-employment, but this is speculation. Furthermore, this specification should be interpreted with particular care, due to the problem of empirically separating the effects of a number of different education-specific variables. Related to this, it is noteworthy that the coefficients on the education-specific variables (earnings, variance of earnings, Math intensity) generally are more sensitive to the choice of specification than the coefficients on the individual-education-specific variables.

For women, in Table 6, we see that the specifications without controls for earnings risk (columns (1) and (5)) give a negative estimated preference for earnings. Other than this, the results are not very sensitive to specification. Adding more labor market outcomes do increase both the estimated preference for earnings and risk aversion, as for men, but much less for women.

Thus, the preferred specification suggests a fairly strong preference for earnings for both genders, more so for men. Furthermore, both genders' educational choices show evidence of risk aversion, more so for women, which decreases with relative ability. All this is as we would expect. However, these patterns are not available neither in the data for completed educations nor in the raw application data. The results in Tables 3, 4, 5 and 6 suggest that there is indeed a strong preference for earnings, but that this is masked by admission requirements and dislike of risk. When large shares of the applicants choose low-paying educations like humanities or nursing, important reasons - although certainly not the only reasons! - for this is that they cannot get in at medicine, and dislike the riskiness of business or law.

As the nonpecuniary attributes in Tables 3 to 6 do not have the same units, the coefficients are difficult to compare. However, from the estimated coefficients and the assumed utility function (13), it is possible to calculate a compensating earnings change for each of the variables in Tables 3 to 6. To compensate a one-unit change in the nonpecuniary attribute x earnings need to change with $-\theta_x/\gamma$ log points, if θ_x is the coefficient on x.This corresponds to multiplying earnings with $1 + \exp(-\theta_x/\gamma)$.

Table 7 reports the relative increase in earnings that would compensate a one-standard deviation change in each of the nonpecuniary attributes reported in Tables 3 to 6. Columns (1) and (3) presents compensating earnings changes based on the preferred specification, for men and women, respectively. Columns (2) and (4) presents earnings changes based on the specification in column (6) in Tables 5 and 6, i.e., the specification with further labor market outcomes. In addition to the variables reported in Tables 3 to 6, Table 7 also reports the estimated earnings increase associated with the level and field dummies. For the latter, the increase corresponds to a one-unit increase, rather than a one-standard deviation, and compensation is relative to unspecified level and humanities. Thus, with σ_x denoting the standard deviation of x, the compensating earnings in Table 7 is calculated as:

$$CY_x = \begin{cases} \exp(-\sigma_x \theta_x/\gamma) - 1 & \text{for continuous variables} \\ \exp(-\theta_x/\gamma) - 1 & \text{for binary variables} \end{cases} \tag{21}$$

For reference, Table 7 also shows the standard deviation of log lifetime earnings, corresponding to about 21 percent. Earnings risk is negative, and to such an extent that across almost all specifications a one-standard deviation increase in risk requires an earnings increase of a 20-30 percent to compensate, i.e., more than a standard deviation of earnings. The exception is the column (1), i.e. the preferred specification for men from Tables 3 and 5, where there is only a small effect of risk.

As for the similarity with parents' education, similarity in level has a large value for women. A one-standard deviation increase in the squared difference from a parent's education correspond to 15-20 percent earnings decrease, marginally less for father's education than

Table 7: Earnings required to compensate for nonpecuniary attributes (share of lifetime earnings)

	Men		Women	
	(1)	(2)	(3)	(4)
Log lifetime earnings	-0.212	-0.212	-0.212	-0.212
	(.)	(.)	(.)	(.)
Variance of log earnings	0.0283***	0.228***	0.217***	0.282***
	(0.00157)	(0.00413)	(0.00495)	(0.00803)
(Length of schooling - mothers length)^2	0.0624***	0.0575***	0.205***	0.155***
	(0.00277)	(0.00207)	(0.00692)	(0.00495)
(Length of schooling - fathers length)^2	0.0615***	0.0585***	0.193***	0.146***
	(0.00257)	(0.00195)	(0.00645)	(0.00464)
Same field as father	-0.0716***	-0.0521***	-0.0909***	-0.0699***
	(0.00157)	(0.00116)	(0.00312)	(0.00239)
Same field as mother	-0.0420***	-0.0309***	-0.0882***	-0.0679***
	(0.00157)	(0.00116)	(0.00267)	(0.00204)
Requires Math	0.294***	0.160***	0.332***	0.175***
	(0.00677)	(0.00737)	(0.0116)	(0.0135)
Bachelor level	0.182***	0.0199***	1.187***	0.679***
	(0.00296)	(0.00335)	(0.0355)	(0.0207)
Master level	0.103***	0.0882***	0.284***	0.194***
	(0.00235)	(0.00259)	(0.00688)	(0.00653)
Health and social work	-0.0106***	0.368***	-0.385***	-0.131***
	(0.00295)	(0.0150)	(0.00632)	(0.0146)
Teaching	-0.0276***	0.272***	-0.284***	-0.0612***
	(0.00279)	(0.0134)	(0.00572)	(0.0158)
Law and social sciences	0.0332***	0.0729***	-0.0712***	-0.0396***
	(0.00189)	(0.00282)	(0.00445)	(0.00470)
Business and administration	-0.0602***	-0.129***	-0.320***	-0.236***
	(0.00517)	(0.00593)	(0.00899)	(0.0105)
Science and engineering	0.0231***	0.0144*	0.333***	0.277***
	(0.00523)	(0.00809)	(0.0153)	(0.0200)
Other fields	0.317***	-0.00843**	0.311***	0.110***
	(0.00396)	(0.00399)	(0.00742)	(0.00790)
Unemployment		0.0198***		0.0231***
		(0.00213)		(0.00318)
Hours work/week		-0.0268***		0.0149***
		(0.00178)		(0.00268)
Share in public sector		-0.0651***		-0.0344***
		(0.00149)		(0.00240)
Share self-employed		-0.137***		-0.0561***
		(0.00202)		(0.00311)
Observations	1708767	1708767	2397723	2397723

Note: Valuation is calculated as in equation (21), based on the estimates from Tables 5 and 6, specification (4) in columns (1) and (3) and specification (6) in columns (2) and (4). For variables other than same field as parents, educational level and field and requires Math, the valuation presented is that of a one standard deviation change, as per Tables 1 and 2. Educational levels are relative to unspecified level, fields are relative to humanities.

Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

mother's. The effect is smaller for men (about 6 percent for both parents, across specifications). The equivalent value of same field as parent is about 3-10 percent, somewhat higher for women than men.

Women show a strong dislike for Bachelor educations (relative to unspecified level), men less so. Women also have a stronger dislike of Master educations than men. Women have a clear preference for health and social work, teaching and business and administration (relative to humanities), and a dislike for science and engineering. Men show a different pattern, with a dislike of health and social work and teaching, but a preference for business and administration. However, for men the estimated effects of field are sensitive to the inclusion of further education-specific covariates, this is much less the case for women. Both genders show a dislike of Math. As for the other education-specific variables (unemployment, work time, shares in public sector and self-employed), these are generally found to be of relatively little importance. The single exception is self-employment, for men a one-standard deviation increase in the share self-employed have the same value as a 14 percent earnings increase.

5.1 Magnitude of the effects

As it can be difficult to gauge the size of the effects from the regression coefficients alone, Table 8 presents predicted number of applicants with the different educations as their first choice in different scenarios. The first column presents the observed number of applicants, for reference. In the second column is the predicted number of applicants, based the preferred specification from Tables 3 to 6, relative to the observed numbers in column (1). We see that the predicted figures largely reproduce the main patterns in choice. For most of the educations the ratio of predicted applicants to actual is between 0.7 and 1.3. There are however some notable exceptions. For women, the shares of engineering and civil engineers are strongly underpredicted. For both genders medicine is underpredicted, while "other health" is overpredicted.

In order to illustrate the significance of earnings and nonpecuniary attributes, columns (3) and (4) presents the predicted number of applicants in two different scenarios: In (3) earnings are equalized across all educations, and in (4) all attributes except earnings are

Table 8: Simulations

Panel A: Men

Education	(1) # observed	(2) Predicted, ratio	(3) Equal earnings	(4) Only earnings	(5) Teacher +5%	(6) Earnings +5%	(7) Elasticity	(8) Elasticity, incl. risk
Nursing	2023	1.17	2.59	0.76	0.99	1.26	5.18	4.34
Social work	1664	1.30	2.47	0.86	0.99	1.26	5.19	4.25
Physio- and ergotherapy	3736	0.40	1.84	1.82	0.99	1.26	5.25	4.04
Other health	2078	1.39	2.17	0.75	0.99	1.26	5.15	4.34
Kindergarten teacher	1354	1.21	3.22	0.84	1.00	1.26	5.21	4.66
Teachers' college	2288	0.85	2.24	0.68	1.26	1.26	5.12	4.57
Other teaching	4740	1.34	2.05	0.35	1.00	1.24	4.86	3.87
Business school	5341	0.77	0.16	3.59	1.00	1.24	4.84	3.65
Other commerce	10823	0.78	0.53	1.21	1.00	1.24	4.80	4.30
Engineering	4454	0.66	0.49	0.84	1.00	1.24	4.70	4.49
Journalism	2357	1.42	0.58	2.58	0.99	1.26	5.12	3.73
Medicine	2666	0.60	0.11	2.80	1.00	1.23	4.57	3.39
Dentistry et. al.	681	0.95	0.38	2.33	1.00	1.25	5.02	4.35
Civil engineering	9479	0.74	0.27	0.65	1.00	1.19	3.89	2.99
Architecture	2038	0.60	0.68	6.25	1.00	1.26	5.28	3.46
Law	6552	0.89	0.30	3.12	0.99	1.25	4.93	3.69
Science	6723	1.36	0.72	0.36	1.00	1.21	4.29	3.74
Social sciences	19223	1.14	0.82	0.27	0.99	1.19	3.90	3.13
Humanities	13463	1.16	1.58	0.19	0.99	1.21	4.28	3.43
Others, unspecificed	7792	1.14	0.42	1.30	0.99	1.24	4.76	4.12

Panel B: Women

Education	(1) # observed	(2) Predicted, ratio	(3) Equal earnings	(4) Only earnings	(5) Teacher +5%	(6) Earnings +5%	(7) Elasticity	(8) Elasticity, incl. risk
Nursing	17148	0.61	1.42	0.62	1.00	1.12	2.32	0.14
Social work	9606	1.16	1.38	0.59	1.00	1.12	2.30	0.02
Physio- and ergotherapy	7647	0.90	1.19	1.16	1.00	1.12	2.39	-0.26
Other health	8200	1.40	1.30	0.61	1.00	1.12	2.31	0.18
Kindergarten teacher	7055	0.84	1.59	0.95	1.00	1.12	2.39	0.55
Teachers' college	5682	0.91	1.32	0.92	1.12	1.12	2.38	0.42
Other teaching	7141	1.50	1.28	0.67	1.00	1.12	2.31	-0.01
Business school	2734	0.80	0.36	3.59	1.00	1.12	2.39	-0.14
Other commerce	9395	0.72	0.64	2.26	1.00	1.12	2.38	0.55
Engineering	601	0.47	0.65	4.16	1.00	1.12	2.47	1.11
Journalism	3440	1.10	0.67	3.71	1.00	1.12	2.45	-0.44
Medicine	4108	0.49	0.34	0.91	1.00	1.10	2.02	-0.27
Dentistry et. al.	2642	0.76	0.59	0.73	1.00	1.11	2.13	0.19
Civil engineering	2534	0.63	0.48	1.00	1.00	1.11	2.23	-0.04
Architecture	2094	0.91	0.74	6.94	1.00	1.12	2.49	-0.73
Law	9596	0.69	0.48	3.08	1.00	1.12	2.38	-0.27
Science	3988	1.26	0.75	0.74	1.00	1.11	2.25	0.39
Social sciences	29957	1.15	0.81	0.34	1.00	1.10	1.91	-0.05
Humanities	20985	1.12	1.12	0.35	1.00	1.11	2.10	-0.03
Others, unspecificed	7873	1.34	0.58	1.55	1.00	1.12	2.33	0.38

Note: "# observed" is the number of first choices for each education. "Predicted, ratio" is the ratio of the number of predicted first choice to observed. Predictions are based on specification (4) in Tables 5 and 6. "Equal earnings" is the predicted number of first choices if there were no differences in earnings between the educations relative to the predicted number in column (2). "Only earnings" presents a similar ratio for the for a situation where all differences are eliminated, expect earnings. "Teacher +5%" gives the predicted number of first choices for all educations if the teachers' college got 5% higher earnings, while "Earnings +5%" measures the effect of an exclusive earnings increase of 5% for each of the educations. "Elasticity" gives the earnings elasticity calculated based on the effect of a 5% increase in column (6). Finally, "Elasticity, incl. risk" calculates an elasticity to a simultaneous increase in earnings and risk, where the relative increases in earnings and risk correspond to the cross-sectional relationship between the two.

equalized. In both cases applicants are relative to the predicted number underlying column (2). It is immediately clear that both earnings and nonpecuniary attributes play a large role in educational choices. Disregarding earnings give a large reduction for high-earning educations, up to almost 90 percent for men's applications to medicine and business school, and reductions of more than 60 percent for women's applications to the same educations. Similarly, disregarding differences in other attributes give very large increases for high-earning educations and large reductions for lower-earning educations.

Column (5) presents the effect of a 5 percent increase with teachers' college. This translates to increases of 26 and 12 percent in the number of applicants for men and women respectively, a large increase. This increase is drawn similarly from all other educations, as follows by the IIA property of the conditional logit.[20] Column (6) presents the effect on the number of applicants to each education of a 5 percent increase in the earnings of that education. For men, the calculated increases range from slightly 19 percent to 26 percent, for women from 10 to 12 percent. Based on these increases column (7) shows the calculated elasticities, which are about 5 for men, and about 2 for women. These are arguably large elasticities. One interpretation is that the earnings measure is assumed to reflect the applicants entire working life, and indeed is one that captures persistent differences between educations, such that a 5 percent increase in an education's relative earnings is actually a large change. However, a concern may be if the estimation succeed in separating the effects of earnings and risk. Thus, column (8) presents an elasticity calculated for joint increase in earnings and risk, where the relative increase in the two corresponds to the cross-sectional correlation. We see that for men, this reduces the estimated elasticity, such that it is now about 4. For women the earnings and risk elasticity is essentially zero.

5.2 Gender differences in educational choice and earnings

In Tables 3, 4 and 8 there are significant gender differences in, among other things, preference for earnings and risk, leading to differences in educational choice. This in turn contributes strongly to large and sustained gender differences in earnings. Assuming all applicants get

[20] In a situation where one wants to predict the effect of, say, an increase in teachers' earnings, and also care about the number of e.g. kindergarten teachers, this is likely to be a severe restriction.

Table 9: Simulated lifetime earnings (M NOK) under counterfactual preferences, by gender

	Specification	Men	Women
(1)	Observed 1st choice	12.46	11.20
(2)	Predicted 1st choice	12.03	11.00
Other gender's preference for			
(3)	Log lifetime earnings	11.28	11.75
(4)	Variance of log earnings	11.60	11.49
(5)	Relative ability	12.08	10.96
(6)	Rel ability · var log earnings	11.95	11.06
(7)	Attributes (3)-(6)	10.88	12.32
(8)	All attributes	11.27	11.67

Note: Each cell presents predicted lifetime earnings. This is calculated as a weighted average of the average earnings of the educations, i.e., the lifetime earnings used in the estimation. The weights are the observed or predicted share of applicants with the relevant education as their first choice. Specification (1) uses the observed shares, while (2) uses the baseline estimates in column (6), Tables 3 and 4. Specifications (3)-(6) replace a single estimated preference parameter with that of the other gender in predicting shares. In (3) the preference for log lifetime earnings ($\hat{\gamma}$) is replaced, in (4) the preference for earnings variability, in (5) the preference for relative ability and in (6) the interaction of earnings variability and relative ability. Specification (8) uses all of the other gender's parameters used in (3)-(6), while (7) uses the other gender's preferences for all attributes of the educations.

their first choice, and subsequently earn the average lifetime of that education (i.e., assuming no gender differences in earnings within education), it is possible to simulate lifetime earnings for the observed and counterfactual preferences. Table 9 presents the results from such a simulation exercise. Specification (1) presents average lifetime earnings by gender, weighted with the the observed choice frequencies (using the applicants' first choices). While the men in the application data have mean lifetime earnings of 12.46M NOK[21], weighting with the first choice probabilities, women have a corresponding mean lifetime earnings of 11.20M NOK, or about 10 percent less. Specification (2) shows similar simulated earnings, but using first choice probabilities predicted using the baseline estimates in column (6), Tables 3 and 4. The gender difference is somewhat reduced, to about 9 percent.[22]

Specification (3) suggests that gender differences in preferences for earnings is a large part of the explanation for the gender earnings difference. Substituting either gender's estimated preference for lifetime earnings, i.e., replacing the estimated $\hat{\gamma}$ for men with the corresponding estimate for women when predicting the choice probabilities and comparing with the predicted mean earnings of women in specification (2) or vice versa, reduces the predicted gender lifetime earnings gap to just over 2 percent. Specification (4) shows that the higher risk aversion of

[21] 1 NOK is equal to approximately 0.14 EUR or 0.17 USD.

[22] The baseline specification is estimated using a rank-ordered logit. A conditional logit for the first choice only gives largely similar results, but more closely reproduces the first-choice probabilities and mean earnings.

women also contributes, although less that the difference in preference for earnings. Exchanging either gender's risk preference reduces the predicted gender earnings difference to about five percent. The differences in the effect relative ability, on its own and interacted with the variance of earnings, has little impact on gender earnings differences, as is visible from specifications (5) and (6). Using the other gender's preference for all attributes studied separately in specifications (3)-(6) reverses the predicted gender earnings gap, see specification (7). This is unsurprising, given the large effects on the gender earnings gap of a change in either earnings preference or risk preference. However, even in spite of this, using either gender's preferences for all attribute gives predicted first choices that result in a earnings gap in favor of men, cf. specification (8). With differences in preferences eliminated, the reason for this earnings gap is a difference in choice sets. Men, on average, have more Maths from upper secondary, and thus more men satisfy the formal qualification requirements for several high-earning educations, such as medicine, business and engineering.[23] Also, note that the women's earnings in (8) are reduced relative to (7), and vice versa for men. This indicates that the combined effect of preferences for all other attributes, including average preference for field, does not contribute to the gender earnings differential. Thus, it seems that women on average earn less because they care less about earnings and more about certainty, not because they prefer low-earning fields like health and teaching.

5.3 Stability and robustness

If the estimates are to be used to predict future applications, this requires preferences to be stable over time. Table 10 investigates the stability of the results. Mostly, the estimated coefficients do not vary much between years. Earnings seems to matter somewhat more for men from 2007 onwards, and in 2006-2008 for women. Earnings risk only have a significant negative effect for men in the years 2006-2008, and is more negative for women from 2006 onwards than in 2004-2005. Again, the individual-education-specific variable, in this case

[23]In principle, differences in the individual-alternative-specific attributes (any x_{ij}-variables, i.e, that varies both between applicants and educations, such as number of courses qualified or interactions of length or type of education with parents' education) could also cause differences gender differences in choices. As well as more Math subjects, the (fewer) men in the sample on average have more highly educated parents but lower admission scores than the women. However, these gender differences have small effects on choices.

relative ability interacted with earnings risk, is more stable than the education-specific ones.

Table 10: Stability over time

Panel A: Men

	(1) 2004	(2) 2005	(3) 2006	(4) 2007	(5) 2008	(6) 2009
Log lifetime earnings	4.457***	3.617***	4.426***	5.582***	5.243***	5.050***
	(0.143)	(0.148)	(0.148)	(0.146)	(0.141)	(0.154)
Variance of log earnings	-0.0224	-0.176	-4.790***	-4.168***	-4.403***	0.318
	(0.369)	(0.370)	(0.357)	(0.372)	(0.378)	(0.407)
Relative ability	-0.836***	-0.840***	-0.766***	-0.744***	-0.774***	-0.538***
	(0.0287)	(0.0270)	(0.0273)	(0.0275)	(0.0276)	(0.0277)
Rel ability · var log earn	2.385***	2.229***	2.200***	2.607***	2.712***	2.089***
	(0.0948)	(0.0906)	(0.0914)	(0.0936)	(0.0876)	(0.0903)
Log likelihood	-97987.6	-105252.9	-100749.0	-100258.9	-105686.9	-100135.2
Pseudo R^2	0.152	0.159	0.164	0.165	0.169	0.150
No. of observations	282743	293777	284409	283746	292682	271410
No. of individuals	18072	18847	18289	18221	18641	17405

Panel B: Women

	(1) 2004	(2) 2005	(3) 2006	(4) 2007	(5) 2008	(6) 2009
Log lifetime earnings	1.827***	1.832***	2.802***	3.125***	2.935***	1.727***
	(0.135)	(0.132)	(0.126)	(0.123)	(0.116)	(0.129)
Variance of log earnings	-7.017***	-6.643***	-10.87***	-10.05***	-11.94***	-8.777***
	(0.328)	(0.318)	(0.305)	(0.304)	(0.313)	(0.366)
Relative ability	-0.927***	-0.788***	-0.758***	-0.766***	-0.791***	-0.789***
	(0.0212)	(0.0200)	(0.0196)	(0.0195)	(0.0188)	(0.0204)
Rel ability · var log earn	2.558***	3.044***	2.924***	3.389***	3.346***	2.690***
	(0.0845)	(0.0798)	(0.0763)	(0.0745)	(0.0689)	(0.0757)
Log likelihood	-160788.0	-172179.5	-177135.7	-180410.0	-197080.9	-173325.9
Pseudo R^2	0.101	0.104	0.106	0.0994	0.0987	0.0966
No. of observations	375641	391576	401783	406890	433369	388464
No. of individuals	25535	26661	27298	27609	29278	26045

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Sample and control variables as in specification (4), Tables 3 and 4. See notes to Table 3. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

As discussed in Section 4, it is not clear which earnings measure best approximates the applicants expectations and preferences. For example, it is not clear if lifetime earnings or earnings early in the career matter most, if applicants condition their expectations on gender, or if the average earnings is the most relevant statistic. Table 11 presents estimates controlling for different earnings measures. In column (1) lifetime earnings is calculated by gender. Columns (2) and (3) present results using a measure of early and late-career earnings, predicted earnings at ages 30 and 50 respectively. Columns (4) and (5) present results using measures of respectively "low" and "high" earnings within the relevant education. The earnings measures used in these columns are calculated using the bottom and top 25 percent of the fixed effect distribution within each education. Finally, column (6) presents results using an earnings measure based not on the entire 1999-2008 earnings panel, but rather just the preceding year.

Table 11: Different earnings measures

Panel A: Men

	(1) Gender-specific	(2) At 30 yrs	(3) At 50 yrs	(4) Bottom 25pct	(5) Top 25pct	(6) Yearly
Log lifetime earnings	6.282***	2.241***	4.036***	5.041***	5.798***	2.195***
	(0.0712)	(0.0635)	(0.0440)	(0.0571)	(0.0649)	(0.0365)
Variance of log earnings	-8.703***	-0.399**	-1.602***	5.201***	-14.09***	0.117
	(0.188)	(0.176)	(0.143)	(0.132)	(0.231)	(0.144)
Relative ability	-0.711***	-0.989***	-0.667***	-0.762***	-0.720***	-0.933***
	(0.0109)	(0.0124)	(0.0113)	(0.0109)	(0.0109)	(0.0109)
Rel ability · var log earn	2.368***	1.995***	2.534***	2.524***	2.550***	2.253***
	(0.0366)	(0.0365)	(0.0365)	(0.0366)	(0.0367)	(0.0366)
Log likelihood	-610553.7	-614016.0	-610407.5	-610720.0	-610529.6	-612836.2
Pseudo R^2	0.159	0.155	0.160	0.159	0.159	0.156
No. of observations	1708767	1708767	1708767	1708767	1708767	1708767
No. of individuals	109475	109475	109475	109475	109475	109475

Panel B: Women

	(1) Gender-specific	(2) At 30 yrs	(3) At 50 yrs	(4) Bottom 25pct	(5) Top 25pct	(6) Yearly
Log lifetime earnings	1.814***	1.538***	1.950***	2.463***	2.936***	1.451***
	(0.0525)	(0.0493)	(0.0423)	(0.0531)	(0.0564)	(0.0322)
Variance of log earnings	-6.121***	-9.163***	-8.133***	-4.763***	-15.79***	-7.986***
	(0.121)	(0.145)	(0.123)	(0.126)	(0.209)	(0.123)
Relative ability	-0.853***	-0.840***	-0.756***	-0.795***	-0.812***	-0.836***
	(0.00791)	(0.00831)	(0.00848)	(0.00804)	(0.00770)	(0.00772)
Rel ability · var log earn	3.010***	2.921***	3.105***	3.088***	3.121***	3.042***
	(0.0308)	(0.0303)	(0.0307)	(0.0306)	(0.0306)	(0.0303)
Log likelihood	-1062870.9	-1062981.6	-1062418.1	-1062400.6	-1062115.1	-1062454.3
Pseudo R^2	0.0993	0.0992	0.0997	0.0997	0.1000	0.0997
No. of observations	2397723	2397723	2397723	2397723	2397723	2397723
No. of individuals	162426	162426	162426	162426	162426	162426

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). In column (1) a gender-specific earnings measure is used. All other earnings measures are pooled for both genders. Specifications (2) and (3) use predicted earnings at age 30 and 50 respectively. Specifications (4) and (5) use predicted earnings from the subsamples with the 25 percent lowest/highest individual fixed effects. Specification (6) use earnings predicted from yearly cross-sections. Sample and control variables as in specification (4), Tables 5 and 6. See notes to Table 3.
Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

The results are mostly consistent across the different specifications. Also, the model fit is very similar, with pseudo R^2 varying from 0.155-0.160 for men, and from 0.099-0.100 for women. For men, specifications (2) (early-career) and (6) (yearly predictions) stand out with a relatively low estimated preference for earnings. These specifications also stand out with relatively low log likelihoods. Specifications (1), (3), (4) and (5) all have higher log likelihood than the preferred specification in Table 5, with specification (3) (late-career earnings) having the highest. However, the differences, both in log likelihood and estimated preference for earnings, are small. For women, specification (5) (top earnings) is the only one in Table 11 with a higher log likelihood than the preferred specification in Table 6. However, as for men, the differences in likelihood and estimated coefficients are small. The coefficient that is most sensitive to the choice of dependent variable is that on earnings risk. This is reasonable, as earnings risk may be given a slightly different interpretation in the different models. If applicants do not know where in the education-specific earnings distribution they will end up, the risk is mostly on the upside (downside) when the earnings measure is the bottom (top) earnings. This is consistent with the results that earnings risk is less (more) deterring when the bottom (top) earnings is the earnings measure.

As discussed in Section 4, earnings is based on the years 1999-2008, while the application data range from 2004-2009. These periods partly overlap, such that, although the earnings differences are stable over time, applicants early in the period has not had an opportunity to observe the same earnings data. Column (6) presents estimates using lifetime earnings constructed from yearly cross sections of earnings. As is visible from the table, the log likelihood is higher for the baseline results (although, again, the difference is not large). The estimated effect of earnings is smaller than in the baseline specification for both genders. While the difference may reflect that earnings expectations adjust quickly, it is also possible that earnings expectations adjust slowly, and that the different estimates are due to measurement error in expectations of long-term earnings.

Finally, it's again noteworthy that the individual-education-specific variable is more robust to specification.

As was evident in Tables 3 and 4, estimation sample matters strongly for the estimated preferences. In Table 12 the sensitivity of the estimates to the sample used is investigated further. In specification (1) the sample is all educations, irrespective of formal qualifications, as in specification (4), Tables 3 and 4. However, in Table 12 column (1) formal qualification is

Table 12: Different estimation samples

Panel A: Men

	(1) All educ	(2) Sufficient points	(3) Ranked	(4) P(ranked)	(5) Ranked 10 courses	(6) Ranked < 10 courses
Log lifetime earnings	4.618***	5.472***	2.037***	5.058***	4.438***	5.262***
	(0.0537)	(0.0771)	(0.0861)	(0.0652)	(0.0960)	(0.0754)
Variance of log earnings	1.039***	-1.638***	-3.416***	-2.522***	-4.257***	-1.810***
	(0.140)	(0.167)	(0.231)	(0.172)	(0.254)	(0.187)
Relative ability	-0.527***	-0.696***	-0.197***	-0.867***	-0.858***	-0.683***
	(0.0102)	(0.0120)	(0.0192)	(0.0124)	(0.0191)	(0.0139)
Rel ability · var log earn	2.916***	1.893***	0.280***	2.792***	2.516***	2.611***
	(0.0343)	(0.0393)	(0.0641)	(0.0406)	(0.0627)	(0.0457)
Formally qualified	1.416***					
	(0.00996)					
Log likelihood	-735254.1	-541924.8	-165071.8	-440856.1	-199379.0	-410852.4
Pseudo R^2	0.160	0.157	0.0206	0.210	0.162	0.159
No. of observations	2189500	1475710	272346	1660377	384444	1324323
No. of individuals	109475	109475	106067	106067	23949	85526

Panel B: Women

	(1) All educ	(2) Sufficient points	(3) Ranked	(4) P(ranked)	(5) Ranked 10 courses	(6) Ranked < 10 courses
Log lifetime earnings	1.720***	0.560***	1.526***	2.433***	2.455***	2.358***
	(0.0442)	(0.0726)	(0.0735)	(0.0587)	(0.0793)	(0.0673)
Variance of log earnings	-3.283***	-10.92***	-4.194***	-9.641***	-8.540***	-9.015***
	(0.113)	(0.142)	(0.185)	(0.147)	(0.201)	(0.167)
Relative ability	-0.628***	-1.016***	-0.196***	-0.885***	-0.886***	-0.748***
	(0.00728)	(0.00919)	(0.0126)	(0.00891)	(0.0131)	(0.0102)
Rel ability · var log earn	3.756***	2.851***	0.709***	3.382***	2.796***	3.323***
	(0.0282)	(0.0324)	(0.0490)	(0.0336)	(0.0497)	(0.0392)
Formally qualified	1.304***					
	(0.00950)					
Log likelihood	-1213274.9	-980391.1	-305911.6	-749916.7	-377201.9	-683881.5
Pseudo R^2	0.140	0.0775	0.0146	0.138	0.108	0.0969
No. of observations	3248520	2091132	454596	2369915	612686	1785037
No. of individuals	162426	162426	160511	160511	40529	121897

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Specification (1) includes all educations, also those for which the applicant not satisfies the formal requirements. Specification (2) excludes educations for which the applicant can not expect to be admitted. Specification (3) restricts the sample to those educations actually ranked by the applicant. Specification (4) estimates a conditional logit model for whether an education is among those ranked. Specifications (5) and (6) restrict the sample to applicants who ranked ten courses and less than ten courses, respectively. Unless otherwise indicated, sample and control variables as in the preferred specification, see notes to Table 3. Standard errors in parentheses. * p < 0.10,** p < 0.05, *** p < 0.01.

controlled for. As expected, being qualified for an education has a large positive effect on the probability of ranking the education. Furthermore, while not controlling for qualifications in any way markedly alters the estimated preference for earnings (cf. Tables 3 and 4), the results controlling for qualifications with a dummy variable give similar preferences for earnings, as when the sample is restricted. This underlines the relevance of explicitly handling the applicants' choice sets, but how information about the choice sets is used seems less important. However, risk is now found to be less deterring.

Specification (2) restricts the sample more than the in the baseline specification, by removing educations for which an applicant - based on admission score and last year's admission thresholds - can not expect to be admitted. This may be argued to be overly restrictive. While there is no point in applying for an education for which you know you don't qualify, the applicant may hope that the there is less competition when she applies. This is supported by the observation that the coefficient on not expecting admission (from Tables 3 and 4) is much smaller (in absolute value) than the coefficient on formal qualifications in specification (1). Still, restricting the sample has a limited impact on the estimates for men. For women the estimated preference for earnings is reduced, and the risk becomes more important.

The probability giving an education a particular rank may be expressed as the probability of ranking it (any rank) times the probability of a specific rank conditional on ranking. Specifications (3) and (4) separate these. There may be limits to the applicants' knowledge of the earnings with the different educations, or even of an education's mere existence. However, the educations actually ranked have been actively considered by the applicant, such that the applicants' may be expected to have more information about these. The estimated preference for earnings is lower restricting the estimations to ranked courses. Also, while men still show a stronger preference for earnings, the gender difference is reduced. Also for risk the gender ranking of the estimated preferences is retained, while the difference is reduced. The preferences estimated from the probability of being ranked are very similar to the baseline estimates. That the preferences estimated from the ranked educations and from the probability of being ranked differ goes against the IIA/logit assumption, indicating that this may be problematic.

Finally, specification (5) and (6) separates the sample by number of courses ranked. Specification (5) presents results for applicants who have ranked 10 courses. This is the maximum number, which is binding for them, indicating that there is a real opportunity cost of ranking a given course. By contrast, specification (6) presents results for applicant who have ranked less than 10 courses. These could have ranked more but chose not to, implying a zero opportunity cost of ranking one more course. For men, estimated preference for earnings is slightly higher and risk less deterring in the unconstrained sample, while for women the estimates are essentially identical.

5.4 Heterogeneity in preferences

The results so far have been concerned with *average* preferences. However, there may also be important differences between applicants with different characteristics. For example, Saks and Shore (2005) find that wealthier individuals choose riskier careers. A straightforward way to address potential heterogeneity is to estimated the model for separate samples, stratified by some relevant characteristic. Table A.2 in Appendix B presents results for each quartile of the applicants' parents' earnings. The coefficients do not differ much with parental earnings. Earnings is found to matter somewhat more for applicants with high-earning parents. Surprisingly, earnings risk is more negative for applicants with high-earning parents.

Table A.3, also in Appendix B, presents results by quartile of score from upper secondary. There are larger differences along this dimension than what was found for parental earnings, but few clear patterns. For men, earnings seem to matter more for applicants in the middle quartiles, in particular the second. Furthermore, risk is positive, except in the fourth quartile. For women, the preference for earnings is strongest in the highest quartile, as is the estimated effect of risk. The results for women with low score, in column (1) of Panel B, indicate that these have a dislike for earnings. This is not credible, and indicates that the model for some reason fails to describe the educational choices of this particular group.

Table A.4 in Appendix B, presents results by age of the applicant. For both genders earnings is found to be more important and risk more deterring for the younger applicants. Without further data, it is hard to interpret this pattern. However, it may be consistent with gradual discovery of preferences for nonpecuniary attributes, such that earnings become less important for choice of education. Also, it may reflect young persons making career choices and a larger share of recreational courses among older individuals.

Finally, Table 13 shows heterogeneous results by choice of education. Choosing a low-paying education may indicate a relatively low preference for earnings. However, as the results so far has shown, other attributes may matter strongly, masking the true earnings preference. Distinguishing between these is relevant both for scientific and policy purposes. A deeper understanding of choice patterns may give a better understanding of persistent earning differences. For policymakers it is relevant wanting to increase e.g. the supply of teachers, it is relevant to know if the marginal applicant for the relevant education has a preference in line with the average, or if the expected earnings response is different.

To investigate this we take advantage of the richness of the application data. Because we know not only the most-preferred education, but an entire rank of up to ten different educations, it is possible to see to what extent applicants to any given education rank educations in their application according to relative earnings. In Table 13 each row restricts the sample to applicants who have ranked the given education in their application (any rank).

To avoid mechanically biasing the results towards a low (high) preference for earnings for applicants to low (high)-paying fields, we restrict the sample to ranked educations (as in Table 12 column (3)), and study the internal ranking of these education. In columns (2) and (4) we furthermore restrict the sample to those having ranked a given education, but who not has it as a first rank. A large share of the applicants get their first ranks. Thus, this will be an indication of the marginal applicants, those closest to ranking an education as number one (and with high probability getting admitted).

For applicants to most educations, also to low-paying ones, the estimated preference for earnings is positive and significant, and often close to the corresponding estimates in Table 12 column (3). For both genders applicants to dentistry and commerce show the strongest preference for earnings, both in the full sample and in the "marginal applicants" (i.e., those ranking the education but not as their first choice). However, applicants to some educations show a weak preference for earnings. For both genders there is only a weak preference for earning among those applying for teachers' college, and no significant effect among the marginal

Table 13: Heterogeneity in estimated preference for earnings by education

	Men		Women	
	(1)	(2)	(3)	(4)
Education (j)	All ranking j	Only $r_j > 1$	All	Only $r_j > 1$
Nursing	2.273***	4.966***	0.275	4.299***
	(0.419)	(0.474)	(0.182)	(0.213)
Social work	1.029*	1.189*	-1.015***	-1.421***
	(0.593)	(0.659)	(0.253)	(0.291)
Physio- and ergotherapy	0.900***	1.947***	1.060***	1.895***
	(0.230)	(0.260)	(0.163)	(0.179)
Other health	0.450	-1.357***	-0.668***	-3.310***
	(0.296)	(0.310)	(0.155)	(0.166)
Kindergarten teacher	2.009**	2.067**	0.409	1.117***
	(0.828)	(0.884)	(0.361)	(0.386)
Teachers' college	0.652*	-0.530	0.792***	-0.134
	(0.367)	(0.401)	(0.270)	(0.298)
Other teaching	0.636***	1.143***	0.800***	1.211***
	(0.237)	(0.251)	(0.189)	(0.201)
Business school	2.690***	1.595***	1.287***	0.318
	(0.200)	(0.241)	(0.198)	(0.231)
Other commerce	2.913***	4.696***	2.335***	3.917***
	(0.185)	(0.207)	(0.177)	(0.196)
Engineering	1.286***	1.369***	0.157	-0.004
	(0.231)	(0.262)	(0.308)	(0.334)
Journalism	0.984***	1.251***	0.936***	0.986***
	(0.277)	(0.304)	(0.251)	(0.272)
Medicine	2.515***	0.423	1.841***	-2.437***
	(0.254)	(0.379)	(0.200)	(0.306)
Dentistry et. al.	3.060***	4.845***	2.321***	4.883***
	(0.292)	(0.338)	(0.180)	(0.225)
Civil engineering	2.399***	2.613***	1.294***	1.646***
	(0.172)	(0.210)	(0.196)	(0.233)
Architecture	2.306***	3.188***	1.644***	2.553***
	(0.285)	(0.321)	(0.236)	(0.267)
Law	2.459***	2.785***	1.490***	1.320***
	(0.189)	(0.216)	(0.163)	(0.183)
Science	1.991***	2.093***	1.396***	1.372***
	(0.144)	(0.160)	(0.135)	(0.146)
Social sciences	1.850***	1.457***	1.543***	1.812***
	(0.119)	(0.131)	(0.101)	(0.110)
Humanities	1.353***	1.461***	1.071***	0.948***
	(0.153)	(0.165)	(0.128)	(0.136)
Others, unspecificed	0.320*	0.269	0.049	-0.036
	(0.187)	(0.201)	(0.166)	(0.176)

Note: Each cell presents the estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Only educations ranked by the applicants are included in the analysis, as in column (3) Table 12. Control variables as in the preferred specification, see notes to Table 3. Each row focuses on one indicated education (j). In columns (1) and (3) the estimation samples are all applicants ranking education j, while in columns (2) and (4) the estimation samples are all educations having education j as one of the ranked educations, but not as the first rank.

Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

applicants to this educations. Applicants to nursing, on the other hand, show sizeable earnings preferences for both genders.

For some groups the estimated preference for earnings is negative. While preferences for earnings may be weak, negative effects are not credible. However, there is still scope for omitted variables, which may matter more for some groups of applicants. Furthermore, the number of individuals in some of the groups is not very high, making some of the estimates more uncertain. Finally, with a large number of groups studied, the results for each group is uncertain, we are likely to make some type I errors.

However, the overall tendency in Table 13 seems quite clear: Preferences for earnings are mostly significantly positive, and fairly close to average preferences. However, there is some heterogeneity. Mostly applicants to high-earning fields have high preference for earnings (e.g. commerce, dentistry, civil engineering, architecture, law) and vice versa (e.g. social work, teachers' college, humanities). However, exceptions exist, e.g. applicants - in particular male - to low-earnings educations nursing and kindergarten teacher have relatively strong preference for earnings, and applicants to high-earning educations journalism and engineering have relatively weak preference for earnings.

6 Conclusion

How young people's educational choices depend on the earnings prospects of the different educations is a question of both scientific interest and policy relevance. However, nonpecuniary attributes correlated with earnings, and differences in the prospective students' comparative advantages and choice sets make it difficult to estimate this relationship.

This paper finds large effects of earnings, controlling for choice sets and average preferences for some nonpecuniary attributes. Thus, there may be a large scope for influencing prospective students' choice of education by moderate changes in earnings.

Controlling for choice sets, which also are likely to capture comparative advantage, is essential for correct inference. Other attributes are also found to matter strongly, in particular earnings risk. Furthermore, as high-earning educations tend to have larger earnings risk, this universities,[2] eight specialized university institutions and a number of university colleges. The universities provide undergraduate and postgraduate educations in a range of fields, while each specialized university institution focuses on one subject, e.g. business, architecture, veterinary science, sports or theology. Among the university colleges, the most important in terms of number of students are the 22 public regional university colleges. These mostly provide undergraduate professionally oriented courses, such as nursing, teaching, commerce and engineering. The entire sector is dominated by public institutions, with about 85 percent of the students attending one of the universities - which are all public, a public specialized university institution or a public university college. The single significant exception is a private business school with about 10 percent of the total number of students. This school also charges a significant tuition fee, which is otherwise absent.

Also, while several of the before-mentioned institutions offer shorter one or two-year courses - which can make up a part of a Bachelor or Masters degree - there is also a number of private institutions providing short vocational and recreational courses, which are not counted as a part of the higher education sector e.g. in official statistics.

Application to higher education is very centralized. Except for the before-mentioned private business school, a single body, Samordna opptak (SO), organizes applications and admissions to all major institutions. Applicants submit a single application to SO, ranking up to ten specific courses, potentially at different universities or university colleges. SO then handles the application process, allocating students to courses according to the number of places at each course and the students' qualifications and admission scores.

In order to qualify for a course an applicant needs to qualify for higher education in general. This is mostly achieved by completing the academic track in upper secondary school.[3] Some courses (e.g. science, engineering, medicine) require specific subjects in math and science from upper secondary school. A few courses have other requirements, e.g. two-year engineering courses for students from vocational school and some arts courses.

[2] Increased from four in 2005 through the conversion of one specialized university institution and three regional university colleges.

[3] There is a range of less common ways to qualify, including already having a certain amount of higher education, and, as long as some further requirements are met, completed vocational education and for those at least 23 years old any combination of work and schooling for at least five years.

will serve to mask the preference for earnings. The strong negative preference for earnings risk also implies a scope for welfare improvements if policies can reduce earnings risk. Preferences for nonpecuniary attributes also matter, but labor market outcomes other than earnings and risk have little quantitative importance.

The results are mostly stable over time and robust to earnings measure, while the specification of the choice set have some impact on the results. However, without individual-level variation in earnings and risk, empirically separating the two is challenging. Increasing both earnings and risk reduces the estimated effects of earnings on choices for men and eliminates it for women.

Men show a much stronger preference for earnings than women, and are less deterred by risk. Both contribute strongly to a gender differential in the earnings of the educations applied.

There are some differences in estimated preferences for earnings between applicants to different educations. However, for almost all educations the estimated preference for earnings are positive and significant. Younger applicant have a stronger preference for earnings and are more deterred by risk than older applicants. There are few clear difference by the applicants' parental income or academic performance.

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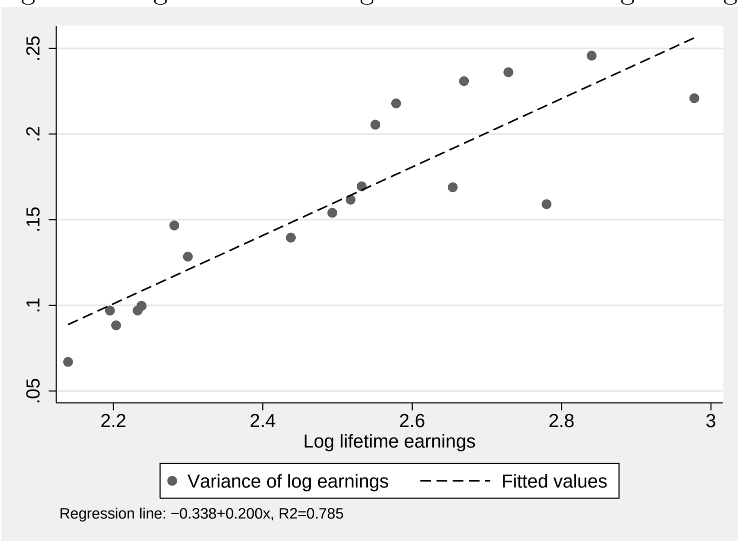
A Classification and attributes of educations

Table A.1: Classification of educations

Bachelor level
Health and social work: Nursing; Social work; Physiotherapy and ergotherapy; Other health
Teaching: Kindergarten teacher; Teachers' college; Other teaching
Business and administration: Business school; Other commerce
Science and engineering: Engineering
Law and social sciences: Journalism
Master level
Health and social work: Medicine; Dentistry, Veterinary Science and Pharmacology
Science and engineering: Civil Engineering; Architecture
Law and social sciences: Law
Unspecified level
Science and engineering: Science
Law and social sciences: Social sciences
Humanities: Humanities
Other fields: Other educations

Figure 2: Log lifetime earnings and variance of log earnings



B Result tables

Table A.2: Estimated preferences by quartile of parental earnings

Panel A: Men

	(1) 1st quartile	(2) 2nd quartile	(3) 3rd quartile	(4) 4th quartile
Log lifetime earnings	4.743***	4.512***	4.662***	5.647***
	(0.168)	(0.160)	(0.148)	(0.124)
Variance of log earnings	-1.856***	-1.759***	-3.043***	-5.640***
	(0.408)	(0.388)	(0.369)	(0.347)
Relative ability	-0.595***	-0.692***	-0.759***	-0.709***
	(0.0284)	(0.0274)	(0.0269)	(0.0276)
Rel ability · var log earn	2.502***	2.369***	2.223***	2.432***
	(0.0964)	(0.0939)	(0.0895)	(0.0833)
Log likelihood	-88040.0	-97321.5	-104796.2	-116008.6
Pseudo R^2	0.145	0.149	0.162	0.190
No. of observations	240021	262084	289606	340536
No. of individuals	15813	17113	18587	21043

Panel B: Women

	(1) 1st quartile	(2) 2nd quartile	(3) 3rd quartile	(4) 4th quartile
Log lifetime earnings	2.410***	1.913***	2.100***	3.138***
	(0.137)	(0.133)	(0.123)	(0.109)
Variance of log earnings	-9.387***	-8.850***	-9.092***	-10.82***
	(0.349)	(0.333)	(0.314)	(0.295)
Relative ability	-0.511***	-0.705***	-0.895***	-0.976***
	(0.0196)	(0.0190)	(0.0196)	(0.0209)
Rel ability · var log earn	3.049***	3.113***	3.110***	3.034***
	(0.0736)	(0.0733)	(0.0743)	(0.0736)
Log likelihood	-179101.0	-194221.1	-183749.2	-169309.1
Pseudo R^2	0.0929	0.0926	0.103	0.122
No. of observations	400254	422592	409993	397667
No. of individuals	27619	28962	27625	26024

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Sample and control variables as in specification (6), Tables 3 and 4. See notes to Table 3.
Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

Table A.3: Estimated preferences by quartiles of score

Panel A: Men

	(1) 1st quartile	(2) 2nd quartile	(3) 3rd quartile	(4) 4th quartile
Log lifetime earnings	4.127***	7.023***	5.599***	4.480***
	(0.233)	(0.233)	(0.200)	(0.0987)
Variance of log earnings	8.066***	8.591***	2.392***	-7.683***
	(0.462)	(0.410)	(0.408)	(0.356)
Relative ability	-0.504***	-1.303***	-1.695***	-1.278***
	(0.0267)	(0.0328)	(0.0355)	(0.0284)
Rel ability · var log earn	4.113***	9.055***	7.870***	2.998***
	(0.155)	(0.241)	(0.266)	(0.138)
Log likelihood	-147547.2	-147195.1	-147050.9	-160867.4
Pseudo R^2	0.151	0.160	0.163	0.202
No. of observations	414836	411419	406542	475970
No. of individuals	29946	27268	25309	26952

Panel B: Women

	(1) 1st quartile	(2) 2nd quartile	(3) 3rd quartile	(4) 4th quartile
Log lifetime earnings	-1.262***	1.460***	1.162***	2.073***
	(0.247)	(0.199)	(0.160)	(0.0785)
Variance of log earnings	-3.971***	-0.774*	-1.079***	-8.121***
	(0.594)	(0.403)	(0.354)	(0.267)
Relative ability	-0.398***	-0.588***	-0.889***	-1.247***
	(0.0222)	(0.0230)	(0.0218)	(0.0170)
Rel ability · var log earn	3.861***	4.682***	3.867***	2.823***
	(0.147)	(0.192)	(0.190)	(0.104)
Log likelihood	-208439.1	-250365.9	-285896.0	-306961.7
Pseudo R^2	0.104	0.0953	0.102	0.129
No. of observations	482598	567050	642977	705098
No. of individuals	35954	39887	43378	43207

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Sample and control variables as in specification (6), Tables 3 and 4. See notes to Table 3.
Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

Table A.4: Estimated preferences by age

Panel A: Men

	(1) Age ≤ 19	(2) Age 20	(3) Age 21	(4) Age 22-23	(5) Age ≥24
Log lifetime earnings	5.509***	5.340***	4.042***	2.582***	1.669***
	(0.103)	(0.114)	(0.135)	(0.139)	(0.180)
Variance of log earnings	-2.925***	-3.214***	-0.935***	1.637***	4.152***
	(0.288)	(0.292)	(0.327)	(0.329)	(0.437)
Relative ability	-0.844***	-0.770***	-0.660***	-0.712***	-0.602***
	(0.0225)	(0.0220)	(0.0235)	(0.0230)	(0.0296)
Rel ability · var log earn	2.484***	2.426***	2.307***	2.093***	1.950***
	(0.0704)	(0.0723)	(0.0790)	(0.0775)	(0.0975)
Log likelihood	-169387.7	-163331.8	-133166.1	-143463.6	-88276.9
Pseudo R^2	0.197	0.174	0.139	0.130	0.142
No. of observations	478293	475312	354367	404991	287613
No. of individuals	29505	30075	23200	26937	19096

Panel B: Women

	(1) Age ≤ 19	(2) Age 20	(3) Age 21	(4) Age 22-23	(5) Age ≥24
Log lifetime earnings	3.354***	2.541***	1.777***	0.569***	0.339*
	(0.0835)	(0.0936)	(0.125)	(0.132)	(0.182)
Variance of log earnings	-10.55***	-9.346***	-7.883***	-4.943***	-3.283***
	(0.217)	(0.232)	(0.305)	(0.323)	(0.455)
Relative ability	-0.818***	-0.775***	-0.760***	-0.819***	-0.778***
	(0.0145)	(0.0144)	(0.0183)	(0.0189)	(0.0257)
Rel ability · var log earn	3.483***	3.123***	2.753***	2.762***	2.740***
	(0.0550)	(0.0566)	(0.0697)	(0.0699)	(0.0925)
Log likelihood	-314382.8	-326078.2	-209187.3	-214890.3	-120701.7
Pseudo R^2	0.102	0.103	0.0952	0.103	0.124
No. of observations	687881	711000	466910	541143	354968
No. of individuals	45550	48082	32029	37353	24492

Note: Estimates of coefficients for the choice model (18), using ranked logit estimation as in (19). Sample and control variables as in specification (6), Tables 3 and 4. See notes to Table 3. Standard errors in parentheses. * $p < 0.10$,** $p < 0.05$, *** $p < 0.01$.

B

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ISSN 0809-733X

Statistisk sentralbyrå
Statistics Norway

Design: Siri Boquist