FACULTY OF SOCIAL SCIENCES
Department of Economics
University of Copenhagen

Master Thesis

Natasha Reimer Thaysen

Human capital accumulation and labor market prospects

An analysis of the effect of internship, exchange and student job on labor market outcomes for Danish master students

Supervisor: Miriam Gensowski

ECTS points: 30

Date of submission: 30/05/2016

Keystrokes: 151.011

Summary

The focus of this thesis have been to identify the labor market effects of supplementary activities, such as internship, student job and exchange for a student enrolled in a master program.

In recent years, the Danish educational system has undergone some changes. Higher education system, including master programs has also been affected. The changes made to higher education have included requirements of full time enrollment (minimum 30 ECTS point every semester) and automatic sign up for re-exams, if an ordinary exam was failed. These changes were brought up as an attempt to ensure students would graduate on time, and enter the labor market sooner. The need for change was the result of long duration of studies and high age of graduates. Some of these changes have been met with severe protest from students and student organizations, arguing that the increasing attainment requirements and the need to follow a study plan, minimizes their possibilities to hold on to a relevant student job, take an internship or travel on exchange. At the same time, a debate has been going on in Denmark about how to prepare the students to the employment challenges they face after graduating. These two debates have not always been aligned, when asked how to change policy for the better? This thesis aims to address this question, by investigating the labor market effects of the supplementing activities during master studies, to contribute to the overall question – what makes our graduates attractive in the labor market?

While much research within economics of education have been focused on how fixed factors, such as parental characteristics or previous achievements in high school, affect labor market status, very little focus have been given to students who are very close to entering the labor market. To address this question, the thesis investigates human capital theory, developed by educational economist and applies it in a setting of higher education. Here, the theory will address the supplementary activities such as an internship, a relevant student job and exchange, as human capital enhancing, with the assumption that the human capital rewarded on the labor market are heterogeneous. Since the variables of interest by design are optional, self-selection will be the largest challenge of the analysis. To deal with this, a comprehensive dataset has been gathered for the purpose of this thesis. This includes family background, socioeconomic measures, high school grades and elective courses, along with other valuable measures.

The main analysis has been carried out as multilevel-models with random effects. A multilevel-model has been used since our data has a nested structure, where students are nested within classes, majors and universities. This structure leads us to believe that students within one major and university is more heavily correlated with each other, compared to a person randomly drawn from the student population. The outcome variables used, are employment and wages one year after graduation, expressing the short term labor market effects of these supplementing activities. The model is built on information from Statistics Denmark and University of Aarhus, which has provided one of the variables of interest, internship. The remaining

information on exchange, student job, wages, employment status, socioeconomic variables, parental characteristics, high school grades etcetera, are from Statistics Denmark.

The multilevel-model was first carried out for the population of students who begun and graduated a master's degree at the university of Aarhus between January 1st 2009 and December 31st 2012. The model reviled that students who engage in a student job during their studies, are more likely to become employed one year after graduation. This is the case for students who only engage in a student job, and those who besides this also have taken on an internship or been on exchange. The same activities resulted in positive when measuring wages. For students who had become employed one year after graduation, the students who had engaged in at least at relevant student job experienced a wage premium.

To expand the interpretation of the estimates to the whole population, a new model with fewer restrictions on the data was created. The information on internships only exists for students at the University of Aarhus. To conduct the analysis on the full population of students, this information must be left out. Since the estimate for internships came to be insignificant, to leave out this information in order to remove the geographical restriction seemed logical. The model was once again estimated, but now with the full population. For exchange and student jobs, the model for the full population showed the same results as the previous model did. Student jobs increased the odds of becoming employed, and the employed students who had been employed in a student relevant job received a wage premium. In both populations, the control variables relating to mothers and fathers socioeconomic status did not influence that labor market outcome for the students.

The main concern throughout the thesis has been the problem of measurement errors linked to estimates of supplementary activities. These problems can arise, as a result of endogeneity and self-selection, biasing the results and make them questionable. To address the question of biased estimates, a small siblings study was conducted. A similar multilevel-model as before was estimated, with students from the former population, who had a sibling that in the period between 2005 and 2012 also obtained a master's degree. In order for the sample to contain enough siblings, the time frame had to be widened, which mend a loss of information with regard to exchange, leaving us with only student jobs to analyze. The result of a robustness check with siblings as control showed that student jobs were still significantly improving the wage and employment prospects. The magnitudes have though declined substantially from a comparable model estimated for the full population, which aligns with theory of upwards biased estimates.

This thesis concludes that there is a positive effect for students who engaged in student job as a supplementary activity during their master studies, and there is potential for positive effect of the other two. It also finds that there is a large fraction of the variation in wages and employment outcome that can be contributed to the studies. In all cases, activities are enhancing the outcome or keeping it status quo. Nothing suggests that activities results in a human capital decline, measured by wages post-graduation.

Preface

Throughout my time as a master student of economics at the University of Copenhagen, my main interest has been the interaction between educational choices and future possibilities, and how this is affected by choice and social indicators. This has led me to employment within lobbying firms, consultancies and public companies in the education sector. This large variety of jobs within the sector has allowed me to apply the economic theories and econometric tools assembled over the last five years as an economics student.

Most recently, this has brought me to work as a thesis graduate at the Danish Evaluation Institute, which hired me to write this thesis for them. In the search for the best subject, it struck me that much has been investigated regarding how early interventions affect adult outcomes, but not much research has been done in a Danish context on how educational choices close to graduation affect these same adult outcomes. In collaboration with some of the most talented educational consultants I have come across in my, admittedly, limited years in the field, the research question of this thesis thus emerged: Can educational choices so far ahead in life really influence labor outcomes, or is it too late?

All of the data used in this thesis has been provided by the Danish Evaluation Institute, mainly through Statistics Denmark's register service. I have personally programmed the process from the raw registers at Statistics Denmark to the datasets that lay the ground for the thesis. All programming and analyses have been done in SAS, while tables and graphs in some cases have been edited in Excel or Word.

I would like to thank my colleagues at the Danish Evaluation Institute for providing me with the opportunity to address this interesting subject in my thesis. I would especially like to thank the head of the division for higher education Jakob Rathlev and special advisor Bjarke T. Hartkopf for their excellent guidance and everlasting encouragement. I will always be more than grateful for your persistency and ability to make me a better thesis graduate and economist. Furthermore, I would like to thank my supervisor Miriam Gensowski who has been beyond excellent throughout this process with professional guidance and motivation.

I claim full responsibility for the entire contents of this thesis.

Natasha Reimer Thaysen

List of tables and figures

1. Introduction

Educational debate in Denmark

Although education always has been on the political agenda, the focus on especially higher education and student qualifications has in recent years increased in Denmark. The former Danish Social Democratic government launched a commission in 2012, The Productivity Commission, which should attempt to provide recommendations to strengthen the productivity of the private and public sectors. The fourth report focused on education and innovation, recommending several changes to higher education.

"Kommissionen anbefaler en undersøgelse af, om opbygningen af de videregående uddannelser sikrer dimittenderne uddannelser med optimal længde og indhold i forhold til det arbejdsmarked, de skal ud på." (Produktivitetskommissionen, 2013)

The recommendation states that the focus of higher education should evolve around the connection to future employment. Most of the recommendations focused on the structure of the study programs to improve their labor market status. Following this and other recommendations, other actors and stakeholders in the Danish educational debate have investigated and replied to the suggestions. One of the actors, The Confederation of Danish Industries, stated in the beginning of 2014 that focus should be directed to tools that worked; and that they did not care which one, as long as it worked (Rønhof, 2015). The former Social Democratic government replied to the commission in 2014 by introducing an adjustment of student intake in higher education programs:

"…to transfer student admission from programs with systematic and notable higher unemployment among graduates to programs which have better employment prospects." (Ministry of Higher Education and Science, 2015)

This focus on labor market performance has also led to investigations of factors beyond those controlled by the universities. A poll conducted by the Danish union Djoef[1] revealed that 66 pct. of master's students held a relevant student job, while 46 pct. responded with the belief that a relevant student job is crucial in being attractive to a future employer (Hjortdal, 2015). Not all parties agreed with the students, and the union's head of science and education commented,

"…på langt sigt risikerer de studerende at gøre arbejdslivet sværere for sig selv ved at konkurrere for hårdt om det første job" (Hjortdal, 2015)

[1] *Lawyers, economists and political & social scientists' employee organization.*

implying that competition for student jobs might end up limiting their subsequent employment chances. The outcome effect of student jobs on labor market participation was later investigated by the Economic Council of the Labour Movement (ECLM)[2]. This investigation focused on the unemployment risks facing new academic graduates in Denmark, and was done on behalf of the unemployment insurance fund for academics (Akademikernes A-kasse) (Dalskov Pihl, 2015). The study tries to estimate the effect on labor market outcomes of having a relevant student job or internship. This case seems highly relevant in relation to the previous recommendations and policy interventions, but the design of the study could be improved, and further econometric modeling as well as a wider range of variables could be used as background and outcome measures, to increase the validity of the analysis.

Problem statement and approach

The number of Danish studies concerning the effect on labor market outcomes of students' supplementary activities while attending university is limited. This thesis will, therefore, investigate this area based on the following problem statement:

- How do students who have supplemented their studies with an internship, exchange or a student job during their master's studies, differ from their non-working peers after graduation in terms of unemployment and wages?

Supplementing is here seen to be something that provides further human capital beyond that which can be attributed to schooling. In academic circles, the subject has been studied on a piecemeal basis, only focusing on internships, student jobs or students on exchange. Results indicate ambiguous outcomes, where considerable differences in timing and relevance of the supplementary activity need to be taken into account.

The most common econometric approaches to investigating the subject have been natural experiments with IV estimation. In a recent paper from 2014, Saniter and Siedler used a change in the laws on internships in Germany to study the causal effect of internships on German students’ labor market outcomes, using OLS and IV estimation (Saniter & Siedler, 2014). The same method was used by Rokicka on English data, using part time work when aged 16 and attending compulsory full time education (Rokicka, 2014). Instrumental variables are estimated with GMM, and are considered more effective than the two-stage least square approach (Wooldridge, 2002). The Danish system has not recently experienced any specific changes in legislation or other such development that might create a reasonable opportunity to undertake a natural experiment. Other instrumental variables applied in previous literature have been regional characteristics such as the number of jobs and infrastructure factors. Most of the literature on the subject has been based on US data concerning working while attending high school, and has presumed a negative relationship between work and further education. The application of a similar strategy to Danish data on master's students would lack an obvious instrument. The number of universities in Denmark is limited, and there are thus

[2]”AE-rådet” In Danish.

fewer differences in regional characteristics, and job opportunities are less strictly separated than would be necessary to create such an instrument.

The estimation of an effect will instead use a multi-level model as used by Thieme and Tortosa-Ausina, which has previously been applied to children in Chilean primary schools to analyze their educational performance (Theieme, Prior, & Tortose-Ausina, 2013). As true randomization is not used, causation should be taken into account when estimating the results. The main choice of model will, therefore, be a multi-level model with random intercept and second estimation using instrumental variables. The models will be estimated with research data from Statistics Denmark accessed through The Danish Evaluation Institute's authorization.

2. Literature review

Studies and recommendations on educational issues are not something new, and the subject of students working while studying has been studied widely in several different contexts, countries and time periods. The effect of students being employed has mainly been studied in two different settings: firstly, on educational measures, and secondly on labor market outcomes. The studies of in-school employment during college attainment have often focused on wages (Light, 2001) (Holtz, Xu, Tienda, & Ahituv, 2002) but are also seen to take an interest in academic performance (Stinebrincker & Stinebrincker, 2003) (Avdic & Gartell, 2015). Both of these views are important in understanding the implications of time allocated to work, but this thesis will mainly be concerned with the use of direct labor market outcomes, such as wages and employment, to relate the measure directly to the problem statement. The remainder of this chapter will focus on papers applying different econometric approaches to exploring possible relationships between acquiring work experience before entering the labor market and future labor market outcomes.

2.1. Employment during schooling

To study the effect of any type of education, one of the most crucial elements that complicates the process and results is the self-selection problem. In our analysis, this would be reflected in differences between people who take on employment while studying and those who do not. Differences between people who take a job could be those concerning interests, knowledge of the study, means, opportunity and skills, etc. These possible differences are widely acknowledged and are dealt with in several ways, depending on the source literature. A paper by Schoehals, Tienda, & Schneider (1998), dedicated to investigating both personal and educational implications of youth employment, cites a long list of prior research exploring the differences between employed and unemployed groups of students (Keithly & Deseran, 1995) (Steinberg, Greenberger, Garduque, & McAuliffe, 1982). This review finds substantial differences depending on sex, minority, family income, school type, grades and other indicators not examined in close detail (Schoehals, Tienda, & Schneider, 1998). The different strategies applied to deal with this problem range from a simple OLS model with control variables (Schoehals, Tienda, & Schneider, 1998), to more complicated models such as multi-level models (Theime, Prior, & Tortosa-Austina, 2013), IV estimation (Stinebrincker & Stinebrincker, 2003) (Light, 2001) (Ruhm, 1997) and in more rare cases natural experiments (Leigh & Ryan, 2008).

The early paper by Schoehals, Tienda and Schneider (1998) investigated the short-term effect of employment during 10th grade, measuring students' academic achievements. The article divides the possible effects of student employment into two groups of outcomes: a persisting group (socialization) and a non-persisting (time allocation), which have both shown positive and negative effects in previous studies. A direct study of how students allocate their time between studies and relevant work could be a good supplement for this thesis, but is beyond its scope. Their study was conducted by using an OLS model based on a large data set, with a wide range of characteristics and knowledge of the individuals. They found no significant effect on grades for those students who were employed while attending school. A slightly significant negative effect (-0.06) was, however, found for students who had previously worked between 11 and 20 hours per week, but were not working at the time of the survey. The study also found a significant difference in the variable concerned with the amount of time spent watching television, which showed that students who were working watched significantly less television. On the basis of this, it might be argued that the time spent working is (partly) taken from leisure activities. This is, though, not the entire story; besides those working less than 10 hours per week, all students who worked were significantly more absent from school than students not previously or currently employed (Schoehals, Tienda, & Schneider, 1998). This does not change the results of the achievement, showing that grades are not affected by employment, even though students spend less time in school. This implies that the employment might provide some of the investment in human capital that would otherwise have occurred if they had been attending as much education as their non-working peers. This is, however, a strong claim since the model was not applied with any assurance of no self-selection or unobserved variables, but used individual characteristics as controls. Nevertheless, the same positive effect on future wages is shown by Christopher Ruhm in an article the year before, *"Is High School Employment Consumption or Investment?"* (Ruhm, 1997). This paper looks at more long term consequences, finding no negative or positive effects from having worked through high school. Ruhm uses IV estimation as a robustness check on his full OLS estimates, finding a decline but still zero or positive effect of work.

The IV estimation has subsequently been used as a main method in the attempt to find the causal effect of student jobs. Stinebrincker and Stinebrincker (2003) used a randomization of student job allocation at Berea College to estimate causal effects of these jobs on students' academic performance. These IV estimations showed that employment during the first semester was harming the students' grades. The instrumental variable was made possible by the structure of the college, where the qualification needed to apply for Berea College is to show great promise but lack the necessary financial support to attain college. This leads students to gain full scholarships, but also requires them to attend a randomly assigned mandatory work-study program, where some jobs can contain more or less hours. The authors argue their choice of estimation method, with this randomization of jobs distributed among students, to be a strong IV estimator. They first estimate an OLS regression on the students' first and second semester GPA, and afterwards a model with IV estimation. Here the results were slightly negative on the GPA from working more hours. This IV estimation seems to have a very strong internal validity, but the external validity is not as strong. Students at Berea College are art students who are considered high potential, but without financial means to achieve the education otherwise. These students would be presumed to have a poorer social background than other students, and have a different set of motivations for their studies. If these students do not represent the average student, their labor market outcomes must be expected to be different as well, lowering the external validity of the results. Furthermore, the jobs at Berea College are categorized as service jobs, and are not necessarily contributing to skills for subsequent use in the labor market. In the model set up in this thesis, the student jobs are relevant to their future professions. These jobs are expected to accumulate human capital (for definition see *Chapter 3- Theory*). The labor market outcomes for students at Berea College and the Danish population with relevant student jobs cannot thus be compared. Other robustness analyses on entire student populations should therefore be taken into account, for instance representative populations looked at later in this thesis, and which have also been considered previously by other economists.

Such a study on the whole student population was done by Audrey Light in 2001, also using IV estimation to find the causal effect of in-school employment (Light, 2001). The strategy of her article was to start out with a model using only schooling, experience and experience squared as variables in the model (further referred to as base). Following this, she expanded the base model six times using generalized least squares (GLS) and afterwards designed three IV estimation models with different instruments[3]. These nine models were all specified twice, first without and then with information on work experience during education attainment. She developed them to visualize the effect of including work experience on coefficient estimates, arguing that the schooling coefficient would drop in size when a variable for student job was included. The first six GLS models showed a decline in the magnitude of the schooling variable as the number of controls were added, meaning that the expected rise in wages from additional years of schooling was declining, arguing that this coefficient was biased upwards before controlling for background information. Four additional years of schooling are expected to raise wages by 30 pct. in the first model, whereas the last model with in-school work experience only predicts this figure to be 16.4 pct. (a decline by almost half: 44.3 pct.). The same decline does not occur when using IV estimation to address the subject; on the contrary, these estimates are increasing in their schooling coefficient more than the GLS estimates. However, the overall result in the article is that models that do not control for in-school work experience seem to have overestimated the effect of schooling, compared to those models that do take prior work experience into account. Light recognizes the difficulty in extracting this information for further analysis, because the data requires detailed knowledge of work information, and that can be hard to obtain and trust if people are interviewed or complete questionnaire surveys.

As argued, a strong instrument has not always been present in the data, which has called for other methodologies to be used to avoid only using OLS estimation. Multi-level models, or hierarchical linear models (HLM), have been used in settings related to our case with student jobs in several ways. Differences in wages have been tested with a multi-level model, used to address the problems of self-selection into the line of education, by decomposing the aggregate level of education into faculties and majors (Rumberger & Thomas, 1993). The article uses individual and college data to create a HLM model that takes major, quality and performance of the students into account but allows for variance between the colleges and between students within each college. Output showed that earnings between schools could account for as much as 8-28 pct. of the future earnings variation from the mean (Rumberger & Thomas, 1993). A similar multi-level model was applied to the effects of formal education, adult education and on-the-job training on salary growth (Xiao, 2002). These studies and their findings lead us to believe that variations between schools and

[3] *Family, siblings and college cost (Light, 2001)*

majors are important to include, and that on-the-job training, such as internships and student jobs, can be used in the line of methodology to estimate the wage returns on such activities.

As noted earlier, some measures might depend on the country of origin of the data. Many empirical analyses, not only in this literature, are conducted on American data. The Danish education system and labor market structure are both very different from the American system. American education often comes with co-payment and tuition fees, and the lack of a post education protection system in the labor market relating to sickness benefits, maternity leave and unemployment benefits is problematic. This is worth noting, since all of these factors influence the degree of external validity that exists when trying to apply American results to Danish students.

2.2. Time away according to the literature

The vast amount of literature has shown that the effects of allocating time away from school to other activities such as work can differ depending on the setting. Even so, most of the literature finds some positive effects of having spent time on supplementary activities. The findings do not seem to be limited to a certain approach or method of application. In the light of the literature review, it is highly relevant to investigate the matter of allocating time towards other activities alongside attaining education, and explore whether this can be seen as a skill enhancing undertaking in a theoretical and, later on, empirical setting.

This literature review was mainly concerned with the time allocation between jobs and schooling, and was not focused on students that chose an internship or travelled to be an exchange student. The application of the results above should, therefore, be carefully considered before applying them directly to other contexts, and this is not what this thesis is doing. The decision to take a job can be an investment that pays out in terms of wages, as seen in the context above. The same consideration could be made when substituting some time spent on education with on-the-job training, e.g. an internship, or a change of scenery from one current setting of educational attainment to another, i.e. to invest in an alternative human capital that can be obtained from another university somewhere else in the world. The results above show that it might be relevant to examine whether a theoretical approach exists that can show these three things combined, and that enables further econometric analysis.

On the basis of the literature review, the theoretical platform will, therefore, be based on the human capital approach outlined by Ben-Porath in his founding article *"The production of human capital and life cycle earnings"* (Ben-Porath, 1967), and further explore strings of human capital. The theory will mainly be based on the work of Robert Willis (Willis, 1986) and further applications of his work by Audrey Light (Light, 2001), which is examined in the following chapter.

3. Theory

The literature review exposed several different approaches to the theoretical aspect of students devoting time to supplementary activities during their educational attainment. The main question to address in the theoretical chapter is, therefore: How can theory help us determine if human capital can be generated from non-school activities? In other words, I would like to address whether the allocation of time spent on these activities seems to be a positive investment in future earnings and job security, or if time spent on student jobs, internships or exchanges are harming the labor market outcomes. One of the first human capital theories states that the only activity that enhances human capital is schooling (Ben-Porath, 1967). In the first model by Ben-Porath, human capital is a non-multiple, meaning that only one type of human capital exists. This human capital can, in Ben-Porath's view, only come from schooling. People's value on the labor market is a direct reflection of their personal level of human capital, which can only increase through an increase in schooling, investment, ability or previous human capital (Ben-Porath, 1967). The main Ben-Porath model is shown in equations 1 and 2, which outline how human capital H_{it} along with the previously mentioned inputs affect wages W_{it}.

$$W_{it+1} = \beta_{t+1}[H_{it}(1-\delta) + (A_i S_{it} E_{it} H_{it})^{\alpha}] \quad (1)$$

$$\rightarrow \frac{\partial W_{it+1}}{\partial S_{it}} = \beta_{t+1}[\frac{\alpha(A_i E_{it} H_{it})^{\alpha}}{S_{it}^{1-\alpha}}] \quad (2)$$

Where H is human capital which is rewarded in the labor market by its marginal productivity rate β, δ is the depreciation rate, A is the ability level, S is the schooling component and E accounts for schooling resources. By taking the first derivative of the equation with respect to S, we see how changes in the additional parameters affect the returns on schooling. We see that students who are of higher ability, have more resources put into schooling and have a previously high level of human capital benefit more from one additional input of schooling. Since no variable for non-study activities is included, H is not seen to rise with activities besides schooling.

This general view does not support our hypothesis that supplementary activities enhance human capital, and by that raise wages. This simplified view of human capital has been challenged multiple times, resulting in expansions of the theory as well as different approaches, such as signaling (Arrow, 1973). To explain this relationship, two different theories are used. Firstly, a theory of human capital as a heterogeneous measure that allows skills to be multiple in terms of both requirement and use, and secondly a theory that allows wages to be a function of schooling and work experience. Section 1.1 will focus on the heterogeneous human capital approach (Willis, 1986), section 1.2 outlines the Mincer Earnings Equation, section 1.3 focuses of the application of this carried out by Audrey Light and section 1.4 concludes.

3.1. Heterogeneous human capital

To answer the research question on how supplementary activities are rewarded on the labor market, a model allows these activities to accumulate human capital for the individual. A model that treats human capital as something that can be obtained from more than one source, and provides different skills in different settings is therefore needed. This can be accomplished in a model that treats human capital as heterogeneous.

One restriction of the Ben-Porath human capital model is that only one type of human capital is produced and demanded in the labor market, and the only way people can be different in the labor market is through the number of years spent investing in human capital through schooling (or by any other inputs other than the ones in equation 2). Even though almost every major in higher education requires the same amount of time spent in school, the accumulation of human capital seems to be rather different and is valued differently in the labor market depending on the employer. The values of an art-major and finance major[4] are not the same to an investment bank. If this were the case, we would expect, taking out one's personal interest, all types of higher education to be spread out equally among all types of jobs requiring a college education. Further, taken to the extreme scenario, a university would only offer one type of education, since this would be cheaper if differences were not relevant to employers. Along this line, the Ben-Porath model seems to view education as the only activity able to enhance skills, excluding any job or employment activity that might influence the human capital and hence change the marginal productivity of the worker. If this were true, our results should show negative wage premiums and employment odds for students who engage in supplementary activities, because they remove time from educational activities.

Robert Willis outlined a model of heterogeneous human capital in his contribution to "*Handbook of Labor Economics*" (Willis 1986). Opposed to the Ben-Porath model, this model was a long run equilibrium model, which changed the interpretation of the final model. However, this thesis will focus on the definition of human capital and leave out further examination of other differences. Where the Ben-Porath model sets all people equal, assuming they have obtained the same number of years' schooling, Willis replaces this homogenous assumption with a theory of heterogeneous human capital. Here, workers are able to produce different types of human capital, and each type is related to a certain occupation. One type of human capital requires a specific amount of time spent acquiring it, so people with the same skill cannot have studied different amount of time, but people who have studied the same amount of time can have used this time differently and, therefore, be qualified for different occupations. Each person has a profound ability related to the different occupational types for human capital. Which particular occupation an individual chooses to pursue depends on this ability. This is modeled as an ability component *l*, a vector where each person $_i$ has a level of ability related to every occupation.

$$l_i = (l_{0i}, \dots, l_{mi}) \tag{3}$$

[4] *Both studied 17 years: nine years of compulsory schooling, three years of high school and five years of college.*

Where l_i is the vector of occupational abilities, l_{0i} is ability related to each occupation, i is the individual and 0 represents the occupational categories ranging from 0 to m. This latter component is the essential component in the Willis model, and distinguishes it from the simpler Ben-Porath model in equations 1-2. The occupations should be regarded as listed in order of how much schooling the occupation demands, where 0 requires the lowest level of schooling and m the highest. Just as we do not observe the actual ability, we do not observe the actual wage per unit produced. The measure that we observe, and what is of interest to the individual is the potential earnings that they will be paid.

$$y_i = (w_0 l_{i0}, \dots, w_m l_{im}) \qquad (4)$$

Where y_i is the potential earnings determined by the product of wages and occupational abilities with occupational categories ranging from 0 to m. Since an occupation requires schooling, no matter how much ability the individual is born with, there is a trade-off between how much education should be obtained and when to join the labor market. The individuals' net gain through attending education is assumed to be their personal income, arising from the potential earnings of the occupation they choose. The individual, therefore, chooses the level of schooling that through occupational wages and personal ability measures gives them the highest present value. The net present value to be maximized here is shown for person i in occupation j:

$$V_{ij} = \int_{s_j+6}^{s_j+n} y_{ij} e^{-r_i t_{\delta i}} \qquad (5)$$

Given that *j=0.* The net present value V_{ij} is measured from age $s_j + 6$ until the schooling ends at age $s_j + n$, and r is the constant rate of discount, defined as a constant between 0 and 1. The $s_j + 6$ is argued by Willis to be the age where the individual can start to earn a wage. From this function, the individual chooses to optimize his/her level of schooling through:

$$s_1^* = s_k \quad if \quad V_{ik} = \max(V_{i0}, \dots, V_{im}) \qquad (6)$$

In the Danish context, we do not have different lengths of schooling; master's students all complete the two year master's program in Denmark, and prior to that have completed at least a bachelor degree as a prerequisite. One important assumption here is that the theory assumes education beyond the minimum requirements for the occupation to be unproductive. Here, students who have completed one year of education and then switched to another line of study, are not more productive than students who avoided this educational detour. This is also the case for people who are overeducated: school teachers with a Ph.D. or a nurse who has a doctor qualification.

The model from Willis allows for heterogeneity in human capital, but only between occupations and not within each one. The heterogeneous human capital approach fits this, but the setting for choosing a level of schooling related to abilities is different, since all Danish students choose the same length of schooling, but have different compositions of learning environments. In our setting, the variable of interest is the composition of the heterogeneous human capital, and how this reflects on the investment. I have, therefore, adapted the model for this thesis to only have one length, but with differences in how that same time is allocated. An extension of the model seems necessary for the further analysis.

Adaption of the model

From equation 9 we know that the individuals have an ability vector, which enables them to be differentiated from each other in terms of which occupations maximize their wages, which is also what we want to examine in the research question. We know that we cannot observe this ability, neither the labor input l nor the skill prices w, which together present us with the potential earnings for a person. But we do observe the actual earnings, which we use as measure of y. Until now, the labor input has merely been a vector of the individual ability endowments related to each occupation. The ability vector was described by Willis as "*their occupational abilities (i.e. their capacity to be trained for a given occupation).*" But since human capital is now viewed as being heterogeneous, and we know from earlier literature that labor market participation before graduation matters, it seems reasonable to decompose the ability endowment vector into two variables, as shown in equation 7:

$$l_i = (a_{oi}\theta_{0i}, \dots, a_{mi}\theta_{mi}) \qquad (7)$$

Where $a \; and \; \theta \geq 0$.

Where the vector *l* still represents the ability measure, but now consists of a term that expresses the capacity to be trained within regular education a_{oi}, and the term θ_{0i} reflecting the capacity to be trained for an occupation through skills acquired from on-the-job training. Together they reflect the total capacity for each individual to be trained within each occupational category.

The new decomposition changes the input into the net present value, which is the function that determines which training and level of such that each individual should obtain. This leaves us with no changes in the appearance of equation 6 in the search for calculating the individual net present value.

The understanding of human capital as heterogeneous enables us to understand the skill formation, but is not concerned with how to model the theoretical knowledge with respect to the labor market. This theoretical formation of an equation that takes these parameters into account was studied and developed by Mincer in 1974.

3.2. Mincers Earnings Equation

Much focus on estimating the individual return on educational choice has been based on the Mincer equation, originally developed by Jacob Mincer (1974). The equation is typically used in the setting for estimating the average percentage change in wages when obtaining one more year of education (Mincer 1974).

$$Ln\, y = \ln y_0 + rS + \beta_1 X + \beta_2 X^2 \qquad (8)$$

In the equation, S represents years of schooling, and X is the potential labor market experience, since this is often applied to cross sectional data. This estimation of potential labor market outcome is not used in the analysis, because the model is only concerned with the short-term effect. A brief mention of this is included to allow the reader to become familiar with the structure of the mincer equation, but the notation of equation 8 will not be used directly. The theory is used as reference in addressing the model that is generated in the handbook by Willis (1986). The theory is crucial in both the Willis handbook chapter, but also in many of the references in the literature review. Wide acknowledgement and empirical use of the Mincer earnings equation makes it highly relevant to use as background. The limitations of the research question and the scope of the thesis restrict the number of main theories that can be applied. The main theories will, therefore, not include Mincers earnings equation, but it is briefly mentioned above to acknowledging the huge impact this earnings equation has had on wage analysis.

Mincers Earnings equation later became the foundation of an academic paper on estimating the effects of in-school work experience (Light, 2001). The earnings equation was used by light to estimate the effect of human capital obtained by in-school work experience, based on the Robert Willis theory from section 3.1. Light's essential paper on the combination of these two papers is outlined and discussed in the next section.

3.3. Audrey Light

Audrey Light performed an econometric application of the Willis theory on the National Longitudinal Survey of Youth (NLSY) in 2001. She argued that the effect previously declared as a schooling effect, from models such as Ben-Porath with a Mincer Earnings Equation application, should instead be interpreted as causal effects of the skills learned in the classroom and another separate effect from training occurring in the labor market, thus reflecting on-the-job training that occurs during educational attainment (Light 2001).

She states the goal of her article is to *"…identify the separate, causal effects on post-school wages of schooling (time spent in school) and in-school work experience (time spent working while in school)"* (Light 2001). This goal has a clear alignment with the subject matter of this thesis, but with the significant difference of the inclusion of internships and exchanges, beyond only student jobs. The inclusion of these two variables is a reflection of the view this thesis holds concerning the decision to work while in school.

Light changes the setting of time allocation, where the allocation is divided between acquiring school ability and work ability. This corresponds to the argument that is presented with equation 13 (Light 2001).

Light based her econometric model on the Mincer earnings equation (Mincer 1974), drawing on the theory of a heterogeneous human capital approach, believing that the time allocated to investing in human capital should take into account two ability measures: school and work ability. The econometric application was presented as a wage equation:

$$w_{it} = \gamma_0 + \gamma_s s_i + \gamma_1 x_{it} + \gamma_2 sx_i + \gamma_3 sx_i * s_i + \eta_{it} \qquad (9)$$

where *w* represents the natural logarithm of average wages earned in the respective period following graduation, S is years of schooling, SX is the in-school work experience and X is post-graduation work experience.

All of these models have assumed that the fraction of one’s time allocated to work is chosen by the individual. The models do not operate with unemployment in any form, making the allocation of time exclusively a personal choice, where the optimum can always be chosen. Whether this is true, or students in reality would find it more attractive to extend the labor supply, either by widening the extensive or intensive margin of the labor supply, is not debated in the theoretical chapter. There will not be a theoretical extension of the theory to account for this, but current labor market status will be taken into consideration in connection with the empirical analysis.

3.4. Conclusion

The above theoretical discussion leads us to believe that despite there being many ways to view human capital production and time allocation, students who devote time to supplementary activities can affect human capital production, and thereby their relationship to future employment, but this should not be viewed as a definitive answer to how much and for whom the activities create a positive or negative effect. These elements will be explored in the empirical model and subsequent analysis in the following chapters.

4. Model

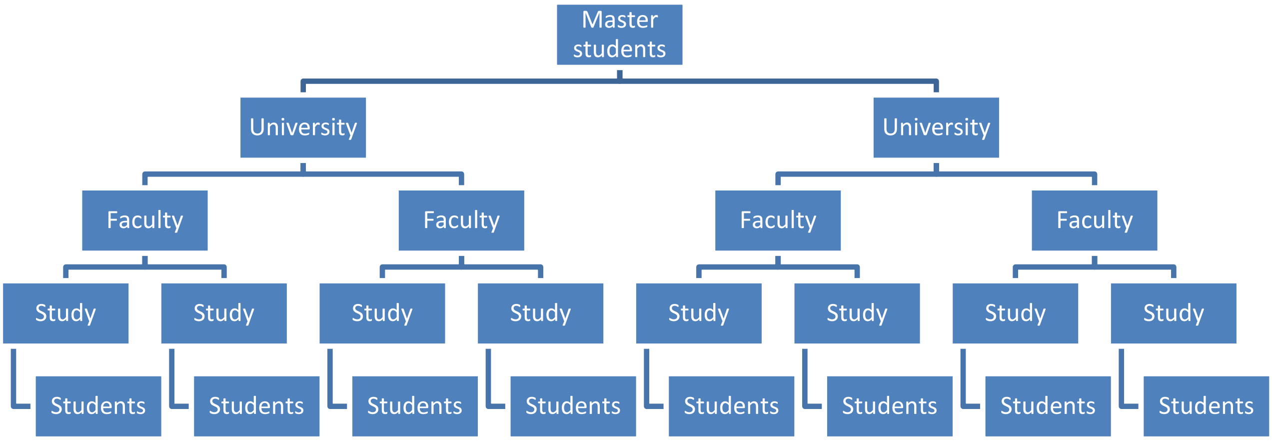
To accompany the theoretical aspect of human capital accumulation, an econometric model is needed. The model used to answer the question of whether there is a relationship between the labor market and supplementary activities, such as student jobs, internships and exchanges, is presented in this chapter. This section will discuss some of the challenges that are faced when trying to estimate the labor market outcomes from educational information. The purpose of this chapter is to provide the reader with a discussion of the choices made in the econometric approach and an understanding of the methodology used in the estimation of how labor market outcomes are affected by supplementary activities.

The research question in this thesis is concerned with labor market outcome, leading us to examine individual educational observation, and which requires us to take this type of data into account. The structure of educational data is not randomly spread, but rather a nested structure. Often when this type of structure has been present in the literature, a multi-level model has been chosen as the model of estimation (Theieme, Prior og Tortose-Ausina 2013). This class of models takes the structure of data into account when dealing with variation of outcome, in order to be able to account for none-random allocation of individuals (Snijders og Bosker 2012). Multi-level models use the structure of the models to include variation within each level of the data. If this is not done, estimates of regressions will not be specified correctly, making the conclusions of the estimation incorrect (Hox 2010). The multi-level class of models will, therefore, be the main model under consideration in the following chapter.

4.1. Multi-level model (MLM)

To answer the question of how student jobs, internships and exchanges affect wages, one must have clear and detailed data on the individual level. In the case of such educational data, samples are naturally constructed as *nested data*. In this case Danish students are structured in universities, within faculties, within institutes, within studies and again within classes. A simplified illustration of this nested structure is shown in the following figure, where the aggregated level is often referred to as the macro level and the detailed structures as the micro level:

Figure 1: Nested structure



When we want to estimate relationships with this type data, regular linear regression models with OLS are not the perfect fit, and will end up causing problems of interpretation. The coefficient estimates will tend to be consistent, but the standard errors will be too small, and the interpretation will tend to conclude that the relationship is significant when true estimation would find it insignificant (also known as a type I error) (Verbeek 2012). This is related to the fact that regular OLS models do not adjust the estimates if observations are not independent at the macro level due to clustering at the micro level. Further, the standard errors are based on an assumption of constant variance σ^2, implying homoscedasticity of the residuals. When the nesting structure is present, closer relationships between students in one area relative to other areas lead to heteroscedasticity, violating an OLS assumption and making the standard errors imprecise (Hox 2010). This means that students who are studying the same thing, such as biology, are more likely to be correlated with each other than with a random student from another line of study, such as economics or philosophy. These differences lead to a stronger correlation between the two co-students than with other subjects in the analysis. When using regular linear regressions models, they are constructed in a way that causes us to predict that variables included in the regression are influencing each outcome variable in the same way at each nested level. Conclusions like these risk forming an aggregate conclusion which over-interprets relations that are not necessarily present at both levels (Calmar Andersen 2007).

Often, multi-level models are concerned with only 2-3 levels, which in this case could be students, their line of study and their school. This type of model not only helps us estimate the relationship between the variables of interest, but also uses the structure of the data to provide us with interesting insights from this nested structure (Calmar Andersen 2007).

The model relevant to the analysis will be a two level multi-level model, where the micro level will be students and the macro level will be educations and universities. This model with random intercept will take the form outlined in the equations below, for individual *i*, attending study *j*:

$$y_{ij} = \alpha_{0j} + \alpha_{1j}X_{ij} + \epsilon_{ij} \qquad \text{1. Level } \textit{(10)}$$

$$\alpha_{0j} = \beta_{00} + \beta_{01}W_j + \gamma_{0j} \qquad \text{2. Leve } \textit{(11)}$$

$$\alpha_{1j} = \beta_{10} \qquad \textit{(12)}$$

$$y_{ij} = \beta_{00} + \beta_{01}W_j + \beta_{10}X_{ij} + \gamma_{0j} + \epsilon_{ij} \qquad \text{Full model } \textit{(13)}$$

The term W is a vector for characteristics at the individual level, and the vector X information at the macro level. Both of the error terms, γ_{0j}& ϵ_{ij}, are expected to be normally distributed ($\gamma_{0j}, \epsilon_{ij} \sim N(0, \tau_{00})$). The random effect component allows variation between studies, γ_{0j}, and the individual variation comes from the other error term ϵ_{ij} (Snijders og Bosker 2012).

The full model is estimated in SAS using PROC MIXED.

4.1.1.Hierarchical generalized linear model (HGLM)

This thesis is concerned with two measures of outcome: wage and employment post-graduation. When the outcome is normally distributed, such as the wage measure, the multi-level-model with random intercept can be described as the model above. However, the outcome related to employment is a binary outcome with a dummy taking the value one if the student has become employed post-graduation, and zero if not. The model specification, therefore, needs to take this into account, requiring the use of a hierarchical generalized linear model. Hierarchical generalized linear models are used when the outcome is not normally distributed, which in this case takes the form of a binary outcome (Snijders og Bosker 2012).

When modelling dichotomous outcomes, a logistics regression is used as the method of regression. To ensure a meaningful outcome where the variable obtained is related to the probability of success/failure, the model should not be allowed to estimate values beyond the range of the actual outcomes. Negative probabilities such as -0.43 or above 1 are not meaningful within the context of the data. When this limitation has been established, the variance that follows this is also limited and no longer constant, which will lead to heteroscedasticity (Snijders og Bosker 2012). These are some of the complications that follow binary outcome data, and this leads to the selection of logistic regression as the structure of the model, which in the case of multi-level models are known as hierarchical generalized linear models.

The equations related to the HGLM model with a two level nested structure are presented below:

$$y_{ij} = \alpha_{0j} + \alpha_{1j}X_{ij} \qquad \text{1. Level } \textit{(14)}$$

$$\alpha_{0j} = \beta_{00} + \beta_{01}W_j + \gamma_{0j} \qquad \text{2. Level } (15)$$

$$\alpha_{1j} = \beta_{10} \qquad (16)$$

$$y_{ij} = \beta_{00} + \beta_{10}X_{ij} + \beta_{01}W_j + \gamma_{0j} \qquad \text{Full model } (17)$$

The full model is the combined level 1 and level 2 equations. The outcome is determined by the individual level predictors given by $\beta_{10}X_{ij}$ and the macro level predictors $\beta_{01}W_j$ and the macro level error term γ_{0j} which is expected to be normally distributed ($\gamma_{0j} \sim N(0, \tau_{00})$).

This combined model allows us to identify the multiple variations in our data. This multi-level model will be estimated in SAS, using PROC GLIMMIX. The default estimation method in SAS PROC GLIMMIX is RSPL, which stands for pseudo-likelihood estimation based on residual likelihood, where the solution is based on a vector of random effects opposed to the mean of the random effects. If the data is subject to large differences in numbers of micro observations at each macro level, or the distribution is uneven, certain estimation methods should be taken into account. For further explanation and examples see Ng, et al. (2006).

4.2. Restrictions and possibilities

The dataset does not provide sufficient structure to analyze the combined problem as a natural experiment; neither does it provide an adequate instrument across all three possible treatments. This restricts us to using a model that is the second best choice when discussing correcting for unobserved variables and self-selection that could end up causing biased estimates.

If we do not succeed in our attempt to control for unobserved ability, and end up having omitted variables or measurement errors, we can be left with biased results and being unable to rely on our findings. Our results could, therefore, be the result of pure correlation and not a causal relationship. A solution to the problems of omitted variables is to use IV estimation, where the instrument needs to be correlated with the endogenous variable, uncorrelated with the error term and not to have any effect on the dependent variable when controlling. This instrumental variable is often hard to find, and does not seem to be directly present in the current data, when taking all three variables of interest into account. When an instrument is not present, sibling studies have in some cases shown themselves to be relevant as a different kind of instrument (Altonji & Dunn, 1996). This siblings structure will be addressed in the robustness check chapter, following the main analysis.

5. Data

In this section, the datasets and variables which are used in the analysis of employment and post-graduation wages for students who supplemented their master's studies with internships, exchanges or a relevant student jobs are considered. Along with this is an outline of some of the descriptive statistics for the main population. This is done to secure understanding and create an overview of the measures that contribute to the analysis and outcome results. The aim of this section is to present the reader with insights into data, and provide a necessary discussion of the restrictions that follow as a consequence of the choice of data. The structure of the chapter is as follows: the first section contains information about the two data sources; the second section is concerned with the data processing of raw data and missing values; the variables used in the model are addressed in the third section; and section four will outline the relevant descriptive statistics.

5.1. Data sources

The data used in this thesis is mainly register data provided from main public registers. None of the data is collected through surveys, but are all full population counts. Access to both of the data sources has been provided by the Danish Evaluation Institute.

5.1.1. Aarhus University (AU)

There exists no national register of internships for Danish students. To be able to implement internship as one of the explanatory variables, a separate collection has to be done. The data gathered to provide a variable for internships has been collected and processed by Aarhus University, Denmark. The data collection has been carried out via administrative registers by the Student Administration and Services - Educational Development and Analysis Department.

The data concerns all students at Aarhus University who in the period September 1st 2009 until August 31st 2012 completed an internship that in return provided the students with ECTS point corresponding to the value of such an internship. The department that had access to the registers and provided us with the data is also responsible for delivering information such as grades, lines of study, dates of starting and terminating studies to Statistics Denmark. I am, therefore, confident of the quality of the data, and that it provides the scope that is relevant to the thesis.

5.1.2. Statistics Denmark

The main part of the data is provided by Research Access at Statistics Denmark (DST), and concerns only individual observations (Statistics Denmark, 2016). The identification of each person through the various datasets is done on the basis of an identification key constructed by DST and relating to each individual's

Danish social security number[5][6]. A large variety of data sets will be used in the construction of the model described in the previous section, such as the population register, income data, several student registers, and employment and social benefits registers. None of the registers are sub-samples of the population, but a full headcount, which helps to eliminate some of the possible difficulties that occur when dealing with samples and selection bias in the data collection.

5.2. Data processing

The population of this thesis has been restricted to students starting their master's at Aarhus University in the period January 1st 2009 until December 31st 2012. To secure a reasonable population for estimation, further criteria have been imposed upon the sample. Students who terminated their master's before graduation are eliminated. Since outcome measurements are related to labor market outcome, students who began and completed a PhD program are also removed. A few students began and completed more than one master's in the relevant period, and in such cases the most recently obtained master's degree is used. A few students began one type of master's, but ended up graduating in another related type. Such students will be recorded with the education obtained at graduation.

The data processing has not only dealt with narrowing of the population, but also missing values. The case of missing values in a data set should always be of great concern and handled with care and caution. Our estimation loses efficiency compared to a case where every observation has information on all variables used in the estimation and when missing values lead to the loss of observations (Verbeek, 2012). In some cases, hot deck imputation of the missing variables has been seen to be used. In this case, either the mean of the distribution or random draws from the actual observations are used to "fill" the missing variable for the observation. This prevents the model from losing efficiency, but the trade-off is possible bias in the imputation variables. Though this method provides us with a larger sample, approximation errors in this imputation should be regarded. Verbeek (2012) also questions the use of such constructed observations equal to real observations. To decide how to address the problem in the current analysis, the cause of the missing value has been taken into account. In this case, missing variables mostly occur when people are living abroad or die, and never due to lack of response. On the basis of this, I choose to leave out observations that are subject to missing values for one or several variables. The following section describes in more depth how different types of variables are subject to missing observations, and how this is dealt with along with potential biases.

5.2.1. Missing variables

The full students sample as defined in the section above is not subject to missing observations or missing educational information. Not one of the observations in the sample is missing information in relation to the

[5] *In Danish = CPR nr.*

[6] *The artificial identification is equal across all registers, offering us a unique and simple way to track the same individuals.*

explanatory variables (see section 5.3 for further definition of these variables). A few students are missing information in relation to some of the control variables.

Students who do not have a reported grade point average from high school are excluded from the data. Information on grades was made digital in 2001/2002, but the first years of the registers are not complete. Older students beginning their master's are, therefore, naturally removed from the population, as well as students who graduated high school outside Denmark, and whose grades have not been transferred into the system. This naturally weakens the estimation, since older students and students who took their education abroad might contribute other skills to the labor market. Data reveals that this makes up 0.02 pct. of the population, and thus not a large number of observations. Even though the removed sample is small, the analysis should not be projected onto these two groups.

Variables on age are measured when the students attend university. If no information exists for the period 2009-2012, the observations are deleted, and this comprises roughly 0.001 pct. of the final population. Age is registered in the population register, containing every individual with residency in Denmark as of January 1st that year. The population register at Statistics Denmark is limited to people living in Denmark at the time of measurement. If individuals are not in these registers, they have either died or left the country. We do not distinguish between these two events in the population. It can be critical to remove people from the population, if they have moved abroad and become employed/unemployed, biasing the result in that direction. This could happen if the group of people who move abroad are different from the average student and are more/less likely to become unemployed than the students who stay in Denmark. The same argumentation can be laid out in relation to the parents of our population: if they have died or moved out of the country, they are not listed in our registers. Another explanation also exists if the identity of one or two parents is unknown. This is a more frequent occurrence for fathers than for mothers, where fathers form the largest proportion of missing parents. There are no such cases in the Aarhus population, but in the full sample, 0.23 pct. of the mothers and 1.41 pct. of the fathers are missing from the sample that is used to measure employment, and correspondingly 0.25 pct. and 1.27 pct. in the sample used to measure wages. These numbers are too small to show for each type of supplementary activity, and are therefore not displayed in the descriptive statistics, but are included in the model.

Information regarding parental income, education and socioeconomic status is measured in the year the student turns 16. The same procedure is conducted on siblings, ancestry and household structure. Some of this information is not present which leads to considerations about how to proceed. All cases of removing observations based on missing information are a problem. The critical aspect here lies in removing individuals if there are systematic differences between groups that have all information and groups that do not, e.g. groups that have information about both parents and groups that do not. This selection comes at a cost to the analysis. If we end up removing these individuals, is the sample of students in this population far different from the average student in Denmark? If this is the case, the effects of the analysis will not be global effects, but rather local treatment effects. It is likely that students who are brought up without knowledge of one biological parent are not similar to those children who have known both their parents, or have even been brought up by both parents. I decided, therefore, to retain these observations, and instead group them with a dummy variable for unknown parent(s).

The models end up being applied to four different populations: two restricted Aarhus samples and two full population samples. The differences between these two types are small, but are related to the availability of the outcome measure, which makes the wages estimate a larger sample than the one used for employment.

Table 1: Population sizes

	Employment	Wages
Aarhus	4,430	5,875
Full population	17,863	22,665

5.3. Variables

The dataset providing the foundation for this thesis consists of a long list of variables that make the analysis possible. Some are a direct take-away from Statistics Denmark, some are calculated and combined and one is as mentioned from AU. To gain a clear understanding of the results later on, the variables are listed and discussed in the following section in order of their relation to the thesis: first the dependent variables, then the explanatory and finally the control variables.

5.3.1. Dependent variables

Several different dependent variables could be used in the measurement of how these three supplements affect students. A number of studies have used grades and academic performance in assessing their impact (Schoenhals, Tienda, & Schneider, 1998), (Stinebrinkner & Stinebrinkner, 2003). To be able to relate the results directly to labor market outcome, dependent variables have been chosen that reflect this, along the line of studies done by (Light, 2001) (Hotz & al, 2002) using wages. The analysis is carried out with two different dependent variables: employment and wages one year after graduation. Both variables capture a relation to the labor market, but the outcomes differ in the measurement of two different effects: if the human capital acquired increases the odds of being employed, and if the human capital acquired increases the wages paid.

The first dependent variable concerns the wage of the students 12 months after graduation. The salary is a pre-tax income measure for all jobs the individual held in the given month[7]. It includes benefits, labor market contributions and the supplementary labor market pension contribution. Beyond this, people who are self-employed and receive net profit from their company feature in the register with this net profit as a measure of income. Here, the monthly income is a more artificial measure, since net profits are not always received monthly; the monthly number is an estimate by DST. It is worth noting that social security benefits are not included in the income measure. The measure does not include the value of unemployment benefits, sick pay or any other state or local government payment. Neither does it include any subsidy to actual payment, such as child support or housing subsidies. Income measures are inflation adjusted to 2015 prices (see table in the appendix for inflation measures). Wages is a monthly measure, and can be measured 12 months after graduation. Wages are sometimes skewed, and therefore log/ln wages are used to normalize the distribution. The wages variable in this data is not more skew than in the actual distribution, so the actual wages measure is used. For distributions of log and actual wages, see the appendix for graphs.

The second dependent variable relates to whether or not a person has become employed one year after graduation. This is constructed as a dummy, taking the value one if a person becomes employed one year after graduation. In Denmark, employment is information that is measured at one point in time every year, namely the end of October. This means the duration of the period from graduation until employment differs depending on the time of graduation. The quarter of graduation is, therefore, included as a dummy variable to capture this effect, where 4th quarter is the baseline, for students who graduated one year before. Students who graduate closer to/further away from the one year mark are corrected by removing the additional variance by a dummy variable.

5.3.2. Variables of interest and control variables

The three different variables of interest come from three different data sources, where two are directly converted to a dummy variable, and the final one, student job, has been created through several steps. Even though student job and exchange come from different datasets, they are both provided through register data.

Exchange: The complete register contains both students from abroad spending a semester in Denmark, and Danish students abroad. The register distinguishes between students who attend an internship and those who take courses at another university. We will here only focus on students who attended another university outside Denmark, replacing ECTS point from the activity with those otherwise obtained by educational courses.

Internship: Data is provided through Aarhus University and then linked to the full registers. The data is, as mentioned, provided from full registers at the university, and not as a sample collection. It contains infor-

[7] *In Danish, A og B indkomst.*

mation on all students that in the relevant period completed an internship to earn credits to use in their educational program. Some studies are subject to mandatory internships. These are studies such as bachelors of engineering[8] and other smaller lines of studies. Most of these mandatory internships take place at bachelor level, making them non-appearing in our data. The data on internships are defined as providing the student with ECTS points, which here is regarded as a substitute for elective courses. If a student engages in an internship but chooses not to take advantage of granted ECTS points, this student will not appear in our register. The choice can be due to lack of skills acquisition during the internship or possibly elective courses being available that the student would not be able to take if the internship was reported. We should, therefore, be aware of possible underreporting by students who have undergone an internship.

Student job: The student job information is not a provided dummy like the two first explanatory variables, but has to be created from income and employment registers in combination. There is no guideline on how to create this variable, but it has been done in some other studies resembling this one[9]. Like in the previously mentioned study, my definition of a student job will be one that is relevant to the type of education the individual attains, though the procedure carried out here is slightly different and involves several steps. Every student in the population is matched with information at industry and DISCO levels[10] for jobs concerning master students. Information is only kept if the person is still studying at the time of recording this information. It shows that over the course of the time spent studying a master's, the relevancy of one's job to the line of study increases. It is, therefore, the most recent information on employment during educational attainment which is used in the classification of student job. The DISCO qualification is used as the best predictor of relevancy. If the job is classified as level 1-3, the job is considered relevant for a student studying their master's; the rest are qualified as non-relevant and will be treated as equal to those who did not possess a job. Jobs that are recorded but do not hold information on DISCO qualification will be determined relevant/not relevant on the basis of a combination of their line of study and the industry in which they work. If the combination is considered relevant, they will be categorized as having had a relevant student job. A list of those industries that are considered relevant, and their interactions with the different master's studies, is provided in the appendix.

Overlapping explanatory variables: To hold a student job is common in Denmark, especially for students who are enrolled in a master's degree. Some of the same students are also taking an internship or have been on an exchange, which is something that should be considered. To be able to distinguish between the effects of the activities, overlaps of explanatory variables within each individual are not reported as interaction terms; instead one dummy is created taking different values depending on which and how many supplementary activities each observation has engaged in. For example, if one person has had a student job and been an intern, the person is only reported in the column "Job & internship" and not in the columns "Job"

[8] *In Danish: Diplomingeniør*
[9] *AE rådet note*
[10] *An international qualification of occupations (ILO, 2010)*

or “Internship” alone. A very small group has done both internship and exchange, and a fraction of these have also had a student job. This group is too small to report on and say anything significant about, and only comprises 36 out of almost 9,000 people. To be able to include these observations, a choice has been made in relation to their internship and exchange stay. Since these cannot have been completed at the same time, the most recent one is used to classify the individual. It can be discussed whether this will make the results biased, i.e. when some people have completed more than one of these activities but the event is not reported. This could potentially be a problem, but not including them in the dataset would seem to present greater bias to the sample, i.e. refusing to include observations that could hold some information on a potential effect. The question is also addressed later on.

Beyond the explanatory variables, the data sets contain a long and comprehensive, but not exhaustive, list of possible influential variables. The advantage of this very rich and reliant set of variables enables us to control a large variety of background information, minimizing the potential bias that the theory imposes on this type of model. Some of these are intuitive in interpretation, like sex and age, whereas others need a more detailed description. Some variables exist in their desired format in the registers, while others need some separate treatment, such as the student job variable just described.

The control variables used to specify the multi-level model are comprehensive, and a full list is available in the appendix. Some of the variables have been specified in further detail below.

High School grades: When attending high school, all students take a combination of subjects, where some are mandatory study program courses and some elective courses. Each course is taken at level A, B or C, equating to the academic level of the course, and certain restrictions are imposed on the possible combinations and the number of hours a high school education can contain (Retsinformation, 2013). Every course is terminated with a grade reflecting the level the student has shown during the academic year. Therefore, not all courses are present for every individual, and some might be listed but at different levels (A, B or C). Mathematics at level A is used as a control variable as a dummy, not dependent on the grade, but just attainment. The grade average is provided by Statistics Denmark, where the weight of courses depending on level and, where possible, exam grades replaces the final grade. The scale by which Danish grades are assessed was changed in 2008. The majority of the Danish population graduated from high school before 2008, and to be able to compare the whole sample, grade point averages of students who graduated after 2008 have had their grades translated back to the old scale (UVM). If a student has more than one high school diploma and related grade point average, the most recent one is used.

Ancestry: Immigrant status is included to capture the relevant socioeconomic factors. Many of the previously mentioned studies have indicated that ancestry can be significant. The relation to education seems obvious, since educational level can be transferred from a previous country, and this may not reveal if a parent has been a part of the Danish educational system and is thus able to pass on relevant knowledge to their children. Statistics Denmark defines immigrants and descendants thereof as "*People who are born abroad, where none of their parents are both Danish citizens and born in Denmark, are labeled as an immigrant. If there is no information about either parent, and a person is born abroad, he/she is considered an immigrant. Descendants are born in Denmark where none of their parents are both Danish citizens and born in Denmark. If no information about either parents exists, and the person is a foreign citizen, he/she is also considered a descendant.*"[11] (Danmarks Statistik)

Parental resources as influence: A large variety of empirical studies as well as theoretical models predict that parental factors influence outcome related to children's educational attainment and, thereby, their human capital (Björklund & Jäntti, 1997). The important influence of family resources on future labor market outcome is pointed out in the study "*The Educational and Personal Consequences of Adolescent Employment*" (Schoenhals, Tienda, & Schneider, 1998).

Parents' education level: It would be expected that the level of education obtained by the parents of students influences the possibilities that a student is exposed to. Here, possibilities not only refer to jobs or internships, but also to help during education and providing an educational environment that encourages relevant characteristics. Parental education is included as dummies describing the level of education as classified by the OECD (OECD, UNESCO, Eurostat, 2015).

Income: The annual income of parents is a purely work related measure. The variable includes payment by employer, profits from own company as well as certain fees. Transfer from social security and other public financing such as child benefit, old age pension, sick pension, etc. are not included in this measure. The income could be, but is not necessarily, related to educational level. People who are business owners often make more money on average, but do not necessarily have the highest education. This statement is backed up by data from Statistics Denmark. In 2013, income before taxes was on average 519,523 DKK for self-employed, whereas the equivalent income for the average employed person was 411,966 DKK, almost 100,000 DKK less. The distribution of education level for self-employed is shown in the appendix. 28 pct. were unskilled in 2013, and 42 pct. had only vocational training, which means that 70 pct. of self-employed people had no tertiary education, but still made more money on average. Since wages are presumed to be a predictor of human capital, and the last decade has seen an expansion of education, it is worth including income as a parameter.

Socioeconomic status: A lack of income is a measure placing people outside the labor market, but is not always a meaningful way of bulking people into the same large category. Alone the vast body of literature on intergenerational persistence should lead us to be interested in whether people are lacking income due to sickness, maternity leave or are declared unfit to hold a job. Sohr-Preston et.al. carried out a three generational longitudinal study on American data, and found that socio-economic

[11] *Personal translation*

status seems to affect children in matters of educational attainment and achievement, and that theory supports an expectation of the same results through better interpersonal and material investment in children (Sohr-Preston & et.al, 2013).

All of these variables and more are used later on to estimate a model to try and explain the effect of these supplementary activities on wages and employment. Descriptive statistics on these is, therefore, presented in the next section to explore whether there are biased distributions in the control variables before estimating the models.

Identification of siblings

In order to perform a robustness check of the model, a small siblings study is conducted. This limits the main population into students who have a biological brother or sister. The identification of siblings is done through two criteria: biological mother and household information. The sibling should have lived in the same household as the student in the original population. This is done to control for characteristics of parental upbringing.

All of this can only contribute to a model estimation, as the data are not subject to differences in distribution between the variables of interest and the control variables. To investigate this, descriptive statistics of the population are shown and analyzed in the following section.

5.4. Descriptive statistics

In the following section, descriptive statistics for the data are presented to uncover any distributional differences between average students and those choosing different supplementary activities. This is done by addressing the different combinations of supplementary activities and considering some background information available in the analysis. The purpose of this is to let us know if there are concerns about any unobserved variable interfering with the population outcome before moving on to the actual analysis.

There are two main analyses in the paper: the effect on wages and employment. These two are not measured at the same time, which affects the number of students that have graduated a year before. The size of the two populations differs, and will therefore have slightly different distributions across the variables. This section will interpret the wage distribution for the population, but since the distributions end up being highly similar, descriptive statistics on the employment populations are subject to the same conclusions; the descriptive statistics are shown in the appendix. Any large difference between the table in the section and the remaining population will be mentioned separately below.

Table 2: Descriptive Statistics: Students at Aarhus University (Wages)

		No Activity	Student job	Job & intern	Job& exchan-ge	Intern-ship	Ex-change	All
		Pct.	Pct.	Pct.	Pct.	Pct.	Pct.	Pct.
Sex	Male	40.54	47.90	42.11	51.67	26.28	46.15	*45.80*
	Female	59.46	52.10	57.89	48.33	73.72	53.85	*54.20*
High level math	No	64.30	64.22	74.27	57.11	71.53	52.88	*64.55*
	Yes	35.70	35.78	25.73	42.89	28.47	47.12	*35.45*
Age*	18-22years	20.69	25.09	17.15	32.01	21.17	30.77	*24.21*
	23-25years	64.07	60.91	66.86	62.76	64.23	66.35	*62.43*
	26+years	15.25	14.00	15.98	5.23	14.60	2.88	*13.36*
High School grade average	6 - 7,5	8.98	6.25	5.85	1.46	4.38	7.69	*6.19*
	7,6 - 9,0	48.11	46.91	50.68	40.59	43.07	57.69	*47.01*
	9,0 - 10,0	37.94	40.39	38.79	46.03	41.61	30.77	*40.18*
	10,1+	4.96	6.45	4.68	11.92	10.95	3.85	*6.61*
Ancestry[1]	Danish	95.04	96.45	97.47	98.12	97.08	97.12	*96.50*
	Immigrant or descending	4.96	3.55	2.53	1.88	2.92	2.88	*3.50*
Family type[1]	Couple	90.90	93.34	91.81	93.72	91.97	94.23	*92.79*
	Single	9.10	6.66	8.19	6.28	8.03	5.77	*7.21*
Mother's educational level[1]	Unknown	0.83	0.92	0.39	0.21	3.65	0.96	*0.86*
	Unskilled	21.04	18.44	16.96	14.64	21.17	12.50	*18.31*
	Skilled	28.61	27.72	27.68	22.38	29.20	26.92	*27.38*
	Short cycle tertiary educ.	5.56	5.77	5.46	5.23	3.65	8.65	*5.65*
	Bachelor’s degree or eq.	35.11	38.14	43.08	44.98	34.31	46.15	*38.85*
	Master’s degree or PhD	8.87	9.01	6.43	12.55	8.03	4.81	*8.95*
Fathers educational level[1]	Unknown	1.54	1.09	0.78	0.63	-	-	*1.04*
	Unskilled	16.08	15.60	18.71	12.97	16.79	16.35	*15.80*
	Skilled	38.30	37.93	33.53	30.33	40.15	29.81	*36.71*
	Short cycle tertiary educ.	6.15	4.23	4.29	5.23	4.38	6.73	*4.71*
	Bachelor’s degree or eq.	20.33	21.65	22.81	23.43	23.36	22.12	*21.77*
	Master’s degree or PhD	17.61	19.49	19.88	27.41	15.33	25.00	*19.97*
No. of children in the household[1]	One child	22.81	23.01	27.49	20.92	24.82	22.12	*23.27*
	Two-three children	71.39	71.83	64.72	72.38	69.34	73.08	*71.04*
	More than three children	5.79	5.16	7.80	6.69	5.84	4.81	*5.69*
Socioeconomic, mother[1]	Employed	91.25	92.80	91.23	94.14	90.51	97.12	*92.53*
	Unemployed	8.75	7.20	8.77	5.86	9.49	2.88	*7.47*
Socioeconomic, father[1]	Employed	92.20	94.71	93.76	95.82	92.70	97.12	*94.29*
	Unemployed	7.80	5.29	6.24	4.18	7.30	2.88	*5.71*
Income, mother[1]	No income	5.08	5.16	6.04	3.77	5.11	3.85	*5.07*
	0-299.999kr.	67.97	63.16	67.25	55.23	68.61	68.27	*63.89*
	3-399.999kr	19.03	22.60	21.64	28.87	18.25	20.19	*22.33*
	4-499.999kr	4.61	5.46	2.73	8.37	3.65	5.77	*5.27*
	500.000kr+	3.31	3.62	2.34	3.77	4.38	1.92	*3.44*

Income, father[1]	No income	6.74	4.75	4.87	3.14	5.11	2.88	*4.91*
	0-299.999kr.	29.31	28.13	31.19	24.27	30.66	25.96	*28.30*
	3-399.999kr	26.36	28.92	27.29	25.31	30.66	24.04	*27.92*
	4-499.999kr	15.13	16.63	18.52	18.83	15.33	19.23	*16.80*
	500.000kr+	22.46	21.58	18.13	28.45	18.25	27.88	*22.07*
Quarter of graduation	Q1	34.99	23.69	25.15	23.22	32.85	31.73	*26.12*
	Q2	17.38	27.76	27.10	19.67	20.44	13.46	*24.67*
	Q3	28.61	29.77	26.71	41.42	24.82	35.58	*30.36*
	Q4	19.03	18.78	21.05	15.69	21.90	19.23	*18.85*

Notes: * Age is at the point in time when entering the master's program. [1] All measured in the year the student turned 16 years old.

Table 2 reveals that the population of females is larger than males in all sub-samples, apart from students who were both employed and went on an exchange, but the drop below 50 pct. does not seem large enough for concern. The population of females is largest within the internship group, making up almost 3/4. This difference might originate from different possibilities for internships between majors. Line of study is chosen as the macro level in the multi-level model to control for differences in this.

Around one third of the students have had high-level math, and this proportion is slightly higher for students who have been on exchange in one of the two possible categories. Between 61 and 67 pct. are between the ages of 23 and 25 when they begin their master's. The rest are mainly concentrated in the younger category, where the concentration is larger in the two exchange categories. Around 90 pct. of the students have a high school grade average between 7.6 and 10.0, whereas the students without any supplementary activity seem to have a larger proportion of grade averages between 6.0 and 7.6.

The ancestry of the students is between 97 and 99 pct. Danish, with the remaining proportion either immigrants or descendants. The same clear division can be seen in family type, where approximately 95 pct. across the groups are brought up in two-parent households. Parental education also appears to be stable across the six groups, with around 5 pct. having short-cycle educations for both mothers and fathers, and the rest shared equally among lower and higher educated parents.

Students who completed an exchange stay are less likely to have unemployed parents or have more than three siblings in relation to both the baseline group and the other explanatory variables. This does not seem unreasonable, since exchange can incur some expenses. The difference should be noted if this leads to higher wages, since it could be an effect originating in parental income, but does not seem to hold an overwhelming significance. Relating this to parental income at the same time, there do not seem to be different distributions between the six separate explanatory variables. The concern about the small difference in socio-economic status is thus not considered essential. The same equal distribution is seen in the quarter of graduation. This measure should be noted to capture not only any cyclic changes in employment during a year, but also the difference between this and the point in time at which the annual employment statistics are obtained (end of October). This is, however, only for employment, since wage is measured monthly and the estimate is purely cyclic.

Similar distributions are seen in the full population for both wages and employment, which can be found in the appendix.

The conclusion to the descriptive statistics is that there is no overall concern over the distribution of the control variables among the different groups of students. I will, therefore, continue to estimate a model based on this dataset.

6. Results

The result of the analysis, estimating the labor market effects of internships, exchanges and student jobs are presented in this section. The first part will be concerned with results found from using a multi-level model on the main population from Aarhus, and the second on the full population sample. The purpose of this chapter is to ascertain the best estimate for the potential labor market effects.

6.1. Multi-level estimation

In this section, multi-level models are estimated to address the labor market question. The multi-level model approach uses regression analysis to estimate the effects, but does not assume independence of observations. This is a regular OLS assumption, which is violated when students within one major are more correlated with each other than with another random draw from the population. The multi-level estimation method is, therefore, highly relevant when there is a nested structure present in the data, since it provides random intercepts for each cluster of students, thus taking the unequal variance into account. This approach is outlined and discussed more carefully in *Chapter 4 - Model*.

6.1.1. Multi-level results, Aarhus

The analysis is concerned with two outcome variables: wages and employment. The two dependent variables are not similar in structure; wages is a continuous variable with a normal distribution, and employment is a variable with dichotomous outcome with a non-normal distribution. This requires the analysis to be separated in order to address these assumptions and interpret the results. The wage measure is the received wage from a job or from being self-employed 12 months after graduation. The employment measure is not as accurate, measured just once a year in the quarter of graduation. For further details on this, see *Chapter 5 – Data*.

Wages

Although the nested structure is present, it is relevant to ask if a multi-level model is preferable to OLS with fixed effects. The multi-level structure, therefore, needs to be verified in order to proceed with the right model. To investigate whether a model with random intercepts for studies is better than a regular OLS model where studies are included as regular fixed effects, two such models are estimated. In the case of this thesis, the clusters that the observations are assumed to be clustered in are the different studies. Studies are thus the variable that is either a fixed or random effect in the following specification. Both models are estimated with no variables of interest or control variables, to enable a pure comparison of model specification. The fixed effect model is also called the empty model, or the ANOVA model (Snijders og Bosker 2012).

Table 3: Specification test of multi-level model

	Fixed effects	Random effects	Test-size(β)*	Pr>chi^2
- 2 log likelihood	128,596.2	128,106.2	490.0	0.000

Notes: *Degrees of freedom=1

The test-size used to compare the two models is the difference between the two log likelihood values against a chi-square distribution, with one degree of freedom as showed in table 3. The single degree of freedom represents the variable removed from the model specification when the macro variable, which here is the study, is controlled for. In comparing our test-size to chi-square distribution with one degree of freedom, $\beta = 490.0 \sim \chi^2(1)$, we see that it exceeds the critical value of 6.63 by far. A multi-level model that includes random effects is, therefore, selected to proceed with.

Even though a model that takes this clustering into account is seen to be preferred, it would be useful to know how much of the variation is to be assigned this type of modelling. To do this, an Intra-Class Correlation Coefficient (ICC) value is calculated between the covariates of the intercept and the residual. The ICC reflects how much of the variation in wages is due to the supply of education, which is modeled as different intercepts.

Table 4: Covariance for ICC calculation

	Estimate	S.E.	Z value	Pr > Z
Intercept	12,111,277	2,427,741	4.99	< .0001
Residual	1,203,700,000,000	2,216,025	54.32	< .0001

In this case, 9.14 pct. of the variation is explained by the multi-level structure. It is a significant amount of the variation which is thus explained, and also a variation that according to the previous test is significant. In order to accept a multi-level structure, the Intra-Class Correlation should be at least around 10 pct. (Hox 2010), which is the case here. The use of a multi-level random intercept model derives, therefore, from both the specification and ICC test. The analysis is therefore preceded with actual estimation results of the multi-level model.

The datasets include several control variables at both the individual and macro levels. Three different models have been estimated in order to determine which model specification has the best fit. Table 5 outlines the variables of interest, the significant control variables along with variables that are surprising in their lack of significance. A full table is shown in the appendix.

Table 5: Results: Multi-level random intercept model on wages for students at University of Aarhus

Solutions for fixed effects	*Model 1*	*Model 2*	*Model 3*

	Effect	Estimate		Estimate		Estimate	
	Intercept	23,311	***	12,795		43,125	
Explanatory variables	Exchange	-887		-891		486	
	Relevant student job	2,245	***	1,953	***	1,921	***
	Exchange & student job	3,961	***	3,650	***	3,560	***
	Internship	224		213		206	
	Internship & student job	1,333	*	1,199		1,257	*
Individual level control variables	Gender			-12,856	***	-13,332	***
	High Level Math			745	*	637	
	Age			902		377	
	High School avg.			119		-191	
	Q1			530		497	
	Q2			1,119	***	-892	
	Q3			-288		-354	
	HS. avg.*Gender			129	***	134	***
	HS. avg.*Age			-91		-32	
Macro level control variables	Humanities					-12,747	
	Science					-16,356	*
	Social Science					-21,866	***
	Health Science					-3,175	
-2 Log Likelihood		128,049.7		125,967.1		125,903.4	

Notes: Significance: *=p<0.05, **=p<0.01, *** (Gicheva, 2013)=p<0.001. Model 1: N (individual level) = 5,968, N (macro level) = 85, Model 2: N (individual level) = 5,875, N (macro level) = 85, Model 3: N (individual level) = 5,875, N (macro level) = 85. Some insignificant coefficients are left out of the table. The full model also includes estimates on family and parent indicators. See the appendix for a full table of estimated coefficients and S.E.

As shown in table 5, model 1 only contains the explanatory variables; model 2 includes both explanatory variables as well as control variables at the individual level; and in model 3, control variables at the macro level have been added to variables from model 2. The estimate differs in significance, and in some cases the estimate shifts from positive to negative or is reversed between the three models. In the search for the optimal estimate, I would like to determine which of the models that fits the data best. To establish this, a likelihood ratio test is carried out, which is done by comparing the fit of the models with each other. The likelihood ratio test values displayed in table 5 can be compared to establish which model fit with the data. Comparing models 1 and 2, model 2 shows a smaller Log Likelihood value, indicating a better fit between the model and data. When comparing model 3 to model 2, model 3 the last model also has a smaller value, indicating that this model has the best fit of all three models. This model will be the source of interpretation in the rest of this section, and will also used in the remainder of the chapter.

The baseline person related to the table is a male who did not attend any supplementary activities, was less than 20 years old when he began his master's studies, had the lowest high school average, graduated in the fourth quarter, studied technical science and was an immigrant or descendent of immigrants. It should be noted that the explanatory variables are mutually exclusive, as noted in the data chapter. They should, therefore, not be seen as interactions, but different groups of students. This is true for all the remaining models throughout this chapter.

Table 5 shows surprising results for both the explanatory and control variables. Taking the variables of interest first, only three of the six categories show significantly different effects on wages post-graduation, which all include student jobs. The model finds no significant difference between the baseline student who did not engage in any activities and students who had an internship or went on exchange. This means that controlling for everything else, a person who went on exchange will not on average see a wage increase, but a student who took a relevant job would on average earn DKK 1,921 more a month, one year after graduation.

An interesting observation is the differences that exist between the magnitudes of the coefficients for the different compositions of supplementary activities. Students who went on exchange and held a student job seem to benefit more from this relative to those who only engaged in a student job, even though exchange is not seen to have a positive effect on its own. The opposite occurs for those who took an internship. Even though taking an internship alone does not influence wages relative to not engaging in any supplementary activity, to have an internship and a relevant student job seems to result in a smaller wage increase than only being employed in a student job. To see if the estimates differ significantly, a two tailed t-test was carried out[12]. This showed that there is no significant difference between those who only had a student job and those who also took an internship. The estimates are therefore treated as equal in the remaining section. The estimate for student job and exchange are on the other hand significantly larger than the estimate for students who only took a student job. This is surprising when the estimate for pure exchange is not significant. This could indicate some degree of unobserved characteristics in the group for students with this combination. This will be addressed later on in the chapter.

Turning our attention to the control variables, gender is shown to affect wage significantly. Studies on this subject have previously found significant gender wage gaps (OECD, 2016) (The Nordic Council of Ministers), stating that females receive a lower wage, but these results are not always the case. Some studies have found no significant gender wage gaps in this type of setting (Manning & Swaffield, 2008) (Bayard, Hellerstein, Neumark, & Troske, 2003). Two reasons seem relevant in order to understand why the gender coefficient is insignificant: the time and the major aspect. The dependent variable is wage one year after graduation, which would require that a wage gap should open up already at the first employment or very shortly afterwards. Other studies have found that this is not the case. Wage does not seem to be different between recent graduates, but as time goes on, the gender pay gap expands (Manning og Swaffield 2008) (Gicheva 2013). Evidence shows that this gap can be due to maternity leave, family engagements, the fact that women have had the opportunity to say no to long hours and promotions or have been unfavored relative to their male colleagues. Another reason for lack of significance could be the self-selection

[12] *T-test used :* $t = \frac{X-\mu}{S/\sqrt{N}}$

into lines of studies, and therefore occupational choices and opportunities post-graduation, which have been found to account for a significant share of the gender pay gap (Bayard, et al. 2003) (Macpherson og Hirsch 1995). Women are in some cases seen to choose majors that point them in the direction of other types of job than men. This has in some cases been shown to explain the wage gap, and since this has been controlled for in the model, we might have taken away some of the factors driving a possible wage gap (Morgan, 2008). A possible wage gap in our analysis would not have been of concern in the interpretation of the model. The interaction between gender and high school average is on the other hand significant and positive. This shows that female students are getting a wage premium with rising grade point averages, while males are not.

A surprising insignificant estimate is the grade point average alone. Students with higher grades from high school are not rewarded for this on the labor market. Only women through the interaction term as mentioned above. This is surprising, since it would be expected that ability as measured by grades has some effect. It should be noted that we are only concerned with students who become employed soon (one year) after graduation. This could bias our results towards only the best students. Furthermore, as the time since graduation has only been 12 months, promotions might not have come into play either.

A set of variables that turned out to be significant are some of the majors. Remembering that the baseline student is majoring in technical science, students within science and social science are receiving significantly lower wages post-graduation. It should be noted that the macro variable is the major line of study, which earlier showed significant wage variation effect via the ICC. The significant variables related to the main area of study only suggest that there is some wage difference beyond this, for groups as a whole. This result for science and social science is surprising, since humanities and technical science are seen to be widely apart, but also significantly different in this analysis (see appendix). This could lead us to believe that the people in the Aarhus population might be different in relation to the average graduates. Another explanation for lower results for students who graduated within social science is the fraction of people who become employed in the public sector. Public sector wages are on average lower than private sector (Lønkommissionen 2010), and since we are not able to control for sector of employment, the bias of this will remain unknown. The question in relation to differences between Aarhus and the full population will be addressed later on in section 6.2.

None of the family indicators are reported to have an effect on wages, neither alone nor as an interaction coefficient with other variables. This accounts for educational level of the parents as well as the number of siblings, type of household (single or two parent), either parent's socio-economic status or the income of the parents, all measured in the year the student turned 16. Some of the missing effect might come from self-selection into a master’s program, so that students from poorer or weaker households are not even present in our dataset. The descriptive statistics showed some indication of this, cf. section 5.4. Turning our attention to variables outside the household or family category, other variables have also turned out to be non-significant. The completion of high level math does not significantly influence the wage outcome.

The insignificant estimates related to parental characteristics might be caused by multicollinearity, where a number of variables are highly correlated, creating an approximate linear relationship between two or more variables making the estimates unreliable (Veerbeek 2013). There are several tests for multicollinearity, both manual and in SAS. In this thesis, the method used is the variance inflation factor *(*VIF) calculated by the SAS procedure VIF to investigate the multicollinearity problem. The VIF estimates do not have a strict upper value to indicate when collinearity is too large and becomes a problem, but the guideline value is by some set to 10 (UCLA 2016). The output is shown in the appendix. One of the variables shows a sign of multicollinearity, the variable for mothers with medium term education. This could indicate some collinearity with other variables, but none of the similar estimates show significant collinearity, and since the variable cannot be removed from the analysis - as it is a part of the dummy variables for mother's education - we leave it, but will consider possible collinearity problems later on.

The remaining significant coefficients affect the results as expected.

The outcome variable in the model is wages only, and does not take job position into account. The data is not able to show us if the wage premium for people who held a student job comes from relatively higher wages in jobs similar to their peers, or if the higher wages are a result of different kinds of jobs or promotions. This could be the case, but it is not the main question of this thesis, and will therefore remain uninvestigated.

<u>Summary</u>

The results on wages do not show any significant wage premiums in the labor market for those who solely took an internship or went on exchange. Since the estimation is not carried out on two groups exposed to randomization, and the effect is estimated by controlling for observable characteristics, we might overestimate the effects, since we cannot control for aspects such as motivation and genetics. This makes the result even more interesting, since we assume that the results might be subject to overestimation. If this is the case, then there could potentially be a negative effect of exchanges and internships, which directs our attention to the discussion from the theoretical chapter on human capital being heterogeneous or homogeneous. This problem will be addressed later on in the siblings estimation and in the discussion.

In relation to the model, we should also note that it only takes those into account who got a job and their difference in wages - but could there be an effect on employment as a measure alone? A student's human capital accumulation through exchange and internship might not have improved their wages relative to others who got employed, but does it make them significantly better in achieving employment one year after graduation? To answer this question, I turn to investigate the main population from Aarhus University again, but with a different outcome measure – employment.

Employment results

The model estimated in this section is slightly different than the one used to estimate the effect on wages. The dependent variable is not normally distributed; the distribution is binary with outcome zero if the student does not become employed, and one if the student does. Such a model requires assumptions on error variance for level 1 predictors, which changes the ICC calculation slightly. This is all presented and can be reviewed in *Chapter 4 – Model*.

As in the previous section on wages, a specification test is done to test whether a multi-level model is a better fit for the data than a regular regression with fixed effects.

Table 6: Specification test of hierarchical generalized linear models

	Fixed effects	Random effects	Test-size(β)*	Pr>chi^2
- 2 log likelihood	3,247.40	3,100.73	146.67	0.000

Notes: *Degrees of freedom=1

The log likelihood specification test reveals that a model which includes a random intercept component is a better fit for the data than one only taking the study variation into account as a fixed effect. How much of the variation in data that can be attributed to the variation between studies is displayed as the Intra-class Correlation. When using a hierarchical generalized linear model (HGLM), a different calculation for ICC is used relative to the regular multi-level model, due to the assumption of no errors at level 1 (see *Chapter 4 - Model* for further explanation). In this new ICC with an assumed no level 1 error, a model with dichotomous outcome is assumed to follow this logistic distribution with mean 0 and variance 3.29 (Snijders og Bosker 2012).

The ICC calculation will therefore use 3.29 as a measure of the level 1 error and level 2 errors (τ_{00}) from the model estimation:

$$ICC = \frac{\tau_{00}}{\tau_{00} + 3.29} \rightarrow \frac{0.6277}{0.6277+3.29} = 0.1602 \qquad (18)$$

The variations in employment between different types of studies are, as a result of equation 2, shown to account for 16.02 pct. of the overall variation of employment within the population.

This exceeds the preferred minimum level of Intra-class Correlation recommended by (Hox 2010) when dealing with multi-level models within education. Three hierarchical generalized linear models are therefore now estimated on the data. The structure of the models is the same as in section 6.1.1 on wages: the first model only includes the explanatory variables; model 2 also controls for information on the individual level; and model three includes macro level variables. Nested models based on logarithmic functions cannot be compared in the same fashion as the regular multi-level model (Mood 2010). The third model, which was the best fit for wages, is also used for employment interpretation. Model 3 is, therefore, the only one reported in table 7, but a full table of all three models and a complete list of controls are displayed in the appendix.

Table 7: Results, Hierarchical generalized linear model on employment for Aarhus students

Odds Ratio Estimates Unit change from the mean	Comparison	*Model 3* Estimate	
Explanatory Variables	Exchange	1.162	
	Relevant student job	5.630	***
	Exchange & student job	7.953	***
	Internship	1.353	
	Internship & student job	6.250	***
Individual level control variables	Gender	0.779	*
	High Level Math	1.160	
	Age	0.903	**
	High School avg.	1.026	***
	Q1	0.730	*
	Q2	0.403	***
	Q3	1.775	***
	High school avg.* Gender	0.964	**
	High school avg.*Age	0.987	***
	High school avg.*Mothers inc	1.000	***
	High school avg.*Fathers inc	1.000	***
Macro level control variables	Humanities	0.356	
	Science	0.735	
	Social Science	0.680	
	Health Science	2.638	

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001. N (individual level) = 4,430, N (macro level) = 81. Some insignificant coefficients are left out of the table. The full model also includes estimates of family and parents indicators. See the appendix for a full table of estimated coefficients and confidence intervals.

The explanatory variables that are significantly changing employment odds are the same as those which in the previous section showed significance in affecting wages post-graduation. A student who was employed in a relevant student job, either as the only supplementary activity or in combination with one of the others, has greater odds of being employed one year after graduation than their peers. The estimates for the explanatory variables are not just significant, but also large in magnitude. The largest estimate is for students who both completed an exchange stay and had a relevant student job during their master studies, as was the case with wage outcome. The odds of being employed are 7.9 times greater than for students who did not complete any supplementary activities, with the 95 pct. confidence interval being [5.16-12.25]. As for the wage models, students who both completed an exchange stay and had a student job seem to be better off than those who only took a student job. The estimate is not within the confidence intervals of the student job estimate, and therefore seems to be significantly larger, as was tested with a t-test in section 6.1.1.

As in the random intercept multi-level model with wages, the gender of the student significantly changes the odds of being employed one year post-graduation. Females have odds of 0.779 for being employed relative to males, when holding everything else constant. In relation to gender, high school averages are also providing women with lower odds. The interaction between gender and high school average is significant, and less than one, meaning that the same increase in high school averages is benefitting women less than men in becoming employed one year after graduation.

The interaction between high school average and age is less than one, suggesting that an increase in the high school average is being valued lower in the labor market the longer the duration between entering the master's study and graduating high school. This was also the case in the previous model in table 5.

The remaining significant estimates are as expected with respect to significance and direction. Compared to the wage model, none of the majors are here seen to be significant.

None of the macro level indicators are significantly changing the odds of becoming employed. This can at first seem counter intuitive as we know that some professions are more in demand in the labor market[13]. The core structure of the model, where each study has its own random intercept, should be taken into account since it has already shown itself to be significant for the ICC. The insignificant estimates of main study areas are, therefore, telling us that beyond this there is no extra positive or negative effect for a group of studies within these areas.

Summary

The results in table 7 show significantly greater odds of being employed post-graduation if a student has been employed in a relevant student job during their master's studies. It is the same explanatory variables that turn out to be significant as in the first analysis, which showed students gaining a wage premium, cf. table 5. One of the variables that was surprisingly insignificant from the wage estimation in table 5 is now significant: high school grade point average is seen here to have a positive effect. This result is more in line with expectations.

One of the limitations of these two results is that they are only concerned with students that attended Aarhus University. Despite the potential endogeneity due to possible differences in student populations, the probability of acquiring one of these supplementary activities, and future labor market prospects, among other aspects, one should be cautious to make any national recommendations based on this subsample. This

[13] Studies with a high unemployment rate have since experienced a reduction in number of seats (Ministry of Higher Education and Science 2015).

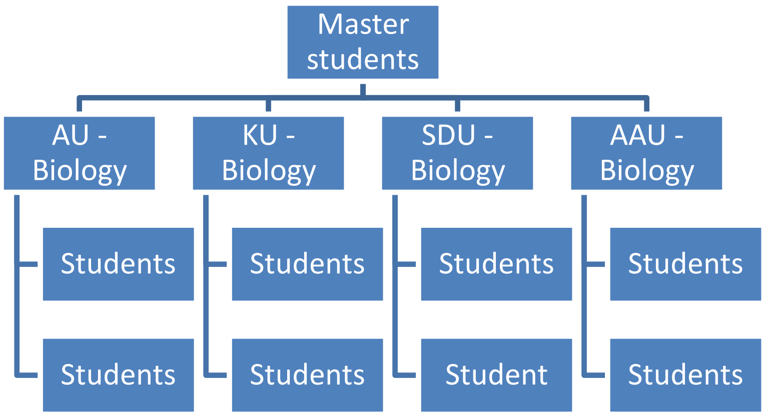
is something that was already mentioned at the beginning of the chapter, where study majors showed a different effect on labor demand to what could be expected.

To strengthen the estimation results, both analyses are, therefore, conducted on the entire population. This limits us to only two types of supplementary activities, since the internship variable is not present for the full population. Reviewing the results from tables 5 and 7, there seems to be no significant effect of having engaged in an internship, and students who completed both an internship and had a relevant student job are not significantly better off when compared to students who only had a student job. A robustness check of the results is, therefore, conducted in the next section by expanding the population to cover all Danish students, but now with only three explanatory variables of interest: student job, exchange, and student job & exchange combined, compared to the student with no supplementary activity.

6.1.2. Multi-level results, full population

The population is now expanded to all master students who began and graduated their study in the period 2009 - 2012. The analysis aims to keep the same multi-level structure as in the previous model, but expand the macro level to also include university. Previously, students were only from one university but are now from several different ones. To avoid a complex three nested multi-level model, each macro level is a combination of university and major. The structure of students in the data is presented in the figure below:

Figure 2: Structure of multi-level mode, full population



[14]

A specification test is also carried out on the model with the full population, where the multi-level model is tested against a model with fixed effects. Table 7 shows the results for the wage specification and table 8 for employment. They both show that a multi-level model is accepted with a 1 pct. significance test against a chi-square distribution with one degree of freedom.

[14] *AU=University of Aarhus, KU=University of Copenhagen, SDU=University of Southern Denmark, AAU=University of Aalborg*

Table 8: Specification test of multi-level model, full population (wages)

	Fixed effects	Random effects	Test-size(β)*	Pr>chi^2
- 2 log likelihood	500,051.0	498,112.5	1,938.5	0.000

Notes: *Degrees of freedom=1

Table 9: Specification test of the HGLM, full population (employment)

	Fixed effects	Random effects	Test-size(β)*	Pr>chi^2
- 2 log likelihood	13,470.23	12,580.3	889.93	0.000

Notes: *Degrees of freedom=1

Similarly, the two Intra-Class Correlations are calculated in order to show how much of the variation in, respectively, wages and employment are to be contributed to the multi-level structure, modeled by random intercepts.

Table 10: Covariance for ICC calculation

	Estimate	S.E.	Z value	Pr > Z
Intercept	13670821	1,384,792	9.87	< .0001
Residual	139,810,000	1,311,377	106.61	< .0001

Covariance estimates from table 10 have been used to calculate the ICC for wages, which in this case accounts for 8.9 pct. of the wage variation. This can be contributed to the nested structure that exists in the data, here the study-supply by university as shown in figure 1.

The difference in employment odds that can be contributed to the multi-level structure is calculated as the share of the variation that the level 2 errors account for. The calculation for this in a model with dichotomous outcomes is shown in equation 2. In the model of employment for the full population, this share is just above 16 pct.:

$$ICC = \frac{\tau_{00}}{\tau_{00} + 3.29} \rightarrow \frac{0.6330}{0.6330+3.29} = 0.1614 \qquad (19)$$

The ICC's are relatively similar, comparing the ones calculated for the Aarhus population. The majors account for a larger share of the variation with employment than with wages. As in the previous section, a multi-level model fits the data better than a regular regression with fixed effects. Those estimations showed that a model which includes all controls is the best fit for the data, estimated as model 3 in both tables 5 and 7. A model with this structure is, therefore, used in the estimation for the full population. Table 11 reports results on both wages and employment for the full population. In order to be able to compare these results to the Aarhus population, models have been applied to the subsample using only the variables of interest that are available for the full population. The estimates in the Aarhus column are, therefore, not identical to the ones reported in the earlier tables, since the two internship variables have been removed.

Table 11: Results, wages and employment for the full population

		Wages		*Employment*	
		Model 3 Full popul.	*Similar Aarhus*	*Model 3 Full popul.*	*Similar Aarhus*
	Comparison	**Estimate**	**Estimate**	**Estimate**	**Estimate**
	Intercept	27,382 *	43,507	-	-
Explanatory Variables	Exchange	785	-126	0.91	1.05
	Relevant student job	2,123 ***	3,567 ***	4.41 ***	5.41 ***
	Exchange & student job	2,707 ***	1,725 ***	4.84 ***	7.09 ***
Individual level control variables	Gender	-6,114 ***	-13,465 ***	0.86 *	0.78
	High Level Math	416 *	630	1.12	1.17
	Age	230	360	0.91	0.90 **
	High School avg.	-77	-195	1.03 **	1.03 **
	Father's income	0	0	1.00 ***	1.00
	Q1	408	472	0.73 ***	0.73 *
	Q2	696 **	879	0.44 ***	0.40 ***
	Q3	-854 ***	-358	1.51 ***	1.76 ***
	Ancestry	109	1,053	1.88 ***	1.98 **
	Family type	-931	-162	0.94	1.26
	Father's socioec .status+	398	137	1.06 *	1.05
	HS. avg.* Gender	2,324	135	0.98 **	0.98
	HS. avg.*Age	557 ***	-3 ***	1.00 *	0.99 **
	HS. avg.*Mothers inc	-20	0	1.00 ***	1.00 ***
	HS. avg.*Fathers inc	0	0	1.00 ***	1.00 ***
Macro level control variables	Humanities	-8,314 **	-12,667	1.63	0.37
	Science	-2,574	-16,081 *	0.73 *	0.72
	Social Science	-11,243 ***	-21,796 ***	0.72	0.68
	Health Science	2,484	-2,247	1.42	2.54
	HS. avg.*Humanities	309	90	1.63	1.02
	HS. avg.*Social Science	0	155 ***	1.01	0.97

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001. Column 1: N (individual level) = 22,665, N (macro level) = 389, Column 2: N (individual level) = 5,875, N (macro level) = 85, Column 3: N (individual level) = 17,863, N (macro level) = 357, Column 4: N (individual level) = 4,430, N (macro level) = 81, Some insignificant coefficients are left out of the table. The full model also includes estimates based on family and parent indicators. See the appendix for a full table of estimated coefficients, S.E. and confidence intervals.

The results in table 11 have different interpretations; results on wages in columns 1-2 are raw estimates that reflect how much monthly wages on average change when the variable changes. The third and fourth columns should be interpreted as the change in the odds of becoming employed if we change one unit from the mean of the variable related to the estimate. In the models that include the full population, a larger number of controls have become significant. This is a natural result of a larger sample (Veerbeek 2013).

The estimates of table 11 show that the explanatory variables decrease in magnitude when using the entire population instead of only the population from Aarhus. Students who engaged in a student job are still the ones who experience a wage premium post-graduation. In the first column, the results tell us that a student who had a relevant student job during his/her master's on average receives 2,123 DKK more than one who was not employed, all other things being equal. This number has decreased in relation to the models with the Aarhus population, where the average expected monthly wage increase was 3,567 DKK. In columns 3 and 4 of table 11 we find the same decrease in the variables of interest. When the population only contains Aarhus students, the odds of becoming employed are 5.41 and significant. This coefficient decreases to 4.51 when the population is expanded to include all students. It should be kept in mind that the sign pattern for the variables of interest is the same when expanding the population, but the magnitude of the main effect decreases.

The results also imply that the gender of the student is significant when the analysis is carried out on the full population (in table 7, gender was significant). The odds of females being employed are 0.86 relative to males. This gap increases along with high school grades, when interpreting the interaction between high school grade average and gender. In the wage estimation reported in columns 1 and 2 of table 11, the gender coefficient is in both cases highly significant, but as the variable of interest, the magnitude declines when using the full population. The decrease with respect to gender is more than half of the Aarhus estimate, from a negative wage premium of -13,465 DKK to now -6,114 DKK.

Finally, at the macro level, the full population results reveal that social science and humanities have a significantly negative estimate. This implies that students who graduated from humanities or social science are on average receiving a lower wage than their peers from other main areas of study. This negative wage premium is -8,314 and -11,243 for humanities and social science, respectively. The corresponding estimate in the restricted Aarhus population is larger, but the main areas of study which turn out to be significant are not the same. Social science is again showing a significantly negative wage premium, while science instead of humanities is significantly negative. This corresponds to the results from the original Aarhus estimation, where this unexpected negative impact of science was one of the reasons to investigate the relationship for a larger population.

<u>Summary:</u>

As the results in table 11 show, the effect of student job on the wage and employment outcomes is still substantial when tested on the full population. While the estimates are still significant and large, the decrease makes us aware that there is some bias in the Aarhus population, and possibly also in the full population. To investigate this further, estimation on siblings will be conducted in the following chapter to address the endogeneity problem that can arise from parental influence. The possibilities of this method are more closely addressed in *Chapter 7 – Robustness check: Siblings*.

7. Robustness check: Siblings

In the previous chapter, the results of the main analysis were presented, trying to explain the labor market outcomes for students who engaged in an internship, went on exchange or held a student job during their studies. These multi-level models were performed on the Aarhus population, and a robustness check of the results was done on a larger population with the limited number of variables that was present for this group. This confirmed the main results that student jobs affect their labor market outcome in terms of employment and wages significantly, while other supplementary activities do not. Another multi-level model with a wider population does not bring us closer to declaring the estimates to be results of causality rather than correlations. There is also the problem of endogeneity, i.e. the self-selection into these supplementary activities is affecting the outcome variable through unobserved characteristics, which if left unsolved affects through the error-term. For further discussion on this problem and how to address it, see *Chapter 4 – Model* and *Chapter 8 – Discussion*.

In this chapter, the problem of endogeneity will be addressed through a model estimated on pairs of siblings. The first section will very briefly touch upon the theoretical approach to a siblings study, the second section will show the results, and the final section will be concerned with any restrictions that are still present with these results.

7.1. Methodology behind siblings estimation

Estimating return to education is filled with complications of unobserved ability that potentially bias the results when using regular estimation. One known way to hold these unobserved ability measures constant is to use siblings data, where there are observable differences in the variable of interest. The literature in labor economics is quite overwhelming, with some of the most relevant studies in this context being conducted by Bronars & Oettinger, along with others (Bronars & Oettinger, 2006) (Light, 2001) (Altonji & Dunn, 1996) (Ashenfelter & Krueger, 1994) (Ashenfelter & Rouse, 1998) (Zimmerman & Ashenfelter, 1997). This robustness check of the main model will be done by applying the siblings approach of family fixed effects on the population already in use.

The theoretical framework applied to the current siblings estimation will be a modified version of the simple model first presented by Zimmerman & Ashenfelter (1997). This includes a single familiy fixed effects component in the wage equations. The model was later applied by Bronars and Oettinger (2006) with ability included in their equations. This model is structured as presented below:

$$\ln W_{1tj} = X_{1jt}\pi_1 + \beta_1 S_{1j} + \gamma_1 A_{1j} + F_j + V_{1jt} \tag{20}$$

$$\ln W_{2tj} = X_{2jt}\pi_1 + \beta_2 S_{2j} + \gamma_2 A_{2j} + F_j + V_{2jt} \tag{21}$$

where *W* is log wage, *S* is schooling, *A* is the ability and *F* is the family specific fixed effect component.

Here it is the impact of the schooling variable S on the log wage that is interesting. It shows how much the wage changes when one person obtains S_2 instead of S_1. The characteristics X and ability A would capture the information that is usually used in cross sectional data, and the family component F would correct for the specific family related effect that is present in both siblings one and two. The variable of interest for us is not continuous, but a dummy as in the main model. The ability measure is not true ability, but the grade point average as used in the previous chapter, along with the remaining personal characteristics.

Siblings are defined as those children who lived in the same household as our students, and should also have obtained a master's degree. To avoid misunderstandings, the original sample will be called "students" and the newly found control group who are this group's siblings will be called "siblings". The small window of time in which our data has been recorded narrows the siblings population a great deal. There are not enough siblings who started and graduated a master's degree within the data window, which runs from primo 2009 till the end of 2012. The number of siblings in this sample without any activity is below 100. To expand the siblings population, the same reasoning is applied as when moving from the Aarhus population to the full population to remove the restriction of the insignificant variables of interest. If we choose to be concerned with only student jobs or not, we have information ranging further back than 2009. This will, therefore, be the approach. To avoid macro trends in employment and educational structure influencing the outcome, yearly dummies are applied. The final siblings sample will contain students from the original sample and their siblings who completed a master's in a Danish university in the period 2005 till 2012. The dataset constructed for this estimation comprises students from the full population who had been employed in a relevant student job, and siblings for these students who have not had a student job during their master's.

7.2. Results of siblings estimation

Suppose that students who hold a student job are more motivated to become employed, because their parents brought them up to work hard and be able to look after themselves as soon as possible. If this were the case, then students who engage in a student job might not become employed because of the student job, but because they were brought up with other norms and values than other children. This would lead to an upward bias in the estimate for student jobs. It might also be the case that students who have been employed in a relevant student job are children of parents with strong networks that led to the student job and later on might also lead to full time employment. These potential unobserved characteristics of parental influence could cause endogeneity and an upward bias in the estimation result for student jobs.

To address this issue, a siblings model with family fixed effects is estimated. To compare the results to a model without the siblings structure, a model for the full population is also estimated.

Table 12: Result of siblings estimation, employment

		Siblings pop.		*Full pop.*	
		Estimate		**Estimate**	
Explanatory variables	Relevant student job	1.64	***	4.44	***
Individual level control variables	Gender	0.75		0.84	
	High Level Math	1.30	***	1.10	
	Age	0.93	**	0.92	*
	High School avg.	1.04	**	1.04	***
	Q1	0.79	***	0.73	***
	Q2	0.46	**	0.45	***
	Q3	1.28	***	1.47	***
	Family	1.00	***	-	
	High school avg.*Gender	1.00		0.99	
	High school avg.*Age	1.00		1.00	**
Macro level control variables	Humanities	0.84		0.57	
	AAU	0.91		0.72	*
	DTU	2.51	***	1,41	
	High school avg.*Humanities	0.99		1.00	
	High school avg.*Social Science	1.00		1.01	

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001. Siblings: N (individual level) = 16,109, N (macro level) = 629, Aarhus: N (individual level) = 18,181, N (macro level) =358. Some insignificant coefficients are left out of the table. The full model also includes estimates on family and parent indicators. See the appendix for a full table of estimated coefficients and confidence intervals. DTU=Technical University of Denmark, CBS=Copenhagen Business School

The results in table 12 show that the explanatory variable for student job remains statistically significant, but is decreasing when comparing the full population estimation to a siblings population with family fixed effects.

The effects of the remaining individual level control variables are similar to the full population estimated on similar variables. One difference is seen with high level math, which is similar in magnitude but has now become significant. The effects of gender are insignificant in both the family fixed effects estimation and the corresponding full population model. Women are, in contrast to the full model in the previous section, not seen to be faced with lower odds of reaching employment in the first year relative to their male peers, all other things being equal[15].

Finally, the macro level controls have also changed. The fixed effects estimation finds that students from the Technical University of Denmark are facing a greater odds ratio than their peers from other universities. The corresponding indication from the regular multi-level estimation with full population shows a similar but slightly smaller and insignificant estimate for DTU. On the other hand, this estimation finds an odds ratio below 0 for students from Aalborg University, which is not the case in the model with siblings. As

[15] *See discussion on this subject in section 6.1.1.*

before, the analysis is carried out for both employment and wages to see the effect of correcting with siblings and family fixed effects. The result of the wage estimation is presented in table 13.

Table 13: Estimation result of siblings estimation, wages

		Siblings pop.		*Full pop.*	
		Estimate		**Estimate**	
Explanatory variables	Relevant student job	1,165	**	2,388	***
Individual level control variables	Gender	-8,065	***	-6,245	***
	High Level Math	579	*	180	
	Age	291		167	
	High School avg.	-15		-14	
	Q1	452		-192	
	Q2	943	**	535	*
	Q3	-794	*	-872	***
	Family	0	*	-	
	High school avg.*Gender	78	**	57	**
	High school avg.*Age	-3		-2	
Macro level control variables	Humanities	-6,750		-9,070	**
	Social Science	-8,839	*	-11,885	***
	ITU	4,815	**	2,151	
	DTU	2,971	*	354	
	CBS	4,357	***	3,422	***
	High school avg.*Social Science	114	**	114	***

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001. Siblings: N (individual level) = 15,864, N (macro level) = 578, Aarhus: N (individual level) = 23,043, N (macro level) =389. Some insignificant coefficients are left out of the table. The full model also includes estimates on family and parent indicators. See the appendix for a full table of estimated coefficients and S.E. ITU=IT University, DTU=Technical University of Denmark, CBS=Copenhagen Business School

The main results from the wage estimation are presented in table 13. Students who have been employed in a student job are still seen to receive a wage premium relative to their peers, everything else being equal. This wage premium is decreasing when moving from a regular multi-level model with the full population, to the model that includes family fixed effect in the siblings population. The average monthly wage premium is now 1,165 DKK, down from 2,388 DKK. Failure to control for this “family/parental effect” does here seem to upward bias the results, as expected. One surprising finding is the gender wage gap, which seems to be rising in the model with family fixed effects. The remaining control variables are behaving as expected. For students who have graduated within social science, there is still a relatively large negative significant estimate. As mentioned in the main results, this could be related to students who are employed in the public sector cf. *Chapter 6 - Results*.

Finally, the results with macro level variables are increasing when compared to the corresponding estimates for the results from a full population without fixed effects on family. Students from DTU, ITU and CBS are on average receiving monthly approximately 3,000 to 5,000 DKK more than students from other universities. In relation to the estimation results on employment, students from DTU are also more likely to be employed one year after graduation.

Summary:

Even though there is a decline in the estimates for the siblings population, which was expected, the estimates for student jobs are still positive and significant. This is thus not enough to say that the relationship is the result of causality, but could be a persistent correlation.

7.3. Restrictions – what is still not explained?

Parental characteristics are said to influence children's ability long after they have moved away from home and started their own lives. Becker & Tomes (1986) argues that human capital is a function that regresses to the mean. He argues that the transmission of human capital from parents to children can be shown as a function of endowments, as laid out in equation:

$$E_t^i = \alpha_t + hE_{t-1}^i + v_t^i \tag{22}$$

Assumed $0 \leq h \leq 1$.

Where a person is linked to *i't* family and generation *t*. The α is the social component, which all families in the generation t are subject to, *h* is the degree to which the student inherits the previous generation's endowments. The last term *v* is the luck component, which unsystematically influences the endowment level (Becker & Tomes, 1986). We see that children are getting some level of endowment from their parents, and since there is no subscript *i* or *t* to the transmission fraction h, this is assumed to be equal among all families and individuals. Siblings are, therefore, assumed to get the same amount of endowment transferred from their parents. α, the generational endowment is also equal for all in a period t, so the luck term *v* is the component that should cause endowments to differ between siblings.

The siblings estimation tries to estimate a more "pure" result of student jobs on labor market outcomes, due to the self-selection and unobserved ability that we know occurs. With this estimation method, the family transmitted endowment is controlled for, but some endogeneity still remains.

Even though siblings are assumed to have the endowment transmitted from parents and that they are raised in the same household, some differences in the household can still be uncontrolled for. Older siblings are sometimes raised differently than younger siblings, inflicting different norms and values on these children than on younger siblings, which is a subject studied widely in psychology (Turner, 2006) (Cicirelli, 1995) (Dunn & McGuire, 1992). A similar difference in upbringing is also in some cases seen between boys and girls. Our sample is not large enough to be restricted further into same sex siblings or identical twins at best. Some of this might still influence the employment and wage effect, and therefore be captured by the error term and bias the estimates. The same thing can be said about ability. Controlling for family does not enable to control for the personal ability or the luck term v. As seen in the equation above, the luck term personally influences each person. This is not controlled for beyond the high school grade point average that we also used in the main analysis. If ability is influencing whether one takes on a student job and wages beyond this grade point average variable, there is still cause for concern regarding endogeneity.

8. Discussion

The results from the main analysis and the siblings estimation are very convincing in their story of significant effects for students who engaged in a student job. Despite the strong results, some uncertainty of the results still remains. Because even though the number of variables is high and seems to explain a great deal of the variation in the data, without a randomization we cannot be certain that an unobserved variable is not present in the relationship between taking a student job, internship or exchange and the labor market outcomes. The results from the analysis can be the subject of endogeneity, which end up biasing the results due to unobserved variables. If data is subject to endogeneity, Instrumental Variable (IV) estimation is the only method that can truly test for this (Wooldridge, 2009). As mentioned in *Chapter 4 – Model*, there are no suitable instruments for the data.

One of the suspected unobserved variables is the ability of the student. This is unobservable in the data, and cannot be controlled for. If students who get the jobs also have greater ability, then the wage outcome is biased in this sense, and the wage premium should not be interpreted as a premium for student job, but ability.

Another unobserved aspect is the personality of the student. Some students might favor unemployment for a while after graduation, and being eligible for unemployment benefits makes this a realistic choice. If the personality of students affects whether a student chooses to travel for a year post graduation or spend time without any attachments before entering the labor force, and this personality component also influences the choice of whether to seek an exchange, this could end up biasing the results. The study programs might also be subject to endogeneity. The structure of studies might affect the ability of students to join the labor market, and therefore change their wage or employment odds.

Parental characteristics are included in the model, but parental ability and upbringing might be causing some endogeneity in the estimation. Students are affected by their parents, and several theoretical and empirical papers have addressed how student abilities are inherited from parents (Björklund & Jäntti, 1997) (Restuccia & Urrutia, 2004). The literature suggests that parental income affects student choice of studies and level of education. Despite this well-known fact that parental ability affects student outcome and possibly their choice of study, the variable on parental IQ or other ability measure is not included in the data. Most of this data is American, and the effect here is not only ability but might very well also be a question about lack of resources in low-income families excluding students from taking up educational opportunities. Although this is not as marked in Denmark, the approach to education and knowledge of the prospects associated with taking a master's degree might not be as well known in low-income households. The personal knowledge of the parent might also influence the student's choice and possibilities for supplementary activities and labor market outcome. Students with parents who have good connections to the local labor market might also be provided with better student job opportunities and full time job opportunities later on.

The labor market effect might then be partially a result of parental knowledge and social networks, causing endogeneity in the error term.

Some of these endogeneity problems are addressed in the robustness check, which included siblings estimation with family fixed effects. In these controls, some parental ability, norms and values are controlled for. Students brought up by the same parents in the same household are expected to be more similar to each other than to a person randomly drawn from the student population. As the results from the siblings estimation are still positive, as shown in *Chapter 7 - Siblings*, belief in the results from our model is strengthened. In the absence of randomization, the addressing of a question with multiple methods is a good way of strengthening the conclusions. But not all parental and individual ability is removed from a siblings study, cf. section 7.3, and therefore it is possible that we have failed to account for the entire endogeneity. One parental characteristic not controlled for could be that children who are the older sibling are raised differently to younger siblings, which could affect their sense of responsibility and cause them take a student job and become employed before their younger siblings. Another endogeneity is the biological factor. We do not have a twin study, and therefore are not able to control for data related effects that could influence the choice of student job or take account of ability. All of these factors might still create endogeneity in the data, and potentially bias the estimates. Since these true ability measures are not within our reach, the information on possible endogenous variables is to be kept in mind when interpreting and extending the results.

Another reason for biased results could be related to the theoretical approach and setup for the thesis. The body of theoretical evidence that is the foundation of the thesis has exclusively focused on human capital theory. The main notion of this theory is that the activities students engage in during their education contribute to building human capital, and that these activities are, therefore, seen as an investment, whereas the returns are labor market wages (Mincer, 1974) (Becker, 1962). Another line of theory explaining the differences in returns to education is signaling. In signaling, the differences between outcomes dependent on education are assumed to be a result of prior obtained human capital, and not due to schooling. These individuals with a higher prior level of human capital are assumed to engage in schooling to signal their higher level of skills to a future employer. Michael Spence developed a job-market signaling model that has been the foundation of the educational and labor markets signaling theory (Spence, 1973). Spence argued that the wage offer from an employer is the expected marginal product of the worker. If all individuals are obtaining the same amount of education, but some have higher human capital levels and hence will be more productive in the job being offered, the employer has no knowledge of who is the better employee, and has no other opportunity than to provide everyone with an average wage. This results in overpaying low human capital employees and underpaying those with high levels of human capital. A signal that can reveal the true productivity is, therefore, of interest to the individual with a high level of human capital. The optimal signal is thus one that only students who truly have high levels of human capital can obtain.

In the context of the thesis, the activities students engage in would not be assumed to be skill enhancing, but a signal to show employers the true level of human capital for these individuals, distinguishing them from people with other levels of human capital. The wage premium for student jobs found in the results is, therefore, not necessarily seen as providing anything more to the individual than a signal that he/she has a higher level of human capital and is being rewarded for this. Students who engage in internship and exchange do not seem to be rewarded for this on the labor market, which can be because these activities are not a good signal to employers of high levels of human capital.

If the true wage premium for students engaged in supplementary activities is only the result of pre-activity human capital levels, no actions should be taken to include more students in student jobs under the expectation of achieving a higher human capital levels and then higher wage premiums. Further use of student jobs would then only weaken the signal of true ability, and high ability students would shift to other signals. The critique to conventional human capital models provided by signaling should be taken seriously into the considerations if we want to address causality of the estimates.

Beyond these challenges with the interpretation of the data, some limitations have shaped the format of the research question and execution of the analysis. Two of the main elements are the limitation of the population to only include master's students, and the interpretation of the supplementary activities.

8.1. Master's student approach

There have been some limitations in the data set provided for the thesis. The records for students engagement in internships and exchanges only dates back to the beginning of 2009 and up until 2014. In order to properly estimate the labor market outcomes, the students must have graduated at least one year prior to the wage measurement. The small window of data limits the study to being concerned with students who have completed their master's in this period. This limitation seems reasonable since most students, as noted in the introduction, go on exchange during their master's. This period is also closer to the transition into the labor market than when the students obtained their bachelor's. Although the limitation seems reasonable, it imposes certain boundaries on our knowledge.

Some students might have exploited the opportunity to attend one of these activities during their bachelor's, but not their master's study. This could potentially influence their labor market outcome through their human capital development. If an activity during their bachelor's goes on to influence their labor market outcome, but is not recorded, these people arrive in our control group. Depending on which effect is expected of the activity, the control group might end up being biased in that direction. As mentioned in the introduction, the largest proportion of exchange takes place during the master studies. These numbers are not true individuals, but the number of times students went abroad to study. If students attend exchange during both their bachelor's and their master's, they will appear twice in the data from Statistics Denmark, but only as students who went on exchange in our data. The limitation of the data makes the approach the best fit at the time, but future analysis of these supplementary activities should be undertaken once additional years of information become available.

8.2. Activities – supplementary or replacement?

Throughout this thesis, all of the variables of interest have been described as activities that supplement time spent at school or studying. This was originally defined in the introduction as an activity that provides human capital beyond what would have been accumulated while studying, which is what was investigated and accepted in the theoretical chapter. Although this was accepted, there might be differences between the three activities.

In the case of student jobs, this is perhaps more relevant than with the other activities. One of the papers cited in the theoretical chapter investigated the time spent on jobs while enrolled in education (Schoehals, Tienda, & Schneider, 1998). They found that part of the time spent on student jobs came from both leisure activities and studies. Student jobs are here seen as something that not only replace some of the educational activity, but also add something by taking time away from leisure activities. Education is, thereby, not given up fully, but only partially, and the remaining hours required for the job might be taken from leisure time. When attending internships or exchanges, some ECTS points are traded for this activity, which could be an argument for replacement rather than a supplement. It could also be argued that students who have engaged in student jobs are just spending more time accumulating human capital, and are therefore rewarded with a wage premium. With internships, this is not the case. Internships are often a full time activity; presumably increasing the number of hours spent on education to around 37 hours a week. If this is the case, it makes the comparison of student jobs and internships more appropriate. But the internship is supposed to replace the classroom study ECTS points which the student gave up, i.e. not requiring more points than was intended by attending courses in the same period. Here it is a question of how much is accumulated during the internship, even if the time spent is more than what would otherwise have been used on classroom studies, i.e. does the internship accumulate the same, more or less human capital? The estimate indicates that it presumably accumulates the same amount as would have been accumulated by attending courses. Hence, the activity might not be supplementary but merely replacement in nature.

When dealing with exchange, the activity could be much more of a replacement than with the two previous examples. The time spent abroad is assigned ECTS points that match the education the student would otherwise have experienced at their own university. On average, we would expect this match to be the case with internships, but one further study could investigate whether students from certain areas around the world or certain types of studies are benefitting more from exchanges than others. But as with internship, the criteria for obtaining these ECTS points are that courses/internships are approved. For these two activities, the goal of the activity is to replace, while that is not the goal of a student job. We assume that some time is taken away when working, time from preparing for classes, but presumably also from actual teaching activities. While this is happing in some cases, students must still pass the courses they signed up for.

This might be achieved at a lower grade than what could have been managed had no time been reallocated to employment, but the course still needs to be completed. Overall, the nature of student jobs might be more supplementary than replacement, which to some extent might explain why this activity pays out a wage premium compared to the other activities.

To say that none of these activities are supplementary would be a stretch. They develop other competences related to taking on responsibility, and in some cases being involved in a workplace. This would seem to be desirable for all students expecting to become employed post-graduation. This discussion merely points out that there might be different degrees of supplementary activities within each choice, and the large premiums related to student jobs might be the result of a greater supplementary aspect.

9. Conclusion

Much attention in the Danish educational debate has been focused on how to prepare students for the labor market. At the same time, some of the activities that students claim are securing them their first jobs and making them better employees have been removed as part of the latest reform of Danish higher education. This analysis has, therefore, investigated whether students' supplementary activities affect their employment status or wages post-graduation. This question has been analyzed through a literature review, a theoretical analysis and an empirical multi-level model paired with rich individual characteristics.

The literature review and theoretical analysis exposed reason to believe that students who choose to allocate time to supplementary activities related to their abilities would accumulate human capital, just as they would have done by spending time studying. The engagement in these activities could be seen as an investment, in line with investing in human capital through schooling. Students who chose to engage in one or more of these activities should, therefore, not expect to be worse off in the labor market than their peers. If these students choose supplementary activities that are more aligned with their ability and occupation choices post-graduation, theory would suggest that they could even be better off. The three supplementary activities analyzed were internship, relevant student job and exchange. Through a preliminary analysis, the descriptive data for the population was examined to determine if any differences existed between students with different choices of supplementary activities, in terms of the distribution of observable characteristics previously known to influence labor market outcomes. This examination showed no significant differences between students who engaged in each of the supplementary activities and the baseline population of students who engaged in none.

Through a multi-level regression analysis, two types of models were estimated to uncover how wages and employment 12 months after graduation were related to the variables of interest[16]. The analysis was first carried out for the populations from Aarhus University. The limitation to Aarhus University was a result of data availability, where only Aarhus had data on internships. Results from this model showed that the supplementary activities which are found to be significant are the ones where students have engaged in at least a relevant student job: *relevant student job, student job & exchange, student job & internship*. These activities result in an average monthly wage premium of 1,921 DKK, 3,560 DKK and 1,257 DKK, respectively. Following this analysis, a t-test has shown no statistical significance in the difference between the estimate for student job and student job & internship. The corresponding estimates for employment outcome tell the same story – only activities including student jobs are significant, and these estimates are positive. The odds-ratio for students with a relevant student job is 5.63 compared to those who did not engage in any supplementary activities. Since the estimation was only conducted on students from Aarhus Universty, the results would not necessarily be the same for the entire population. In the light of the insignifi-

[16] No activities, relevant student job, exchange, internship, student job & exchange, student job & internship

cant estimates in relation to internship, this information was removed from the data, creating an opportunity to expand the population to students throughout all Danish universities.

The empirical analysis of the entire population displays the same overall picture: students who have had a student job have greater odds of becoming employed, and when employed they receive a higher wage relative to their peers, everything else being equal. Estimates for student jobs and those who also went on exchange have centered around each other, compared to the Aarhus estimation. Student jobs are now on average paying 2,123 DKK more, and those students who had both a job and went on exchange receive an additional monthly wage averaging 2,707 DKK.

The results from the main populations for Aarhus and Denmark attempt to deal with the effects of self-selection on supplementary activities by including socio-economic variables and by estimating the effects with a multi-level model. Despite this, the results cannot be interpreted as a pure causal relationship between outcome and the choice of activities. The problem of endogeneity is addressed in an additional analysis, where siblings are identified and pairs of siblings used as controls. Because not everyone in the full population has siblings who have completed a Danish master's degree, the time period needs to be extended to include all those who obtained a master's degree between 2005 and 2012. This expansion of the time frame causes us to lose the information on exchange, and leaves us with only student job as the variable of interest. The result of this siblings population multi-level model with family fixed effects re-confirms the first results, i.e. student jobs are improving employment odds and wages. Even though the estimate from the siblings estimation is positive and significant, it has decreased. A model estimated with similar variables shows a wage premium from student jobs of 2,388 DKK, which has decreased to 1,165 DKK in the siblings fixed effects model. An even larger decrease is observed with the average odds for student jobs. Here, the siblings fixed effects model returns an odds ratio of 1.65 for student job and the corresponding estimate is 4.44, i.e. 2.7 times greater.

This analysis finds that students who engage in certain supplementary activities (student jobs) are experiencing elevated wage levels and employment odds compared to their peers. This finding concerning student jobs is in line with the theory of heterogeneous human capital. As models have been expanded and family fixed effects in the siblings study have been included, a decline in the expected average effect is found. This result combined with the lack of better estimation methods leaves us unable to reveal if the relationship is causal. Despite this, the observable characteristics show no alarming difference between the populations that indicates different students in relation to the supplementary activities. A causal relationship is, therefore, not precluded.

Literature

Altonji, J. G., & Dunn, T. A. (1996). Using Siblings to Estimate the Effect of School Quality on Wages. *The Review of Economics and Statistics*, s. 665-671.

Arrow, K. J. (1973). Higher education as a filter. *Journal of Public Economics*, s. 193-216.

Ashenfelter, O., & Krueger, A. (1994). Estimates of the economic return to schooling from a new sample of twins. *American Economic Review*, s. 1157-1173.

Ashenfelter, O., & Rouse, C. (1998). Income, Schooling and Ability: Evidence from a new sample of identical twins. *The Quarterly Journal of Economics, MIT Press*, s. 251-284.

Avdic, D., & Gartell, M. (2015). Working while studying? Student aid design and socioecnonomic achievement disparities in higher education. *Labour Economics*, s. 26-40.

Bayard, K., Hellerstein, J., Neumark, D., & Troske, K. (2003). "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Dat. *Journal of Labor Economics*.

Becker, G. S. (October 1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, s. 9-49.

Becker, G. S., & Tomes, N. (1986). Human Cpaital and the Rise and Fall of Families. *Journal of Labor Economics*, s. 1-39.

Ben-Porath, Y. (1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy*, s. 352-365.

Ben-Porath, Y. (August 1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy*, s. 352-365.

Björklund, A., & Jäntti, M. (1997). Intergenerational Income Mobility in Sweden Compared to the United States. *The American Economic Review*, s. 1009-1018.

Bronars, S. G., & Oettinger, G. S. (2006). Estimates of the return to schooling and ability: evidence from sibling dataB. *Labour Economics*, s. 19-34.

Calmar Andersen, S. (2007). Multilevel modeller: en introduktion og et eksempel. *politica*(3), s. 294-316.

Cicirelli, V. G. (1995). *Sibling Relationships Across the Life Span.* New York: Plenum Press.

Dalskov Pihl, M. (14. September 2015). Hentede 4. January 2016 fra AE rådet: http://www.ae.dk/analyser/ledighedsrisiko-blandt-nyuddannede-akademikere

Danmarks Statistik. (u.d.). *IE_TYPE* . Hentede 04. February 2016 fra Danmarks Statistik: http://www.dst.dk/da/TilSalg/Forskningsservice/Dokumentation/hoejkvalitetsvariable/udlaendinge/ie-type

Dunn, J., & McGuire, S. (1992). Sibling and peer relationships in childhood. *Journal of child psychology and psychiatry, and allied disciplines*, s. 67-105.

Gicheva, D. (2013). Working Long Hours and Early Career Outcomes in the High-End Labor Market. *Journal of Labor Economics*.

Hjortdal, M. (14. May 2015). *Danmark*. Hentede 4. January 2016 fra Politiken: http://politiken.dk/indland/uddannelse/ECE2668970/studerende-studiejob-er-vigtigst/

Holtz, V. J., Xu, L. C., Tienda, M., & Ahituv, A. (2002). Are There Returns to the Wages of Young Men from Working While in School? *The Review of Economics and Statistics*, s. 221-236.

Hox, J. J. (2010). *Multilevel Analysis Techniques and Application.* New York: Routledge.

Keithly, D., & Deseran, F. (1995). Households, Local Labor Force Markets, and Youth Labor Force Participation. *Youth and Society*, s. 463-492.

Leigh, A., & Ryan, C. (2008). Estimating returns to education using different natural experiment techniques. *Economics of Education Review*, s. 149-160.

Light, A. (2001). In-School Work Experience and the Returns to Schooling. *Journal of Labor Economics*, s. 65-93.

Lønkommissionen. (28. May 2010). *Lønkommissionen.* Hentede 19. May 2016 fra Offentlig-privat sammenligning : http://www.lonkommissionen.dk/pdf/Sammenligning_af_loen_offentlig-privat.pdf

Macpherson, D. A., & Hirsch, B. T. (1995). Wages and Gender Composition: Why do Women's Jobs Pay Less? *Journal of Labor Economics*.

Manning, A., & Swaffield, J. (2008). The gender gap in early-career wage growth. *The Economic Journal*.

Mincer, J. (1974). *Schooling, Experience, and Earnings.* New York: Columbia University Press.

Ministry of Higher Education and Science. (29. June 2015). *Higher Education*. Hentede 4. January 2016 fra Ministry of Higher Education and Science: http://ufm.dk/en/education-and-institutions/higher-education/adjustment-of-student-intake-in-higher-education-programmes

Mood, C. (2010). Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It . *European Sociological Review*, s. 67-82.

Morgan, L. (2008). Major Matters: A Comparison of the Within-Major Gender Pay Gap across College Majors for Early-Career Graduates. *Industrial Relations: A Journal of Economy and Society*, s. 625-650.

OECD. (2016). *OECD.STAT*. Hentede 20. May 2016 fra Organisation for Economic Co-operation and Development: http://stats.oecd.org/index.aspx?queryid=54751

OECD, UNESCO, Eurostat. (2015). *ISCED 2011 Operational Manual, Guidelines for classifying national education programmes and related qualifications.* European Union.

Produktivitetskommissionen. (2013). *Faktaark 6.* Hentede 4. January 2016 fra Produktivitetskommissionen: http://produktivitetskommissionen.dk/media/159686/Faktaark_6_Anbefalinger%20vedr%C3%B8rende%20de%20videreg%C3%A5ende%20uddannelsers%20opbygning.pdf

Restuccia, D., & Urrutia, C. (2004). Intergenerational Persistence of Earnings: The Role of Early and College Education. *The American Economic Review*, s. 1354-1378.

Retsinformation. (26. June 2013). *Bekendtgørelse om uddannelsen til studentereksamen*. Hentede 2. February 2016 fra Retsinformation: https://www.retsinformation.dk/forms/r0710.aspx?id=152507

Rokicka, M. (2014). *The impact of students' part-time work on educational outcomes.* Educational Research Institute (IBE) .

Ruhm, C. J. (1997). Is High School Employment Consumption or Investment? *Journal of Labor Economics*, s. 735-776.

Rumberger, R. W., & Thomas, S. L. (1993). The Economic Returns to College Major, Quality and Performance: A Multilevel Analysis of Recent Graduates. *Economics og Education Review*, s. 1-19.

Rønhof, C. (1. October 2015). *Policy og analyser*. Hentede 4. January 2016 fra Dansk Industri: http://di.dk/Opinion/Uddannelse/Pages/Universitetsuddannelserskalmaalrettestiljob.aspx

Saniter, N., & Siedler, T. (2014). Door Opener or Waste of Time? The Effects of Student Internships on Labor Market Outcomes. *IZA*.

Schoehals, M., Tienda, M., & Schneider, B. (1998). The Educational and Personal Consequences of Adolescent Employment. *Social Forces*, s. 723-762.

Schoenhals, M., Tienda, M., & Schneider, B. (December 1998). The Educational and Personal Consequences of Adolescent Employment. *Social Forces*, s. 723-762.

Snijders, T., & Bosker, R. (2012). *An Introduction to Basic and Advanced Multilevel Modeling.* London: SAGE Publication.

Sohr-Preston, S. L., & et.al. (May/June 2013). Parental Socioeconomic Status, Communication, and Children’s Vocabulary Development. *Child Development*, s. 1046-1062.

Spence, M. (1973). Job Market Signaling. *Quarterly Journal of Economics*, s. 355-374.

Statistics Denmark. (2016). *Data for research*. Hentede 23. May 2016 fra Statistics Denmark: http://www.dst.dk/da/TilSalg/Forskningsservice

Steinberg, L., Greenberger, E., Garduque, L., & McAuliffe, S. (1982). High School Students in the Labor Force: Some Costs and Benefits to Schooling and Learning. *Educational Evaluation and Policy Analysis*, s. 363-372.

Stinebrincker, R., & Stinebrincker, T. R. (2003). Working during School and Academic Performance. *Journal of Labor Economics*, s. 473-490.

The Nordic Council of Ministers. (u.d.). *The Nordic Council of Ministers*. Hentede 20. May 2016 fra The Nordic Council of Ministers, Nordic Welfare Model: http://www.norden.org/en/nordic-council-of-ministers/ministers-for-co-operation-mr-sam/sustainable-development/indicators-for-sustainable-development-1/the-nordic-welfare-model/gender-pay-gap

Theime, C., Prior, D., & Tortosa-Austina, E. (2013). A multilevel decomposition of school performance using robust nonparametric frontier techniques. *Economics of Education Review*, s. 104-121.

Turner, B. S. (2006). *The Cambridge Dictionary of Sociology.* Cambridge: Cambridge University Press .

UCLA. (2016). *Institute for Digital Research and Design*. Hentede 06. April 2016 fra http://www.ats.ucla.edu/stat/sas/webbooks/reg/chapter2/sasreg2.htm

UVM. (u.d.). *7point grading scale*. Hentede 23. March 2016 fra Ministry of Childre, Education and Gender Equality: http://eng.uvm.dk/Education/General/7-point-grading-scale

Verbeek, M. (2012). *A Guide to Modern Econometrics.* Wiley.

Willis, R. J. (1986). Wage determinants: a survey and reinterpretation of human capital earnings function. I O. Ashenfelter, & R. Layard, *Handbook of Labor Economics* (s. 525-602). Elsevier Science Publishers.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* Cambridge: MIT Press.

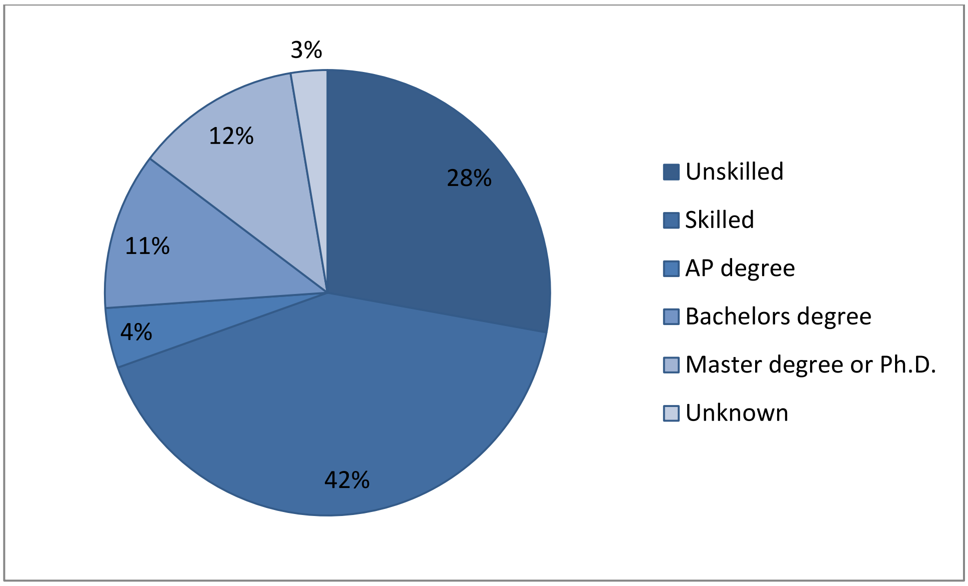
Wooldridge, J. M. (2009). *Introductory Econometrics, A Modern Approach.* South-Western Cengage Learning.

Xiao, J. (2002). Determinants of salary growth in Shenzhen, China: an analysis of formal education, on-the-job training, and adult education with a three-level model. *Economics of Education Review*(21), s. 557-577.

Zimmerman, D. J., & Ashenfelter, O. (1997). Estimates of the Returns to Schooling from Sibling Data: Fathers, Sons, and Brothers. *The Review of Economics and Statistic, MIT Press*, s. 1-9.

Appendix

Figure 3: Number of self-employed people by level of education



Source: Statistics Denmark, RAS2012

Table 14: Consumer price index (2015=100)

	Yearly average	Yearly increase
2005	84.0	1.8
2006	85.6	1.9
2007	87.1	1.7
2008	90.1	3.4
2009	91.2	1.3
2010	93.3	2.3
2011	95.9	2.8
2012	98.2	2.4
2013	99.0	0.8
2014	99.6	0.6
2015	100.0	0.5

Source: Statistics Denmark, PRIS112

Table 15: Industries, categorized as relevant

All	Communication	Engineers	Medicine	Pedagogical	Veterinarian
Organizations and associations	Libraries, museums, etc.	Construction contractor	Hospitals	Nursing homes, etc	Veterinarians
International organizations and embassies	Movie, television and music production	Construction contractor	Doctors, dentists, etc.	Day care and day centers	
Colleges and vocational schools	Radio - and TV stations	Building installation	Pharmaceutical Industry		
Higher educational institutions	Publishers	Building Completion			
Adult education etc.					
Public administration					
Defense, police and judiciary institutions					
Law firms					
Accounting and bookkeeping					
Consultancies					
Architects and engineers					
Research and development					
Advertising and research agency					
Other knowledge serivce					
Telecommunications					
IT consultants etc.					
Information services					
Banks					
Credit unions etc.					
Insurance and pension					
Financial services					

Table 16: Descriptive Statistics, Full population (Wages)

		No activity	Student job	Exchange	Job & exchange	All
		%	%	%	%	%
Sex	Male	39.13	48.87	49.67	40.55	*47.05*
	Female	60.87	51.13	50.33	59.45	*52.95*
High level math	No	67.22	62.68	58.27	58.07	*62.73*
	Yes	32.78	37.32	41.73	41.93	*37.27*
Age*	18-22years	23.02	26.86	32.93	29.13	*27.10*
	23-25years	59.15	58.21	60.43	63.19	*58.81*
	26+years	17.83	14.93	6.63	7.68	*14.09*
High School grade average	6 - 7,5	10.25	6.69	2.93	6.30	*6.78*
	7,6 - 9,0	51.04	50.73	42.07	50.59	*49.58*
	9,0 - 10,0	33.30	36.11	43.54	35.43	*36.63*
	10,1+	5.40	6.48	11.45	7.68	*7.01*
Ancestry[1]	Danish	93.19	95.33	96.37	93.31	*95.04*
	Immigrant or descending	6.81	4.67	3.63	6.69	*4.96*
Family type[1]	Couple	91.90	91.92	91.17	91.34	*91.80*
	Single	8.10	8.08	8.83	8.66	*8.20*
Mothers educational level[1]	Unknown	1.32	1.15	1.23	1.18	*1.19*
	Unskilled	20.17	17.87	12.26	12.20	*17.34*
	Skilled	27.66	27.83	20.40	24.41	*26.67*
	Short cycle tertiary educ.	5.25	5.11	5.48	6.89	*5.24*
	Bachelor’s degree or equivalent	35.51	36.92	42.27	42.52	*37.57*
	Master’s degree or PhD	10.10	11.12	18.36	12.80	*11.99*
Fathers educational level[1]	Unknown	1.44	1.30	0.96	0.79	*1.26*
	Unskilled	16.97	16.17	11.84	16.54	*15.72*
	Skilled	35.79	34.03	23.91	25.79	*32.71*
	Short cycle tertiary educ.	4.82	4.75	4.28	3.15	*4.65*
	Bachelor’s degree or equivalent	22.13	22.01	25.45	23.43	*22.55*
	Master’s degree or PhD	18.85	21.73	33.55	30.31	*23.11*
No. of children in the household[1]	One child	24.34	24.77	24.37	21.26	*24.54*
	Two-three children	70.10	70.00	71.04	73.43	*70.26*
	More than three children	5.56	5.23	4.59	5.31	*5.20*
Socioeconomic status, mother[1]	Employed	90.15	91.92	93.52	93.70	*91.88*
	Unempl. or outside the l. market	9.85	8.08	6.48	6.30	*8.12*
Socioeconomic status, father[1]	Employed	92.82	93.88	95.64	95.28	*93.98*
	Unempl. or outside the l. market	7.18	6.12	4.36	4.72	*6.02*
Income, mother[1]	No income	6.81	5.88	4.17	4.92	*5.78*
	0-299.999kr.	61.26	59.56	50.60	60.43	*58.64*
	3-399.999kr	21.21	23.32	28.77	21.85	*23.67*
	4-499.999kr	5.68	5.88	8.52	5.31	*6.20*
	500.000kr+	5.03	5.35	7.94	7.48	*5.71*

Income, father[1]	No income	6.02	4.83	3.90	4.33	*4.89*
	0-299.999kr.	28.51	28.22	20.75	22.44	*27.08*
	3-399.999kr	26.64	26.47	23.68	24.80	*26.06*
	4-499.999kr	14.92	15.86	17.51	15.35	*15.91*
	500.000kr+	23.91	24.63	34.17	33.07	*26.06*
Quarter of graduation	Q1	30.39	21.91	23.79	26.77	*23.79*
	Q2	24.09	31.02	27.73	22.44	*29.12*
	Q3	22.19	25.32	28.73	26.18	*25.27*
	Q4	23.33	21.75	19.75	24.61	*21.83*

Table 17: Descriptive Statistics, Students at University of Aarhus (Employment)

		No activity	Student job	Job & intern	Job& exchange	Internship	Exchange	All
		%	%	%	%	%	%	%
Sex	Male	39.20	47.24	38.55	52.44	26.72	46.03	*44.98*
	Female	60.80	52.76	61.45	47.56	73.28	53.97	*55.02*
High level math	No	76.31	67.62	77.32	61.32	83.62	68.25	*69.83*
	Yes	23.69	32.38	22.68	38.68	16.38	31.75	*30.17*
Age*	18-22years	19.08	23.93	15.65	30.09	25.86	34.92	*23.14*
	23-25years	63.31	61.43	67.12	64.76	52.59	61.90	*62.40*
	26+years	17.61	14.64	17.23	5.16	21.55	3.17	*14.46*
High School grade average	6 - 7,5	9.43	6.56	6.12	1.72	4.31	11.11	*6.43*
	7,6 - 9,0	57.23	48.54	50.79	45.27	50.86	58.73	*49.88*
	9,0 - 10,0	30.40	38.89	39.46	42.12	37.93	28.57	*37.95*
	10,1+	2.94	6.02	3.63	10.89	6.90	1.59	*5.74*
Ancestry[1]	Danish	94.76	97.04	97.73	98.28	98.28	96.83	*96.98*
	Immigrant or descending	5.24	2.96	2.27	1.72	1.72	3.17	*3.02*
Family type[1]	Couple	93.29	93.40	90.93	94.56	93.10	90.48	*93.14*
	Single	6.71	6.60	9.07	5.44	6.90	9.52	*6.86*
Mothers educational level[1]	Unskilled	22.22	18.72	18.14	14.61	24.14	7.94	*18.70*
	Skilled	29.14	28.78	28.34	22.92	30.17	25.40	*28.21*
	Short cycle tertiary educ.	4.19	5.57	6.58	4.58	4.31	14.29	*5.53*
	Bachelor’s degree or eq.	37.32	38.30	39.68	45.56	37.93	46.03	*39.15*
	Master’s degree or PhD	7.13	8.62	7.26	12.32	3.45	6.35	*8.41*
Fathers educational level[1]	Unskilled	18.66	15.13	16.55	14.04	17.24	19.05	*15.79*
	Skilled	40.88	38.98	36.28	28.65	38.79	22.22	*37.63*
	Short cycle tertiary educ.	6.50	4.31	3.85	5.44	3.45	4.76	*4.63*
	Bachelor’s degree or eq.	20.75	21.64	22.90	24.07	27.59	33.33	*22.30*
	Master’s degree or PhD	13.21	19.94	20.41	27.79	12.93	20.63	*19.66*
No. of children in the household[1]	One child	22.64	22.50	25.85	22.35	22.41	28.57	*23.01*
	Two-three children	70.65	72.43	67.35	71.06	70.69	65.08	*71.28*
	More than three children	6.71	5.07	6.80	6.59	6.90	6.35	*5.72*
Socioeconomic, mother[1]	Employed	90.78	93.31	91.38	93.41	92.24	93.65	*92.73*
	Unemployed	9.22	6.69	8.62	6.59	7.76	6.35	*7.27*
Socioeconomic, father[1]	Employed	92.87	95.11	94.78	94.84	91.38	95.24	*94.64*
	Unemployed	7.13	4.89	5.22	5.16	8.62	4.76	*5.36*
Income, mother[1]	No income	7.13	4.49	6.58	4.58	4.31	6.35	*5.12*
	0-299.999kr.	69.60	65.02	68.71	55.01	74.14	65.08	*65.40*

	3-399.999kr	16.14	21.91	19.73	28.94	15.52	19.05	*21.32*
	4-499.999kr	4.82	4.85	2.72	7.16	3.45	7.94	*4.82*
	500.000kr+	2.31	3.73	2.27	4.30	2.59	1.59	*3.35*
Income, father[1]	No income	5.87	4.67	4.31	3.44	6.90	4.76	*4.74*
	0-299.999kr.	34.80	28.65	31.97	24.64	29.31	34.92	*29.59*
	3-399.999kr	26.83	29.01	26.98	22.92	30.17	19.05	*27.77*
	4-499.999kr	13.42	16.75	17.46	19.20	18.10	17.46	*16.69*
	500.000kr+	19.08	20.93	19.27	29.80	15.52	23.81	*21.21*
Quarter of gradua-tion	Q1	23.27	21.87	26.53	23.21	23.28	25.40	*22.84*
	Q2	35.22	35.88	30.84	27.79	33.62	33.33	*34.30*
	Q3	25.79	25.37	22.22	34.10	23.28	30.16	*25.89*
	Q4	15.72	16.88	20.41	14.90	19.83	11.11	*16.96*

Table 18: Descriptive Statistics, full population (Employment)

		No activity	Student job	Exchange	Job & exchange	All
		%	%	%	%	%
Sex	Male	37.73	48.30	44.38	49.12	46.58
	Female	62.27	51.70	55.62	50.88	53.42
High level math	No	74.48	65.27	68.30	61.32	66.32
	Yes	25.52	34.73	31.70	38.68	33.68
Age*	18-22years	21.97	26.00	28.53	31.20	26.10
	23-25years	57.69	58.58	60.52	61.32	58.85
	26+years	20.34	15.43	10.95	7.48	15.05
High School grade average	6 - 7,5	11.39	6.95	9.51	3.27	7.24
	7,6 - 9,0	54.52	52.52	51.87	44.50	51.75
	9,0 - 10,0	29.89	34.45	33.43	41.23	34.59
	10,1+	4.20	6.08	5.19	11.01	6.41
Ancestry[1]	Danish	93.19	96.09	93.95	97.04	95.70
	Immigrant or descending	6.81	3.91	6.05	2.96	4.30
Family type[1]	Couple	92.68	91.85	91.07	92.11	92.00
	Single	7.32	8.15	8.93	7.89	8.00
Mothers educational level[1]	Unskilled	20.43	18.59	10.95	12.72	17.91
	Skilled	28.65	28.63	25.65	21.24	27.57
	Short cycle tertiary educ.	5.05	5.15	6.63	5.50	5.21
	Bachelor's degree or equivalent	36.32	37.17	43.23	43.15	37.98
	Master's degree or PhD	9.55	10.47	13.54	17.39	11.33
Fathers educational level[1]	Unskilled	18.37	16.14	19.88	12.05	16.04
	Skilled	37.13	35.12	25.36	25.08	33.86
	Short cycle tertiary educ.	4.71	4.76	4.90	4.57	4.73
	Bachelor's degree or equivalent	22.18	22.16	23.63	25.49	22.65
	Master's degree or PhD	17.60	21.81	26.22	32.81	22.71
No. of children in the household[1]	One child	25.31	24.95	23.05	24.09	24.85
	Two-three children	68.78	70.06	71.18	71.03	70.01
	More than three children	5.91	4.99	5.76	4.88	5.14
Socioeconomic status, mother[1]	Employed	89.89	92.02	91.64	93.72	91.89
	Unempl. or outside the l. market	10.11	7.98	8.36	6.28	8.11
Socioeconomic status, father[1]	Employed	92.63	94.11	93.08	95.95	94.09
	Unempl. or outside the l. market	7.37	5.89	6.92	4.05	5.91
Income, mother[1]	No income	7.28	5.56	5.48	4.26	5.66
	0-299.999kr.	63.81	61.30	59.08	52.49	60.47
	3-399.999kr	19.57	22.89	23.05	28.66	23.13
	4-499.999kr	4.97	5.37	6.05	7.01	5.54
	500.000kr+	4.37	4.88	6.34	7.58	5.19
Income, father[1]	No income	5.61	4.65	5.19	3.84	4.71
	0-299.999kr.	31.86	29.25	27.67	22.01	28.66
	3-399.999kr	26.85	26.50	23.63	23.31	26.06

	4-499.999kr	15.03	15.59	15.85	17.76	15.80
	500.000kr+	20.64	24.00	27.67	33.07	24.77
Quarter of graduation	Q1	21.71	20.01	19.88	21.44	20.48
	Q2	42.23	39.41	44.09	37.33	39.70
	Q3	17.69	21.01	17.00	23.47	20.70
	Q4	18.37	19.57	19.02	17.76	19.12

Figure 4: Distribution of monthly income

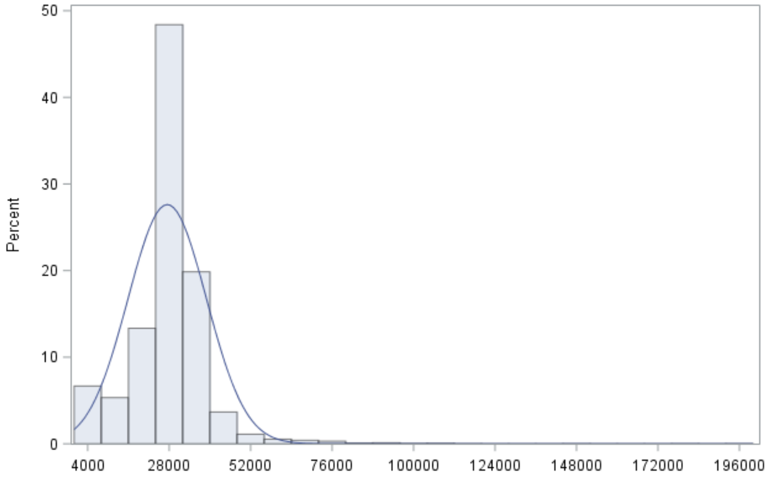


Figure 5: Distribution of log (monthly income)

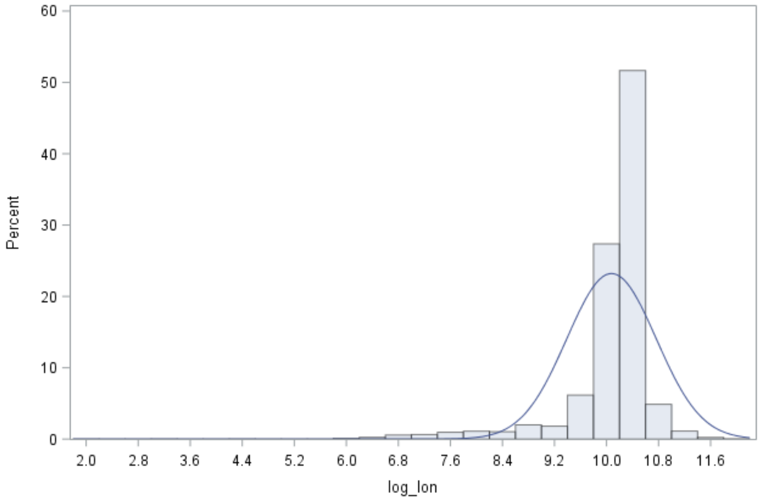


Table 19: Wage estimation, Aarhus students

	Model 1			*Model 2*			*Model 3*		
	Estimate	**S.E.**		**Estimate**	**S.E.**		**Estimate**	**S.E.**	
Intercept	23,311	548	***	12,795	22,999		43,125	23,995	
Exchange	-887	1,072		-891	1,073		486	1,070	
Relevant student job	2,245	399	***	1,953	404	***	1,921	403	***
Exchange & student job	3,961	600	***	3,650	609	***	3,560	607	***
Internship	224	962		213	970		206	960	
Internship & student job	1,333	625	*	1,199	628		1,257	621	*
Gender				-12,856	3,149	***	-13,332	3,267	***
High Level Math				745	362	*	637	367	
Age				902	893	***	377	910	
High School avg.				119	258	***	-191	270	
No. children in the household				-835	169		-787	169	
Mothers income				0	0		0	0	
Fathers income				0	0		0	0	
Q1				530	446		497	444	
Q2				1,119	463	*	892	463	
Q3				-288	426		-354	424	
Ancestry				950	825		1,025	823	
Family type				-153	482		-167	481	
Mothers socioec. status+				-176	189		-170	188	
Fathers socioec .status+				147	160		140	159	
Mothers educ(Unskilled)				-231	958		-304,3	956	
Mothers educ(Skilled)				-434	948		-495	946	
Mothers educ(Short term)				-769	1,101		-854	1,098	
Mothers educ(Medium term)				-471	959		-505	956	
Mothers educ(Master og Ph.D)				673	1,117		625	1,114	
Fathers educ(Unskilled)				-1,046	770		-1008	768	
Fathers educ(Skilled)				-435	722		-427	720	
Fathers educ(Short term)				-581	957		-630	954	
Fathers educ(Medium term)				-928	774		-954	772	
Fathers educ(Master og Ph.D)				-1,252	830		-1,228	827	
Mother unknown				-1,184	7,962		-2925	7943	
Father unknown				506	1,692		473	1685	
HS. avg.* Gender				129	352	***	134	365	***
HS. avg.*Age				-91	101		-32	103	
HS. avg.*Mothers inc				-0	0		-0	0	
HS. avg.*Fathers inc				0	0		0	0	
Humanities							-12,747	6,631	
Science							-16,356	7,646	*
Social Science							-21,866	6,360	***
Health Science							-3,175	8,983	
High school avg.*Humanities							912	751	
High school avg.*Science							157	858	
HS. avg.*Social Science							252	716	***
HS. avg.*Health Science							627	996	

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001. Model 1: N (individual level) = 5,968, N (macro level) = 85, Model 2: N (individual level) = 5,875, N (macro level) = 85, Model 3: N (individual level) = 5,875, N (macro level) = 85. Some insignificant coefficients are left out of the table. The full model also includes estimates on family and parents indicators..

Table 20: Multicollinearity estimates, wages estimation, Aarhus students

Parameter Estimates

Variable	**Estimate**	**S.E**	**t Value**	**Pr > |t|**	**Tolerance**	**VIF**
Intercept	24145	3.567	6.77	<.0001	.	0.00
Exchange	-3	1.080	0	0.9975	0.90	1.11
Relevant student job	2.165	404	5.36	<.0001	0.52	1.91
Exchange & student job	3.720	606	6.13	<.0001	0.66	1.51
Internship	-456	937	-0.49	0.6263	0.87	1.15
Internship & student job	906	587	1.54	0.1227	0.67	1.49
Gender	-1.778	302	-5.89	<.0001	0.91	1.09
High Level Math	771	363	2.12	0.0338	0.70	1.43
Age	-19	100	-0.19	0.8486	0.71	1.42
High School avg.	59	19	3.09	0.0020	0.81	1.24
No. children in the household	-87	171	-0.51	0.6085	0.93	1.08
Mothers income	0	0	0.4	0.6911	0.57	1.74
Fathers income	0	0	0.93	0.3532	0.92	1.08
Q1	757	441	1.72	0.0859	0.55	1.82
Q2	708	461	1.54	0.1245	0.53	1.88
Q3	-251	424	-0.59	0.5535	0.55	1.83
Ancestry	1.201	826	1.45	0.1462	0.84	1.19
Family type	-181	488	-0.37	0.7098	0.73	1.37
Mothers socioeconomic status+	-229	191	-1.2	0.2305	0.55	1.82
Fathers socioeconomic status+	148	161	0.92	0.3578	0.39	2.59
Mothers educ(Unskilled)	-324	969	-0.33	0.7379	0.15	6.74
Mothers educ(Skilled)	-360	958	-0.38	0.7070	0.11	8.72
Mothers educ(Short term)	-898	1.110	-0.81	0.4187	0.33	3.00
Mothers educ(Medium term)	-560	968	-0.58	0.5631	0.09	10.63
Mothers educ(Master og Ph.D)	465	1.129	0.41	0.6805	0.20	4.97
Fathers educ(Unskilled)	-1.156	777	-1.49	0.1368	0.28	3.52
Fathers educ(Skilled)	-559	729	-0.77	0.4432	0.18	5.64
Fathers educ(Short term)	-759	967	-0.79	0.4323	0.55	1.80
Fathers educ(Medium term)	-1.198	780	-1.54	0.1246	0.22	4.60
Fathers educ(Master og Ph.D)	-1.477	836	-1.77	0.0772	0.20	4.91
Mother unknown	-5.752	8.019	-0.72	0.4732	0.95	1.06
Father unknown	613	1.704	0.36	0.7191	0.84	1.18
Humanities	-4.191	631	-6.64	<.0001	0.25	3.93
Science	-2.634	699	-3.77	0.0002	0.46	2.18
Social Science	803	591	1.36	0.1747	0.24	4.11
Health Science	4.035	718	5.62	<.0001	0.39	3

Notes: N = 5,875

Table 21: Employment estimation, Aarhus students

Comparison	Estimate	95 % Confidence Limits		Estimate	95 % Confidence Limits		Estimate	95 % Confidence Limits	
Exchange	1.029	0.58	1.81	1.152	0.62	2.14	1.162	0.66	2.06
Relevant student job	6.334	4.95	8.10	6.571	5.07	8.52	5.630	4.47	7.09
Exchange & student job	10.044	6.28	1.61	9.477	5.81	15.45	7.953	5.16	12.25
Internship	1.299	0.80	2.12	1.360	0.81	2.29	1.353	0.86	2.14
Internship & student job	5.390	3.64	7.97	6.261	4.15	9.44	6.250	4.34	9.03
Gender				0.765	0.61	0.96	0.779	0.64	0.96
High Level Math				1.277	0.96	1.70	1.160	0.89	1.51
Age				0.916	0.85	0.98	0.903	0.85	0.96
High School avg.				1.031	1.02	1.05	1.026	1.01	1.04
No. children in the household				1.008	0.89	1.14	1.059	0.95	1.18
Mothers income				1.000	.	.	1.000	.	.
Fathers income				1.000	.	.	1.000	.	.
Q1				0.712	0.52	0.98	0.730	0.55	0.97
Q2				0.425	0.32	0.57	0.403	0.31	0.53
Q3				1.955	1.37	2.79	1.775	1.30	2.42
Ancestry				1.167	0.65	2.09	1.966	1.29	3.00
Family type				0.970	0.66	1.43	1.262	0.94	1.69
Mothers socioeconomic status+				0.999	0.91	1.10	0.923	0.83	1.03
Fathers socioeconomic status+				1.078	0.98	1.19	1.052	0.97	1.14
Mothers educ(Skilled)				0.837	0.63	1.12	0.910	0.71	1.17
Mothers educ(Short term)				1.318	0.78	2.24	1.411	0.87	2.28
Mothers educ(Medium term)				0.995	0.74	1.34	0.999	0.78	1.30
Mothers educ(Master og Ph.D)				0.938	0.57	1.55	0.857	0.55	1.33
Fathers educ(Skilled)				1.150	0.86	1.54	1.189	0.92	1.54
Fathers educ(Short term)				0.789	0.48	1.30	0.750	0.48	1.18
Fathers educ(Medium term)				1.283	0.92	1.80	1.298	0.95	1.77
Fathers educ(Master og Ph.D)				0.997	0.69	1.45	1.096	0.77	1.55
High school avg.* Gender				0.975	.	.	0.964	.	.
High school avg.*Age				0.990	.	.	0.987	.	.
High school avg.*Mothers inc				1.000	.	.	1.000	.	.
High school avg.*Fathers inc				1.000	.	.	1.000	.	.
Humanities							0.356	0.18	0.71
Science							0.735	0.34	1.59
Social Science							0.680	0.32	1.46
Health Science							2.368	1.01	6.87
HS. avg.*Humanities							1.041	.	.
HS. avg.*Science							0.978	.	.
HS. avg.*Social Science							0.982	.	.
HS. avg.*Health Science							1.052	.	.

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001, Model 1, 2 & 3: N (individual level) = 4,430, N (macro level) = 81. (**), + Socioeconomic Status: 0=Unknown, 1=outside the labor force, , 2=unemployed, 3=wage worker, 4=leader, 5=business owner

Table 22: Employment estimation, Full population

Comparison	Estimate	95 % Confidence Limits	
Exchange	0.905	0.698	1.174
Relevant student job	4.405	3.928	4.939
Exchange & student job	4.837	4.009	5.837
Gender	0.861	0.770	0.962
High Level Math	1.120	0.978	1.283
Age	0.914	0.885	0.944
High School avg.	1.032	1.025	1.040
No. children in the household	1.033	0.975	1.094
Mothers income	1.000	.	.
Fathers income	1.000	.	.
Q1	0.725	0.617	0.852
Q2	0.441	0.382	0.510
Q3	1.508	1.259	1.805
Ancestry	1.883	1.483	2.390
Family type	0.941	0.789	1.123
Mothers socioec. status+	1.036	0.993	1.080
Fathers socioec .status+	1.059	1.011	1.110
Mothers educ(Skilled)	1.015	0.880	1.171
Mothers educ(Short term)	1.093	0.853	1.401
Mothers educ(Medium term)	1.012	0.876	1.170
Mothers educ(Master og Ph.D)	0.944	0.754	1.181
Fathers educ(Skilled)	1.094	0.949	1.260
Fathers educ(Short term)	0.906	0.712	1.153
Fathers educ(Medium term)	1.161	0.989	1.364
Fathers educ(Master og Ph.D)	1.030	0.863	1.229
HS. avg.* Gender	1	.	.
HS. avg.*Age	1	.	.
HS. avg.*Mothers inc	1	.	.
HS. avg.*Fathers inc	1	.	.
Humanities	1.631	0.933	2.851
Science	0.725	0.542	0.970
Social Science	0.716	0.499	1.029
Health Science	1.423	0.913	2.217
HS. avg.*Humanities	1.008	.	.
HS. avg.*Science	1.004	.	.
HS. avg.*Social Science	1.009	.	.
HS. avg.*Health Science	1.003	.	.

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001 . N (individual level) = 17,863, N (macro level) = 357. (**),+ Socioeconomic Status: 0=Unknown, 1=outside the labor force, , 2=unemployed, 3=wage worker, 4=leader, 5=business owner

Table 23: Wage estimation, full population

	Model 3		
	Estimate	**S.E.**	
Intercept	-311.983	111.226	**
Exchange	-13.426	4.366	**
Relevant student job	36.047	1.879	***
Exchange & student job	39.326	2.741	***
Gender	9.217	16.372	
High Level Math	5.522	1.871	**
Age	16.919	4.329	***
High School avg.	5.704	1.248	***
No. children in the household	1.411	871	
Mothers income	0	0	
Fathers income	0	0	
Q1	-34.243	2.361	***
Q2	-107.042	2.210	***
Q3	31.476	2.306	***
Ancestry	12.838	4.055	**
Family type	-6.657	2.653	*
Mothers socioec. status+	872	687	
Fathers socioec .status+	2.309	772	**
Mothers educ(Skilled)	182	2.247	
Mothers educ(Short term)	-450	3.637	
Mothers educ(Medium term)	-322	2.238	
Mothers educ(Master og Ph.D)	-2.752	3.264	
Fathers educ(Skilled)	5.447	2.227	
Fathers educ(Short term)	256	3.807	*
Fathers educ(Medium term)	3.437	2.441	
Fathers educ(Master og Ph.D)	-1.848	2.592	
HS. avg.*Gender	-310	184	
HS. avg.*Age	-182	490.614	***
HS. avg.*Mothers inc	-0	0	
HS. avg.*Fathers inc	-0	0	
Humanities	-95.288	30.038	**
Science	-34.339	31.485	
Social Science	-120.168	27.355	***
Health Science	62.491	40.401	
HS. avg.*Humanities	724	328	*
HS. avg.*Science	324	341	
HS. avg.*Social Science	1.486	291	***
HS. avg.*Health Science	-383	436	

Notes: Significance: *=p<0.05, **=p<0.01, ***=p<0.001 . N (individual level) = 22,665, N (macro level) = 389. Socioeconomic Status: 0=Unknown, 1=outside the labor force, , 2=unemployed, 3=wage worker, 4=leader, 5=business owner

Table 24: Danish wages, masters 2014

Artistic	DKK 37.747
Masters' unknown degree	DKK 40.715
Humanities	DKK 43.401
Pedagogical	DKK 43.633
Agricultural Sciences	DKK 47.560
Science	DKK 49.197
Food and nutrition	DKK 49.748
Social Science	DKK 51.230
Technical Science	DKK 51.982
Health Science	DKK 53.559

Notes: Fulltime employed wage earners in all sectors without management responsibility.