How Risky Is the Choice of a University Major?

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Abstract

This paper estimates the monetary returns to different university majors and the risks related to them. The residuals from a Mincer-type income regression are decomposed into unobserved heterogeneity (known to the individual when making her education choice) and risk (unknown to the individual). The risk estimates are corrected for selection by applying the selection correction model of Lee (1983) and an instrument based on the local supply of education in different majors. The differences in risks between different majors are found to be mostly statistically insignificant but differences in returns to majors are larger and significant. Both, income uncertainty and mean returns are found to be larger for men than for women.

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1 Introduction

Human capital assets are perhaps the most important form of investments made by individuals. In a standard human capital accumulation framework, individuals invest time (and possible tuition fees) in their education and the potential return to education materializes as higher future earnings.

Since the returns to human capital are uncertain and they are realized only several years after the choice of education is made, there is an inherent uncertainty in human capital investments. This paper studies the risk-return association of a particular type of human capital assets, namely university level degrees from different majors.

There are considerable differences in earnings of people who have graduated from different majors. For instance, the raw mean earnings of people who major in medicine are roughly 60% higher than those of arts majors. In addition, there are differences in unemployment risks and earnings variances across fields. However, it is not clear, if the differences are due to the fact that different people choose to major in different fields or differences in majors as such.[1]

This paper answers two interrelated questions. First, I study how much different university majors differ in their return. In addition, I study if there are differences in the earnings uncertainty related to these majors.

Comparing monetary returns of major subjects is complicated by the fact that people self-select into their major subjects. Therefore, it remains unclear whether the earnings differences between particular fields are due to different types of education or due to differences in observable (e.g. school grades and family background) or unobservable characteristics (e.g. abilities, motivation, taste for risk) between individuals who choose different majors. This *unobserved heterogeneity* may bias estimates for mean returns to major subjects upwards or downwards.[2] The unobserved heterogeneity also com-

[1] A pioneer in the literature studying the risk-return nexus of human capital investments is Palacios-Huerta (2003) who studies the risk-return trade-off in education levels and compares them to financial investments. Christiansen *et al.* (2007) take a similar approach, but they study majors in addition to levels. Relatedly, Hartog & Vijverberg (2007) and Diaz-Serrano *et al.* (2008) study the association of mean income and higher moments of the income distribution between education groups. None of these papers explicitly model selection into education.

[2] Willis & Rosen (1979) formulate a structural model for selection into education and

plicates the estimation of variances. This is because the realized dispersion in observed earnings is a result of two distinct components: an unexpected permanent income shock and unobserved heterogeneity across workers.[3]

Self-selected education causes the returns to a major to differ from the return we would expect to observe if the education was randomly allocated. To understand the effect of self-selection into a major subject, I correct for selection when estimating income premia and uncertainty related to major choice using the multinomial selectivity correction of Lee (1983) and a parametric assumption on the distribution of unobservables. I model each major as a distinct "market" which gives rise to a distinct earnings process.

The measure of uncertainty in this paper is the *ex ante* variance of earnings. It is the variance of earnings that is not captured by observable characteristics or unobserved heterogeneity, which is inferred from agents' choices. I decompose the ex ante variance into two components: a permanent component and a transitory component which reflects idiosyncratic shocks to their income streams.[4] The transitory component is allowed to vary with time and with education. Ths unobserved heterogeneity is identified from the actual education choices made by the agent. This paper studies an unordered multinomial education choice (choice of major) rather than an ordered one

study how the selection biases the estimated returns to college education. Card (2001) surveys problems that arise due to unobservable characteristics, which affect both selection into education and the returns to it, and discusses solutions to these problems.

[3]Cunha *et al.* (2005) and Chen (2008) model the selection into education and decompose permanent income differences within an education level into unobserved heterogeneity and uncertainty using U.S. data on levels of education. The main focus of Cunha *et al.* (2005) is the distribution of returns of a college education, whereas Chen (2008) studies the potential variances of different levels of education corrected for selectivity effects and makes a distinction between permanent income variance and transitory income shocks.

Charles & Luoh (2003), Beffy *et al.* (2012), Arcidiacono *et al.* (2012), Mazza (2012) and Montmarquette *et al.* (2002) study the flip side of the same issue. They study how expected earnings and their dispersion affect schooling choices. The riskiness of majors is either estimated from a structural model, a survey, or a combination of the two.

[4]The measure of earnings risk is rather standard in the literature, but it disregards the higher moments of the income distribution. In particular, it has been shown that gamblers may be risk-averse but skew-loving at the same time (e.g. Golec & Tamarkin 1998). Further Hartog & Vijverberg (2007) show that high variance is positively correlated with income and higher skew is negatively correlated with income when comparing different majors in their data. These are consistent with the fact that workers dislike risk but are attracted to positive skew when choosing their occupation.

(high school versus college).[5]

The model presented in this paper is estimated using Finnish registry data. An attractive feature of the Finnish tax code for the current purposes is that virtually all of the income transfers, including unemployment benefits are taxable and are therefore observed in the tax registry. Therefore, the biases inherent in survey based approaches are not an issue in the current paper.

The results of this paper also have policy relevance. The perceived riskiness of some human capital investments is a subject of an on-going debate on the financing of higher education. For example, a claim persists that certain fields of education have such an inherent risk involved that without large subsidies for schooling, no one would choose those majors. By deriving major subject specific income uncertainty measures corrected for selection, this paper provides a test for differences in riskiness of different majors.

Estimating a selection model necessitates an instrument, which affects only the probability of graduating with a degree from a given major, but does not affect potential post-graduation earnings. To construct the instrument, I take advantage of an institutional feature in Finnish tertiary education. Namely, in Finland students apply directly to a university-major combination. Universities have strict quotas for how many students they accept each year for each major. These quotas define how competitive the admission to each university-major combination is and, consequently, how difficult it is to be admitted to study a given subject in a given university. For example, since the ratio of applicants to starting places is higher in medicine in Oulu compared to medicine in Helsinki, an upper secondary school graduate in Oulu is more likely to be admitted to study and to eventually graduate from medicine compared to an upper secondary school graduate from Helsinki. Even though upper secondary school graduates from Helsinki may apply to Oulu and vice versa, this mobility incurs both monetary and psychic moving costs, which make people reluctant to move. The exclusion restriction builds on the assumption that, for a marginal student, these moving costs matter so much that they affect their tertiary education choices.

[5] In a recent working paper, Reyes *et al.* (2013) present a model of (an unordered) university choice which features observed and unobserved heterogeneity and their effect on early career wages using Chilean data. Also Napari (2008) estimates field specific returns to higher education using Finnish data but does not model selection into majors.

The vast majority of papers studying monetary return to education use either hourly wages of workers or mean incomes over a long period of time as a dependent variable. This approach disregards one of the most important source of earnings uncertainty; namely, the risk of unemployment. Instead of hourly wages, this paper studies yearly total taxable income, which, in addition to income from employment, includes unemployment benefits and other taxable transfers. This measure gives a more complete picture of the income uncertainty related to a level of education. Using total taxable income as the measure of income also mitigates the problem of endogenous selection into employment, as people are observed even if they are not working.

I estimate separate models for men and women. In most of the comparable studies attention is limited to men, because female workforce participation in most countries has been much lower until recent years. Nonetheless, female workforce participation in Finland has been very high as early as the 1990s, which warrants doing a similar analysis also for females. Furthermore, since both female education and female workforce participation has also increased internationally, I find that calculating comparable measures for males and females is also interesting in its own right from an international perspective. In addition, I am able to test whether there are differences in the uncertainty of career paths between men and women.

As a preview of the results, I find that the differences in the returns to majors are found to be far greater than the differences in risks associated with them. Further, the proportion of unobserved heterogeneity is found to be statistically indistingquishable from zero for most majors. This, in turn, suggests that the differences in returns to majors outweigh the differences in risks associated with them.

The outline of the paper is as follows. Section 4.2 discusses data; sample construction, descriptive statistics, grouping of major subjects, the definition of concept and the instrumental variables. Section 4.3 describes the empirical model. Section 4.4 discusses the first and second stage estimates. The uncertainty estimates are presented in Section 4.5. Section 4.6 concludes the paper.

2 Data

2.1 Sample construction and observables

The data used in this paper is based on longitudinal census data collected by Statistics Finland. It contains rich information on individuals' educational attainment, income, mother tongue, and region of residence and on their parental socioeconomic status (based on the occupation of both parents) and education (highest level of education of both parents); it spans the years 1990-2006. Table 1 gives the descriptive statistics for the main explanatory variables.

In addition to demographic and income information, the data has been linked to matriculation examination grades for years 1990-1995. Finnish upper secondary school graduates all take part in a standardized examination, which gives students a general qualification to apply for universities and vocational colleges. The examination is centrally administered and graded according to uniform criteria across the country and the results are scaled so that they are comparable across years.

There are four compulsory exams in the matriculation examination: mother tongue, the second official language, one foreign language and either mathematics or a science and arts exam. In addition, students may take exams in other foreign languages and take both the mathematics and the science and arts option. Finally, there are two alternatives versions of the mathematics exam; a basic level exam and an advanced level exam. Generally, to be accepted to study a mathematically oriented major in the university, students have to have taken the advanced level exam in mathematics.

The data used in this paper includes four measures related to the matriculation examination. I observe the average grade of all tests taken (general grade). In addition, I observe grades in mother tongue and in mathematics. Finally, there is an indicator for whether a student has taken the basic level or the advanced level exam in mathematics. The exams are graded on a scale of 0-5, where 0 indicates a failed exam.[6]

I consider the matriculation examination grades as a rather good measure for general academic ability for two reasons. First, it is a standardized test which has a central role in the university admissions, so matriculation

[6]The grades are given on an ordinal scale as Latin words from *improbatur* (fail; 0) to *laudatur* (excellent; 5).

exam is a high-stakes exam. In addition, it is taken by all upper secondary school graduates regardless of whether they are planning to apply to tertiary education or not, so the grading does not suffer from selection bias. The proportions of different degrees vary between males and females in the data. For instance, technology is clearly a male-dominated field and arts a female-dominated field.

Three notes can be already made from the descriptive data. First, the university graduates earn more than the non-graduates. Further, they have less work experience, and are more academically able as evidenced by their matriculation examination grades.

2.2 Classification of majors

To make sure that each major cell has enough observations. I have pooled the education majors into five fairly homogenous categories. These are:

- $S = 0$; Upper secondary level education,
- $S = 1$; Arts, education and social sciences,
- $S = 2$; Law,
- $S = 3$; Business,
- $S = 4$; Engineering and natural sciences, and
- $S = 5$; Medicine and pharmacy.

Pooling the majors in the aforementioned fashion reduces the number of parameters to be estimated, and therefore reduces the complexity of the model considerably.[7] The pooling of categories is, to some extent, arbitrary. Nonetheless, categories are homogenous with respect to their matriculation examination grades and mean incomes after graduation.[8] Nonetheless, if

[7] I have excluded fine arts graduates from the model because of the very small sample size in those subjects.

[8] Each major category consists of several major subjects. I tested if the major subject specific means of income and matriculation examination grade variables differed from one another within each grouped major category. The null hypothesis of same means was not rejected for any of these variables within a major at 5 % risk level.

there is heterogeneity within the categories, this will interfere with the uncertainty estimates. The schooling $S = 0$ is used as a reference group to which all other higher education majors are compared to.

I also do a second simplification. Namely, I restrict the return to a major to be the same across different universities. I do this because the data does not have information on the actual institution from which people have graduated but only their place of residence at the time of graduation. To control for regional earnings differences, I include dummies for the region of residence at the time of graduation in the earnings regression.

I classify people according to their tertiary degrees and exclude decisions related to post-tertiary education (for example, an engineer who has later completed a doctoral degree in the arts is classified as an engineer). Furthermore, I limit my attention to people who have either completed a university level master or a bachelor level degree or, alternatively, have not finished any post-secondary degree, who are used as comparison group. Because I only have information on completed degrees, I classify university drop-outs as upper secondary school graduates. Finally, I exclude people with a vocational tertiary education. This exclusion is done because the selection into vocational tertiary education is less standardized and consequently more difficult to measure.

2.3 Measure of income

I observe the individuals for the time period between the years 1990 and 2006. I limit my attention to people who had completed their secondary level education between 1990 and 1995. For the people who have a post-secondary degree, I include only the earnings observations past their graduation. Further, I exclude observations where people are classified as students, retired or outside of the workforce.

The outcome variable in income regressions is the log of total yearly taxable income which, in addition to wages, includes taxable income transfers. As a result, the observed income streams allow for spells of unemployment. This reflects the fact that the risk of unemployment constitutes a considerable part of total income uncertainty. However, if a person drops out of the workforce entirely, she only contributes to the estimation for the years for which she is part of the workforce. This income concept may introduce a problem of its own, since unemployment may be voluntary or involuntary. To separate these from one another, solely individual-year observations where the main type of activity of an individual is either working or unemployed are included in the estimation[9]. The approach chosen leaves some observations with zero income. I exclude these observations. This does not affect the main results, because the share of zero-observations is very small (less than 1% of yearly observations)[10]. To ensure comparability between years, the measure of income is deflated to EUR 2006 using the Consumer Price Index.

It should already be noted that the people in the sample are, on average, rather young and at the beginning of their careers. Therefore, the earnings of individuals are observed from the beginning of their career. This may drive some of the results, but I still perceive the findings as indicative of the earnings uncertainty faced by recent university graduates.

[9] In general, for an individual to be classified as unemployed (and be eligible for unemployment benefits), she must agree to accept a job if offered one.

[10] None of the results qualitatively change whether I exclude them or replace the zero observations with a small positive income value.

Table 1: Descriptive statistics of the main explanatory variables.

	Men					
		University level				
Education	Upper secondary school degree	Arts, education, social science	Law	Business	Engineering and science	Health
Sample size	1308	504	87	270	1018	121
Age and potential experience						
Potential experience	8.89	4.89	4.70	4.81	4.52	4.78
	(4.42)	(3.06)	(3.00)	(3.01)	(2.81)	(2.96)
Age	28.35	31.99	31.55	31.64	31.25	31.89
	(4.58)	(3.46)	(3.24)	(3.37)	(3.07)	(3.46)
Matriculation examination grades						
Average grade	2.95	3.56	4.19	3.86	3.91	4.12
	(1.42)	(1.34)	(0.95)	(1.30)	(1.16)	(1.25)
Mother tongue grade	3.26	3.83	4.09	3.8	3.83	4.19
	(1.24)	(1.12)	(0.83)	(1.10)	(1.08)	(0.87)
Proportion with advanced math grade	0.54	0.45	0.51	0.61	0.92	0.8
Advanced math grade	3.06	2.94	3.71	3.62	4.11	4.02
	(1.49)	(1.39)	(1.16)	(1.31)	(1.06)	(1.09)
Basic math grade	2.39	3.09	3.67	3.2	3.06	4.35
	(1.68)	(1.62)	(1.38)	(1.72)	(1.68)	(1.22)
Dependent variable						
Log total yearly taxable income	9.89	10.41	10.70	10.83	10.65	11.04
	(0.89)	(0.50)	(0.61)	(0.71)	(0.52)	(0.64)

	Women					
		University level				
Education	Upper secondary school degree	Arts, education, social science	Law	Business	Engineering and science	Health
Sample size	882	1481	100	306	511	314
Age and potential experience						
Potential experience	8.69	4.97	4.69	5.08	4.68	4.96
	(4.68)	(3.24)	(2.92)	(3.19)	(2.98)	(3.12)
Age	28.15	31.17	30.93	31.06	30.89	31.12
	(4.93)	(3.64)	(3.21)	(3.38)	(3.45)	(3.47)
Matriculation examination grades						
Average grade	3.20	3.92	4.46	4.27	4.22	4.04
	(1.45)	(1.18)	(0.98)	(1.11)	(1.02)	(1.30)
Mother tongue grade	3.56	4.12	4.47	4.22	4.24	4.18
	(1.18)	(0.96)	(0.66)	(0.93)	(0.89)	(0.98)
Proportion with advanced math grade	0.19	0.23	0.43	0.45	0.75	0.63
Advanced math grade	2.76	2.89	3.32	3.50	3.87	3.69
	(1.45)	(1.36)	(1.18)	(1.19)	(1.14)	(1.22)
Basic math grade	2.18	3.00	3.47	3.69	3.53	3.07
	(1.63)	(1.65)	(1.73)	(1.54)	(1.48)	(1.71)
Dependent variable						
Log total yearly taxable income	9.68	10.15	10.50	10.50	10.35	10.52
	(0.69)	(0.45)	(0.47)	(0.52)	(0.52)	(0.51)

Notes: Standard deviations in parenthesis. The matriculation examination grades are converted to numbers. Potential experience, and age are measured as full years since graduation. The time-varying variables (age, experience and income) are measured at individual means. In addition to variables reported, all regression specifications include controls for first language, family socioeconomic status and parental education.

2.4 Exclusion restriction

To ensure that the joint identification of schooling choice and earnings equations is not solely based on functional form assumptions, I utilize an instrument, which is assumed to monotonously affect the probability of choosing a particular major subject, but not to affect the earnings after graduation.

Since post-secondary education is state sponsored in Finland, there are no cost side instruments available. Instead, I use a proxy measure for local supply of education as an instrument. Local supply of education is measured by the ratio of annual number of starting places to applicants at region level for each major[11]. There are some regions with more than one study program offering the same major (e.g., Finnish and Swedish language universities in Varsinais-Suomi and Uusimaa). For these regions, an average of applicants-to-places ratio weighted by the number of starting places is calculated. For the regions that do not have a university or a program in a particular major, an average of applicants-to-places ratio weighted by the distance to each university region where one can study each major is calculated. The supply is measured at the year of matriculation at region level.[12]

The admission to university is based on a combination of the matriculation examination grades and the university entrance exams. It is merit-based and objective. In particular, there is no minority support or weight for extra-curricular activities. Different majors and universities give different relative weights to different subjects in the matriculation exam. Generally, the more competitive a major is, the more weight is given to the entrance examination relative to the matriculation examination.

The supply of education may be correlated with the outcome through some other channels beside its effect on choice of majors, which would threaten the validity of the instrument. As discussed by Card (1993), this may happen because families living in university regions have different educational or social backgrounds than families living in non-university regions. I address this worry by controlling for a variety of family background variables. Card's critique is also likely less valid in the context of this paper because it seems much less likely that parental characteristics would be cor-

[11]Finland is divided into 20 administrative regions, which are the regional cultural and administrative divisions.

[12]These data are downloaded from the KOTA database maintained by the Ministry of education: `https://kotaplus.csc.fi/` (downloaded 2013-01-08).

related with a supply in particular major compared to supply of general university education.

In addition, there might be differences in upper secondary school quality between regions. This might affect both the education choice and subsequent earnings of individuals, which might threaten the validity of the instrument. This is a small concern in the case of Finland because the secondary education is arranged in public schools with a standardised curriculum, very small differences in resources and quality. Furthermore, since the matriculation examination is standardized and centrally administered, it is reasonable to assume that controlling for matriculation examination grades would control also for differences in the quality of secondary education.

A third possible source of omitted variable bias is that the location of residence at the time of graduation from upper secondary school might be correlated with both the choice of university major and labour market conditions after graduating, which, in turn, would create a correlation between the instrument and the outcome. I address this concern by controlling for the region of residence at the time of graduation from upper secondary school in the earnings equation.[13] Finally, I assume that yearly changes in starting places are so small in magnitude that they do not have any general equilibrium effects.

The instrument distribution is plotted in 1 in a box-whiskers plot for each year[14]. The medians are the smallest for law, and largest for science and engineering. Further, as evidenced by the interquartile ranges of the instrument, the variation between regions is largest in business and technology, and the smallest in arts. In addition, the box-and-whiskers plots reveal that for all majors there is both time and cross-sectional variation, which helps in identification of the model. Further, for the identification of the choice model, the instruments should also have some independent variation and not simply act as proxies for living in a university region. To show

[13]It would also be possible to include region of residence dummies from the year of observation in the outcome equation. This would increase the precision of the estimates. However, since the region of residence is determined after the choice of education has been made, it is potentially endogenous.

[14]In each of the plots, the strong black lines mark yearly medians for each year; boxes represent the interquartile range between 25th and 75th quantiles, and whiskers represent 1.5 times the interquartile range. Observations lying outside of the whiskers are marked as dots.

that this is the case, I report the correlation matrix of instruments in Table 2. The correlations are considerably smaller than 1 ranging from .085 to .512 which supports the assumption that the instruments truly capture differences between university regions.

Table 2: Covariance matrix of starting places to applicants in fields.

	Ratio in major 1	Ratio in major 2	Ratio in major 3	Ratio in major 4	Ratio in major 5
Ratio in major 1	1	0.422	0.502	0.461	0.512
Ratio in major 2		1	0.466	0.085	0.377
Ratio in major 3			1	0.486	0.298
Ratio in major 4				1	0.450
Ratio in major 5					1

Notes: Ratio is calculated as starting places divided by number of applicants to each major. The major subjects are 1: arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

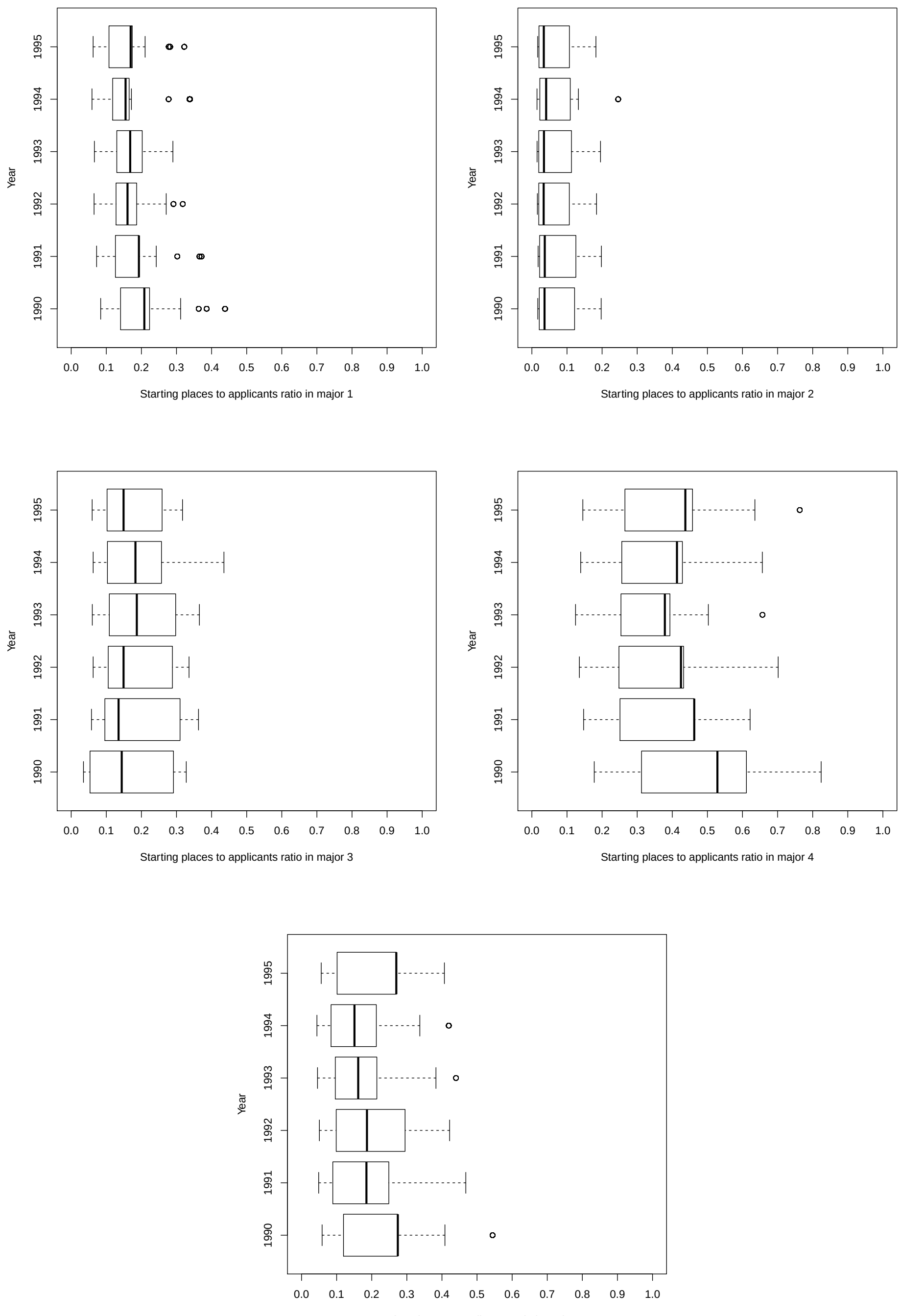
3 Empirical model

In this section, I present the selection correction methodology of Lee (1983) applied to the context of major choices.

3.1 Selecting into major and income processs

The model features an unordered schooling decision. Conditional on observed and unobserved characteristics, agents make their major choice based on the comparison of the expected utility associated with each major subject. This utility includes both monetary and non-monetary benefits as well as monetary and psychic costs. I assume that the earnings processes of individuals are determined by the agent's observed and unobserved characteristics plus a permanent earnings shock and a yearly transitory shock, both of which may depend on the choice of education made by the agent. In essence, I allow for observationally similar individuals to have different realizations for the return to completing a degree. I interpret the variance of these returns as uncertainty related to the choice of education.

The stylized model consists of two stages. In stage one, each high school graduate chooses their preferred major subject or, alternatively, enters the labour market with a high school education. In the second stage, university graduates enter the labour market and face income streams which are determined by major specific mean incomes, permanent earnings differences and transitory shocks. There are N individuals who are observed over T periods



Note: The major subjects are 1: arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

Figure 1: Distribution of the instruments.

and have to make the their education choice over alternatives $S_i = 0, 1, ..., M$. The log total income of individual i with education s in year t is given by

$$y_{sti} = \alpha_s + x_{ti}\beta + \sigma_s e_{si} + \psi_{st}\varepsilon_{sti}, \tag{1}$$

where α_s is a major specific intercept and x_{it} is a vector of observables.x_{ti} is a vector of control variables, which includes year of birth, parental education, socioeconomic status, mother tongue dummies, and matriculation examination grades from mathematics, mother tongue, the mean of all examination grades and a dummy variable which indicates whether the students have completed a basic or an advanced syllabus in mathematics. In addition, I include a measure for potential experience and its square. It is calculated as the difference of the observation year and the year of graduation.

The error term of (1) consists of two uncorrelated standard normal components, with

$$\begin{bmatrix} e_{si} \\ \varepsilon_{sti} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right).$$

The variances of two independent shocks are scaled by σ_s and ψ_{st}.

e_{si} captures the time-invariant earnings potential for major s. $\sigma_s e_{si}$ are allowed to be correlated with the observable characteristics x_{it}. The term ε_{sti}, on the other hand, captures the transitory income shocks, which are assumed to be uncorrelated with the other terms in (1).

The potential problem of selection arises because agents' major choices and their earnings potential in the major might be correlated with one another. I formalize the selection into education as a multinomial selection model of Lee (1983). Denote the utility individual i from choice s as

$$V_{si} = z_{si}\gamma_s + \eta_{si},$$

where the vector $z_i = (z_{1i}, \ldots, z_{Mi})$ includes all time-invariant components of x_i, and a major-specific instrument which is assumed to only affect the choice of major, but not the monetary returns of graduating from a major. I assume that the error terms η_{si} in the utility functions are identically and independently Gumbel distributed, and independent of z_{si}. The error terms η_s capture the private information related to agents' major choice, such as motivation, tastes, and the unobserved ability.

Agents choose major s if and only if

$$V_{si} \quad > \quad V_{ji}, \; \forall \, j \neq s,$$

which is equivalent to

$$\begin{aligned} z_{si}\gamma_s + \eta_s &> z_{ji}\gamma_j + \eta_j,\ \forall\, j \neq s \\ \Leftrightarrow \max_j \{z_{ji}\gamma_j - z_{si}\gamma_s + \eta_s - \eta_j\} &< 0,\ \forall\, j \neq s \\ \Leftrightarrow \nu_{si} &< \Phi^{-1}(P_{Si}), \end{aligned}$$

where $\nu_{si} \sim N(0,1)$, and

$$P_{Si} = P(S_i = s \mid z_i) = \frac{exp(z_{si}\gamma_s)}{\sum_{j=1}^{M} exp(z_{ji}\gamma_j)}. \quad (2)$$

It is further assumed that the joint distribution of the transformed variable ν_{si} and e_{si} is bivariate standard normal with a correlation coefficient ρ_s. Now the analysis of Heckman (1979) (which relies on the joint normality of error terms) can be applied to the transformed random variable ν_{si}.

Under these assumptions, the expected earnings of an individual who has chosen s, read as

$$\begin{aligned} E[y_{sti} \mid S_i = s, x_{ti}, z_{ti}] &= E[y_{sti} \mid z_{si}\gamma_s > \nu_{si}, x_{ti}, z_{ti}] \\ &= \alpha_s + x_{ti}\beta - \sigma_s\rho_s\lambda_s(z_i), \quad (3) \\ &= \alpha_s + x_{ti}\beta - \mu_s\lambda_s(z_s), \quad (4) \end{aligned}$$

where

$$\lambda_s(z_i) = \frac{\phi\left(\Phi^{-1}(P_{si})\right)}{P_{si}},$$

and $\mu_s = \sigma_s\rho_s$.

Selection also implies that the observed earnings distribution is truncated, and its variance reads as:

$$\begin{aligned} Var[y_{sti} \mid S_i = s, x_{ti}, z_{ti}] &= Var[\sigma_s e_{si} + \psi_{st}\varepsilon_{sti} \mid z_{si}\gamma_s > \nu_{si}, x_{ti}, z_{ti}] \\ &= \sigma_s^2(1 - \rho_s^2\delta_{si}) + \psi_{st}^2, \quad (5) \end{aligned}$$

where

$$\delta_{si} = \left(\Phi^{-1}(P_{si}) + \lambda_s(z_i)\right)\lambda_s(z_i)$$

gives the degree of understatement of the observed earnings variance compared to potential earnings variance, which would be observed if the education was randomly assigned[15].

[15] The expressions for and δ_{si} and λ_{si} are derived in Bourguignon *et al.* (2007).

Equation (3) captures the observed earnings given that agents have chosen s. In particular, it demonstrates, that if $\mu_s \neq 0$, not correcting for selection will give biased estimates for the returns to each major.

$$\tau_{st} = Var\left(\sigma_s e_{si} + \psi_{st}\varepsilon_{sti} \mid \eta_{0i}, \ldots, \eta_{Si}, x_{ti}, z_i\right) = \sigma_s^2\left(1 - \rho_s^2\right) + \psi_{st}^2 \qquad (6)$$

is the unforeseeable component of the earnings residual, or earnings uncertainty, which is corrected for selection and truncation.

The uncertainty related for each major in expression(6) consists of two parts. The first term is the permanent component net of unobserved heterogeneity, and the second component is the yearly-varying transitory shock. Equation (6) also directly implies that whenever $\rho_s \neq 0$, observed earnings inequality is smaller than the potential earnings inequality, which we would observe if the major subjects were randomly assigned.

Further, it is worth noting, that the difference between expressions (5) and (6) is that (5) captures the observed variance of earnings conditional on observables, and (6) captures the potential variance, which we would observe major subjects were randomly assigned.

3.2 Identification of variance components

Equations (3), and (5) suggest a step-wise approach for identifying the components of (6). First, selection equation (2) is estimated by maximum likelihood. Thereafter, the terms $\hat{\lambda}_{si}$ and $\hat{\delta}_{si}$ are estimated. In the second step, a within-individual model

$$y_{sti} - \bar{y}_{si} = \left(x_{ti} - \bar{x}_{si}\right)\beta + \left(\vartheta_{sti} - \bar{\vartheta}_{si}\right), \qquad (7)$$

where $\vartheta_{sti} = \psi_{st}\varepsilon_{sti}$, and $\bar{y}_{si}$, $\bar{x}_{si}$ and $\bar{\vartheta}_{si}$ denote individual means of the corresponding variables, is estimated. Note that the selection bias terms λ_s are time-invariant, so they are incorporated in the fixed effects. Term ψ_{st}^2 can be solved from the variance of the residual terms (See Appendix for derivation).

Parameters $\hat{\alpha}_s$, $\hat{\beta}$, and $\hat{\mu}_s$ can be estimated from the between-individuals model.

$$\bar{y}_{si} = \alpha_s + \bar{x}\beta + \mu_s\lambda_{si} + w_i. \qquad (8)$$

Residual term in (8) equals

$$w_i = \sigma_s e_{si} + \bar{\vartheta}_{si} - \mu_s \lambda_{si},$$

and by the inclusion of $\mu_s \lambda_{si}$ its expectation is zero, which also ensures that the estimate for α_s is unbiased.

Variance of w_i reads as

$$Var\left[w_i \mid S_i = s, \bar{x}_{ti}, z_i\right] = \sigma_s^2 e_{si} - \mu_s^2 \delta_{si} + \frac{\sum_t \psi_{st}^2}{T}.$$

Replacing each parameter with their consistent estimate, and solving for $\hat{\sigma}_s$, gives a consistent estimate for the permanent earnings variance.

$$\hat{\sigma}_s^2 = \hat{Var}\left[w_i \mid S_i = s, \bar{x}_{ti}, z_i\right] + \mu_s^2 \hat{\bar{\delta}}_s - \hat{\bar{\psi}}_s^2.$$

Each term in (6) is now identified:

$$\hat{\tau}_{st}^2 = \hat{\sigma}_s^2 - \hat{\mu}_s^2 + \hat{\psi}_{st}^2.$$

4 Estimation results

4.1 First stage

The first stage of the model is estimated by a maximum likelihood multinomial logit. Each of the models includes the following background variables: gender, year of birth, parental education, socioeconomic status and mother tongue dummies. Academic ability of individuals is measured by matriculation examination grades from mathematics, mother tongue, the mean of all examination grades and a dummy which indicates whether students have completed a basic or an advanced syllabus in mathematics. In addition, the selection model includes the instrument, which is the ratio of starting places to applicants for each of the major choices. I estimate separate selection models for men and women.

Since the applicants-to-places ratio varies in time and across majors, the data would also allow me to estimate a more flexible model where the effect of applicants-to-places ratio would vary across major choices. Because of small sample sizes in some majors the coefficient on the ratio is indistinguishable from the model where the coefficient of the ratios are restricted to be identical between majors, I have therefore opted to use a simpler model where the effect of the applicants-to-places ratios are restricted to be the same across majors.

The parameter estimates are reported in Table 3. Association between the probability of graduating from arts and the grade in mother tongue are positively associated with one another at conventional statistical significance levels. Scoring high in the mathematics exam is associated with the probability of graduating from medicine and engineering, and the general grade is statistically significantly positively associated with the probability of graduating from business, arts, and law.

To facilitate the interpretation of the impact of the instrument on selection, Table 4 reports the marginal effect of the places-to-applicants ratio on the selection into different majors. The marginal effects are evaluated at major means. A ten percent increase in the applicants-to-places ratio implies an increase for the probability of graduating from a major between 13 percentage (for engineering) and 2 percentage (for medicine) for men. The corresponding marginal effects range between 24 percentage (for arts) and 2.7 percentage (for law).

4.2 Return to major estimates

I present the estimates based on the between individuals equation (8) in this subsection. The results are given in Table 5.

Adding the estimated λ_s's as regressors gives unbiased estimates for the return to education estimates, but the estimated covariance matrix of the estimates is biased because it disregards the sampling error in the generated regressors. To correct for the extra sampling variability, I have resorted to a block bootstrap procedure where 250 samples of size N are drawn with replacement from the original population. For each bootstrap draw k, the estimates $\hat{\alpha}_s^k$,$\hat{\beta}^k$ and $\hat{\mu}_s^k$ are calculated. Expected values and standard errors of the parameters are calculated from the distribution of these bootstrap draws.

The first column of Table 5 reports the return estimates calculated from a model without any controls. Second column in Table 5 reports the return estimates with after controlling for x, and the third column reports the return estimates controlling for x, and λ_s. Comparing the return estimates of

Table 3: Multinomial logit estimates of major choice

	Men	Women
General grade × Arts	0.322***	0.178***
	(0.065)	(0.047)
Mother tongue grade × Arts	0.285***	0.294***
	(0.066)	(0.056)
Advanced level exam in math × Arts	0.426*	0.637**
	(0.217)	(0.228)
Math grade × Arts	0.03	0.217***
	(0.043)	(0.029)
Advanced level exam in math × math grade × Law	-0.34	-0.075
	(0.061)	(0.071)
General grade × Law	0.962***	0.563***
	(0.191)	(0.177)
Mother tongue grade × Law	0.065	0.366***
	(0.161)	(0.174)
Advanced level exam in math × Law	-0.042	1.495**
	(0.593)	(0.522)
Math grade × Law	0.010	0.292***
	(0.089)	(0.072)
Advanced level exam in math × math grade × Law	-0.182	-0.027
	(0.146)	(0.140)
General grade × Business	0.449***	0.369***
	(0.096)	(0.098)
Mother tongue grade × Business	-0.017	0.089
	(0.088)	(0.099)
Advanced level exam in math × Business	0.312	1.505***
	(0.320)	(0.364)
Math grade × Business	0.152**	0.508***
	(0.062)	(0.052)
Advanced level exam in math × math grade × Business	0.022	0.223***
	(0.078)	(0.097)
General grade × Engineering	0.043	0.003
	(0.064)	(0.081)
Mother tongue grade × Engineering	-0.021	0.112
	(0.058)	(0.086)
Advanced level exam in math × Engineering	0.279	1.262***
	(0.251)	(0.315)
Math grade × Engineering	0.145**	0.467***
	(0.066)	(0.056)
Advanced level exam in math *imes*math grade × Engineering	0.632***	0.641***
	(0.053)	(0.081)
General grade × Medicine	0.294*	-0.021
	(0.146)	(0.083)
Mother tongue grade × Medicine	0.300**	0.222*
	(0.136)	(0.092)
Advanced level exam in math × Medicine	0.407	1.067***
	(0.576)	(0.336)
Math grade × Medicine	0.226.	0.332***
	(0.121)	(0.058)
Advanced level exam in math ×math grade × Medicine	0.309**	0.469***
	(0.115)	(0.089)
Ratio	0.609**	1.00***
	(0.287)	(0.290)

Notes: Omitted category is upper secondary school. Ratio is calculated as starting places divided by number of applicants to each major. In addition to the variables reported, both models include controls for regression specifications include controls for year of birth, first language, family socioeconomic status and parental education dummies. Significance levels in both models: *** 0.1%, ** 1%, * 5% and . 10%.

Table 4: Marginal effects of the instrument.

	Men	Women
Arts	0.081**	0.242***
	(0.038)	(0.070)
Law	0.015**	0.027***
	(0.007)	(0.008)
Business	0.046**	0.077***
	(0.022)	(0.022)
Engineering	0.13**	0.118***
	(0.061)	(0.034)
Medicine	0.021**	0.081***
	(0.010)	(0.024)

Notes: Marginal effects evaluated at means of each major. Significance levels in both models: *** 0.1%, ** 1%, * 5% and . 10%.

the first and the second and third column reveals that controlling for family background, matriculation examination grades and potential experience increases the return estimates considerably. The effect of selection correction is much smaller.

The Wald test for the joint significance of the correction function terms can be interpreted as a test for the significance of the unobserved heterogeneity over the entire sample. The p-value of 0.15 for suggests that the impact of unobserved heterogeneity is rather inaccurately estimated in the male sample. The corresponding value of p=0.08 for women is borderline significant. Selection correction increases the return estimates for all majors, but the differences of corrected and uncorrected estimates are not statistically significant, as evidenced by the Hausman test statistics reported in Table 5. This is driven by the fact that selection correction inflates the standard errors of the return estimates.

If the selection correction terms were not statistically significant, both OLS and the selection corrected models would be unbiased, but OLS is more efficient. Under the alternative hypothesis, OLS is biased, but the selection corrected estimates are unbiased. The Wald test statistics reported in Table 5 are insignificant for males, and weakly significant for females.

There are considerable differences in the returns to majors.[16] For both sexes, the largest corrected return estimates are for health (169 log points for men, and 129 log points for women). The smallest corrected return estimates are for the arts degree, which are 104 log points for men, and 92 log points

[16] Differences are significant at $p < 0.05$ significance level for both sexes and uncorrected and corrected specifications.

for men.[17] The return estimates are larger and earnings profiles steeper for males than for females. A potential explanation for this is that fertility decisions of women in their late 20s and early 30s cause longer breaks in their careers than they do for men (see, e.g., Lundberg & Rose 2000).

[17]Though not discussed in detail, I have also experimented with a specification where the potential experience terms are interacted with the major dummies to allow the income trajectories vary between majors. I find that the interaction terms do not jointly statistically significantly differ from one another, but the returns to major estimates are unrealistically large.

Table 5: Estimated earnings equation.

	Men			Women		
	No controls	Uncorrected	Corrected	No controls	Uncorrected	Corrected
(Intercept)	9.765***	9.569***	9.416***	9.518***	8.709***	8.668***
	(0.016)	(0.400)	(0.477)	(0.015)	(0.841)	(0.811)
Arts, education,	0.596***	0.987***	1.043***	0.606***	0.815***	0.923***
and social sciences	(0.030)	(0.048)	(0.12)	(0.020)	(0.036)	(0.089)
Law	0.867***	1.205***	1.399***	0.930***	1.108***	1.134***
	(0.063)	(0.071)	(0.272)	(0.049)	(0.059)	(0.281)
Business	0.987***	1.323***	1.531***	0.956***	1.124***	1.27***
	(0.038)	(0.053)	(0.207)	(0.030)	(0.043)	(0.152)
Engineering	0.844***	1.181***	1.427***	0.758***	0.912***	1.095***
and technology	(0.024)	(0.046)	(0.12)	(0.026)	(0.039)	(0.108)
Medicine	1.263***	1.561***	1.689***	1.010***	1.176***	1.294***
	(0.055)	(0.066)	(0.149)	(0.030)	(0.041)	(0.11)
Experience		0.117***	0.125***		0.011	0.011
		(0.015)	(0.021)		(0.014)	(0.014)
Experience^2		-0.003***	-0.004***		0.002*	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)
General grade		-0.017.	-0.023.		-0.017	-0.02
		(0.012)	(0.015)		(0.009)	(0.009)
Advanced level		0.031	0.037		0.011	0.017
exam in math		(0.042)	(0.043)		(0.036)	(0.038)
Mother tongue grade		-0.002	-0.004		0.014	0.012
		(0.011)	(0.013)		(0.01)	(0.01)
Math grade		0.029***	0.024*		0.023***	0.021***
		(0.009)	(0.011)		(0.005)	(0.005)
Math grade ×		0.042***	0.026.		0.037***	0.032***
advanced exam		(0.011)	(0.014)		(0.01)	(0.013)
μ_0			0.133*			0.037
			(0.067)			(0.054)
μ_1			0.044			-0.077
			(0.072)			(0.06)
μ_2			-0.034			0.011
			(0.125)			(0.129)
μ_3			-0.042			-0.059
			(0.109)			(0.075)
μ_4			-0.114**			-0.103*
			(0.052)			(0.053)
μ_5			0.014			-0.045
			(0.096)			(0.045)
Wald test for joint significance of correction function (df=6)	-	-	9.37	-	-	10.53.
			[0.15]			[0.08]
Hausman test for difference between uncorrected and corrected returns to education (df=5)			9.03			7.43
			[0.11]			[0.20]

Notes: Standard errors in parenthesis; p-values in brackets. Standard errors are calculated by bootstrap. The matriculation examination grades are converted to numbers. Potential experience is measured as full years since graduation. In addition to variables reported, uncorrected and corrected regression specifications include controls for year of birth, first language, family socioeconomic status, parental education and dummies for region of residence at the time of graduation. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.

4.3 Uncertainty estimates

This subsection discusses the uncertainty estimates related to each of the majors. The uncertainty is defined as the ex ante variance of earnings not captured by the observable characteristics or the correction function. Uncertainty is further decomposed into two orthogonal components: permanent earnings inequality and transitory shocks. The uncertainty estimates are presented in Table 6.

I start by discussing the variance of transitory shocks given in the first row of Tables 6 A and B. Since the transitory shocks are time-varying, I concentrate first on their time means. Comparing the first column in 6 A and B to the others reveals that completing a university degree decreases transitory uncertainty considerably. The decrease is almost four-fold for men and over two-fold for women. The differences between majors are rather small and do not differ from one another at conventional risk levels. The yearly transitory shock variances are plotted in Figure 2. Yearly transitory shocks are particularly large for the year 1993. This is likely explained by the exceptionally deep recession which took place in Finland in the early 1990's. Further, the sample sizes for the years in the start of the sample are very small.

Second rows in Tables 6 A and B report permanent earnings differences. People with a university education face somewhat larger permanent earnings differences compared to upper secondary school graduates, but the smaller transitory shocks of the university graduates compensates for the increase in permanent earnings differences so, in total, university graduates face smaller earnings uncertainty than upper secondary school graduates.

Among male university graduates, engineering graduates face 30 % smaller permanent earnings differences in comparison to other major groups' average ($p = 0.05$). Among female graduates, no statistically significant differences emerge.

Permanent earnings shocks are further decomposed into two parts: permanent earnings uncertainty and unobserved heterogeneity. Unobserved heterogeneity is reported in row three of Tables 6 A and B. The estimates for unobserved heterogeneity are inaccurately estimated and small; and nondiscernible from zero at conventioal significance levels. Shares of unobserved heterogeneity in total uncertainty are visualized in Figure 3.

Transitory effect dominates permanent earnings differences for both genders and all education groups. This observation may be driven by the fact that people in the data are in the beginning of their careers. As young people are more likely to be engaged in job shopping and are less likely to be protected by tenure. The finding that younger workers face larger transitory shocks than older ones is a common finding from several developed countries. Nonetheless, it is often the case that early career earnings shocks tend to evolve into permanent earnings differences as people gather more work experience and are able to secure their employment (see e.g., Baker & Solon, 2003).

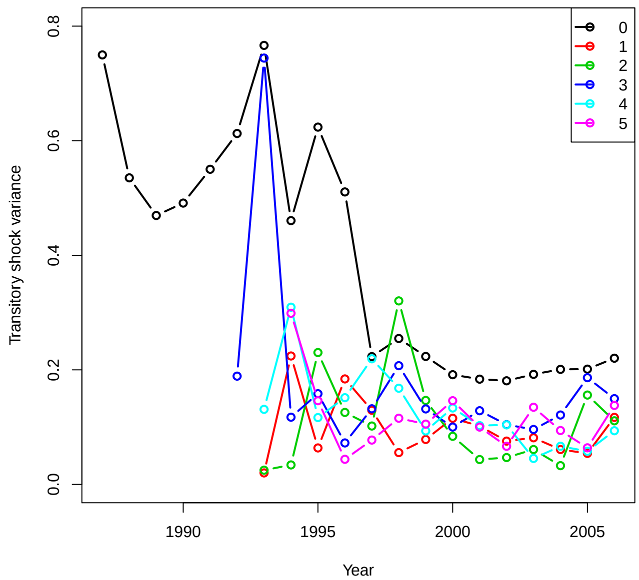
Key empirical findings of this section are three. First, completing major decreases uncertainty regardless of major and gender. Second, no differences between majors arise, with the exception of males who have graduated from engineering. Third, the impact unobserved heterogeneity is estimated to be economically small and statistically insignificant.

Table 6: Uncertainty estimates

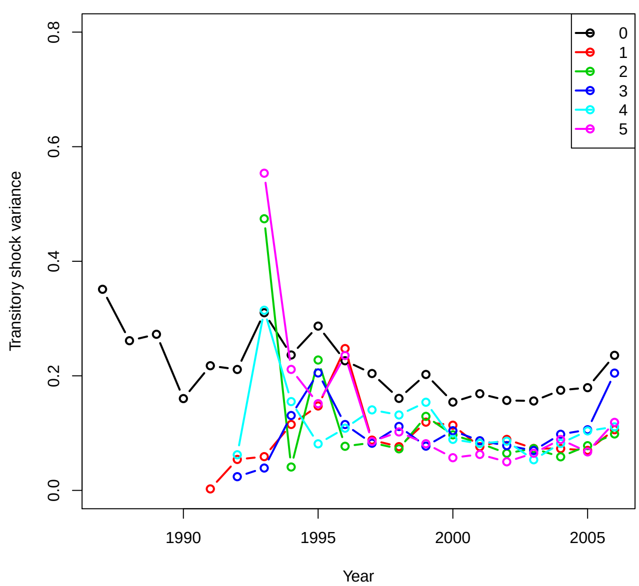
A	Men	*University level*				
	Upper secondary school degree	Arts, education, social science	Law	Business	Engineering and science	Health
Transitory shocks[1]	0.392***	0.097***	0.112***	0.153***	0.128***	0.114***
	(0.024)	(0.014)	(0.023)	(0.030)	(0.016)	(0.016)
Permanent earnings variance[2]	0.031	0.086***	0.109**	0.101**	0.035*	0.137***
	(0.038)	(0.024)	(0.059)	(0.048)	(0.018)	(0.036)
Unobserved heterogeneity[3]	0.022	0.007	0.017	0.014	0.016	0.009
	(0.019)	(0.01)	(0.026)	(0.021)	(0.012)	(0.015)
Total uncertainty[4]	0.423***	0.187***	0.217***	0.257***	0.162***	0.246***
	'(0.031)	'(0.022)	'(0.06)	'(0.047)	'(0.012)	'(0.036)
B	Women					
Transitory shocks[1]	0.216***	0.095***	0.103***	0.104***	0.119***	0.133***
	(0.013)	(0.01)	(0.019)	(0.013)	(0.018)	(0.028)
Permanent earnings variance[2]	0.057**	0.068***	0.064	0.037*	0.063***	0.042**
	(0.022)	(0.015)	(0.072)	(0.020)	(0.019)	(0.029)
Unobserved heterogeneity[3]	0.004	0.010	0.017	0.009	0.013*	0.013*
	(0.006)	(0.011)	(0.022)	(0.013)	(0.007)	(0.006)
Total uncertainty[4]	0.269***	0.153***	0.150***	0.132***	0.169***	0.171***
	(0.020)	(0.016)	(0.068)	(0.020)	(0.020)	(0.024)

[1] Given by $\frac{\psi_{st}^2}{T}$
[2] Given by σ_s^2
[3] Given by μ_s^2
[4] Given by $\sigma_s^2 - \mu_s^2 + \frac{\psi_{st}^2}{T}$

Notes: Bootstrapped standard errors in parentheses. Estimates refer to elements of Equation (4.11). Significance levels in all specifications: *** 0.1 %, ** 1%, * 5% and . 10%.



(a) Men



(b) Women

Figure 2: Yearly transitory shock variances by education categories. Majors are classified as follows: 0: Upper secondary school graduate; 1: Arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health. The vertical dashed lines represent 95% confidence intervals calculated by bootstrap.

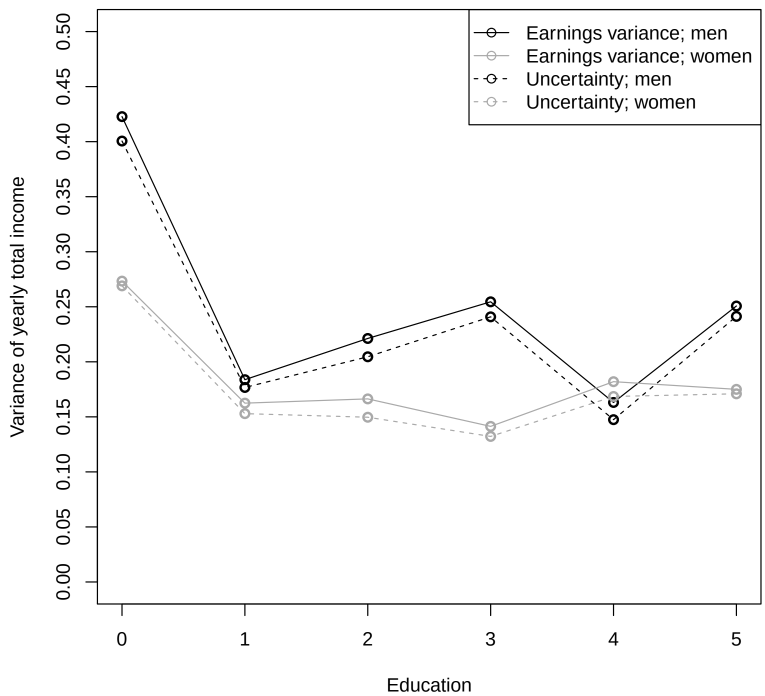


Figure 3: The solid lines represent the total observed earnings variances for men (black) and women (gray). The dashed lines represent the estimated uncertainty. Education category 0 refers to no university education, and categories 1–5 refer to university majors. The majors are classified as follows: 1: Arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

5 Conclusions

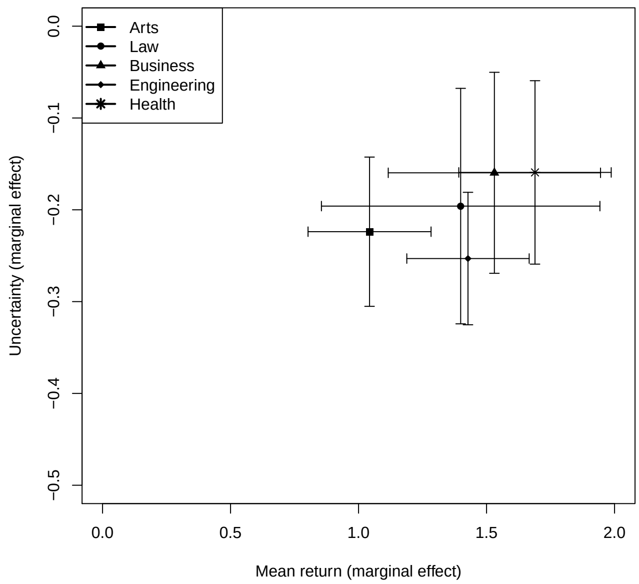
This paper studies returns to university majors, and the uncertainty related to them in the presence of selection bias and unobserved heterogeneity. Using this model, the residuals of a earnings regression are decomposed into two types of earnings shocks: permanent earnings differences, and a yearly transitory earnings shocks; and to an unobserved heterogeneity component, which is known to the agent, but unobservable to the researcher. In addition to wages, measure of income used in this study includes transfers to people who are not working. This gives a possibility also to include the unemployed in the estimation allowing for a more complete picture of income uncertainty.

University majors are aggregated into five roughly similar categories. Local differences in the supply of education measured by the starting places to applicants ratio are used as instruments for selection into majors. Possible bias due to self-selection is controlled by applying a multinomial selection correction model of Lee (1983), and an instrument based on local variation in the selectivity of different majors.

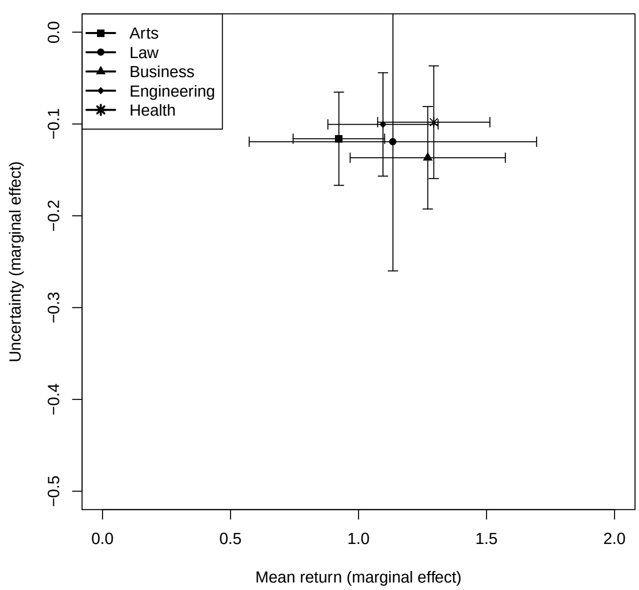
Substantive results of this paper are summarized in Figure 4. The effect of completing an academic degree ranges between 104 and 169 for men and between 92 and 129 log points for women over the earnings of an upper secondary education. In addition to increasing expected returns, university education also is found to decrease earnings uncertainty for both sexes. The differences in the earnings uncertainty are found to be statistically significant at 5% risk level, whereas the confidence intervals for the uncertainty estimates of different majors overlap making them statistically indistinguishable from one another.

Selection correction terms do not enter statistically significantly to either of the models, which implies that the corrected and uncorrected returns estimates are statistically indistinguishable from one another, and that the estimate for the unobserved heterogeneity is very close to zero. This is likely partly due to the small sample sizes in many of the majors, and broad set of control variables utulised.

Notwithstanding the caveats related to small sample sizes, this paper contributes another piece of evidence suggesting that (higher) education is a good investment from the point of view of the individual. In addition to increasing expected earnings, graduating from a university decreases earnings uncertainty. This notion holds regardless of the major subject.



(a) Men



(b) Women

Figure 4: Mean-variance plots. Notes: vertical and horizontal lines represent 95% confidence intervals for estimates.

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Appendix: Estimating $\hat{\psi}^2_{st}$ from the residuals of the within-model

Equation 7:

$$y_{sti} - \bar{y}_{si} = (x_{ti} - \bar{x}_i)\,\beta + \left(\vartheta_{sti} - \bar{\vartheta}_{si}\right)$$

Assuming that observations are missing at random and that ε_{st} and ε_{st-k} are independent for all $k \neq 0$, the residual variance can be written as

$$Var\left(\vartheta_{sit} - \bar{\vartheta}_{si}\right) = W_{st} = \left(1 - \frac{2}{T}\right)\psi^2_{st} + \frac{\Omega_{si}}{T_i^2},$$

where T_i is number of observation years of observation i and $\Omega_{si} = \sum_{t=1}^{T_i}\psi^2_{st}$. Summing both sides up over t gives

$$\sum_{t=1}^{T_i} W_{st} = \left(1 - \frac{2}{T}\right)\Omega_{si} + \frac{\Omega_{si}}{T}$$

and solving this for Ω_{si} gives

$$\Omega_{si} = \frac{\sum_{t=1}^{T_i} W_{st}}{\left(1 - \frac{1}{T}\right)}.$$

Plugging this back to the expression of $Var\left(\vartheta_{sti} - \bar{\vartheta}_{si}\right)$ and solving for ψ^2_{st} gives

$$\psi^2_{st} = W_{st}\frac{T_i}{T_i - 2} - \frac{\Omega_{st}}{T_i\left(T_i - 2\right)}.$$

Finally, replacing T_i's their sample average and W_{st} with its consistent estimate gives

$$\hat{\psi}^2_{st} = \hat{W}_{st}\frac{\bar{T}}{\bar{T} - 2} - \frac{\hat{\Omega}_s}{\bar{T}\left(\bar{T} - 2\right)},$$

where $\hat{\Omega}_s = \dfrac{\sum_{t=1}^{T_i}\hat{W}_{st}}{\left(1 - \frac{1}{\bar{T}}\right)}$.