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Measuring the Relationship Between Resources and Outcomes in Higher Education in Norway

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Preface

This report is an extended version of a paper presented at the 11th Transition in Youth (TIY) Conference in Funchal, Madeira 4.-6. September 2003 ("Competences and Careers").

The objective of the report is to analyse the connection between the allocation of resources in higher education and the subsequent effects on graduates' labour market outcome. The analyses are based on data from different sources matched for the first time. Graduate level data are derived from The *NIFU Graduate Survey 2000* while the faculty level data are either from registers or from *NIFU University Survey 2000.*

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The report is written by Sverre Try and Jens B. Grøgaard. Pål Børing, Lars Nerdrum, Bjarne Strøm and participants at the TIY-Network have commented on earlier drafts.

Oslo, November 2003

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Summary

The paper estimates the gross effects of educational resources in the Norwegian university sector on the subsequent labour market outcome of recent graduates. Society spends an increasing amount of money on higher education, and a growing proportion of the population enters higher education. The increased financial and human investments in higher education require more insight into the use of resources and the outcome of the investments.

Objective and subjective indicators of institutional resources are measured by student composition, financial and staff resources and staffs' priorities. Graduates' outcome in the labour market is measured by job probability, skills mismatch and initial wages. The analysis is based on hierarchical linear modelling (HLM).

The results show that student composition matters: the most selective faculties reduce skills mismatch and increase wages. Wage-models show that the most selective faculties are also most equitable across age-cohorts, and that the effect of academic performance is not uniform for graduates from different faculties. We do not find significant effects of financial or staff resources or staffs' priorities.

1 Introduction

Institutions of higher education (HE) are expected to serve society with a variety of functions, assessed by cultural, political, economic, social as well as moral standards. One primary task of HE is to serve society with particular skills and knowledge. Phrased in economic terms, two narrow but important goals are to *produce graduates* and to *produce research output*. This paper focuses on the first of these goals, and it does so by investigating the production function relationship between the allocation of resources in HE and the labour market outcomes for HE graduates in Norway in 2000. The use of resources is indicated by traditional measures as expenditure per student, the student-staff ratio and the number of applicants per admitted student (intake selectivity score). These three measures capture the distribution of financial resources, staff resources and student input resources between faculties. The resource indicators are supplemented with subjective judgements of the resource situation, as assessed from the academic staffs' point of view. The combination of objective and subjective measures of resources is quite unique to this study. The outcome of the university-to-work transition is indicated by three measures; the employment probability, the incidence of overeducation and the initial wages. These output measures focus on the relevance of education to the labour market, and goes beyond many HE-studies that concentrate on effects within the educational system itself, as for instance the flow of students, satisfaction scores and educational gains (e.g. Hu & Kuh 2000, Toutkoushian & Smart 2001).

Questions related to the issue of the connection between resources and returns in HE have become relevant for several reasons. A growing proportion of the population enters HE. At present more than 50% of each cohort in Norway is expected to undertake some kind of HE before the age of 35 (Næss 2000) and the Norwegian society spends more money on education than on the health services (Try & Aamodt 2000). This also means that society may face the possibility of a spiralling growth in educational costs without concomitant increases in quality. In addition this volume of students represents human resources that obviously have several alternative uses in the labour market. From a political point of view, the increased financial and human investments in HE pinpoints the need of acquiring increased insight into the spending of resources as well as to obtain knowledge about the results of these investments.

The financing and organizational framework of Norwegian HE is centralized. The university sector is public and financed through the state budget, and there are basically no tuition fees. Even though parts of the educational system are highly selective, the effort to obtain equality of opportunity and standardisation of evaluation regimes constitute important characteristics of the system. Most subject fields impose national standards of student assessments through a body of examiners who are external to the institution. It is of interest to investigate to what extent the graduates' labour market returns correspond to the educational resources within this regulated system. Recent reforms in Norwegian HE have brought into focus how institutions use their resources, and current changes amplify the importance of using quantitative measures of institutional performance to monitor and evaluate the sector. Determining whether institutional characteristics influence student gains is therefore of urgent interest.

The hypothesis is that educational resources have a positive impact on graduates' labour market outcome, but former international studies have not succeeded in strongly and consistently confirming such a relationship. There may be several reasons for this. First, many studies cover primary and secondary education and only a few relates to HE. There is a huge time span from primary and secondary education input to subsequent outcomes for adult employees. Several intermediate factors and mediating effects may obscure the relationship. Pupils at the lower levels of education, for example, will often move between different schools and participate in continuing education to a varying degree. Second, many studies focus on long term earning effects. But workers may receive training beyond school, for example in-plant training, and vocational or general training at work may compensate for or support the impact of formal education. Third, many studies are marked by inadequate sets of data and the resource indicators are often rough. In this study, we avoid the first two limitations by focusing on short term labour market outcomes among HE graduates. By combining resource measures from different data sources, we will confront the third point directly.

Three main questions will be raised in this paper: First, to what extent can institutions of HE explain graduates' labour market outcome? Second, how do possible institutional effects work, and especially to what extent can subjective assessments of the resource situation from the university staff contribute to further evidence, as compared to the explanatory power of the traditional objective resource measures? Third, we want to investigate the interplay between institutional and individual effects. The paper is arranged as follows: The next section describes earlier research, part 3 outlines the methods briefly while part 4 describes the data. The data description is rather detailed, because we use data sets that are unknown to most people and because we introduce new resource variables. Part 5 shows the empirical results and part 6 concludes.

2 Previous Research

A large part of the research within this field is carried out in the USA, and many studies are directed towards lower levels of education. Hanushek (1997) sums up this research and concludes that no strong and consistent connection exists between school resources and pupil outcome. Hanushek's interpretation of this result is that in many ways the school's use of resources is inefficient, and that more knowledge is needed about *the use* of resources. Upon re-estimating Hanushek's material, others have concluded that allocation of resources is indeed of importance to the quality of the schools (e.g. Krueger 2003).

Reviews of the more limited number of studies of HE within this field often conclude in concord with Hanushek. Astin (1991) sums up earlier research by claiming that there is no systematic connection between institutional factors and the students' returns. Pascarella & Terenzini's (1991) overall conclusion is that institutional characteristics are not linked with major differences in net impacts on students, apart from a moderate impact of selectivity on earnings.

Several studies have supplemented the picture in recent years. Rumberger & Thomas (1993) investigate the relationship between an institutions' selectivity, college major and educational performance (measured by self-reported college grades) on the one hand and recent graduates' earnings on the other hand. They find that initial earnings are influenced by all three qualitative factors, and such factors will also be included in the present study.
The positive relationship between selectivity and earnings, in the sense that those institutions having the most restrictive intake regime contributes to the highest returns, is also found by James et al. (1993). Expenditures per student, on the other hand, have no such impact. The relationship between selectivity and subsequent earnings is also confirmed by Fox (1993), Loury & Garman (1995) and Thomas (2003). Many related US studies focus on the question whether it is profitable to be educated at the expensive – but prestigious – universities (Brewer & Ehrenberg 1996; Eide et al. 1998; Brewer et al. 1999). This question is tied up to particular features of the US educational system with large variation in tuition fees, and is only to a less extent applicable to Norwegian conditions characterised with a public HE system without such fees.

Robst (1995) examines the relationship between college quality and skill mismatch, and finds negative effects of three different college quality measures (intake selectivity, expenditure per student and prestige rating) on the likelihood of being overeducated. Hu & Kuh (2000) test a learning production function where subjective and objective institutional measures are used to explain student learning. They find that the subjective measures are better predictors than the objective institutional characteristics. The subjective measures are constructed from students' assessment of aspects of college environment. Toutkoushian & Smart (2001) find that expenditure per student and selectivity are positively related to the students' self-perceived educational gains. However, they report no clear evidence of the impact of student-staff ratios.

Recent European studies include Bosker et al. (2001), who find systematic institutional effect – although rather weak – with respect to labour market outcomes both regarding job entry, skill-match and wages in Holland. In a study from UK, Belfield & Fielding (2001) find positive basic correlations between expenditure per student or student-staff ratios and graduates' subsequent earnings, but these correlations are significantly reduced and no substantively significant results are found when other controlling factors are included.

All in all, previous research shows ambiguous results. No clear conclusions can be drawn, although the evidences concerning the impact of resources related to the composition of the student body (selectivity) seem to be more convincing than the evidence concerning the impact of financial or staff resources. [1]

[1] Selectivity may produce a motivation effect among the admitted students which partly compensates for other weaknesses of the institution related to the social climate, the quality of teaching and instruction, teaching facilities, etc. The motivation caused by the knowledge of being among the chosen ones (the selected) increases the level of overall satisfaction among Norwegian students (Wiers-Jenssen et al. 2002). This normally leads to self-confidence, stronger efforts, endurance and better results (Bandura 1977).

3 Methodology

The question in focus is related to how differences in resources may contribute to explaining variations in the graduates' labour market returns. These returns can be tied to individual factors like the human capital level as well as to demography and to institutional factors like resources. Graduates may also be affected by grouping effects at the institutional level. This means that groups of students are nested within institutional units. Thus, students are neither statistically nor substantially independent from each other. One method of dealing with such data structures is provided by multilevel model analysis.

Three important arguments for using this approach can be mentioned briefly.[2] First, the multilevel model handles the problem of dependency of observations. This problem arises when graduates from one institution are more closely resembled with each other than with graduates from other institutions. Second, this technique takes account of the fact that there are different numbers of observations at the two levels respectively. In our case, the number of graduates is much larger than the number of institutions. The multilevel model includes the proper sample size in the statistical tests at each level simultaneously. Third, the model treats each level explicitly, making it easier to interpret the effects of each level. If the model structure is presented without consideration to the nested structure of observations, one may easily analyse the data at one level and draw conclusions at another level. In the literature this is referred to as "the fallacy of the wrong level". Previous research on school resources that have used multilevel analysis includes Rumberger & Thomas (1993), Hu & Kuh (2000), Bosker et al. (2001), Belfield & Fielding (2001) and Thomas (2003).

Let Y_{ij} represent the dependent variable measuring labour market outcome for individual *i* in institution *j*. This is a 2-level nested structure, where level 1 refers to the individual level and level 2 to the institutional level. The model can be presented in the following simple form:

(1) $$Y_{ij} = F(\alpha_{1j} + \beta_{1j}X_{ij})$$

(2) $$\alpha_{1j} = \alpha_2 + \beta_2 Z_j + \varepsilon_{2j}$$

(3a) $$\beta_{1j} = \gamma$$

X_{ij} represents the individual variables of graduate *i* in institution *j*; Z_j is the institutional variables for institution *j*; α_{1j} and α_2 are intercepts at level 1 and 2 respectively; β_1 and β_2 are the coefficients describing the relationships between the variables at level 1 respectively level 2 and the labour market outcome. Equation (1) describes a structural model at level 1 where the relationship between individual factors and outcomes are supplemented with an institution-specific intercept. Equation (2) is a structural model at level 2 explaining the intercept as a function of a mean intercept across all institutions plus the effect of institutional attributes and

2 We will not describe multilevel models in detail, but refer the interested reader to more thorough introductions like Goldstein (1995), Hox (1995), Snijders & Bosker (1999) or Raudenbush & Bryk (2002).

an error term ε_{2j} at level 2. This second level intercept is assumed to have mean 0 and constant variance. The specification of the error term at level 1 depends on the link function F(η). In the wage-level models, the linear identity link function is specified:

(4) $F(\eta) = \eta + \varepsilon_{1ij}$

where $\eta = \alpha_{1j} + \beta_1 X_{ij}$ and ε_{1ij} are the error term at level 1, assumed to have mean 0 and constant variance. Models predicting the probabilities of job or overeducation use the logit link function to ensure that the predictions are constrained within the interval (0,1):

(5) $F(\eta) = \log [\ 1 / \{1+\exp(-\eta)\ \}\ ]$

As a starting point equation (3a) specifies the regression slopes at level one as fixed. To extend to the model above, random slopes for chosen first-level variables are introduced in order to investigate whether the effects of these variables vary across institutions:

(3b) $\beta_{1j} = \gamma + \mu_j$

As a final expansion of the model, institutional factors are included in order to explain variation across institutions in equation (3c):

(3c) $\beta_{1j} = \gamma + \delta\ Z_j + \mu_j$

Institutional variables explaining the slopes of individual effects generate interaction terms between the first and the second-level variables. Only significant institutional variables from the previous steps are retained in this final model. Models employing relation (3a) is referred to as fixed-effect models, and those using (3b) or (3c) are called random-coefficient models.[3]

The models assume that labour market outcomes are a function of the individual and educational background characteristics. Job-specific variables like sector, industry, occupation, firm- size, etc. are not included in the models predicting overeducation or wages. The assumption underlying this choice of model specification is that all job-related variables are regarded as outcome variables, and such variables should not be held constant in the model (Belfield & Fielding 2001). Our task is not to disentangle all the job-specific elements that may explain mismatches or wages within a certain job, but to estimate gross effects of educational resource variables. In section 5.3.3 we will discuss this question in further detail and show the implication of including job characteristics in the estimations.

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3 Parameters are estimated by HLM5, using full maximum-likelihood estimation in the wage model and penalized quasi-likelihood estimation in the logit models.

The institutional unit of the analysis is faculty, which is an administrative unit of departments within a university, and Z represents resource variables at the faculty level. The faculty level is further described and discussed in the next section.

Resources are also indirectly related to subject field through the national finance model, and graduates are clustered in subjects as well as in faculties. This structure could invite to the addition of subjects as a third level of the hierarchical model. Faculties, however, are not clustered into subjects or vice versa. The relation between faculties and subjects are complex in the HE system of Norway, blurring the nested structure. Thus, we chose to include major subjects among the personal attributes X in the analyses as a measure of educational experience and individual credentials, in line with other studies in this area (Thomas 2003).

4 Data

Individual data are drawn from the NIFU Graduate Survey 2000. This survey comprises university graduates with four to six years of HE. The respondents graduated in the spring terms and were followed up by a questionnaire half a year later, when most of them had entered the labour market. Graduates from the four Norwegian general universities and from three specialised universities are included in the analysis in this paper. The three specialised universities are Norwegian School of Economics and Business Administration, Agricultural University of Norway and The Norwegian School of Veterinary Science. The overall response rate is 70%.

The study focuses on the university-to-work process. For that reason, graduates who continued to study and who did not search for a job are excluded from the data set. The proportion of excluded respondents is 4% (79 persons) of the initial sample, leaving us with a final sample of 1887 graduates nested within 34 faculties.

Table A1 in the Appendix shows the distribution of dependent and independent variables used in the analysis. Three different measures of the short term job outcome are included: the job probability, the probability of overeducation and the wage level.[4] In the sample, 90% are employed at the time of the interview. Among those employed, 19% state that they have more education than their job requires. This measure for overeducation is a subjective assessment of skills mismatch.[5] Among full-time wage earners, the monthly wage is NOK 23 083 or 2885 €.[6] The wage models uses log-wage as the dependent variable in order to make it invariant to exchange rates and inflation.

Demographic variables include gender, age and family situation by indicators for married or cohabitant graduates and responsibility for children. These variables indicate the degree of economic dependency, and may affect both the graduates' reservation wage and their job probability. Children may affect men and women differently, and this will be accounted for by an interaction term. Social background is measured by parents' educational level. In addition, an indicator for non-western immigrants is included in the model.

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4 For the analyses of job entry, the total sample is used. For the overeducation analyses, the sample is restricted to those graduates who held a job at the time of the survey, amounting to 1707 cases. For the wage analyses, the sample is restricted to full-time wage earners, amounting to 1294 cases.

5 Other methods used to determine the mismatch between the skills workers possess and the skills their jobs requires are the objective method based on some independent assessment of skill requirement or the comparative method where the education levels of current job holders are compared with those of other current or past job holders. Each method has limitations but all has been used in past research (Hartog 2000, Borghans & de Grip 2000).

6 Wages are measured as monthly earnings before tax, not including overtime or extra income. Part-time workers are excluded from the wage analysis because it is not possible to convert monthly income to hourly wages. Self-employed are excluded because their income may include returns to capital investment and since unmeasured variation in working time complicates the comparisons.

The dispersion of education and work experience in years is limited in the sample, as all respondents are university graduates with a final degree. For this reason, we diverge from the Mincerian measure of experience and education in years, and only include dummy indicators for those who have earlier work experience (of at least three months duration) or tertiary education additional to the education included in the degree in question.

The graduates are grouped in seven main subject fields. The normed duration of the different subjects varies by a few years, even though all subjects lead to a major degree. The business administration (B&A) study is the shortest, requiring 4 years of tertiary study, while the other subjects generally requires between 5 years of study (natural sciences, primary industry sciences and most of the health care sciences) and 6 years of study (law and most fields within humanities and social sciences).[7] Natural science is the largest group in the sample and B&A is the smallest.

In addition to field of study, we separate the human-capital level by achieved grade level (marks), as a measure of academic performance. Most graduates in the sample received grades within the range of 1.0 and 4.0, with 1.0 as the best grade level. Nevertheless, grades across subject fields are not a standardised measure. Grades vary systematically from subject to subject. For instance, the average grade level of 2.2 is an outstanding grade in law, but a rather poor grade in the natural sciences. For this reason, grades are normalised within subject fields with mean 0 and standard deviation 1.[8] In addition, the scale is inverted. Thus, the better the grade level, the higher is the value of the z-score. The grade level is unknown for 2% of the sample, and their z-score is set to the average 0 in the analyses. It could be discussed whether academic performance should be treated as a dependent or independent variable in the analyses. One important reason for including academic performance among the independent variables is that we want to investigate the connection between institutional factors and individual performance. In addition, the inclusion of academic performance may compensate for the lack of intake ability scores, because of the high correlation between intake and outcome scores (Baird 1985, Anaya 1999). We will discuss this question in further detail in section 5.3.2.

The unit of analyses at institutional level is the faculty. Faculty is an administrative unit for different departments covering specific disciplines (e.g. sociology) within a broader academic field (e.g. the social sciences). This is the central unit in the national HE finance model in Norway at the time of the surveys, with lump-sum allocation from the state to the universities followed by target figures on student and graduate numbers on faculty level published in the state budget.[9] Student mobility is also large within each faculty, and students generally

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7 The health care sciences include pharmacy, dental studies and veterinary medicine, but do not include general medicine.

8 For those graduates that follow other grade level systems than 1.0-4.0, we have normalised within the system. After normalisation, we find no indication of different grade regimes across institutions (Try 2000). A national grade level system within subjects is maintained by the external examiners.

9 The national finance model of HE is changed from 2003, as a part of the “Quality of HE – reform”.

compose a university degree containing subjects from different departments within the same faculty. Faculties thus seem to be the most relevant institutional unit to focus on, both seen from the graduates' as well as the resource point of view.

Faculty level characteristics are either collected from registers or from the NIFU University Survey 2000 (Table A1). The latter is a questionnaire study among all faculty members of the rank of assistant professor or higher at the same universities as above. The response rate is 60%. There has been a slightly declining response rate over time in these types of studies, partly reflecting a general overload of surveys of different kinds. Compared to international studies, the response rate is acceptable (e.g. Altbach 1996).

The three objective resource measures are the student-staff ratio, selectivity and expenditure-per-student. Student-staff ratio is defined as the %-share of registered students per academic staff members of the rank of assistant professor or higher. This is a relative measure of student crowd or teaching load per staff member. Selectivity relates to the admission of students and is defined as the ratio between the number of applicants and the number of admitted students at each faculty. The more applicants behind each admitted student the more popular is the faculty, and selectivity is thus a measure of the excess in student demand. In this paper selectivity is used as an imperfect indicator of initial student body quality. However, high quality studies may have lower scores on this particular selectivity measure than the most popular subject fields have at the time, because of self-selection of applicants to studies with strict admission demands.

Expenditure-per-student covers spending on wages and operating costs per registered student. This is a problematic measure for several reasons. One problem is related to the large variations in operating costs between disciplines due to different teaching requirements. For example, equipment related to teaching in health care sciences like veterinary science or dentistry is much more expensive than equipment generally required within traditional academic subjects like humanities or social sciences. To some extent such differences across subjects can be controlled for by including subject variables in the analysis, but the problem may still appear at a finer level. A second problem is related to how one should treat common costs at university level. The division between faculty costs and common costs in the universities accounts may be determined by institutional or organisational conditions as well as by arbitrary accounting practice. In the expenditure data used in this analysis, the common costs are divided proportionally at faculty level. The expenditure data thus deviates somewhat from the official numbers.[10] A third problem is that expenses on research and other activities may obscure the actual resources used on teaching and education.

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[10] Expenditure at faculty level is derived from NIFU Database on resources and expenditures in HE. The expenditure in this register deviates from the official Database on HE in two respects: First, the common costs are proportionally distributed at faculty level according to scale of wage costs. Second, the gross figures from the faculties' accounts are adjusted according to OECD (1994) in order to achieve true expenditure at institutional level. The expenditure-per-student variables based on the two alternative measures are highly correlated (r=0.92, p=0.00). We prefer the adjusted expenditure data though, because it treats the common

The problems related to the objective resource measures underline the importance of having access to alternative measures of the resource situation. The academic staff is asked to assess the resource situation within their department according to a panel of statements. From this panel, we use the aggregated answers on faculty level from the three statements that seems most concrete and theoretically interesting. The first statement is: "The teaching suffers from scarce resources". The staff is asked to assess this measure on a 5 point scale.[11] This variable can be interpreted as a subjective alternative to the objective expenditure-per-student variable. However, the correlation coefficient between the two variables (r=0.18, p=0.30) suggests no connection between the objective measure and the subjective assessment, supporting the view that the budget allocation across faculties to a large extent is based on subject-specific conditions. The correlation matrix between resource variables is displayed in Table A2 in the Appendix.

The *Heterogeneous student body*-variable (HSB) is derived from the statement: "The teaching is hampered by large differences in level of knowledge among students". This variable can be interpreted as an alternative to the objective selectivity measure, but with opposite sign (r=-0.52, p=0.00).

The last variable – *Uninterested staff* – is derived from the statement: "Low interest/priority among academic staff makes an important hindrance for better teaching". This variable has no direct parallel among the objective measures, but is nevertheless correlated with the student-staff-ratio (r=0.37, p=0.03), suggesting that heavy teaching load may reduce the staffs commitment.

costs thoroughly. It turns out, however, that the results of the analyses are invariant to the choice of expenditure measure.

11 Values for the three subjective variables are defined as follows: "Agree strongly"=2; "Agree weakly"=1; "Neither nor"=0; "Disagree weakly"=-1; "Disagree strongly"=-2.

5 Results

5.1 Analysis of Variance

The first step in multilevel modelling is usually to calculate the proportion of variability in the dependent variable that can be ascribed to the individual level and to the group level respectively. This is done by estimating a base model that is equivalent to a one-way random-effect ANOVA. This model has no level-1 or level-2 predictors, equal to constraining $\beta_1=\beta_2=0$ in our model (1)-(3a). The purpose is to estimate institutional level variance in labour market outcome as a proportion of total variability in the outcome variable, or the intra-class correlation coefficient ρ. In the wage level model with the identity link function (4), the decomposition of the variability within institutions or among graduates (pooling variances calculated within each institution) and variability due to between-institution differences is straightforward. Table 1 shows that 13% of the total wage variance is a function of between-institution differences.

In the logistic model case, with the job-probability or the probability of overeducation as dependent variables, the error term at level-1 does not appear explicit in the link function (5) and the within-institution variance is not directly available. There are several definitions of "quasi intraclass correlation coefficient" in this case, and here we take advantage of the property of the logistic distribution, implying a level-1 residual variance of $\pi^2/3$ (Snijders & Bosker 1999). The "quasi intraclass correlation coefficient" can then be calculated to 7% for the job-probability and to 11% for the probability of overeducation.

Table 1: Residual variance components and intraclass correlation coefficients

	P[job]	P[overeducation]	ln(wage)
Variance between graduates, $\sigma^2(\varepsilon_{1ij})$	–	–	0.026
Variance between faculty, $\sigma^2(\varepsilon_{2j})$	0.250	0.394	0.004
Intraclass correlation coefficient, ρ (1)	0.071	0.107	0.133

– not available

Note 1: The intraclass correlation coefficient for the logistic models is estimated in accordance with Snijders & Bosker (1999, p: 224): $\rho = \sigma^2(\varepsilon_{2j}) / [\sigma^2(\varepsilon_{2j}) + \pi^2/3]$.

These results show that the labour market outcomes can mainly be explained by the distribution of individual attributes, suggesting that students are the primary actor in HE. A moderate but statistically significant part of the variance in graduates' employment outcome is a function of between-institutional differences. Subsequently this variability of institutional means will be modelled by using alternative resource variables.

5.2 Structural Fixed-Effect Models

Table 2 shows the results from the structural fixed-effect model with the objective resource variables included. In judging the coefficient estimates, we should keep in mind that the significance tests for individual level variables are conducted on the basis of the number of graduates, while the significance tests for faculty level data are based on the number of faculties. Due to the limited number of faculties (34), we will comment on faculty-level effects where $p<0.1$, while we only discuss those individual-level variables where $p<0.05$.

Among the objective resource measures only selectivity has a significant impact, and only on the probability of being overeducated and on the wage level. The job-probability is not affected by any of the faculty variables. On the margin, increasing the selectivity score by 1 unit decreases the probability of overeducation with 2 percentage points from the mean and increases the average wage level with 2%.[12]

Turning to the individual level data, all demographic variables have significant effect on at least one of the dependent variables. Female graduates without children have higher job-probabilities (3 %-points) [13] but also higher probabilities of being overeducated (6 %-points) and they receive lower initial wages (-4%) compared to their male colleagues. Females with children have a significant and substantially lower job-probability than females without children, reducing the mean probability with 18 percentage points, while children have no effect on males. Married or cohabitant graduates have a higher job probability (3 %-points) than other graduates. Age is positively correlated with wages, with an estimated elasticity of 0.29.

The social background of the graduates has no effect on their labour market outcome. It is noteworthy that non-western immigrants have lower job-probabilities than others, reducing the mean probability of obtaining a job with 11 percentage points. Once non-Western immigrants have a job, we cannot conclude that they are overrepresented among the overeducated or that they receive lower wages than others. These results are in line with Støren (2002), who also found that non-Western-immigrants have lower job-probabilities but the same skill-usage as others in a study of graduates over several cohorts. One explanation could be that the non-western graduates are a selected part of the minority population, and those who are employed are even more selected.

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[12] The quantitative effect from the logistic models is calculated on basis of the logit-value (η_0) that gives the mean probability $F(\eta_0)$. In other words, the reference person has the attributes corresponding to mean probability through the link-function (5). In this case, the mean probability of overeducation $F(\eta_0=-1.45)=0.19$ compared to $F(\eta_0 - 0.123)=0.17$. For the wage model, the quantitative effect in percent is 100*exp(coefficient)-1, which is equal to 100*coefficient for small values.

[13] For the job-probability, $F(\eta_0=2.197)=0.90$, in this case compared to $F(\eta_0 + 0.440)=0.93$.

Table 2: Job, overeducation and wage model estimates with objective resource measures. Multilevel analyses.

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty level data:						
Intercept	-1.585	2.389	-0.937	1.792	8.921***	0.116
Student-staff ratio	0.022	0.013	-0.008	0.012	0.000	0.001
Selectivity	0.026	0.054	-0.123*	0.065	0.018***	0.004
Expenditure per student	-0.002	0.003	0.002	0.004	0.000	0.000
Graduate level data:						
Female	0.440**	0.183	0.340**	0.148	-0.036***	0.009
ln(age)	0.738	0.693	0.123	0.508	0.290***	0.033
Married/cohabitant	0.401**	0.178	-0.212	0.142	0.021*	0.009
Children	0.305	0.394	0.211	0.286	-0.016	0.018
Female*Children	-1.243***	0.471	-0.243	0.382	-0.017	0.025
Mother higher education	0.069	0.188	-0.005	0.152	0.001	0.010
Father higher education	0.142	0.185	-0.056	0.150	-0.007	0.010
Non western immigrant	-0.876**	0.412	-0.520	0.574	-0.052	0.032
Work experience	0.826***	0.206	-0.871***	0.159	0.037***	0.009
Additional education	-0.180	0.207	-0.168	0.177	0.007	0.011
Grade level (z-score)	0.129	0.086	-0.383***	0.070	0.026***	0.004
Grade level unknown	-0.258	0.473	0.447	0.435	-0.028	0.031
Social sciences	0.433	0.383	0.543*	0.321	-0.016	0.021
Law	-1.291	0.876	0.841	0.725	0.008	0.045
Natural sciences & Technology	0.239	0.320	-0.139	0.355	0.058***	0.021
Health care sciences	0.326	0.477	-1.115**	0.542	0.048**	0.024
Primary industry sciences	0.764	0.517	0.332	0.443	0.002	0.027
Business administration	1.618**	0.732	-0.791	0.663	0.177***	0.034
Model statistics:						
Variance between graduates	–		–		0.022	
Variance between faculty	0.104		0.238***		0.001***	
Deviance	–		–		-1245	
Number of graduates	1887		1707		1294	
Number of faculties	34		34		34	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

Graduates with earlier work experience have significant higher job-probabilities (5 %-points), lower overeducation-probabilities (-10 %-points) and higher wages (4%) than others. Academic performance affects type of job. Increasing the grade-level z-score by 1 unit leads to a 5 percentage point reduction in the mean probability of overeducation and a 3% increase in the average wage level. Grade level has no impact on the job-probability, a result that could be ascribed to the boom at the time of the survey. In 2000, the economic activity was high in Norway, with strong demand for labour and low levels of unemployment (OECD 2001). In a favourable labour market like this most graduates get a job. They do, however, queue up for "good jobs" partly according to grades.

The labour market outcome is most favourable among business and administration (B&A)-graduates. Compared to the mean, the B&A-graduates have a job probability that is 8 percentage points higher and receive a wage level 19 percent above average. The latter result

Table 3: Job, overeducation and wage model estimates with subjective resource measures. Multilevel analyses.

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty level data:						
Intercept	-1.460	2.414	-3.150*	1.844	9.033***	0.120
Scarce resources	0.037	0.386	-0.127	0.409	0.037	0.027
Heterogeneous student body	-0.034	0.380	1.126**	0.437	-0.076***	0.026
Uninterested staff	-0.243	0.596	-0.855	0.596	0.003	0.043
Graduate level data:						
Female	0.420**	0.184	0.346**	0.148	-0.034***	0.009
ln(age)	0.791	0.692	0.323	0.507	0.285***	0.033
Married/cohabitant	0.422**	0.178	-0.198	0.142	0.020**	0.009
Children	0.238	0.392	0.235	0.285	-0.016	0.018
Female*Children	-1.160**	0.469	-0.275	0.381	-0.019	0.025
Mother higher education	0.073	0.188	-0.003	0.152	0.001	0.010
Father higher education	0.139	0.185	-0.054	0.150	-0.006	0.010
Non western immigrant	-0.860**	0.412	-0.488	0.572	-0.053	0.033
Work experience	0.826***	0.206	-0.859***	0.159	0.034***	0.009
Additional education	-0.161	0.207	-0.174	0.177	0.006	0.011
Grade level (z-score)	0.133	0.086	-0.387***	0.070	0.027***	0.004
Grade level unknown	-0.288	0.471	0.430	0.433	-0.018	0.031
Social sciences	0.707*	0.403	0.640**	0.319	-0.003	0.023
Law	0.290	0.511	1.031**	0.495	0.030	0.033
Natural sciences & Technology	0.222	0.340	-0.273	0.323	0.106***	0.024
Health care sciences	0.260	0.466	-0.738	0.490	0.061**	0.027
Primary industry sciences	0.631	0.540	0.217	0.417	0.046	0.030
Business administration	1.945**	0.795	-0.312	0.681	0.181***	0.044
Model statistics:						
Variance between graduates	–		–		0.022	
Variance between faculty	0.160**		0.186***		0.001***	
Deviance	–		–		-1232	
Number of graduates	1887		1707		1294	
Number of faculties	34		34		34	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

is consistent with other studies that have examined differences in the initial and subsequent earnings of college graduates across majors in USA (Rumberger & Thomas 1993, Thomas 2003). If differences in labour market prospects across subjects are lasting and well-known, they could influence the choices that students make when deciding what major to select in college. The estimated differences across subjects could therefore partly be a result of self-selection, which is the case in all studies of these types (Thomas 2003).

Table 3 shows the results from the same structural multilevel models as above, but now the objective resource variables are substituted with the subjective indicators. Basically the effects of the graduate level variables are not affected by this change in the specification of the model. The only difference worth mentioning is the change in some of the subject-major variables contained in the overeducation model. Law graduates now face a significantly higher probability of overeducation compared to the reference group (humanities), and the health-care science variable is no longer significant. The sensibility of the subject-major variables to the introduction of new institutional variables illustrates the inter-relationship between faculty and subject fields.

Introduction of a subjective resource indicator does not alter much of the faculty effect either. Neither scarce resources nor the staffs' interest level have significant impact in any of the models. The only variable that matters is the one for heterogeneous student body (HSB). A one unit change in the HSB-variable is followed by an increase in the probability of overeducation of 23 percentage points from the mean together with a 7% reduction in average wage level.

The results in Table 2 and 3 are consistent: the faculty level variables representing student composition has effect on the quality of the first job. Student resources are important, but we cannot conclude that financial or staff resources or staffs' priorities affect graduates' subsequent labour market outcomes.

5.3 Alternative Estimation Procedures and Model Specifications of the Fixed-Effect Model

5.3.1 Comparison Between Individual Level and Multilevel Analyses

All models presented above are re-estimated by ordinary least square (OLS) or ordinary logit models at individual level, see Table A3-A4 in the Appendix. The results from the multilevel analyses are close to those observed at the individual level in terms of coefficient estimates, but the standard errors for the coefficients are generally smaller in the individual analyses. It is usually the case that the individual-level standard errors are underestimated because of the dependence among individuals within groups. In addition, the faculty-level variables are counted with the individual number of observations in the individual level analysis. As a consequence one would be more likely to conclude that an effect is statistically significant in an individual-level analysis, even though the magnitude of the coefficients are robust and generally similar to those obtained from the multilevel analysis (Ethington 1997, Raudenbush & Bryk 2002). This is especially the case with the faculty-level variables in our analyses.

In the individual-level analysis with objective resource measures in Table A3, the student-staff ratio turns out to be significant in the job-probability model. In the individual-level analysis with subjective resource measures in Table A4, the indicator for uninterested staff is significant in the overeducation model and the indicator for scarce resources turns significant in the wage model. If we had based the analyses on ordinary logit-model or OLS at the individual level, we might therefore have concluded that the student-staff ratio has a positive impact on the students' subsequent job probability (!); that students graduating from institutions where the academic staff is uninterested are associated with low probabilities of being overeducated (!); and that scarce resources within an institution have a positive effect on graduates earnings (!). All these results are contrary to the expectations. None of these results turned out to be significant in the multilevel analysis. We did not, on the other hand, find any significant results in the multilevel analysis that were not confirmed in the individual-level analysis. The results illustrate the major difference between the two analytic techniques and underline the necessity to base the different parts of the model estimations on the right level.

5.3.2 Fixed-Effect Models Excluding Academic Performance

It may be argued that grades should not be included among the independent individual variables in the model because academic performance is the outcome of education according to human capital theory. When we control for students academic performance, we may expect rather small effects of faculties, since the direct human capital effect on academic output is levelled out. Table A5 and A6 in the Appendix show the results of estimations without the grade variable included in the model. The effects are actually weakly affected by this change in the specification of the model. The impact of faculty variables seems to be robust across model specifications. Thus, we may conclude that grades do not remove an initial difference across faculties. We will therefore continue to include academic performance in the following analysis, because we – among other things – also want to investigate the relationship between institutional factors and individual performance. In addition, the wage models with grades included fits better than does the restricted model, tested by difference in deviance (significant at 1%-level by χ^2, d.f.=2). [14]

5.3.3 Fixed-Effect Models with Job-Characteristics

Our task is to estimate gross effects of education. As a consequence, no job-related variables are included in the model, since such factors may be regarded as outcomes in the labour market. At the same time, the educational institutions and the labour market represent two sides of an inter-dependent system. Institutional effects of education on labour market outcomes could be interpreted as at least partly structured by the labour market itself. There is always the possibility that statistical associations depict causality both ways, and even spurious relationships. Introduction of job-specific variables in the model may help to strip the statistical effects of institutions of potential external influences, but may at the same time remove important outcome effects. It is therefore an open question whether we should include job-specific factors or not. In our main models, we chose to exclude such factors. In this section, we illustrate the implication of including job-specific variables in the overeducation model and the wage model. These models may visualise the content of the gross educational effects. In a thoroughly regulated labour market, job quality (skill-match and wage level) may be tied up to job-characteristics related to sector and contract.

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[14] A similar test cannot be applied for the binary models because deviance is not calculated in the logit case.

We lack strong indicators of demand-side features on the labour market. Available variables are sector and contract form (permanent versus temporary contract, with research fellowship as an intermediate contract form with 3-4 years of fixed-term contract).[15] In addition, variables for self-employed and part-time workers are included in the overeducation model, while these workers are not included in the wage model.[16]

Table A7 and A8 in the Appendix display the results of the estimations with sector and the other job-specific variables included in the models. Both sector and contract form have impact on skills-mismatch and wages. Graduates working in private sector are more often overeducated than those in public sector, but the wage-level is also significantly higher in private sector. The temporary employed have higher probabilities of being overeducated and they receive lower wages than those engaged on permanent contracts (reference group). Research fellows also receive significantly lower wages than those on permanent contracts, and even though the coefficient of being overeducated is not significant (because of a small number of observations) the size of the coefficient is high and negative, implying that research fellows are rarely overeducated. Finally, part-time workers are more often overeducated than full-time workers.

Controlling for sector may potentially explain some of the faculty effect of selectivity and student composition that we found in section 5.2, because of the important role of public sector in Norway and the differences in wages and skills-mismatch between sectors. But sector does not change the effect of selectivity and student composition. The coefficient estimates of selectivity in Table 2 and the heterogeneous-student-body (HSB)-variable in Table 3 are almost the same as in the comparable models in Table A7-A8 where sector is introduced. But when we include the other job-specific variables in addition, the effects of selectivity and student composition are roughly halved, but they are still significant in most model alternatives.

Thus, we can conclude that the impact of selectivity and student composition cannot be explained by the allocation of graduates across public and private sector in the Norwegian labour market. On the other hand, about half of the effect can be traced back to the distribution of job contracts (temporary or permanent contracts, part-time or full-time jobs). Such job features can be viewed as important outcome variables in the labour market, and one should be careful to include such factors when estimating gross effects of education.

5.4 Random Coefficient Models

The results above are based on fixed-effect models. Here the intercept coefficient α_{1j} is random across institutions, while the slopes β_{1j} are constrained to have a common effect for all groups.

15 In our sample, 46% of the employed graduates report to work in the private sector, 49% in the public sector while the sector is unknown for the remaining 5%. 52% of the employed graduates work in permanent contracts, 40% are in temporary contracts while 5% are engaged as research fellows.

16 Among the employed graduates, 3% are self employed and 13% are part-time workers.

In this section, we will extend the analysis to random-coefficient models. In these models, the slopes are conceived as varying randomly across faculties. As we are primarily interested in gross effects of education, job characteristics will not be included in the models.

Table 4: Alternative job, overeducation and wage model estimates. Multilevel analyses.

	P(job)				P(overeducation)					
	Model 0		Model 1		Model 0		Model 1		Model 2	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty data:										
Intercept	-1.358	2.316	-1.492	2.305	-2.813	1.773	-2.712	1.773	-2.858	1.776
HSB					1.081**	0.415	1.160***	0.408	1.418***	0.455
Graduate data:										
Female	0.425**	0.183	0.560*	0.295	0.349**	0.148	0.371**	0.166	0.685**	0.281
ln(age)	0.791	0.686	0.818	0.683	0.285	0.505	0.253	0.506	0.243	0.506
Married/cohab.	0.414**	0.178	0.412**	0.180	-0.205	0.142	-0.203	0.142	-0.210	0.142
Children	0.245	0.391	0.250	0.399	0.252	0.285	0.274	0.285	0.286	0.285
Female*Children	-1.158**	0.468	-1.125**	0.479	-0.289	0.381	-0.338	0.383	-0.348	0.383
Mother higher ed.	0.071	0.188	0.069	0.190	-0.001	0.151	-0.002	0.152	-0.002	0.152
Father higher ed.	0.137	0.184	0.117	0.186	-0.053	0.150	-0.058	0.150	-0.051	0.151
Non western imm.	-0.873**	0.410	-0.863**	0.415	-0.492	0.572	-0.510	0.574	-0.507	0.573
Work experience	0.829***	0.206	0.829***	0.206	-0.857***	0.158	-0.855***	0.159	-0.853***	0.159
Additional educ.	-0.166	0.207	-0.145	0.209	-0.173	0.177	-0.165	0.177	-0.170	0.177
Grades (z-score)	0.132	0.085	0.131	0.087	-0.385***	0.070	-0.388***	0.070	-0.390***	0.070
Grades unknown	-0.299	0.467	-0.344	0.480	0.406	0.432	0.425	0.432	0.430	0.431
Social sciences	0.684*	0.361	0.780**	0.335	0.557*	0.301	0.520*	0.299	0.552*	0.305
Law	0.216	0.375	0.321	0.314	0.678	0.428	0.509	0.421	0.601	0.435
Natural sc.&Techn.	0.182	0.301	0.242	0.269	-0.406	0.306	-0.465	0.299	-0.477	0.308
Health care sc.	0.214	0.348	0.296	0.331	-0.866*	0.482	-0.902*	0.482	-0.942*	0.493
Primary ind. sc.	0.628	0.508	0.840*	0.474	0.078	0.405	0.072	0.394	0.038	0.405
Business administ.	1.895***	0.718	1.753***	0.659	-0.455	0.667	-0.591	0.649	-0.495	0.674
Random parts:										
Var[female]			1.298**				0.094***		0.046***	
Cross-level interaction:										
Female*HSB									-0.534	0.384
Model statistics:										
Var between fac.	0.107*		0.368**		0.181***		0.080***		0.113***	
N graduates	1887		1887		1707		1707		1707	
N faculties	34		34		34		34		34	

Table 4 continues

	ln(wage)							
	Model 0		Model 1		Model 2		Model 3	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty data:								
Intercept	8.925***	0.115	8.958***	0.159	8.165***	0.285	8.171***	0.271
Selectivity	0.016***	0.003	0.016***	0.003	0.149***	0.044	0.145***	0.042
Graduate data:								
Female	-0.036***	0.009	-0.034***	0.009	-0.034***	0.009	-0.035***	0.009
ln(age)	0.291***	0.033	0.281***	0.047	0.520***	0.084	0.517***	0.080
Married/cohabitant	0.021**	0.009	0.021**	0.009	0.021**	0.009	0.022**	0.009
Children	-0.016	0.018	-0.016	0.018	-0.014	0.018	-0.015	0.018
Female*Children	-0.016	0.025	-0.018	0.025	-0.020	0.025	-0.017	0.025
Mother higher education	0.001	0.010	0.002	0.010	0.002	0.010	0.002	0.010
Father higher education	-0.006	0.010	-0.004	0.010	-0.005	0.010	-0.006	0.010
Non western immigrants	-0.052	0.032	-0.050	0.032	-0.047	0.032	-0.046	0.032
Work experience	0.037***	0.009	0.034***	0.009	0.035***	0.009	0.036***	0.009
Additional education	0.007	0.011	0.009	0.011	0.008	0.011	0.006	0.011
Grades (z-score)	0.026***	0.004	0.019***	0.007	0.043**	0.017	0.050***	0.013
Grades unknown	-0.028	0.031	-0.034	0.031	-0.030	0.031	-0.026	0.031
Social sciences	-0.010	0.020	-0.010	0.019	-0.007	0.019	-0.006	0.019
Law	0.039	0.026	0.011	0.023	0.027	0.022	0.045**	0.023
Natural sciences & Techn.	0.056**	0.022	0.048**	0.020	0.053***	0.019	0.056***	0.020
Health care sciences	0.046*	0.024	0.053**	0.023	0.060***	0.023	0.057**	0.023
Primary industry sciences	0.000	0.028	-0.010	0.026	-0.004	0.026	-0.001	0.026
Business administration	0.187***	0.036	0.173***	0.031	0.182***	0.031	0.186***	0.033
Random parts:								
Var[ln(age)]			0.021*		0.003**		0.001	
Var[grades]			0.001***		0.0005***			
Cross-level interaction:								
ln(age)*Selectivity					-0.040***	0.013	-0.039***	0.013
Grades*Selectivity					-0.004	0.002	-0.004**	0.002
Model statistics:								
Var between graduates	0.022		0.021		0.021		0.022	
Var between faculties	0.001***		0.225*		0.034**		0.013	
Deviance	-1244		-1262		-1268		-1254	
Number of graduates	1294		1294		1294		1294	
Number of faculties	34		34		34		34	

* p<.1, ** p<0.05, *** p<0.01. – not available
HSB: Heterogeneous student body.

Table 4 shows the results of the estimations. The modelling process is based on a sequential procedure, where only significant faculty-level variables from the previous sections are retained. Then we insert a random slope on all significant level-1 variables, and keep the significant random parts. Finally, we include interaction-terms between faculty-level and graduate-level variables in order to explain the variation.

Model 0 is the fixed-effect models used as a starting point. No faculty-level variables are included in Model 0 for the job-probability because we did not find any of them significant above. Earlier we found significant effects of both the objective selectivity variable and the subjective HSB-measure in the estimation of overeducation and wages. When these two variables were introduced simultaneously, they performed rather weakly. As argued above, these two variables probably capture the same phenomenon, and they are highly correlated. For that reason, we chose only to include the best-performing variable in each model, ending up with the HSB-measure in the overeducation model and the selectivity variable in the wage model. The subjective measure gives the best prediction of skills-mismatch, while the objective measure is preferred in the wage model.

In the next step the random coefficient models are introduced, by examining possible random slopes on all significant graduate level variables. The institutional level has a random impact on all three dependent variables, and the significant random slopes are included in Model 1. In the job-probability and the overeducation models, the gender-effect varies across faculties. In the wage model, the age-effect and the grade-effect differ significantly across faculties. These results suggest that there is considerable variation among faculties. Under the normality assumption, we would expect the gender-effects on the job log-odds ratio to fall within the range of (-1.37 , 2.49) for 90% of the faculties.[17] Even if the structural parameter for the gender effect is significantly positive, there are individual faculties where the slope estimate is negative, implying that men from some faculties have higher job-probabilities than women from the same faculties, although the general picture is quite the opposite. Likewise, for 90% of the faculties we would expect the gender-effects on the overeducation log-odds ratio to fall within the range of (-0.15 , 0.89). Also in this case, individual faculties produce the opposite gender-effect than implied by the underlying structure. In terms of these models, equitable faculties would have weak differentiating gender effects, and it may come as no surprise that we find faculties where the gender-effect is around zero, meaning that male and female graduates face the same job-probabilities and probabilities of overeducation.

Plausible values for faculty-specific effects in the wage model lies within the 90% range of (0.04 , 0.53) for the age-effect and (-0.03 , 0.07) for the grade-effect. Graduates' wages can be expected to increase by age in nearly all faculties, since the value of zero is not included in the range. The grade effect varies from negative to positive values, however, implying that academic performance does not affect subsequent wages within all faculties.

In the final step, Model 2 includes the remaining faculty-level variables as a possible explanation of the random slopes. This makes up to cross-level interaction-terms. In the overeducation model, the interaction-term between gender and HSB is not significant, even though the slope variance is nearly halved (from 0.094 to 0.046). In the wage model, the introduction of level interaction-terms reduces most of the variance in the age-slope (from 0.021 to 0.003) and reduces the variance of the grade effect (from 0.001 to 0.0005). The

[17] The 90%-range is derived from the formula: $est(\beta) \pm 1.69\ [est(var(\beta)]^{1/2}$, where $1.69=t_{\alpha=0.05,v=34}$.

interaction-term between age and selectivity is negative and significant, implying that the selective faculties moderate the original age effect. The largest wage differences across age are then to be found in the least selective faculties, varying from an age-wage elasticity of nearly 0.5 for non-selective faculties to 0.1 for high-selective faculties.[18] Initially, graduates from the selective faculties have a wage premium, but the wage difference across selectivity is reduced as age increases, see Figure 1. Within 90% of the age distribution, however, the age-effect in the least selective faculties is not strong enough to fully close the gap.

The interaction-term between grades and selectivity is not significant in Model 2, although it is close to p=0.1. This interaction term turns out significant in other model specifications however, e.g. in Model 3 where the grade-slope is fixed. In this case, also the interaction-term between grades and selectivity is significant. Thus, the results are mixed and depend on model specification.[19] Based on the results from Model 3, we find that the selective faculties moderate the original grade effect. In non-selective faculties the grade-effect on wages is about (0.043-1*0.004)≈4%, while the grade-effect in the average selective faculties is reduced to (0.043-7.2*0.004)≈1½%. In high-selective faculties the grade effect is nullified (0.043-10.51*0.004≈0). One explanation for this phenomenon could be the strong signalling effect of being admitted to the selective faculties, while the non-selective faculties use grades as the signalling device. Students are either tested in the beginning or at the end of the study. But the grade-effect in the least selective faculties is not strong enough to fully compensate for the initial wage difference between high-selective and non-selective faculties, not even for the best graduates, see Figure 2.

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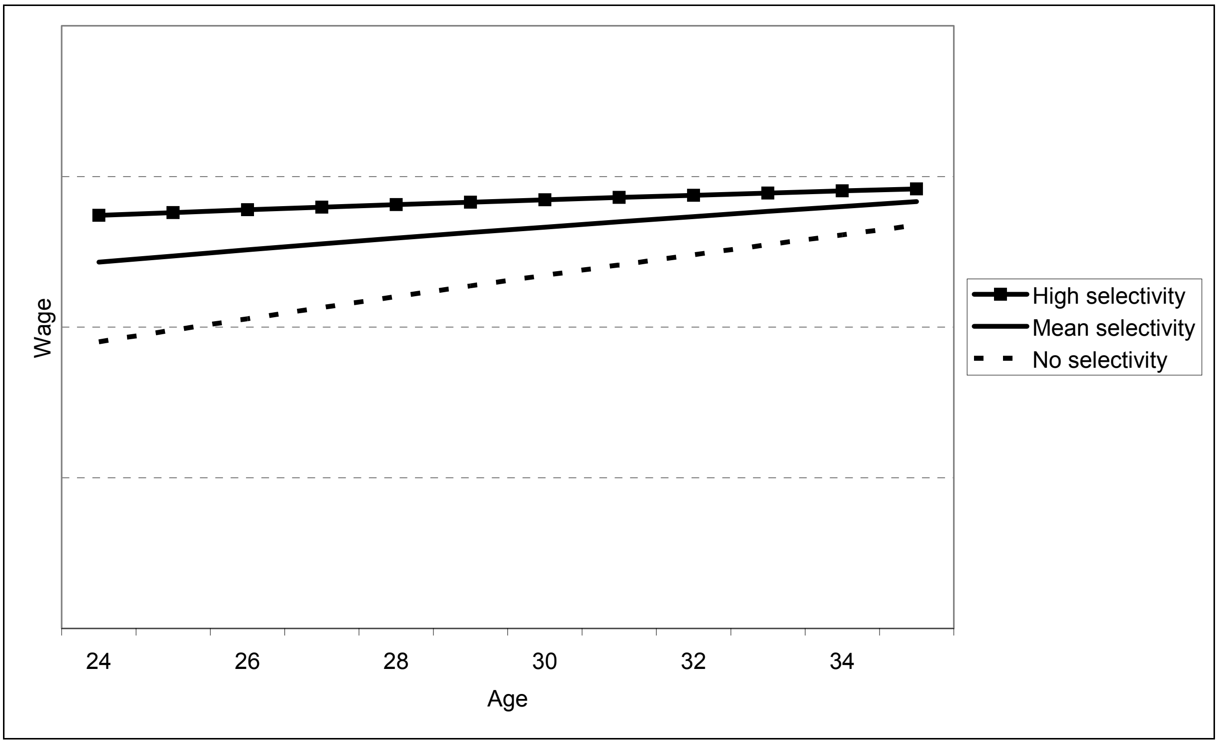
18 The selectivity-score for a (hypothetical) non-selective faculty where all applicants are admitted is 1, giving the age-effect: 0.52-1*0.04. High selectivity faculties are defined as faculties with a score 1SD above mean, that is (7.2+3.31)=10.51 from Table A1, giving the age-effect: 0.52-10.51*0.04.

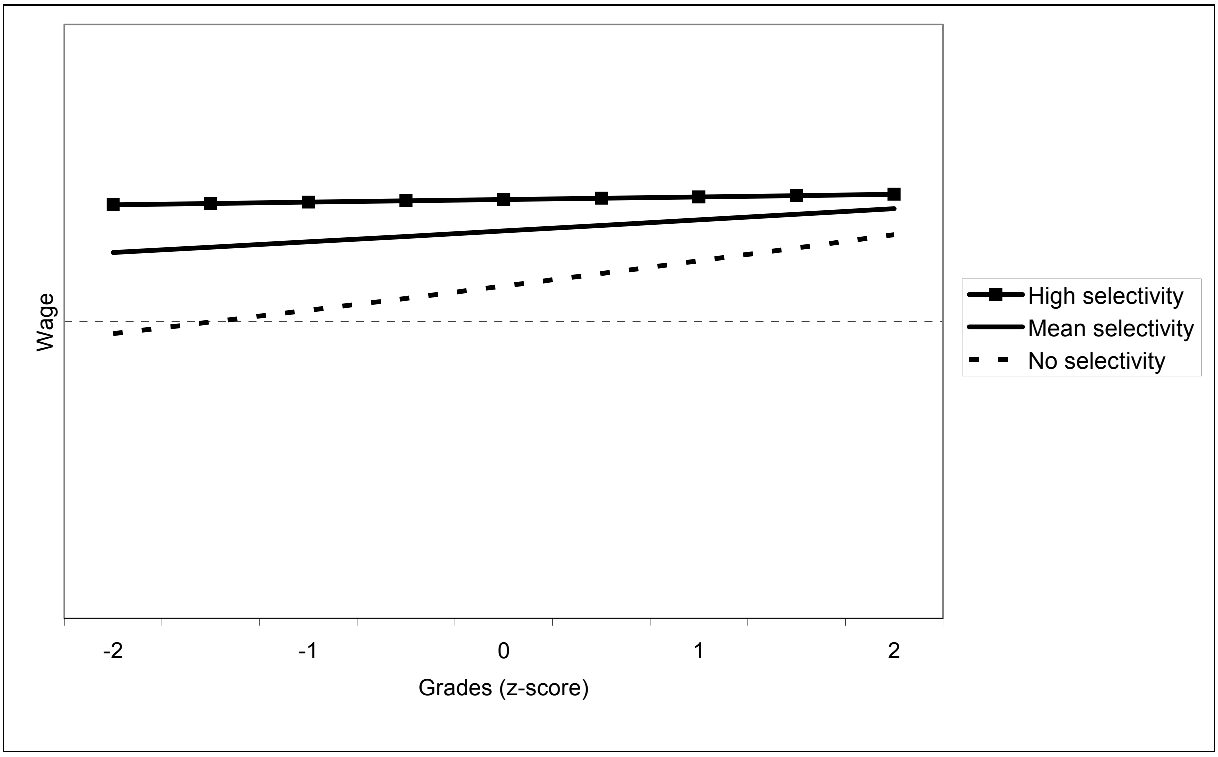
19 It should be noted that Model 2 is statistically superior to Model 3. Although the random coefficient of the grade level slope is very small in Model 2, it is highly significant. A deviance test between the two models also shows that Model 2 fits better than does Model 3 (χ^2=14, df=4).

Figure 1: Illustration of the age-wage relationship across faculty selectivity



Note: Predicted wage from Model 2, Table 4, for average values on independent variables. The age distribution from 24-35 covers 90% of the sample.

Figure 2: Illustration of the grade-wage relationship across faculty selectivity



Note: Predicted wage from Model 3, Table 4, for average values on independent variables

6 Discussion and conclusions

Three main questions have been addressed in this paper. First, to what extent can institutions of HE explain graduates labour market outcome in terms of job probability, skill-mismatch and wages? We found that a moderate but not negligible part of the variation in graduates' employment outcome is a function of between-faculty differences. Most of the variation can be linked to differences between graduates, and this points toward students as the primary actors in HE. But both institutional and individual aspects have explanatory power as well and should be included in a school-to-work transition analysis.

The second question relates to how potential institutional effects work. Both traditional objective resource indicators and subjective assessment variables were introduced in the analyses. We did not find any impact of the faculty-level variables on graduates' job probability. This result could be explained with reference to the favourable business cycle in the Norwegian labour market at the time of the survey (2000), offering plenty of job opportunities for the graduates. This is underlined by the fact that individual academic performance, in terms of grades, did not influence job probabilities either. However, as expected, academic performance affects skill-mismatch and wages. Not all vacancies are necessarily relevant for university graduates, and they queue up for the "good jobs" partly according to their academic performance. Thus, one could also expect that faculty resources contribute to explaining skill-mismatch and wages.

Both the objective and the subjective indicator of student composition, in terms of intake-selectivity and heterogeneous-student-body measures, turned out to have an impact on the quality of the job. Other things being equal, graduates from the most selective and most homogenous faculties face the lowest risk of overeducation and the highest wages. One aspect of this interpretation is that professional interests can regulate wages through supply control in the labour market by introducing admission restrictions in the educational system. We did not find any impact of the allocation of financial or staff resources or the staffs' priorities. Rather than contributing to additional evidence, the introduction of subjective assessment indicators confirm the estimated effects of the objective variables. The results are in line with earlier research on the importance of the composition of the student group.

The third question raised is whether there is any interaction between institutional and individual effects. We found that faculty level has a random impact on all three dependent variables. In the job-probability and the overeducation models, the gender-effect varies systematically across faculties. In the wage model, the age-effect and the grade-effect differ across faculties. The age-wage effect across faculties can partly be explained by intake selectivity, in the sense that the least selective faculties are associated with the strongest age-effect. In other words, the most selective faculties are also the most equitable faculties across age-cohorts. We also found some evidence pointing towards the same between-faculty variation on the grade-effect, namely that the least selective faculties are associated with the strongest grade-effect. The statistical significance of this result is sensitive to model specification though, but taking the evidences at face value, it suggests that students are effectively tested one time or another. In the selective faculties they are tested at intake, in the less selective faculties they are tested at final exams.

The unambiguous effect of selectivity and student composition can be explained in different ways. First, it could be a pure selection effect where students are allocated across faculties according to innate abilities. Second, it could be that the best faculties attract the most able students, thus being a combination of individual selectivity and institutional effect. Third, selectivity may produce a motivation effect, contributing to self-confidence and extra effort among the “chosen” students. And forth, the most selective institutions have the most homogeneous student bodies, and this may in some circumstances produce advantageous teaching and learning conditions. None of these explanations can be ruled out. The observed effects of selectivity and student composition result from combinations of all four factors.

These explanations illustrate the interdependence between institutions and students. In this paper, we have taken explicit account of the institutional and the individual level in common models. We have demonstrated that the multilevel techniques used in this study prevent us from drawing fallacious conclusions arising in simple individual-level analysis. However, although the multilevel techniques are powerful, the study is not without limitations. The most serious problem is probably the lack of individual intake ability scores. This shortage is partly compensated for by collective student-composition measures and by measures of academic performance through grades.

Even though academic performance may capture important aspects of individual heterogeneity among graduates, it could be discussed whether grades should be included as an explanatory variable in a model built on an education production function relationship. According to human capital theory, academic performance is the outcome of education and should not be included among the explanatory variables. We have documented that the results do not depend on whether grades are included in the model or not. Therefore we chose to include academic performance (grades) in the model in order to investigate the relationship between institutional factors and individual performance. If we had excluded grades from the model, we would not have been able to analyse the relationship between grades and selectivity.

Our aim has been to estimate gross effects of education. Thus, job-specific variables are not included in our preferred models, because such aspects may be regarded as outcome in the labour market. At the same time, labour market outcomes could be a result of labour market structure. The educational system and the labour market system are two sides of an inter-dependent structure. For these reasons, we have also included job-specific variables in alternative estimations. The effect of selectivity and student composition is not changed by including sector in the analyses. Aspects of the job contract, such as temporary or permanent contract and part or full time employment, explains about half of the faculty effect of selectivity and student composition. But one should be careful holding such job characteristics constant in a model estimating gross effects of education. The reason for this is that such factors are likely to be an integral part of the labour-market outcome that we try to explain.

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Appendix

Table A1: Data source and means of all variables, standard deviation of continuous variables

	Data source	Total sample		Subsample of employed		Subsample of full-time wage earners	
		Mean	(SD) [1]	Mean	(SD) [1]	Mean	(SD) [1]
Dependent variables:	**NGS**						
Job		0.90		–		–	
Overeducation		–		0.19		0.16	
Wage (full-time wage in NOK)		–		–		23083	(4051)
Independent graduate variables:	**NGS**						
Female		0.54		0.55		0.53	
Age (years)		29.2	(5.9)	29.2	(6.0)	28.9	(5.6)
Married/cohabitant		0.55		0.55		0.55	
Children		0.13		0.14		0.13	
Mother higher education		0.43		0.44		0.44	
Father higher education		0.55		0.55		0.54	
Non western immigrant		0.02		0.02		0.02	
Work experience		0.37		0.39		0.39	
Additional education		0.23		0.23		0.23	
Grade level (z-score)		0.00	(0.98)	0.01	(0.99)	0.04	(0.99)
Grade level unknown		0.02		0.02		0.02	
Humanities		0.17		0.17		0.15	
Social sciences		0.15		0.16		0.15	
Law		0.16		0.16		0.17	
Natural sciences & Technology		0.28		0.27		0.29	
Health care sciences		0.12		0.12		0.10	
Primary industry sciences		0.06		0.06		0.07	
Business administration		0.05		0.06		0.07	
Number of observations		**1887**		**1707**		**1294**	

Independent faculty variables:		Mean	(SD)
Objective measures:			
Student-staff ratio	Register (DBH / RPR)	21.46	(19.92)
Selectivity (searchers/admitted)	Register (DBH)	7.20	(3.31)
Expenditure per student (1000NOK)	Register (ND / DBH)	106.9	(76.9)
Subjective measures:			
Scarce resources	NUS	0.84	(0.37)
Heterogeneous student body (HSB)	NUS	0.41	(0.49)
Uninterested staff	NUS	-0.23	(0.24)
Number of observations		**34**	

NGS: NIFU Graduate Survey 2000. NUS: NIFU University Survey 2000. DBH: The Norwegian Database on Higher Education. RPR: NIFU Research Personnel Register. ND: NIFU Database on resources and expenditures in higher education in Norway.

– not available

Note 1: SD of a dummy variable is a function the estimated probability and thus superfluous to display.

Table A2: Correlations between faculty level resource variables (N=34)

	Student-staff ratio	Selectivity	Expenditure per student	Scarce resources	Heterogeneous student body	Uninterested staff
Student-staff ratio	1					
Selectivity	-0.25 (0.15)	1				
Expenditure per student	-0.57 (0.00)	0.68 (0.00)	1			
Scarce resources	0.08 (0.67)	0.08 (0.65)	0.18 (0.30)	1		
Heterogeneous student body	-0.07 (0.70)	-0.52 (0.00)	-0.33 (0.05)	0.12 (0.48)	1	
Uninterested staff	0.37 (0.03)	-0.06 (0.74)	-0.03 (0.86)	0.04 (0.83)	-0.21 (0.23)	1

Significance level in brackets

Table A3: Job, overeducation and wage model estimates with objective resource measures. Individual level analyses: Ordinary logit models (on job and overeducation) and ordinary least square (on wages)

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Student-staff ratio	0.020*	0.011	-0.007	0.009	0.001	0.001
Selectivity	0.020	0.045	-0.101**	0.045	0.017***	0.003
Expenditure per student	-0.001	0.002	0.002	0.003	0.000	0.000
Female	0.470**	0.182	0.355**	0.146	-0.038***	0.009
ln(age)	0.733	0.688	0.015	0.500	0.289***	0.033
Married/cohabitant	0.385**	0.177	-0.196	0.141	0.021**	0.009
Children	0.329	0.393	0.219	0.285	-0.018	0.019
Female*Children	-1.262***	0.470	-0.227	0.379	-0.016	0.026
Mother higher education	0.062	0.187	-0.014	0.150	0.002	0.010
Father higher education	0.128	0.184	-0.058	0.149	-0.005	0.010
Non western immigrant	-0.916**	0.408	-0.608	0.571	-0.049	0.033
Work experience	0.837***	0.205	-0.879***	0.158	0.036***	0.009
Additional education	-0.190	0.206	-0.149	0.175	0.009	0.011
Grade level (z-score)	0.127	0.085	-0.362***	0.069	0.026***	0.004
Grade level unknown	-0.248	0.469	0.403	0.432	-0.032	0.032
Social sciences	0.437	0.342	0.350	0.237	-0.027	0.017
Law	-1.279*	0.755	0.800	0.603	-0.031	0.040
Natural sciences & Technology	0.259	0.261	-0.319	0.239	0.054***	0.016
Health care sciences	0.250	0.431	-1.511***	0.495	0.044**	0.021
Primary industry sciences	0.985**	0.457	0.162	0.319	-0.026	0.022
Business administration	1.570**	0.643	-1.155**	0.450	0.160***	0.022
Intercept	-1.519	2.362	-0.632	1.737	8.926***	0.114
Model statistics:						
R^2-adj.	–		–		0.205	
-2 log likelihood	1111.485		1503.540		–	
Number of observations	1887		1707		1294	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

Table A4: Job, overeducation and wage model estimates with subjective resource measures. Individual level analyses: Ordinary logit models (on job and overeducation) and ordinary least square (on wages)

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Scarce resources	0.107	0.306	-0.082	0.298	0.037**	0.018
Heterogeneous student body	0.169	0.313	0.919***	0.342	-0.082***	0.018
Uninterested staff	-0.271	0.480	-0.819**	0.410	0.005	0.027
Female	0.448**	0.182	0.351**	0.146	-0.037***	0.009
ln(age)	0.862	0.686	0.399	0.500	0.264***	0.033
Married/cohabitant	0.406**	0.177	-0.172	0.141	0.020**	0.009
Children	0.259	0.391	0.244	0.284	-0.021	0.019
Female*Children	-1.174**	0.467	-0.268	0.378	-0.015	0.026
Mother higher education	0.066	0.187	-0.003	0.151	0.002	0.010
Father higher education	0.129	0.184	-0.049	0.149	-0.004	0.010
Non western immigrant	-0.892**	0.408	-0.498	0.568	-0.054	0.033
Work experience	0.843***	0.206	-0.848***	0.158	0.030***	0.009
Additional education	-0.171	0.206	-0.165	0.175	0.010	0.011
Grade level (z-score)	0.133	0.085	-0.370***	0.069	0.026***	0.004
Grade level unknown	-0.299	0.466	0.394	0.431	-0.021	0.032
Social sciences	0.858	0.346	0.415*	0.240	-0.006	0.017
Law	0.391**	0.384	0.942***	0.349	0.004	0.021
Natural sciences & Technology	0.247	0.274	-0.359	0.235	0.096***	0.016
Health care sciences	0.357	0.401	-1.017**	0.428	0.055**	0.021
Primary industry sciences	0.781*	0.461	-0.057	0.306	0.018	0.022
Business administration	1.999***	0.667	-0.641	0.497	0.150***	0.024
Intercept	-1.880	2.382	-3.228*	1.782	9.116***	0.117
Model statistics:						
R^2-adj.	–		–		0.190	
-2 log likelihood	1116.548		1497.719		–	
Number of observations	1887		1707		1294	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

Table A5: Job, overeducation and wage model estimates with objective resource measures. Multilevel analyses.

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty level data:						
Intercept	-0.869	2.310	-2.741	1.701	9.058***	0.115
Student-staff ratio	0.021	0.013	-0.006	0.011	0.000	0.001
Selectivity	0.021	0.054	-0.114*	0.061	0.017***	0.004
Expenditure per student	-0.002	0.003	0.002	0.003	0.000	0.000
Graduate level data:						
Female	0.431**	0.183	0.371**	0.146	-0.038***	0.009
ln(age)	0.529	0.669	0.642	0.483	0.253***	0.033
Married/cohabitant	0.424**	0.177	-0.242*	0.140	0.023**	0.009
Children	0.282	0.393	0.257	0.283	-0.020	0.018
Female*Children	-1.221**	0.470	-0.300	0.377	-0.013	0.026
Mother higher education	0.081	0.188	-0.026	0.151	0.003	0.010
Father higher education	0.152	0.185	-0.081	0.149	-0.006	0.010
Non western immigrant	-0.931**	0.408	-0.336	0.562	-0.068**	0.033
Work experience	0.850***	0.206	-0.923***	0.157	0.041***	0.009
Additional education	-0.180	0.206	-0.190	0.175	0.009	0.011
Social sciences	0.424	0.382	0.535*	0.305	-0.016	0.021
Law	-1.291	0.877	0.761	0.701	0.018	0.045
Natural sciences & Technology	0.234	0.319	-0.099	0.329	0.052**	0.021
Health care sciences	0.350	0.475	-1.227**	0.526	0.052**	0.025
Primary industry sciences	0.733	0.517	0.419	0.418	-0.007	0.027
Business administration	1.594**	0.731	-0.710	0.611	0.165***	0.034
Model statistics:						
Variance between graduates	–		–		0.023	
Variance between faculty	0.104		0.168***		0.001***	
Deviance	–		–		-1209	
Number of graduates	1887		1707		1294	
Number of faculties	34		34		34	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

Table A6: Job, overeducation and wage model estimates with subjective resource measures. Multilevel analyses.

	P[job]		P[overeducation]		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty level data:						
Intercept	-0.750	2.343	-4.883**	1.766	9.165***	0.119
Scarce resources	-0.012	0.389	0.017	0.391	0.031	0.027
Heterogeneous student body	0.008	0.379	0.965**	0.414	-0.067**	0.026
Uninterested staff	-0.237	0.599	-0.836	0.559	0.000	0.042
Graduate level data:						
Female	0.408**	0.183	0.375**	0.146	-0.037***	0.009
ln(age)	0.578	0.669	0.850*	0.485	0.246***	0.033
Married/cohabitant	0.445**	0.178	-0.229	0.140	0.022**	0.009
Children	0.217	0.392	0.273	0.283	-0.021	0.018
Female*Children	-1.140**	0.468	-0.323	0.377	-0.014	0.026
Mother higher education	0.086	0.188	-0.024	0.151	0.003	0.010
Father higher education	0.150	0.185	-0.079	0.149	-0.005	0.010
Non western immigrant	-0.917**	0.408	-0.293	0.561	-0.070**	0.033
Work experience	0.848***	0.206	-0.904***	0.157	0.039***	0.009
Additional education	-0.163	0.207	-0.197	0.175	0.008	0.011
Social sciences	0.684*	0.404	0.657**	0.307	-0.005	0.023
Law	0.306	0.514	0.957**	0.469	0.035	0.033
Natural sciences & Technology	0.189	0.342	-0.177	0.305	0.095***	0.024
Health care sciences	0.274	0.466	-0.846*	0.477	0.066**	0.027
Primary industry sciences	0.578	0.542	0.333	0.399	0.035	0.030
Business administration	1.930**	0.799	-0.263	0.640	0.168***	0.043
Model statistics:						
Variance between graduates	–		–		0.023	
Variance between faculty	0.167**		0.142***		0.001***	
Deviance	–		–		-1195	
Number of graduates	1887		1707		1294	
Number of faculties	34		34		34	

Note: * p<.1, ** p<0.05, *** p<0.01. – not available

Table A7: Overeducation and wage level model estimates with objective resource measures and job-specific variables included. Multilevel analyses.

	P(Overeducation)		P(Overeducation)		ln(wage)		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty data:								
Intercept	-2.270	1.833	-3.961**	1.923	8.841***	0.113	9.116***	0.107
Student-staff ratio	-0.006	0.012	-0.011	0.010	0.000	0.001	0.001	0.001
Selectivity	-0.152**	0.065	-0.072	0.048	0.016***	0.003	0.010***	0.003
Expenditure per student	0.002	0.004	0.000	0.003	0.000	0.000	0.000	0.000
Graduate data:								
Female	0.406***	0.151	0.286*	0.158	-0.032***	0.009	-0.023***	0.009
ln(age)	0.458	0.521	0.633	0.551	0.308***	0.032	0.252***	0.030
Married/cohabitant	-0.234	0.145	-0.178	0.151	0.021**	0.009	0.013	0.008
Children	0.231	0.294	0.276	0.307	-0.014	0.018	-0.014	0.017
Female*Children	-0.311	0.392	-0.561	0.411	-0.017	0.025	-0.017	0.023
Mother higher education	-0.027	0.155	-0.082	0.162	0.001	0.009	0.001	0.009
Father higher education	-0.033	0.153	-0.093	0.159	-0.004	0.009	0.000	0.009
Non western immigrants	-0.433	0.580	-0.478	0.587	-0.049	0.032	-0.046	0.030
Work experience	-0.908***	0.161	-0.857***	0.167	0.035***	0.009	0.030***	0.009
Additional education	-0.133	0.181	-0.105	0.188	0.012	0.010	0.009	0.010
Grades (z-score)	-0.384***	0.072	-0.285***	0.075	0.026***	0.004	0.023***	0.004
Grades unknown	0.560	0.444	0.475	0.476	-0.025	0.031	-0.024	0.029
Social sciences	0.396	0.329	0.361	0.260	-0.024	0.020	-0.020	0.017
Law	0.599	0.769	0.859	0.670	-0.009	0.043	-0.026	0.038
Natural sciences & Techn.	-0.296	0.358	-0.145	0.261	0.040**	0.020	0.041**	0.016
Health care sciences	-1.125**	0.549	-1.281**	0.512	0.051**	0.024	0.051**	0.020
Primary industry sciences	0.022	0.448	0.057	0.350	-0.023	0.026	-0.017	0.022
Business administration	-1.262*	0.663	-0.972**	0.471	0.133***	0.033	0.091***	0.025
Private sector	0.921***	0.142	1.287***	0.161	0.075***	0.009	0.034***	0.009
Sector unknown	-0.780*	0.399	-0.426	0.432	0.035	0.039	0.019	0.037
Temporary employment			1.116***	0.163			-0.113***	0.009
Research fellow			-1.210	0.738			-0.105***	0.018
Self employed			0.046	0.476				
Part time worker			1.181***	0.181				
Model statistics:								
Var between graduates	–		–		0.021		0.019	
Var between faculties	0.230***		0.001**		0.0006***		0.0002**	
Deviance	–		–		-1317		-1469	
Number of graduates	1707		1707		1294		1294	
Number of faculties	34		34		34		34	

* p<.1, ** p<0.05, *** p<0.01. – not available

Table A8: Overeducation and wage level model estimates with subjective resource measures and job-specific variables included. Multilevel analyses.

	P(Overeducation)		P(Overeducation)		ln(wage)		ln(wage)	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Faculty data:								
Intercept	-4.348**	1.885	-5.977***	1.980	8.959***	0.116	9.243***	0.108
Scarce resources	-0.212	0.426	-0.140	0.335	0.042*	0.024	0.027	0.018
HSB	1.127**	0.459	0.652*	0.378	-0.085***	0.023	-0.061***	0.018
Uninterested staff	-0.580	0.627	-0.710	0.462	0.016	0.038	0.030	0.028
Graduate data:								
Female	0.405***	0.151	0.278*	0.157	-0.030***	0.009	-0.022**	0.009
ln(age)	0.642	0.518	0.904	0.552	0.301***	0.032	0.240***	0.030
Married/cohabitant	-0.217	0.145	-0.156	0.151	0.021**	0.009	0.012	0.008
Children	0.260	0.292	0.310	0.305	-0.015	0.018	-0.015	0.017
Female*Children	-0.345	0.391	-0.593	0.410	-0.018	0.025	-0.017	0.023
Mother higher education	-0.023	0.155	-0.071	0.162	0.001	0.009	0.001	0.009
Father higher education	-0.035	0.153	-0.094	0.160	-0.003	0.009	0.001	0.009
Non western immigrants	-0.423	0.579	-0.457	0.589	-0.049	0.032	-0.047	0.030
Work experience	-0.888***	0.161	-0.843***	0.167	0.032***	0.009	0.027***	0.009
Additional education	-0.143	0.180	-0.116	0.188	0.011	0.010	0.010	0.010
Grades (z-score)	-0.388***	0.072	-0.290***	0.076	0.027***	0.004	0.023***	0.004
Grades unknown	0.528	0.442	0.407	0.472	-0.016	0.031	-0.015	0.029
Social sciences	0.457	0.333	0.368	0.272	-0.017	0.021	-0.010	0.017
Law	0.715	0.526	0.728*	0.398	-0.004	0.030	-0.005	0.022
Natural sciences & Techn.	-0.540	0.339	-0.183	0.265	0.084***	0.021	0.068***	0.016
Health care sciences	-0.882*	0.504	-1.084**	0.461	0.054**	0.025	0.053**	0.021
Primary industry sciences	-0.168	0.438	-0.083	0.347	0.015	0.028	0.009	0.022
Business administration	-0.823	0.710	-0.597	0.541	0.121***	0.039	0.076***	0.027
Private sector	0.888***	0.142	1.260***	0.162	0.078***	0.009	0.038***	0.009
Sector unknown	-0.761*	0.398	-0.362	0.429	0.026	0.039	0.011	0.037
Temporary employment			1.147***	0.162			-0.115***	0.009
Research fellow			-1.164	0.739			-0.109***	0.018
Self employed			0.020	0.472				
Part time worker			1.152***	0.182				
Model statistics:								
Var between graduates	–		–		0.021		0.019	
Var between faculties	0.220***		0.012***		0.0009***		0.0002***	
Deviance	–		–		-1308		-1462	
Number of graduates	1707		1707		1294		1294	
Number of faculties	34		34		34		34	

* p<.1, ** p<0.05, *** p<0.01. – not available