University Graduates in Germany: Determinants of Time To Degree, Final Grades, and Pay at Labor Market Entrance

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1

General Introduction

1.1 Motivation

In recent years, German tertiary education institutions have undergone some reforms in the course of the European harmonization of the higher education system, the so called Bologna reforms. In addition, the reform of the financial aid system is a recurrent topic in political discussions on the German higher education system. Recently, the "Hochschulrektorenkonferenz" (German rectors' conference) calls for a reintroduction of tuition fees in Germany. Moreover, an increase of BAföG (Federal Education and Training Assistance Act) payments is currently debated. Therefore, investigations on the German tertiary education system are of particular interest.

The four studies included in this thesis address various topics on students' academic performances and determinants of pay at labor market entrance in Germany. In the first two studies, the impact of working beside studies on time to degree is investigated. The third study focuses on how university grades are affected by students' socio-economic background as well as by A-level grades. In the fourth study, determinants of graduates' pay at labor market entry and of the gender pay gap in entry wages are analyzed. From an economic point of view, long study durations and worse university grades may result in forgone income and unfavorable job offers leading to lower wages at labor market entrance and also to lower future earnings. As in Germany there is an increasing proportion of students entering university over the last years, analyzing graduates' academic performances, labor market conditions and wages becomes increasingly important in the future.

Students' performance is a key factor for measuring the efficiency of higher education systems, which is a highly recurrent topic in political debates. Germany is characterized by a high average duration of study. Moreover, regular durations are often exceeded. One potential reason might be the high proportion of students working during their

studies as they probably face time restrictions leading to less time available for studying. Recent reforms of the German university system, e.g. the Bologna reforms, were all aimed at reducing time to degree. Nevertheless, as recently claimed by a leading German newspaper, the mean duration of students in North Rhine-Westphalia (which covers about 25% of all enrolled students in Germany) finishing with a bachelor's degree was about 8.64 terms, thereby exceeding the standard duration of 6 terms considerably (see Füller (2014)). Identifying causes of high durations is one of the key aspects for improving efficiency of the German academic system and national and international career entry chances of graduates.

In this context, discussions on the selection criteria of universities raise the question if e.g. A-level grades are a reliable signal for future academic performance. Do students with good A-levels also obtain better exam grades at university than their fellows performing less well at school? University grades are of considerable importance as they serve as signals for qualification and motivation on the labor market. They reflect human capital acquisition and may determine graduates' opportunities at labor market entrance.

The impact of students' social background on academic performance is a recurrent topic of political debates on the social selectivity of the German academic system. Given evidence that A-level grades are affected by social origin (see e.g. PISA reports) there probably exists a disadvantage for underprivileged students to participate in higher education. Moreover, if students' academic performance varies with social background, also later earnings may differ between graduates' from different social origins. Therefore, it is of particular interest to investigate whether disadvantages for socially underprivileged students' at earlier levels in the educational career extend towards university and further towards the labor market.

It is well known that in most industrialized countries wages for women are lower than those for men. Every year, the international "equal pay day" calls attention to the existing gender pay gap. Current salary differentials are to a great extend a result of starting salary differentials. Moreover, pay rises and other forms of payment are often based on current salaries. Since a persistence of pay differentials is assumed, a detailed analysis at labor market entry can help to understand the causes and origins of the gender pay gap later in the career.

The results of the four studies reveal determinants affecting academic performances, i.e. time to degree and final university grades, and provide insights on how students'

performances affect their integration into the labor market and wages. These findings are probably useful to evaluate the German academic system, i.e. the Bologna reforms, the financial aid system, and social selectivity. Furthermore, a closer look at the processes determining graduates entry wages may identify reasons for the existing wage gap between men and women, and probably reveals requirements for action.

1.2 Facts and Figures on the German Higher Education System

In the following, I will give some detailed information on the German higher education system. In addition, some figures on students' social composition, their characteristics over social classes, study durations and the gender pay gap are presented.

As already mentioned, in recent years the German university system has undergone some reforms in the course of the European harmonization of the higher education system (Bologna reforms). The main objectives were to ensure more comparable systems of higher education in Europe, to support international mobility for students and to facilitate exam recognitions across countries. In Germany, the former degrees (Diplom, Magister, Staatsexamen) with relatively long standard durations of 8-10 semesters were substituted by the two-tier bachelor/master structure. The standard duration of a bachelor's degree is 6 and of a master's degree 4 semesters. The bachelor's degree is aimed to provide students a fast qualification for the labor market entrance. In the winter term 2013/14, approximately 87% of all study programs have been reformed towards the bachelor/master system.

Furthermore, several reforms of the student aid system and of tuition fee policies were implemented. The supremacy of the states (Länder) in Germany in the field of education leads to different regulations. Until the introduction of general tuition fees in most western German states since 2007, attending a university has been free of charge. Since October 2014, there are no general tuition fees at all. In some federal states tuition fees only for long term students were charged.

The main source of financial aid for students from low income families is provided by BAföG (Federal Education and Training Assistance Act). The eligibility for BAföG and the amount of payment is means tested with a maximum amount of monthly payment of

about 600 Euro. The maximum period of assistance is determined by the standard period of study. 50% of the credit has to be repaid. Furthermore, there are so called education loan programs providing low-interest financial support to students. Scholarships are awarded to students with excellent academic performance.

According to the German Federal Statistical Office, in 2013/2014 there were approximately 2.6 million students enrolled at German universities. The majority of universities are public institutions, financed by the states (Länder). The German tertiary education system is based on two types of institutions: universities and universities of applied sciences (Fachhochschulen). Universities mainly focus on theoretical and research-oriented components, whereas universities of applied sciences are much more vocationally oriented. A-level (typically after 12 to 13 years of schooling) is the most common entrance qualification. But there exist other ways to gain access to higher education in Germany, e.g. through a university of applied sciences entrance qualification. Despite a numerus clausus for several fields of study, there are usually no further admission rules.

In 2012 (winter term 2011/12 and summer term 2012), 498,854 students were enrolled for the first time at a German university. The strong increase of students entering university over the last years[1] reflects two main facts: an increase in the fraction of students obtaining an A-level (2009: 46.2% and 2012: 53.5%[2]) and an increase in the fraction of school leavers entering university (2009: 43.0% and 2012: 51.4%[3]). The proportion of first enrolled female students varies between 47% and 50%. The comparable low proportion of 47% is partly due to suspension of compulsory military service in Germany in 2012 (see Statistisches Bundesamt (2014b)). The so called "academization" is an intensively discussed topic in political debates. According to the German Federal Statistical Office, in 2012 about 30.7% (only first degree, expressed as a proportion of the age specific population) finished with an academic degree. This is a substantially increase of about 14 percentage points referred to 2000 (16.9%).

Altogether, in 2013 approximately 436,400 students obtain a higher education degree at a university or at other higher education institutions. This is an increase of 6% in comparison to 2012 (approximately 413,300 graduates). The greatest proportion of students (47.5%)

[1] In 2000: 284,343 and in 2010: 417,218 students first enrolled.

[2] Figures adjusted for the introduced G8 reform, i.e. students obtain an A-level after 8 years (instead of 9 years) of secondary schooling.

[3] Figures adjusted for the introduced G8 reform.

finished with a bachelor's degree, followed by former degrees (e.g. diploma, 18.7%) and a master's degree (18%). 9.5% obtain a teacher's training certificate and 6.3% attain one's doctorate (see Statistisches Bundesamt (2014a)).

About one third of all students graduate in a field of law, economics and social sciences. 19.5% finish with a degree in engineering, followed by linguistic and cultural sciences (18%), maths and natural sciences (17%) and human medicine and health care (5.9%). 7.5% graduate in other fields of study. There is a great difference in the choice of fields of study between male and female students. E.g. in 2012, the proportion of women was highest in humanities, arts and educational sciences (70.9%), followed by "social" fields and fields of health care (70.1%). The proportion of female students was lowest in engineering (22%) and maths and informatics (27.8%). These fractions remain relatively constant over the last years. The overall proportion of female graduates rises from 45% in 2000 up to about 50% in the last years. The mean age of graduates (first degree) decreased from 28.2 in 2001 to 26.5 in 2013. In comparison to other OECD countries, Germany was characterized by high mean ages of graduates. The reduction is mainly due to the implementation of the bachelor/master system. In 2013, the mean age of students finishing with the old diploma and master's degree was about 28.3. A bachelor graduate was on average 25.7 (see Statistisches Bundesamt (2014a)).

Over the last years, higher education institutions were entered more frequently by non-traditional students, i.e. students from non-academic households. In 2005, approximately 42% of children from non-academic households decided not to participate in tertiary education, whereas in 2008 this proportion declines substantially to 35%. However, the German educational system is regarded as highly socially selective. There seems to be a dependency between parental educational and academic background and children's participation at upper secondary school and institutions of higher education. In 2007 three out of four young adults with a highly educated father (A-level) participate in higher education. On the other hand, only between 20 and 25% of children from lower educated households attend university (see BMBF (2010)).

Variables indicating several levels of parental educational attainments reveal a detailed view on students' social composition. The lowest level of educational background indicates that no more than one parent has a (non-academic) professional qualification. The next level indicates that both parents have a (non-academic) professional qualification, followed by the third level characterizing that one parent has a university degree or a degree at a German university of applied science. The highest level of parental educational background

denotes that both parents have obtained an academic degree. In 2012, the largest share of students comes from an household belonging to the second category (41%), 28% do have at least one parent with an academic degree. Over the last decades, the fraction of students with the highest educational background increases substantially from only 8% in 1985 up to 22% in 2012, whereas the fraction of students with the lowest educational background decreases from 29% in 1985 to 9% in 2012. This development is partly due to the fact that there is an increasing proportion of well educated (academic) parents. Furthermore, there seems to be an association between students' educational background and their choice of study fields. In 2012, a comparatively great proportion of university students in social sciences and humanities were so called educational climbers (from a non-academic households). On the contrary, students graduating in medicine/health care and in engineering tend to come from highly educated households (see BMBF (2013)).

Regarding students' financial situation, support from parents is the most important source of financing. In 2012, 87% of students receive financial support from their parents, 63% cover a part of their living costs by personal earnings. The proportion of BAföG recipients amounts to 32%. Between 1991 and 2000, the proportion of personal earnings as one part of students' monthly income has risen from 25% to 31%. After a downward trend until 2006 the evolution reversed until 2009 to a level of 26%. In 2012, the proportion of personal earnings is about 24%, which is still high. Breaking down the monthly income according to social origins reveals a linkage between the source of financing and students' educational background. In 2012, the importance of personal earnings increases from 20% in the "upper" to 26% in the "low" group of social origin, whereas the proportion of the parental financial support decreases considerably (from 63% to 27%). In the lowest group of social origin, BAföG provides the largest part to students' monthly income (37%). During the last decades, the proportion of German students working part-time increased from 51% in 1991 to 68% in 2003. After a decline until 2006 (64%), the proportion of working students increased again up to 67% in 2009. In 2012, 62% of the students reported to work during their studies. This decrease is mainly driven by the G8 reform and the suspension of compulsory military service in Germany. In this year, the proportion of male and young students, which tend to work less during studies than women and older students, was very high and therefore the overall proportion of working students very low. The main motive for employment is the necessity to cover living costs. The socioeconomic background strongly affects students' working status as students coming from an upper social group are less likely to work constantly during their

studies (see BMBF (2013)).

As already mentioned, Germany's tertiary education system has been characterized by long time spent to obtain the first university degree. In 1998, that is before the process of Bologna reforms started, in most fields of study the proportion of students obtaining their degree within legal duration was below 30% (see Wissenschaftsrat (2001)). After the reforms, in 2012, 39.3% of all students graduated within regular study time. This proportion varies with fields of study, ranging from 90.5% in administrative sciences to e.g. only 23.9% in sports/sports science. Even within the new two-tiered bachelor/master structure, in 2012 only 49.4% obtain a bachelor's degree and 42.3% a master's degree within legal duration (see Statistisches Bundesamt (2014b)).

Information on median durations (until first degree) between 2000 and 2012 of the "old" degrees and of the bachelor's and master's degrees after the Bologna reforms is presented in Table 1.1 (data: Statistisches Bundesamt (2014b)).

year	uni_old	appl.sc_old	BA	MA
2000	11.50	8.50	5.90	9.90
2005	11.20	8.40	6.10	9.70
2010	11.20	8.80	6.00	10.50
2011	11.40	9.00	6.30	10.60
2012	11.70	9.10	6.50	10.80

Table 1.1: Evolution of median durations by degree (2000-2012)

Note that regular study durations are 9 terms for the old university degrees (uni_old) and 7 for the old degrees from universities of applied sciences (appl.sc_old). Obtaining a bachelor's degree (BA) lasts regularly 6 and a master's degree (MA) 10 terms. In 2012, median durations exceed the regular durations for all degrees, indicating that the majority of students do not manage to meet the proposed timeline. Furthermore, we observe an upward trend for times to degree, even for the bachelor‘s and master‘s degrees.

As the last paper of this thesis deals with gender pay differentials, some figures on wages and of the existing gender pay gap are presented. The German Federal Statistical Office states a raw gender pay gap, i.e. the difference between male and female earnings expressed as percentage of male earnings, of 22%-23% between 2006 and 2013. The most important reasons seem to be differences in sector and job choices between men and

women; women seem to be employed in sectors with comparable low wages. According to Statistisches Bundesamt (2013), average gross earnings of full-time workers vary substantially between sectors. In 2013, sectors like energy supply, information and communication, and financial and insurance services report the highest mean gross monthly earnings (about 4500 Euro), whereas the sector accommodation activities reports the lowest earnings (about 2000 Euro). Altogether, differences in characteristics between men and women explain about two third of the raw gender pay gap. The remaining unexplained third (about 7 %), defined as the adjusted pay gap, is often referred to discrimination. In 2012, the gender pay gap in Germany exceeds the average of the European Union (16%) substantially. Moreover, only two countries report a higher pay gap as Germany (Austria and Estonia). Since gender wage differentials seem to be a serious issue in Germany and current salary differentials are to a great extend a result of starting salary differentials, analyzing determinants of pay at labor market entry is of great importance.

1.3 Overview of the Four Studies

For Germany, empirical literature on students' academic performance and graduates' transition into the labor market are very scarce and this thesis tries to partly fill this gap. In the first paper, I try to identify factors influencing time to degree. I apply the Cox Proportional Hazards Model, a very popular model within survival analysis, and focus on students' working behavior, which is assumed to influence study durations strongly.

Working and non-working students differ considerably with respect to their characteristics and obviously a random assignment to both groups could not be assumed. Therefore, the second study makes use of randomization tests, which have been put forward strongly by Paul Rosenbaum. The appealing feature of randomization tests is that the stochastic stems solely from random assignments contrary to 'normal' statistical modeling, where social events are assumed to have been generated by random mechanisms, often called data generating processes. The testing procedure is aimed to mimic as closely as possible the procedure in random experiments. As we face self-selection in observational studies, the application of randomization must (or can eventually) be enabled by means of matching procedures.

The third study focuses the effect of students' socio-economic background and prior qualifications on university grades. As previous research reveals a relationship between social origins and performance at school, I analyze whether this association extends towards university. Here, I treat grades as ordinal and apply ordered probit regressions. Furthermore, possible effects of A-level grades on university performance are investigated.

As already mentioned, academic performance serves as signal for ability and motivation on the labor market. Therefore, in a next step it is analyzed whether graduates' entry wages are affected by their academic performances. In this regard, a possibly gender wage gap at labor market entry is investigated by identifying and disentangling several impact factors. An extended decomposition method, which allows analyzing complete income distributions, is applied. While numerous studies analyze gender pay differentials in general, the literature on gender pay gaps of graduates at career entry is rather scarce. This study tries to partly fill this gap by providing evidence for Germany.

These empirical analyzes are based on data from the German Absolventenpanel 2001 of the HIS (Hochschul-Informations-System), which includes a random sample of all graduates receiving their first degree in 2001 at a German university. The first wave of the survey was conducted 6-18 month after graduation, the second wave 5 years later and a third wave 10 years after graduation. The panel includes a wide range of social and demographic characteristics and detailed information about the course of study and the integration into the labor market. I only use the first wave of the survey because it contains information e.g. about times to degree, grades, fields of study and wages of the first job after graduation. I analyze fields of study separately, because comparisons of durations and grades across very different fields are regarded as inappropriate. In the following, I will give a closer overview of the four studies.

Paper 1: The Working Status of Students and Time to Degree at German Universities

In the first paper, I focus on the relationship between the working status of students and their time to degree. Since tuition fees have been abolished in most federal states, students are allowed to stay at university for an unlimited amount of time without additional costs. From an economic point of view, longer times to degree imply higher costs in the form of forgone income. In Germany, the regular time to degree is often exceeded. One potential reason might be the high proportion of students reporting part-time work during their

studies. The aim of this paper is to examine and quantify the effect of time students spent for work on their duration of study. In addition, the amount of hours spent at part-time work, i.e. whether students report episodes of part-time work or working throughout their whole study, and its effect on time to degree is investigated.

To determine causal effects of the covariates on time to degree, a survival analysis model is applied. A popular regression model within survival analysis was introduced by Cox (1972). The Cox Proportional Hazards Model (Cox PH) is a semi-parametric method. In contrast to parametric models it is free of distributional assumptions and leads to estimators which are robust towards misspecifications of the underlying model, with only a marginal loss of efficiency in comparison to the correct parametric model.

I find working and non-working students to differ considerably with respect to personal as well as parental characteristics. A dependency between students' social background and their working behavior is observed. Educational climbers seem to be more likely to work during their whole study time than their fellow students coming form well educated household. Moreover, students with a bad final grade at school are more likely to work intensively.

As a main finding I observe that working throughout studies reduces the hazard of graduation in the majority of fields considerably. A further important attribute affecting time to degree is students' prior qualification. The hazard of graduation increases with decreasing (better) A-level grades. Surprisingly, the effect of the parental educational background seems not to play a role for academic performance. However, this effect is probably captured by the effects of students' working status and A-level grades on times to degree.

Paper 2: The Causal Effect of Off-Campus Work on Time to Degree

In this study, my co-author and I try to estimate the "causal" effect of work on time to degree by applying a matching strategy.

As observed already in the first paper, working and non-working students differ considerably with respect to personal as well as parental characteristics. Obviously, they have not been assigned to the working or non-working group randomly. Simple comparisons of the time to degree may be severely biased due to self-selection into the groups. We try to avoid this potential biasing effect by using matching methods as suggested by Rosenbaum and Rubin (1983) and Rosenbaum (2002). The aim is to control as much as possible

for potential selection effects using all relevant available information on the students under analysis. The idea of the matching approach applied is to come ex post through statistical analysis as close as possible to a randomized experiment in which students would be assigned randomly towards the groups, e.g. not working or working outside the university.

The difference in study duration is highly significant under the assumption of random assignment for the complete sample of all students (difference of 0.841 terms) as well as in eight out of ten fields at the 1%-level. Students working off-campus during their whole study time reveal significant higher times to degree than their non-working counterparts.

Controlling for selection effects results in lower and less significant estimates of the effect of working on study duration making evident the unreliability of simple comparisons. Accounting for the overt bias on observables in the matching routine the overall difference decreases toward 0.667 terms but remains highly significant. For six out of ten fields a significant (at the 10%-level) prolonging effect of off-campus work on the duration of study is found. Controlling for potential self selection into both groups seems to be very important for assessing causal effects of off-campus work on duration.

Paper 3: The Effect of Students' Social Background and A-level Grades on University Performance

In this paper I try to estimate the effect of students' social background and A-level grades on their final grade at university. University grades are of considerable importance as they serve as signals for qualification and motivation on the labor market. One of the most important studies, the PISA study, reports a strong disadvantage for socially underprivileged students as they perform less well at school. This paper analyzes whether these disadvantages extend towards university.

A methodological issue is whether grades should be treated as metric or ordinal in statistical models. Simple linear regression models assume that grades are metric. That means that the "interpretable" difference between two grades is always the same. But this assumption usually does not hold in the German grading system.

I treat grades as ordinal and use an ordered probit regression without and with controlling for students' prior qualification. Moreover, I construct a variable indicating students' educational background as used by BMBF (2013). Without controlling for

prior qualification, students from less educated households obtain very good grades with a lower probability than students with both parents having an academic degree. The results indicate an increasing negative effect on educational success over social classes.

Including A-level grades, the effect of students' academic background on their own academic performance only remains important between higher levels of social origin. A-level grades seem to be a reliable predictor of future academic performance with a probability decreasing effect of obtaining very good university grades with worsening A-level grades.

As a main result, I find that the strong effect of academic background on A-level performance (as found in literature) does not carry over to performance at university in its entirety after controlling for A-level grades. Differences between lower and higher social classes seem to be captured by prior qualifications on an earlier stage of the educational career.

Paper 4: The Gender Pay Gap at Labor Market Entrance: Evidence for Germany

In the last paper, my co-author and I investigate entry wages of German graduates and the gender pay gap at labor market entrance. Analyzing entry wages is important as current salary differentials are to a great extend a result of starting salary differentials. Moreover, pay rises and other forms of payment are often based on current salaries.

Most of the mentioned studies apply standard Oaxaca-Blinder decomposition techniques to evaluate the explained and unexplained part of the gap in mean wages. We extend these approaches applying a decomposition method, which allows to analyze the complete income distribution and differences between groups' incomes at all percentiles. Applying a single-index model as suggested by DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1998) the gender pay gap is decomposed in endowment, price and return-to-skill function effects. Detailed insights into the origins of the gender pay gap are provided.

Wage regressions reveal university performance and fields of study to affect entry wages of men and women significantly. We detect only slight differences in male and female characteristics. An exception is the choice of field of study, which seems to have a

strong effect on entry wages. A considerable fraction of 45% of male graduates obtain their degree in fields of sciences, whereas a great fraction of women major in social sciences.

Our main finding is that the extent of the gender pay gap at labor market entry is of about the same magnitude as the overall pay gap in Germany. The difference in average hourly starting wages is 25%, what is surprisingly large and much higher than entry wage gaps of graduates found for other countries.

We observe higher starting salaries for men at all percentiles of the income distribution. The overall wage gap and the three isolated effects behave quite differently at different percentiles. The endowment and skill price effects are inversely u-shaped and both favorable for men throughout. The effect of the difference in the returns-to-skill function is advantageous for female graduates at the lower part of the wage distribution, but less strong than the two other effects.

2

The Working Status of Students and Time to Degree at German Universities

The Working Status of Students and Time to Degree at German Universities

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Abstract

This paper analyzes time to first degree at German universities. The data base is the "Absolventenpanel" 2001, a panel study conducted by the "Hochschul-Informations-System" (HIS). The German university system is characterized by a long duration of study; the regular time is often exceeded. One potential reason might be the high proportion of students reporting part-time work during their studies. This paper focuses on the relationship between the working status of German students and their time to degree. Besides that, additional individual characteristics and parental background are included. Analysis is carried out for ten fields of study separately. The descriptive analysis reveals a positive correlation between the amount of part-time work and the duration of study. In the empirical analysis, the Cox Proportional Hazards model is applied. The results confirm that part-time work has an increasing effect on time to degree. These results and the aspect that mainly socially underprivileged students are engaged in part-time working during their studies should be considered in the political discussions of tertiary education financing and the Bologna process.

JEL classification: C41; I21; I22; I28
Keywords: Educational economics, Academic outcome, Time to degree, Part-time work, Social background

2.1 Introduction

In discussions of the German tertiary education system, two key factors are most often mentioned: the proportion of students achieving their degree and the time spent to obtain the degree. Both are main indicators for the internal efficiency of a university system which in turn is part of political debates. Germany is characterized by a high average duration of study. Moreover, regular study time is often exceeded. In 2012 only 39.3 percent of all students achieved their degree in regular time. For comparison, regular study duration for achieving a diploma at a university amounts to 9 semesters. Between 1995 and 2012 the median duration varies around 11.4 semesters. At a German university of applied science (Fachhochschule), regular duration amounts to 7 semesters. The median time to degree is between 8 and 9 semesters (see Statistisches Bundesamt (2014)).

Identifying causes of high durations is one of the key aspects for improving efficiency of the German academic system. Shortening time to degree is regarded as important for improving national and international career entry chances of German graduates. From an economic point of view, long study durations may result in forgone income and unfavorable job offers (leading to lower earnings).

Recent reforms of the German university system, e.g. the reform of the student aid system, the introduction of tuition fees and the implementation of the Bologna process, are all aimed at reducing time to degree. Regarding the effect of tuition fees, there is uncertainty about the net effect, as on the one hand higher costs of studying provide incentives to shorten study time, but on the other hand higher costs may increase employment of students in order to cover their costs. This last mentioned effect and its influence on time to degree is often neglected.

During the last decades, the proportion of German students working part-time increased substantially. A very important characteristic of the Bologna process is to reduce time to degree by a more structured course of study. This loss of flexibility could strengthen a possible negative effect of working during studies on time to degree. For students it will be more difficult to combine study and work. Thus, under the described developments of the students' working behavior the Bologna process may result in even longer durations of study.

The aim of this paper is to examine and quantify the effect of time students spent for work[1] on their duration of study. In this context I also analyze the amount of hours spent at part-time work, i.e. whether students report episodes of part-time work or working throughout their whole study and its effect on time to degree. The results will be of relevance in discussions of tertiary education financing and of the evaluation of the Bologna process in Germany.

This paper is organized as follows: the second section presents a theoretical and institutional background and also research hypotheses, the third section provides an overview of the relevant literature on study duration. In section 4 I elucidate the data base and discuss the variables used in the analysis. Section 5 contains a descriptive analysis and the estimation methodology is discussed in section 6. Empirical results are presented in section 7, section 8 concludes.

2.2 Theoretical and Institutional Background

2.2.1 Theoretical Background and Hypotheses

Since tuition fees have been abolished in most federal states, students are allowed to stay at university for an unlimited amount of time without additional costs. From an economic point of view, longer times to degree imply higher costs in the form of forgone income.

There are many factors affecting students' time to degree. They could be categorized into two groups: personal characteristics and institutional factors. The first one includes e.g. sex, age, students' educational background, experiences, working behavior and the parental socio-economic background. Institutional factors are those factors determined by the university or the area of study, e.g. the structure of the curriculum or legal durations. This study aims to answer two general research questions:

> Which factors do affect study duration?
>
> How and to what extend do they affect study duration?

[1] With "work" we refer throughout to on-campus or off-campus part-time work (usually to earn money) in distinction to studying.

In particular, the effect of students' working behavior and of their socio-economic background is analyzed.

Between 1991 and 2000 (which covers the time period relevant for the cohorts analyzed), the proportion of personal earnings as one part of students' monthly income has risen from 25 to 31 percent. After a downward trend until 2006 the evolution reversed until 2009 (to a level of 26 percent, which is still high, see BMBF (2010)). The source of financing seems to be linked to the social background. As low income families are not be able to finance their living costs, students are probably forced into work beside studying. According to BMBF (2010) the importance of personal earnings increases from the "upper" to the "low" group of social origin, whereas the proportion of the parental financial support decreases considerably. The socioeconomic background strongly affects students' working status as students coming from an upper social group are less likely to work constantly during their studies. These facts seem to be of great relevance as higher education institutions are more and more entered by non-traditional students, i.e. students from low income families. This leads to my first specific research question:

> Is there a relationship between students' working behavior and their socio-economic background?

During the last decades, the proportion of German students working part-time increased from 51 percent in 1991 to 68 percent in 2003. After a decline until 2006 (64 percent), the proportion of working students increased again up to 67 percent in 2009 (see BMBF (2007) and BMBF (2010)). Some of these students even work full-time. The main motive for employment is the necessity to cover living costs. According to time allocation theories, this coincides with a reallocation of students' time with less time available for studying and possibly a prolongation of time to degree. Here, the work intensity seems to play an important role. Moreover, working students face time restrictions leading e.g. to missed lectures or even exams. Based on these considerations, I formulate a second research question:

> Is time to degree negatively affected by students' working status and the intensity of work?

In this context it has to be mentioned that acquiring work experience while studying could be a signal for motivation and ability and may affect employment probability and earnings after graduation positively. Here, the net effect of work experience on time to degree is of key interest. A paper by Häkkinen (2006) concludes e.g. that the positive

effect of work on earnings is much lower and insignificant if the model allows for an effect of work on time to degree.

A relationship between the parental educational background and students' academic performance is postulated by the cultural capital theory (advanced by Bourdieu). It is stated that students from non-academic households and therefore with less cultural capital endowments face an adverse educational environment leading to a lower level of academic performance. Children of highly educated parents being involved in academic processes probably benefit from their skills, experiences and academic connections. Educational climbers are therefore less successful than students from traditionally academic households are. Moreover, lower levels of education are mostly associated with lower financial resources. According to economic capital theories, lower resources negatively affect academic performance as well. Cultural and economic capital theories therefore imply the parental academic background to be highly predictive for students' performance. These aspects lead to a third research question:

> Is time to degree positively affected by an academic parental background?

From a theoretical point of view, there are two aspects justifying a relationship between prior qualifications and time to degree. On the one hand, signaling theory states that A-level grades serve as signal for motivation and learning abilities. On the other hand, in the sense of human capital theory, good A-level grades and also working experiences before studying indicate a large amount of acquired human capital which is assumed to promote academic performance. Based on these considerations, I try to answer a fourth research question:

> Is time to degree positively affected by good A-level grades and working experiences before studying?

To capture the previously mentioned institutional part, the semester of enrollment and fields of study are included in the analysis. In Germany, students traditionally first enroll at university in the winter term and the curriculum is adjusted to that course of study. Therefore, studying against the regular lecture rotation (i.e. being first enrolled in the summer term) maybe prolongs time to degree.

Legal durations and the structure of the curriculum vary substantially across fields, but there are further important distinctions between fields of study. According to Bourdieu, a differentiation could be made between fields leading to authority and power, e.g. medicine

and law, and fields leading to scientific status and prestige, e.g. humanities and social or nature sciences. A distinction could also be made between so called "hard" and "talent" fields. Hard fields are those requiring hard work and time. Talent fields require mainly talent to be successful.

Categorizing fields is not consistent in literature and therefore I do not state any specific hypothesis concerning covariate effects for different fields of study. However, all of these theories imply possibly varying effects of covariates on academic performance across fields (e.g. cultural capital is more relevant in talent fields). Therefore, my last research question is:

> Do covariate effects on time to degree differ across fields of study?

According to these considerations and the fact that e.g. the exceedance of legal durations as well as student characteristics differ considerably between fields of study, the analysis is carried out separately for ten aggregated fields.

Based on the previously mentioned theories, I postulate five hypotheses, which are evaluated in the following analysis.

> H1: Working students differ in their characteristics from non-working students. In particular, the working behavior is linked to the social background with higher work intensity of students from less educated households.
>
> H2: Working during studies and high work intensities prolong times to degree.
>
> H3: High cultural capital, i.e. parents having obtained an academic degree, decreases times to degree.
>
> H4: High human capital, measured as good A-level grades and experiences before studying, leads to shorter times to degree.
>
> H5: Covariate effects on time to degree differ across fields of study.

In the literature review, I present the results for the most interesting covariates found in previous research. Hypotheses for other control variables are postulated in the data section.

2.2.2 The German Higher Education System

The German tertiary education system is based on two types of institutions: universities and universities of applied sciences (Fachhochschulen). Universities mainly focus on theoretical and research-oriented components, whereas universities of applied sciences are much more vocationally oriented. A-level (typically after 12 to 13 years of schooling) is the most common entrance qualification. However, there exist other ways to gain access to higher education in Germany, e.g. through a university of applied sciences entrance qualification (for more details see e.g. Weiss and Steininger (2013) or Schindler and Reimer (2011)). Despite a numerus clausus for several fields of study (e.g. medicine, law, business administration), there are usually no further admission rules.

The German educational system is regarded as highly socially selective. There is a high dependency between parental educational and academic background and children's participation at upper secondary school and institutions of higher education. According to BMBF (2010), in 2007 three out of four young adults with a highly educated father (A-level) participate in higher education. On the other hand, only between 20 and 25 percent of children from lower educated households attend university.

Most of the German universities are public institutions, financed by the states (Länder). The supremacy of the states in the field of education leads to different regulations. After some experiments with tuition fees starting in 2007, almost all states dropped these fees in reaction to massive protests.

In recent years, the German university system has undergone reforms in the course of the European harmonization of the higher education system (Bologna reforms). The former degrees (Diplom, Magister, Staatsexamen) with relatively long legal durations of 8-10 semesters were substituted by the two-tier structure of bachelor's and master's degrees with legal durations of 6 and 4 semesters, respectively. The bachelor's degree is aimed to provide students a fast qualification for the labor market entrance. In the winter term 2013/14, approximately 87 percent of all study programs have by now been reformed towards the bachelor/master system.

Traditionally Germany's tertiary education system has been characterized by long time spent to obtain the first university degree. For example, study duration for achieving a diploma at a university averages approximately at 12 semesters exceeding considerably the regular study time which is 9 semesters (in most fields of study).

In 1998, that is before the process of Bologna reforms started, in most fields of study the proportion of students obtaining their degree in the legal duration was below 30 percent and in 2003 the duration of study exceeded 11 terms on average, thereby exceeding the legal duration by about 2 terms (see Wissenschaftsrat (2001) and Wissenschaftsrat (2005)).

After the reforms, in 2012 39.3 percent of all students graduated within regular study time. This proportion varies with fields of study, ranging from 90.5 percent in administrative sciences to e.g. only 23.9 percent in sports/sports science. Within the new two-tiered bachelor/master structure, in 2012 49.4 percent obtain a bachelor's degree and 42.3 percent a master's degree within legal duration (Statistisches Bundesamt (2014)).

Information on median durations between 1995 and 2012 of the "old" degrees (of universities and universities of applied sciences) and of the bachelor's and master's degrees after the Bologna reforms is presented in Table B.1 in the appendix. In 2012 median durations exceed the regular durations for all degrees, indicating that the majority of students do not manage to meet the proposed timeline. Furthermore, we observe an upward trend for times to degree.

2.3 Review of the Literature

2.3.1 Literature on Time to Degree

Previous international research has primarily focused on PhD students and the determinants of their time to doctorate. A paper by Booth and Satchell (1995) examines completion and withdrawal rates for British PhD students in 1980. Using a parametric competing risk model, they find no effect of student aid on completion rates. A study by Ours and Ridder (2003) focuses on institutional aspects including characteristics of the thesis supervisor. There is a wide range of research about different determinants of time to doctorate for several countries (see for Canada Sheridan and Pyke (1994), for USA Valero (2001) and Ehrenberg et al. (2007) or for Belgium Visser, Luwel, and Moed (2007)).

An early study which analyzes the effect of employment on completion time for PhD students in USA is done by Abedi and Benkin (1987). They find that doctoral students who

had to support themselves through off-campus earnings had longer durations of study. On-campus work seems to reduce time to degree and to reflect positive selection effects. These results are supported by Ehrenberg and Sherman (1987).

The impact of different types of financial support on completion rates is investigated by Ehrenberg and Mavros (1995). They use data of students enrolled in doctoral programs at Cornell University. Estimating a discrete time duration model they conclude that students with teaching assistantship have lower completion rates and tend to be more likely to drop out than students with fellowships requiring no work. There is a similar effect for students with other forms of financial support (e.g. loans, tuition wavers, self support).

A similar conclusion is drawn by more recent studies by Siegfried and Stock (2001) and Stock and Siegfried (2006). Using data on PhD graduates in economics, their results indicate that students who consume pure fellowships and do not have to work completed their degrees faster than those holding pure assistantships. Analyzing determinants of time to dropout and time to PhD completion by the use of a discrete-time competing risks survival model, also Haert et al. (2014) state that students with doctoral fellowships have the lowest dropout hazards and the highest completion hazards in comparison to e.g. unfinanced students or teaching assistants.

There is less research conducted on time to a first university degree. Most studies focus on the effect of student aid or tuition fees on graduation and/or duration. For Finland Häkkinen and Uusitalo (2003) estimate the effect of a student aid reform (higher study grant, shorter duration of aid) in 1992 on graduation. The authors find that students entering after the reform have higher graduation hazards. However, this is mainly explained by large changes in the unemployment rate. Studies for other countries focusing on time to degree at universities exist e.g. for Italy by Garibaldi et al. (2012) or for Canada by Sheridan and Pyke (1994). None of these studies includes variables of students' employment status to analyze their effect on duration of study.

An early study already mentioned focussing on different effects of employment on academic achievement and post-college labor market success is conducted by Ehrenberg and Sherman (1987). Using the National Longitudinal Survey of the High School Class of 1972, they distinguish between on-campus and off-campus employment and find a positive impact of on-campus work on academic achievements while off-campus work reduces academic success.

Stinebrickner and Stinebrickner (2003) investigate the correlation between working during studying and academic performance at a special College, the Berea College. They address the problem of endogeneity concerning the students' working hours. The authors claim that academically successful individuals tend to have more motivation and thus are more involved in non-academic activities like working. As a consequence simple econometric models, which do not fully control for motivation, may underestimate the negative effect of working on academic performance. The results of a OLS regression indicate a positive relationship between hours worked and the grade. A fixed-effects estimation, controlling for person-specific permanent attributes, leads to an insignificant effect of additional hours of work on grade performance. To control for non-permanent factors, an Instrumental Variable (IV) approach is used. After controlling for endogeneity of work, the results indicate that working during studies affects the academic outcome negatively.

A recent paper by Aina, Baici, and Casalone (2011) analyzes different impacts on time to obtain a bachelor's degree in Italy. They identify a negative effect of work on the probability of graduating within a minimum period.

For Germany literature on higher education is scarce. A relevant topic is e.g. social selectivity in access to higher education (see for instance Weiss and Steininger (2013) and Schindler and Reimer (2011), also for a short description of the German higher education system).

There are only very few studies analyzing times to degree for Germany. Heineck, Kifmann, and Lorenz (2006) estimate the effect of tuition fees on long-term students at the University of Konstanz. Using a discrete time duration model with competing risks, they find a significant effect of tuition fees on the students' behavior. In most cases the expectation of accruing tuition fees in the following semester increases the hazard for obtaining a degree, transferring to another university or dropping out.

There is only little work done in the analysis of the effect of employment on time-to-degree in Germany. A recent study, which focuses on the effect of student aid (BAföG[2]) on the duration of study and the probability of graduation, is Glocker (2011). The analysis is based on the German Socio-Economic Panel (GSOEP), an annual household panel which started in 1984. The sample consists of 787 individuals (with 240 successful

[2]BaföG (Federal Education and Training Assistance Act) is the main source of financial student aid in Germany for students from low income families.

completions). For the analysis a discrete time duration model with competing risks is estimated. A positive effect of student aid on success of tertiary education is stated as students receiving financial aid on average work less than those not receiving support. In contrast to other papers mentioned above, the study finds no effect of time spent on working on the probability to graduate or to drop out. However, time spent on studying is found to increase the hazard to graduate and to decrease the hazard to drop out. The author concludes that part-time working only has a negative effect on graduation if it results in less time available for studying.

Amann (2005) focuses on the effects of the type of employment on time to degree in higher education. The data are derived from the GSOEP and include 269 individuals (with 105 completed spells). The working variable is defined as the proportion in each unit of time (during the terms) used for full- or part-time employment. A discrete time duration model with a proportional hazard and a piece-wise constant baseline hazard is specified. Amann (2005) finds that both types of employment affect the hazard for graduation negatively; full-time employment has the strongest effect. To control for possible endogeneity of the working status an IV approach is used. While full-time work has still a negative effect on graduation, the coefficient for part-time work becomes insignificant.

2.3.2 Main Findings, Similarities and Differences

The review of the literature reveals that there is no consensus about the effect of several determinants on academic performance. In the following, I will present a comparative overview on previous research results.

A detrimental effect of work for PhD students is found by Ehrenberg and Mavros (1995). Students with assistantships have lower completion rates and higher dropout rates than those receiving pure fellowships. Similarly, the results of Siegfried and Stock (2001) and Haert et al. (2014) indicate that students with assistantships have higher durations than those students who do not have to work. Comparing different types of work, Abedi and Benkin (1987) conclude that off-campus earnings increase time to doctorate.

Focusing on time to first university degree, Ehrenberg and Sherman (1987) find an adverse effect of off-campus employment on time to degree but a positive effect of on-campus employment on the probability of enrolling in a graduate school. Amann

(2005) distinguishes part-time and full-time employment and claims that only full-time employment reduces the hazard for graduating, as the coefficient for part-time employment is insignificant in an IV estimation approach. Hood, Craig, and Ferguson (1992) find students with moderate amounts of work to have the best academic outcome. Finally, there are some papers (e.g. Glocker (2011)) finding no significant effect of the students' working status on time to degree. Most of the research therefore confirms the hypothesis of a prolonging effect of working during studies on time to degree. As presumed, the work intensity plays an important role.

Another variable of interest is the parental background. The findings are ambiguous. A positive effect of mothers' and fathers' education on the graduation probability is claimed by Aina, Baici, and Casalone (2011). Amann (2005) reports that a low educated father decreases the hazard for graduation, but education level of the mother is irrelevant. No effect of the parental background is found by Glocker (2011).

Only very few of the mentioned studies control for students' ability. The results of Aina, Baici, and Casalone (2011) indicate a positive association between prior high school grade and probability of graduation. Ehrenberg and Mavros (1995) find no effect for student's verbal and mathematics graduate record examination test scores on completion rates. Therefore, the postulated hypotheses of an advantageous effect of high cultural and human capital on time to degree are not verified in previous literature.

Similarly, the way other personal or parental characteristics influence academic success is not answered consistently. Most studies, e.g. Siegfried and Stock (2001), Glocker (2011) and Aina, Baici, and Casalone (2011) find no significant gender differences. Whereas Häkkinen and Uusitalo (2003) find female students to have higher completion hazards, Abedi and Benkin (1987) report shorter times to doctorate for male students. However, this difference is mainly explained by the differing choices of fields of study.

There exists a similar disagreement regarding the effect of age on time to degree. Whereas e.g. Siegfried and Stock (2001), Amann (2005) and Glocker (2011) find no effect of age at the beginning of study, Häkkinen and Uusitalo (2003) find higher completion hazards for older students. Similarly, Aina, Baici, and Casalone (2011) claim a positive effect of age at enrollment on graduation probabilities.

Regarding the last hypothesis, i.e. covariate effects differ across fields of study, there is one study by Ehrenberg and Mavros (1995) carrying out the analysis for four

fields of study separately. As expected, they find some inconsistent effects across fields.

The lack of consensus could be explained by several differences between these studies. Obviously, they concentrate on different countries and data sets. Some studies focus on few universities or even a single university (e.g. Ehrenberg and Mavros (1995) or Stinebrickner and Stinebrickner (2003)), whereas some only analyze one field of study (e.g. Siegfried and Stock (2001)). Another obvious difference is the sample size. Some studies use very small data sets of a few hundred individuals (e.g. Siegfried and Stock (2001) or Glocker (2011)) which results in larger standard errors of parameters. Furthermore, some of the authors make use of an outflow sample (e.g. Aina, Baici, and Casalone (2011)) whereas most of the studies are based on a survey of individuals still studying and therefore contain right censored durations.

In addition, the methodological approach varies between the mentioned studies. Whereas most studies use survival models, there is no consensus on the specification of the hazard functions. Aina, Baici, and Casalone (2011) estimate a discrete survival model with a complementary logistic hazard, Amann (2005) used a piecewise constant baseline hazard specification; both imply proportional hazards. In the continuous case the Weibull model dominates (e.g. Siegfried and Stock (2001)). Studies based on data allowing for different events (e.g. completion, dropout) most often make use of competing risks settings (e.g. Glocker (2011) and Haert et al. (2014)).

Additionally, the set of explanatory variables included in the models differs. Whereas personal characteristics as gender and age are mostly included in the regressions, the parental educational background and the own ability most often are not. Especially the last one mentioned seems to be important when analyzing the effect of employment on academic achievement. Stinebrickner and Stinebrickner (2003) claim that the decision to work during studies is endogenous. Academically successful students have a high level of motivation and therefore a higher probability to work. Thus, the negative effect of work might be underestimated in simple econometric models. Ehrenberg and Mavros (1995) discuss this problem in the context of the type of financial support. The fact that students receiving pure fellowships have higher completion rates may reflect mainly unmeasured ability, because more able students are more likely to be supported. Thus, if available, individual characteristics to capture ability and motivation should be included in the analysis. Unfortunately, only a few studies were able to control for ability, e.g. Ehrenberg and Mavros (1995) and Aina, Baici, and Casalone (2011). The parental educational

background, which is assumed to play an important role for academic success, is also included only in a few studies (e.g. Amann (2005), Glocker (2011) and Aina, Baici, and Casalone (2011)). Different impacts of these variables may be a consequence of varying definitions and operationalizations.

In previous research, mostly PhD students were analyzed. There are only a few studies analyzing the effect of work during studies on time to degree. Additionally, studies for Germany are scarce. This study contributes to the existing literature using a comprehensive data set - the Absolventenpanel for the year 2001 - including graduates from many different universities in Germany covering a wide variety of fields of study. The rich data set contains many information on students' own educational background, e.g. A-level grades, which seem to be important for predicting academic success and are very well suited to control for unobservable motivation and ability. Furthermore, the data set provides relevant indicators of students' socioeconomic origin, e.g. the parental academic background. The focus of the analysis is the effect of the working status of students on time to first university degree. The following section provides an overview of the data and variables.

2.4 Data and Variables

The empirical analysis is based on data from the German Absolventenpanel (panel survey of graduates) 2001 of the HIS (Hochschul-Informations-System)[3]. The first wave of the survey was conducted 6-18 month after graduation, the second wave 5 years later and a third wave 10 years after graduation. The survey includes a random sample of all graduates receiving their first degree in the respective year (here 2001) at a German university and is obtained as a (stratified) cluster sample. The clusters are defined by the following characteristics: field of study, type of diploma and university. The panel includes a wide range of social and demographic characteristics and detailed questions about the course of study and the integration into the labor market[4]. I use only the first wave of the survey, because it contains relevant information about times to degree, field of study and the course of study. The second and third wave focus on job performance and employment history which is not relevant for this analysis.

[3]Additional panels started in the years 2005 and 2009, but are not yet available. Also the third wave of the Absolventenpanel 2001 is not yet available.

[4]For more information see Schramm and Beck (2010).

A drawback of the data is that it is a retrospective survey after graduation. Study durations are only observed for those who obtained a degree. There is no information available on dropouts. However, students' working status may affect the propensity to drop out. If work has an increasing effect on the propensity to drop out as well as on the time to degree, we may conjecture that this will lower the observed effect on times to degree using an outflow sample. Unfortunately, the data set does not allow to analyze this issue further.

The data is organized by the year graduates earn their degree, a so called outflow sample. So there is a risk of biased absolute values of time to degree if the size of the entering cohorts and the distribution of time to degree did significantly change over the years. E.g. if the entering cohorts decrease, there will be an overestimation of time to degree and of its increase over time (see Bowen, Lord, and Sosa (1991) or Siegfried and Stock (2001)). The preferable strategy to analyze times to degree would be sampling from the inflow of students and following them up to their graduation or dropout. However, this study neither focuses on the absolute value of time to degree nor on the evaluation of its increase (or decrease) over time. The main intention is to identify factors influencing duration of study, mainly students' working behavior. So using an outflow sample is acceptable. Nevertheless, information about the evolution of entering cohorts in Germany are of some interest. Figure B.1 shows the evolution of entry cohorts (at the level of the German population) between 1980 and 2011[5]. During 1992 and 1997, which are the main entry cohorts students under analysis come from (96 percent), there is only a slight change of the number of students in entry cohorts. The strong increase of the number of enrolled students between 2005 and 2009 reflects several factors: an increase in the fraction of students obtaining an A-level, an increase in the fraction of school leavers entering university (see Statistisches Bundesamt (2014)) and larger cohorts (secondary effect of the baby-boom in the 60s). An advantage of the underlying data is the great number of graduates. Data sets which do not focus on graduates or which are sampled from the inflow most often contain only a small number of students completing their studies.

The sample consists of 8117 observed individuals (first wave, response rate of 30 percent). For the analysis a subset with variables of interest has been constructed. The dependent variable is time until graduation (*duration*), measured as the number of semesters until the first graduation (i.e. subject related semesters). Graduation is possible

[5]Source: Statistisches Bundesamt (2014)

at every time point, but the usual way of measuring time to degree is in half term years.

According to the theoretical considerations in section 2.1, the following predictor variables are included in the analysis. The study focuses on the effect of students' working status on their time to degree. Based on a survey question about the work intensity during studies, three dummy variables were constructed. The variable *nowork* takes the value 1 if the student did not work while studying and 0 otherwise. Working in parts during study time, that is records showing spells of work and spells of no work, is captured by the variable *partwork* and the dummy variable *fullwork* takes the value 1, if the student worked throughout the whole time of studying. The time spend on work includes jobs with no relation to study but also subject-specific jobs, e.g. being a student assistant at the department. Students who work presumably have less time available for studying, possibly leading to a prolongation of time to degree. Therefore, the variables *partwork* and *fullwork* are expected to decrease the hazard of graduation, with a higher quantitative effect for *fullwork*.

Another aspect of interest concerning time to degree is students' ability. Some researchers claim that the working status may reveal unobserved motivation and ability and therefore the estimated effect of work on time to degree may be biased. Here, own ability is approximated by observable skills acquired before studying, i.e. the final grade at school. *grade* takes values between 1.0 and 4.0 in steps of 0.1 and it is expected that time to degree increases with *grade*, i.e. the higher the grade the longer the time to degree. Note that in Germany there is an "inverse" grading system (i.e. the higher the grade the worse performance at school) with 1.0 the best and 4.0 the worst grade.

Since own working experiences before studying may have an effect on time to degree, the dummy variable *experience* indicates whether an individual was employed before enrollment or not. Having gained some working experience, compared to only have experienced school, might promote personal responsibility and discipline, both important for a successful study. A positive effect on the hazard of graduation is expected. Additionally, sex (*female*, dummy for women, males being the base category) and age at enrollment (*age*) are considered. For both the expected effect on time to degree is ambiguous. Especially for *age* there are two opposing views. On the one hand, the older at enrollment, the more knowledge and experience a student has attained which possibly will shorten time to degree.

On the other hand, older age at enrollment could hint for some waste of time and perhaps little motivation. This may result in longer time to degree.

Not only personal but also parental characteristics, in particular the parental educational background, may have an affect on the course of study. In contrast to students from non-academic households, a student from an academic household may be more encouraged to obtain his degree in a short time. This aspect is captured by a dummy variable indicating if the mother (*acadmo*) and the father (*acadfa*), respectively, has a university degree or a degree at a German university of applied science. For both an increase of the graduation hazard is expected.

An important characteristic of study is the field of study. The original data set[6] includes 33 fields which have been categorized into 10 fields: social sciences (*social*), economics (*econ*), law (*law*), humanities (*human*), engineering (*engin*), informatics and maths (*informath*), natural sciences (*science*), medicine (*medicine*), teaching (*teach*) and other fields of study (*other*). Not surprisingly, many papers find that the field of study has an effect on time to degree (e.g. Aina, Baici, and Casalone (2011)). However, these effects differ between different studies. Furthermore, the standard period of study is established by study regulations of the special field. To capture these legal durations it is important to aggregate fields in a reasonable way. A description of the way of aggregation to the 10 fields are presented in Table B.2 in the appendix.

Finally, I control for the semester of first enrollment (*summer*), i.e summer or winter term. Students traditionally first enroll at university in the winter term (October until April) and the curriculum is adjusted to that course of study. Therefore, studying against the regular lecture rotation maybe affects academic performance negatively. It is expected that being first enrolled in the summer term prolongs time to degree.

Because of the disparity of universities and universities of applied sciences, there is a high heterogeneity between students from both types of establishment. Thus, the empirical analysis is based only on graduates from universities. The final sample of graduates with valid observations on all variables has 4966 observations. Table B.3 provides an overview of the variables and their definitions.

[6]For more details about the variables of the Absolventenpanel 2001 see Schramm and Beck (2010).

2.5 Descriptive Statistics

For a first analysis of the data, some descriptive statistics and interrelationships of the variables are presented. The Figures B.2 (whole sample) and B.3 (without outliers, i.e. durations exceeding 24 semesters) show a right-skewed distribution of study time. The mass of the distribution is concentrated on the left with only few values of high duration.

In Table 2.1 some statistics of duration and the covariates are shown. The mean study time amounts to 12.13 semesters. The final grade at school averages at 2.15. 56 percent of the students have a father with an academic background, and about 34 percent have a mother with a degree from a university or a university of applied sciences. Not listed in the table, but also of some interest: more than 39 percent are so called educational climbers (first generation academics), i.e. these students have neither an academic father nor an academic mother.

	mean	min	max	std
duration	12.13	5	49	3.06
female	0.61	0	1	0.49
age	21.13	14	52	2.71
grade	2.15	1	4	0.63
nowork	0.08	0	1	0.27
partwork	0.51	0	1	0.50
fullwork	0.41	0	1	0.49
experience	0.32	0	1	0.47
acadmo	0.34	0	1	0.47
acadfa	0.56	0	1	0.50
summer	0.10	0	1	0.30

Table 2.1: Descriptive statistics: duration and covariates

A majority of the students worked during parts of the study time (51 percent), only a few were never employed. Even more than 41 percent work during the whole study time. It is of interest to get some information about the very few non-working students. On the one hand, these might be students from wealthy families. On the other hand, it might be the case that these students benefit from student aid or scholarships and so they possibly graduate faster only because of strict requirements they have to fulfill. The analysis shows that the proportions of non-working students having an academic father (64 percent) or an academic mother (39 percent) exceed the corresponding proportions in

the working-sample substantially. Here, only 48 percent have an academic father and 26 percent have an academic mother. As there is a correlation between the educational background of parents and income one can conclude that non-working students have a relatively privileged familiar background.

	social	econ	law	human	engin	inf.	science	med.	teach	other
nowork	0.05	0.06	0.18	0.06	0.06	0.05	0.13	0.12	0.06	0.08
partwork	0.38	0.47	0.50	0.44	0.61	0.57	0.65	0.56	0.45	0.49
fullwork	0.58	0.46	0.32	0.50	0.32	0.38	0.22	0.32	0.49	0.42
female	0.80	0.41	0.53	0.70	0.44	0.40	0.46	0.67	0.80	0.67
grade	2.34	2.28	2.07	2.17	2.12	1.93	1.81	1.93	2.32	2.27
experience	0.39	0.37	0.30	0.36	0.26	0.23	0.25	0.36	0.33	0.35
acadmo	0.23	0.27	0.39	0.33	0.36	0.34	0.40	0.41	0.32	0.34
acadfa	0.40	0.52	0.62	0.56	0.60	0.58	0.62	0.67	0.54	0.52

Table 2.2: Mean of covariates by field of study

	mean	median	min	max	q75-q25	std
social	12.51	12	7	28	3.00	2.82
econ	11.30	11	6	23	2.75	2.29
law	10.57	10	7	19	2.00	1.75
human	12.63	12	5	37	3.00	3.14
engin	12.74	12	8	32	3.00	2.89
informath	13.64	12	5	33	4.00	4.22
science	11.63	11	6	49	2.00	2.96
medicine	13.45	14	8	27	2.00	2.81
teach	11.29	11	6	30	4.00	3.20
other	12.00	11	7	33	2.00	2.76

Table 2.3: Duration in ten fields of study

Table 2.2 shows how covariates differ between fields of study. It is obvious that characteristics of students are very heterogeneous. The proportion of non-working students is very high (in comparison to the average over all fields) in law, science and medicine. Here, also the proportion of students having an academic background exceeds the average substantially. Contrary, in social sciences there is a very high share of students working full-time and coming from non-academic households. Thus, there seems to be a relation between these two factors. Not surprisingly, women are more likely to study fields like social sciences, humanities and teaching, whereas men are overrepresented in subjects like economics, engineering, informatics and maths, and natural sciences.

Also the A-level grade varies with the highest (worst) grade in social sciences and teaching and the lowest (best) grade in informatics and maths, natural sciences and medicine.

Table 2.3 provides a first overview how the duration differs between different fields of study. According to the mean as well as the median, the shortest duration is observed in law, whereas the longest mean duration is found for informatics and maths and for medicine. The largest standard deviation (4.22) is observed in informatics and maths.

To get an impression how the duration of study differs between subgroups of the explaining variables within different fields, Table 2.4 displays conditional mean durations which reveal two very interesting facts, i.e. the noteworthy differences in time to degree when splitting the sample according to the variables *grade* and *work*. In all ten fields of study the time to degree of students working during the whole study time exceeds the duration of their non-working counterparts [7].

	social	econ	law	human	engin	inf.	science	med.	teach	other
nowork	12.13	10.92	10.25	12.03	11.53	14.31	10.87	11.54	10.65	11.31
partwork	11.99	10.88	10.63	12.14	12.41	12.78	11.32	13.11	11.02	11.57
fullwork	12.88	11.79	10.65	13.12	13.60	14.83	12.98	14.78	11.61	12.64
men	12.67	11.54	10.38	12.82	12.94	13.69	11.81	13.91	11.90	12.15
women	12.47	10.96	10.73	12.54	12.48	13.56	11.42	13.23	11.13	11.93
grade: 1	11.66	10.23	10.26	11.73	11.46	12.07	10.79	12.99	11.70	11.02
grade: 2	12.58	10.87	10.52	12.55	12.51	13.32	11.53	13.42	11.22	11.75
grade: ≥ 3	12.63	12.29	10.90	13.24	14.09	17.00	14.29	14.29	11.31	12.68
no exp.	12.30	11.35	10.52	12.60	12.52	13.42	11.38	13.05	11.13	11.98
experience	12.84	11.22	10.67	12.68	13.35	14.38	12.38	14.16	11.60	12.04
no acadmo	12.63	11.49	10.56	12.76	13.01	14.13	12.00	13.63	11.14	12.19
acadmo	12.11	10.80	10.58	12.35	12.26	12.67	11.07	13.19	11.59	11.63
no acadfa	12.45	11.55	10.50	12.69	13.15	15.04	12.12	13.36	11.15	12.16
acadfa	12.61	11.07	10.61	12.58	12.47	12.63	11.32	13.50	11.40	11.85

Table 2.4: Duration by covariates and fields of study

To illustrate how the own ability, measured as final grade at school, affects study duration, the variable *grade* is categorized into the grades 1, 2 and grades ≥ 3. I find an almost linear increase of time to degree in nine out of ten fields of study. The only exception is

[7] An aggregated (over all fields) comparison is displayed in Figure B.4 showing the whole distribution of durations conditionally on work intensity

teaching. Finally, grouping students according to the academic background of the parents reveals no large differences.

In the context of the relation between the working status of students and time to degree, it is of interest to analyze the characteristics of working students. In the following these characteristics are analyzed in detail. The Tables 2.5, 2.6 and 2.7 present the most relevant characteristics.

	non-academic	academic
nowork	0.08	0.09
partwork	0.47	0.59
fullwork	0.46	0.31
sum	1.00	1.00

Table 2.5: Working status conditional on mothers academic background

	non-academic	academic
nowork	0.07	0.09
partwork	0.45	0.56
fullwork	0.48	0.35
sum	1.00	1.00

Table 2.6: Working status conditional on fathers academic background

It is immediately visible that students with a non-academic mother or father are more likely to work during the whole duration of study. The proportion raises from 31 to 46 percent and 35 to 48 percent, respectively. Obviously, academically educated parents are able to provide more financial support to their studying children. Hence, one can conclude that socially underprivileged students have a higher work intensity.

	grade: 1	grade: 2	grade: ≥ 3
nowork	0.10	0.08	0.08
partwork	0.62	0.54	0.40
fullwork	0.28	0.38	0.52
sum	1.00	1.00	1.00

Table 2.7: Working status conditional on grade

Another interesting aspect is the correspondence of grade obtained when completing the A-level and the working behavior during the study. There is a linear increase of

the proportion of students working during their whole study time by grade. In the group of students with grade 1, only 28 percent work throughout their studies. This share increases substantially to 52 percent in the group of students with a grade of 3 or worse.

In summary, I find that the characteristics of students are very heterogeneous across fields of study. Furthermore, working students differ in their characteristics from non-working students. Students coming from non-academic households and having obtained a bad A-level grade tend to be more likely to work during the whole study time. Therefore, hypothesis H1 is validated. Regarding study duration within different fields, the working behavior and the own ability seem to play an important role. In the next section the estimation methodology is described.

2.6 Methodology

To determine causal effects of the covariates on time to degree, a survival analysis model is used. Survival analysis[8] has its origin in clinical investigations and examines the time until an event occurs. The variable of interest is the survival time T ($T \geq 0$), here the time to degree. The *survival function* S(t) states the probability of an individual to survive longer than t:

$$S(t) = P(T > t) = 1 - F(t). \tag{2.1}$$

The *hazard rate* is the instantaneous probability (the instantaneous risk) of the event to occur in the interval $[t, t + \triangle t]$ conditional on the individual surviving to time t. The hazard in the continuous case is defined as:

$$h(t) = \lim_{\triangle t \to 0} \frac{P(t \leq T < t + \triangle t | T \geq t)}{\triangle t} = \frac{f(t)}{S(t)}. \tag{2.2}$$

A popular regression model to analyze the effect of covariates on survival time was introduced by Cox (1972). The Cox Proportional Hazards Model (Cox PH) is a

[8]Synonym: duration analysis, event history analysis, time to event analysis, failure time analysis. For a more detailed description of the methodology see e.g. Kalbfleisch and Prentice (2002) and Tableman and Kim (2004) for an application with S.

semi-parametric method. In contrast to parametric models it is free of distributional assumptions. The hazard rate is defined as:

$$h(t, \mathbf{X}) = h_0(t) e^{\sum_{j=1}^{p} \beta_j X_j}, \tag{2.3}$$

with $\mathbf{X} = (X_1, X_2, ..., X_p)$ as exogenous variables. The term $h_0(t)$ is the so called baseline hazard, which depends on time t but is independent of the covariates. The exponential expression includes only time constant covariates[9] and ensures only positive hazards. Because of the unspecified baseline hazard (no distributional assumption has to be employed) and the linear function of the covariates in the exponentiated part, it is called a semi-parametric method.

A great advantage of the Cox model is that it leads to estimators which are robust towards misspecifications of the underlying model, with only a marginal loss of efficiency in comparison to the correct parametric model. In parametric models an incorrect assumed distribution of survival times will lead to seriously biased estimations.

For the estimation of the parameters, Cox (see Cox (1975)) introduced the partial likelihood method. The partial likelihood function can be written as:

$$L_p(\beta) = \prod_{i=1}^{m} \frac{\exp(\mathbf{X}_i' \beta)}{\sum_{i^* \in R(t_i)} \exp(\mathbf{X}_{i^*}' \beta)} \tag{2.4}$$

with $\beta = (\beta_1, \beta_2, ..., \beta_p)$, m observed event times and i^* as the individuals in the risk set $R(t_i)$ at time t_i. The risk set contains all individuals who have survived at least to time t_i, i.e. who have a survival time of t_i or longer.

This likelihood has to be maximized. The baseline hazard $h_0(t)$ is not needed to be estimated. The Cox model is especially suitable for handling censored observations. In this analysis the aspect of censoring is not relevant because an outflow sample is used. For tie handling there exist several methods, e.g. approximations by Breslow (see Breslow (1974)) and Efron (see Efron (1977)). Here, the Efron approximation is used because with a large number of ties the computational time for the exact method (considering all permutations) will be excessive.

[9] It is also possible to include time variant variables in the model (extended Cox model). This leads to a violation of the PH assumption.

A key assumption of the Cox PH model is the proportional hazards (PH) assumption, which states that the hazard ratio of two individuals is constant over time[10]. The hazard ratio for two individuals i and i^* with different specifications of the set of covariates $\mathbf{X}$ and $\mathbf{X}^*$, respectively, is defined by :

$$\widehat{HR} = \frac{\widehat{h}(t, \mathbf{X})}{\widehat{h}(t, \mathbf{X}^*)} = \frac{\widehat{h}_0(t) \exp[\sum_{j=1}^{p} \widehat{\beta}_j X_j]}{\widehat{h}_0(t) \exp[\sum_{j=1}^{p} \widehat{\beta}_j X_j^*]} = \exp[\sum_{j=1}^{p} \widehat{\beta}_j (X_j - X_j^*)] = \widehat{\theta}. \tag{2.5}$$

This expression is constant over time. In the following empirical part this hazard ratios are estimated by the explained partial likelihood procedure.

2.7 Estimation Results and Discussion

2.7.1 Subject Specific Analysis

Because of the non-negativity of the duration of study and the fact that the distribution of these durations is skewed to the right, a Cox model as described in the previous section is used. The estimation is carried out with the statistic software R and is mainly based on the survival-package (see Therneau (2012)).

Fields of study itself (e.g. different regulations and legal durations) and students from these fields are very heterogeneous. Hence, estimations are done for all ten fields of study separately. Due to correlations, the social background covariates *acadmo* and *acadfa* are summarized into a variable *acad* indicating if a student has at least one parent (i.e. mother or father or both) with an academic degree.

Table 2.8 shows for all ten fields the estimated coefficients of the Cox regression. The included variables are coded as described in Table B.3. For the key variables indicating the working status of students, the variable *nowork* serves as basis category and is omitted from regression. The first column shows the fields of study and the number of students n in each field. The second column displays the regression estimates and statistics, e.g. in the first row within each field (labeled coef) the estimated coefficients[11]. Their numeric values can not be interpreted directly, but the signs of the estimated coefficients give a

[10] The PH assumption is tested by Schoenfeld residuals and holds in all models for the most relevant variables e.g. the working status.

[11] Notice that there is no intercept; it is part of the baseline hazard, which is canceled out of the estimation.

first insight in the direction of the impact on the hazard of graduation. The second row labeled exp(coef) displays hazard ratios (the multiplicative effects of covariates onto the hazard). For dummy variables they can be interpreted as the ratio of the estimated hazard for those students with a value of one to the hazard of those with a value of zero. The last rows present the associated statistics, the standard error (se) and the p-value (p). The last column gives the test statistic and the p-value of the likelihood ratio (LR) test.

fields	estimates	female	age	grade	partw.	fullw.	exp.	acad	summer	LR.p
social	coef	-0.0160	-0.0161	-0.1862	0.1216	-0.1743	-0.1190	-0.0451	-0.1119	17.7811
n= 328	exp(coef)	0.9841	0.9840	0.8301	1.1293	0.8400	0.8878	0.9559	0.8941	0.0229
	se(coef)	0.1439	0.0145	0.0845	0.2783	0.2736	0.1276	0.1155	0.1691	
	p	0.9116	0.2687	0.0275	0.6621	0.5240	0.3508	0.6962	0.5080	
econ	coef	0.1247	0.0017	-0.6528	-0.1364	-0.5686	0.0994	-0.0078	-0.0911	78.6440
n= 410	exp(coef)	1.1328	1.0017	0.5206	0.8725	0.5663	1.1045	0.9922	0.9129	0.0000
	se(coef)	0.1070	0.0250	0.0931	0.2124	0.2135	0.1190	0.1033	0.1945	
	p	0.2438	0.9470	0.0000	0.5208	0.0077	0.4038	0.9396	0.6396	
law	coef	-0.2241	0.0091	-0.2974	-0.2362	-0.2441	-0.1377	-0.0950	0.2277	15.5250
n= 307	exp(coef)	0.7992	1.0091	0.7428	0.7896	0.7834	0.8714	0.9094	1.2557	0.0497
	se(coef)	0.1174	0.0215	0.1053	0.1587	0.1757	0.1394	0.1251	0.1837	
	p	0.0562	0.6734	0.0047	0.1366	0.1647	0.3235	0.4476	0.2151	
human	coef	0.1540	0.0321	-0.2575	-0.0228	-0.3771	-0.0173	0.0411	-0.1325	43.6315
n= 638	exp(coef)	1.1664	1.0326	0.7730	0.9775	0.6858	0.9828	1.0420	0.8759	0.0000
	se(coef)	0.0900	0.0147	0.0656	0.1734	0.1738	0.0896	0.0834	0.1183	
	p	0.0872	0.0292	0.0001	0.8954	0.0300	0.8469	0.6221	0.2625	
engin	coef	0.1296	0.0131	-0.4829	-0.4063	-0.6991	-0.1468	0.0922	-0.0238	110.3433
n= 740	exp(coef)	1.1384	1.0132	0.6170	0.6661	0.4970	0.8634	1.0965	0.9765	0.0000
	se(coef)	0.0770	0.0220	0.0642	0.1551	0.1674	0.0950	0.0819	0.2463	
	p	0.0921	0.5520	0.0000	0.0088	0.0000	0.1221	0.2603	0.9231	
informath	coef	-0.2590	-0.0491	-0.5697	0.5672	0.3183	-0.1006	0.4451	0.9979	72.2635
n= 282	exp(coef)	0.7718	0.9521	0.5657	1.7634	1.3747	0.9043	1.5606	2.7127	0.0000
	se(coef)	0.1318	0.0328	0.1143	0.3048	0.3135	0.1513	0.1386	0.3892	
	p	0.0494	0.1349	0.0000	0.0627	0.3101	0.5063	0.0013	0.0103	
science	coef	0.2311	0.0110	-0.5099	-0.0995	-0.4805	-0.3739	0.1861	-0.3772	88.3228
n= 480	exp(coef)	1.2600	1.0110	0.6006	0.9053	0.6185	0.6880	1.2046	0.6858	0.0000
	se(coef)	0.0973	0.0361	0.0899	0.1392	0.1669	0.1129	0.1012	0.2069	
	p	0.0176	0.7613	0.0000	0.4749	0.0040	0.0009	0.0658	0.0682	
medicine	coef	0.0852	-0.0266	-0.1284	-0.6983	-1.1238	-0.1608	-0.1087	-0.0325	56.8073
n= 374	exp(coef)	1.0889	0.9738	0.8795	0.4974	0.3250	0.8515	0.8970	0.9680	0.0000
	se(coef)	0.1146	0.0194	0.0969	0.1685	0.1880	0.1233	0.1257	0.1299	
	p	0.4572	0.1704	0.1850	0.0000	0.0000	0.1925	0.3873	0.8025	
teach	coef	0.1855	-0.0423	0.0519	-0.1207	-0.3072	-0.0078	-0.1045	-0.5053	45.8544
n= 792	exp(coef)	1.2038	0.9585	1.0533	0.8863	0.7355	0.9922	0.9008	0.6033	0.0000
	se(coef)	0.0901	0.0166	0.0605	0.1511	0.1505	0.0830	0.0746	0.1209	
	p	0.0395	0.0105	0.3906	0.4246	0.0412	0.9248	0.1613	0.0000	
other	coef	0.0581	-0.0126	-0.3665	-0.1448	-0.5315	0.0167	-0.0071	0.0187	61.7419
n= 615	exp(coef)	1.0598	0.9875	0.6931	0.8652	0.5877	1.0168	0.9929	1.0188	0.0000
	se(coef)	0.0884	0.0154	0.0696	0.1511	0.1549	0.0919	0.0858	0.1284	
	p	0.5110	0.4130	0.0000	0.3381	0.0006	0.8561	0.9337	0.8845	

Table 2.8: Results of the Cox regression

The coefficients of *partwork* and *fullwork* have a negative sign in almost all fields of study. As expected they reduce the hazard of graduation and therefore increase time to degree (controlling for the other covariates). The effect of *partwork* is only significant at

the usual levels for engineering and medicine. The quantitative effect can be seen in the second column, which shows the hazard ratios. E.g in engineering those students working in parts of their study time have a hazard of 66.61 percent of the hazard of those who do not work. That means, the risk of graduation decreases by over 33 percentage points.

Similarly, the variable *fullwork* has a detrimental effect on the hazard of graduation. This effect is significant at the 5 percent level in seven out of ten fields. Exceptions are social sciences, law and informatics and maths. Taking again the example of engineering, the hazard of graduation for those students who have to work during their whole study time is - in every time interval - only 49.70 percent of the hazard of those who did not work at all. The effect is strongest in medicine. Hence, the working behavior and the intensity of work seem to play an important role. Hypothesis H2 is validated.

As the descriptive analysis already indicated, the estimation results confirm a strong effect of own ability on time to degree. An increase in *grade* decreases the hazard of graduation in almost all fields of study significantly, exceptions being medicine and teaching. Employment experiences before studying seem not to affect duration of study (only significant in sciences). However, hypothesis H4 is supported.

Considering the academic background of parents, it is somewhat surprising that the effect of *acad* is insignificant in almost all fields. Only in informatics and maths having at least an academic father or mother increases the hazard of graduation substantially (by 56 percentage points). In summary, we may conclude that there is no strong effect - controlling for the other covariates - of academic background on the duration of study; hypothesis H3 could not be confirmed.

Furthermore, the coefficient for *female* is only significant (at the 5 percent level) in informatics and maths, natural sciences and teaching. In these fields female students have a higher hazard rate than male students implying a shorter time to degree. The covariate *age* is mostly insignificant with ambiguous signs. The same is true for the semester of enrollment. As assumed in hypothesis H5, there seem to be varying covariate effects across fields of study.

According to the effect of employment during studies, there might be some students who keep their jobs and enroll at university only as a side-activity (e.g. to improve job opportunities). This maybe leads to overestimation of the work-effect. The data does not allow to distinguish between “standard” and “non-standard” students, but

there are information about vocational training before studying. As a robustness check, regressions are run without students having a vocational training. The results do change only slightly. The negative effect of *fullwork* becomes even stronger in economics and insignificant in teaching. The effect of *partwork* becomes insignificant in engineering.

2.7.2 Aggregated Analysis

This section shows the results of an aggregated analysis, i.e. an analysis over all fields, but with field-dummies included.

Table 2.9 provides the results of the Cox regression. Again, *nowork* serves as base category and is omitted from the regression. The columns are to be interpreted as described in the previous subsection.

	coef	exp(coef)	se(coef)	z	p
female	0.0851	1.0889	0.0308	2.7624	0.0057
age	-0.0062	0.9939	0.0059	-1.0498	0.2938
grade	-0.2892	0.7489	0.0243	-11.8952	0.0000
partwork	-0.1733	0.8409	0.0537	-3.2263	0.0013
fullwork	-0.4693	0.6254	0.0558	-8.4116	0.0000
experience	-0.0646	0.9375	0.0332	-1.9482	0.0514
acad	0.0309	1.0313	0.0303	1.0191	0.3081
summer	-0.1566	0.8550	0.0488	-3.2083	0.0013
econ	0.4652	1.5923	0.0760	6.1204	0.0000
law	0.6781	1.9701	0.0816	8.3129	0.0000
human	-0.1266	0.8811	0.0688	-1.8411	0.0656
engin	-0.1705	0.8432	0.0690	-2.4701	0.0135
informath	-0.4961	0.6089	0.0838	-5.9173	0.0000
science	0.1354	1.1450	0.0749	1.8081	0.0706
medicine	-0.5003	0.6063	0.0777	-6.4397	0.0000
teach	0.2320	1.2611	0.0666	3.4848	0.0005
other	0.1379	1.1479	0.0692	1.9940	0.0461

Table 2.9: Aggregated Cox regression

The coefficients of *partwork* and *fullwork* reduce the hazard of graduation. Those students who work in parts of their study time have a hazard of 84.09 percent of the hazard of those who do not work. The risk of graduation decreases by almost 16 percentage points. The effect is much stronger for *fullwork*. The hazard of graduation for those students who have

to work during their whole study time is only 62.54 percent of the hazard of those who did not work at all. Both coefficients are highly significant.

Moreover, as the results separately for all fields already indicated, the A-level grade has a considerably effect on time to degree. Students with a better grade have a higher hazard of graduation.

Considering the educational background of the parents, the covariate *acad* is statistically insignificant at the 5 percent level and - confirming the previous findings - we may conclude that there is no strong effect of academic background on the duration of study. The distinction between educational climbers and students with at least one academic parent does not lead to a significant difference in times to degree.

The coefficients for the different fields of study can be interpreted relative to the baseline category *social*. However, as mentioned above, these coefficients are difficult to interpret because of e.g different legal study durations.

Female students have a slightly higher hazard rate than male students implying a shorter time to degree. The age at enrollment seems to have no effect on time to degree [12].

2.8 Conclusion

The efficiency of the academic system in Germany is an intensively discussed topic in the political arena. In this context the proportion of students achieving their degree and the time to degree is of special interest, both being key performance indicators. The present situation is characterized by the fact that the regular study time is exceeded by the majority of students. Furthermore, many students work during studies, mainly to be able to cover living costs. There are only a few studies analyzing the effect of work during studies on time to degree. This aspect is often neglected in investigations of the academic success of students and this study is aimed to at least partly fill this gap.

This paper examines the relationship between the working status of students and their times to degree in detail. Besides that, the impact of other covariates like the own

[12] An alternative way of modelling the time to degree is the poisson model. In the poisson model the covariates affect the expected value of terms studied. The results of the poisson model confirm the findings of the Cox-model regarding the covariate effects on duration and their significance

characteristics of students, their social background and characteristics of study is analyzed. The estimations are based on the Cox model, a very flexible model within time to event analysis avoiding strong distributional assumptions. There are five hypotheses to be tested. At first, it is assumed that working students differ by their characteristics from non-working students with a dependency between working behavior and parental background (H1). The second hypothesis (H2) postulates that high work intensities lead to lower academic performances. Additionally, it is assumed that coming from a highly educated household (H3) and having acquired human capital (H4), measured as A-level grade and employment experiences before studying, decrease times to degree. At least, hypothesis 5 (H5) states that covariate effects on time to degree differ across fields of study.

Characteristics of students differ considerably between fields of study; therefore, the analysis is carried out for each of the ten fields separately. A first descriptive analysis reveals a rather strong relationship between the variables indicating the working status of students and time to degree in almost all ten fields of study. Higher intensities of work are associated with higher durations of study. In the same way, the final grade at school seems to affect time to degree. The worse the grade, the higher the duration until a student obtains a degree.

Furthermore, I observe a dependency between students' work intensity and their social background. So called educational climbers seem to be more likely to work throughout their studies than students coming from an academic household are. Therefore, the expected relationship between the social background and the working behavior (H1) is supported. Beside this fact, also students with a bad final grade at school are more likely to work intensively.

The results of the estimated Cox models confirm these descriptive findings. High working intensity is found to affect the duration strongly. Working throughout studies reduces the hazard of graduation in the majority of fields considerably. In almost all fields working only in parts of study time seems not to affect times to degree. The second hypothesis is therefore supported for the majority of fields. The results correspond to the findings of Amann (2005), who distinguishes between full-time work and part-time work (based on hours worked). He finds a negative effect of full-time work on graduation but an insignificant effect of part-time work. On the contrary, Glocker (2011) finds no effect of the working status on academic performance, but time spent on studying is found to increase the graduation hazard. Therefore, students' employment has a negative effect

on graduation if it results in less time available for studying. This coincides with my considerations.

Furthermore, prior qualifications are assumed to affect academic performance. Students' ability is often regarded as unobserved heterogeneity, which may bias the results. More able students have a higher motivation and therefore are more involved in non-academic activities, e.g. part-time work. Hence, I include measures of students' ability in the model. The data allows for approximating students' ability by working experiences before studying and A-level grades, information that is missing in most data sets. The results confirm my fourth hypothesis: the higher students' human capital, here good final grades at school, the higher the hazard of graduation. This result corresponds to the findings of Aina, Baici, and Casalone (2011), who also uses high school grades as proxy for students' abilities.

Additionally, the data allows controlling for the parental educational background, which is regarded as important to evaluate educational careers and possible associations between covariates and the socio-economic background (here e.g. the link between the working status and academic background of parents). Surprisingly, the effect of the parental educational background on time to degree is not significant. An interesting exception is the field informatics and math, where a higher educational background increases the hazard of graduation. Therefore, the third hypothesis could not be validated by the data. This is probably due to the fact that social background effects on university performance are mainly driven by disadvantages of socially underprivileged students on earlier levels in the course of education. These disadvantages are e.g. reflected by bad A-level grades of students coming from a lower social class, which in turn affect further educational outcomes. These considerations are confirmed by the study of Amann (2005) who finds a duration decreasing effect for the fathers' academic background, but does not control for A-level grades.

Due to the richness of the data set, this study provides insights into the effects of the covariates on duration within different fields of study. The effect of *partwork* is only found to be significant in two fields, whereas working during the whole study time affects time to degree significantly in seven out of ten fields. A-level grades seem to be relevant in almost all fields, whereas the academic background of parents seems to matter only in one field. As assumed in hypothesis H5, there are varying covariate effects across fields of study. The ambiguous results of previous work are maybe reflected partly by

this fact. A detailed analysis of these differing effects should become a focus of further research.

One limitation of this analysis is the fact, that exact hours of work are not available in the data set. This information would probably give more detailed insights in the effect of the work intensity during studies. E.g. Hood, Craig, and Ferguson (1992) find students with moderate amounts of work to have the best academic outcome. In addition, departmental factors, which seem to be important for academic success (see e.g. Valero (2001)) could not be included in the analysis. Furthermore, the study is based on an outflow sample with no information on dropouts and the retrospective survey after graduation does not contain information on time varying predictors. Including e.g. time varying working variables maybe provides information on how students' working behavior on different stages in the course of study affect academic performance. Despite these limitations, the data allows for a detailed analysis of graduates' academic success and contributes to the existing literature on time to first university degree.

In summary, working intensively during studies increases time until graduation. Furthermore, mainly students from non-academic households work throughout studies. The results are based on data for the old Diploma degrees, but could be even more relevant after the Bologna reforms. A more structured curriculum and tighter schedules of the bachelor's and master's degrees could strengthen the detrimental effects of work on time to degree and result in even higher exceedance of regular durations of study.

Therefore, the findings should be considered in the ongoing discussion about the implementation of tuition fees and the design of the financial aid system. High students' employment rates and high work intensities probably point for a weak financial aid system. As already mentioned, in Germany there is an increasing proportion of students working. Hence, there is a need to improve financial aid policies to ensure that students are not forced to work intensively to cover their living costs.

The main source of financial aid for students from low income families is provided by BAföG (Federal Education and Training Assistance Act). The eligibility for BAföG and the amount of payment is means tested (own and parental wealth and income) and the maximum period of assistance is determined by the standard period of study. Only 50% of the credit has to be repaid. The maximum amount of payment is about 600 Euro. Furthermore, there are so called education loan programs providing low-interest financial support to students (irrespective of own or parental income). Scholarships are

only awarded to students with excellent academic performance. An improvement of these forms of financial aid probably leads to lower work intensities and therefore to shorter study durations. Improvements may be e.g. higher BAföG subsidies (this is currently debated in Germany), more attractive student loans or an easier access to study grants. However, there is a need to evaluate net effects of financial aid reforms more elaborately in future research. According e.g. to Glocker (2011), an increase in student aid leads to lower drop out probabilities, but there are only small effects on times to degree. One exception is students from low income families. An increase in the amount of BAföG increases graduation probabilities substantially.

Regarding a reintroduction of tuition fees, it should be considered that higher costs of tertiary education may well increase the engagement in work of lower income students and may result in higher durations of study.

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2.10 Appendix

year	uni_old	appl.sc_old	teach	BA	MA
1995	11.40	8.00	9.10		
2000	11.50	8.50	9.70	5.90	9.90
2005	11.20	8.40	9.10	6.10	9.70
2010	11.20	8.80	8.90	6.00	10.50
2011	11.40	9.00	9.00	6.30	10.60
2012	11.70	9.10	8.90	6.50	10.80

Table B.1: Median duration by degree

area of study (aggregated)	field of study (in the original data set)
social sciences	Psychologie; Pädagogik
economics	Wirtschaftswissenschaften
law	Rechtswissenschaften Staatsex.
humanities	Sprach- und Kulturwissenschaften; Magister
engineering	Architektur, Raumplanung; Bauingenieur-, Vermessungswesen; Elektrotechnik; Maschinenbau, Wirtschaftsingenieurwesen
informatics and maths	Informatik; Mathematik
natural sciences	Physik; Biologie; Chemie
medicine	Pharmazie, LM-Chemie Staatsex.; Humanmedizin Staatsex.
teaching	Lehramt Primar., Sonder.; Lehramt Real., Sek. I; Lehramt Gym., Beruf., Sek. II
other fields	Agrar- und Ernährungswissenschaften; sonstiges

Table B.2: Aggregation of fields of study

Variable (subset)	Definition
characteristics of study:	
duration	semesters (half term years) until first graduation
summer	semester of first enrollment: summer term
social	studying a field of social sciences
econ	studying a field of economics
law	studying a field of law
human	studying a field of humanities
engin	studying a field of engineering
informath	studying a field of informatics or maths
science	studying a field of natural sciences
medicine	studying a field of medicine
teach	studying for teachers training certificate
other	studying other fields
uni	studying at university
personal characteristics:	
female	sex: 1 if female, 0 otherwise
age	age at enrollment
educ	type of qualification: 1 if German A-level; 0 otherwise
grade	final grade at school: 1.0, 1.1,..., 3.9, 4.0
nowork	no employment during study time: 1 if true, 0 otherwise
partwork	employment during parts of study time: 1 if true, 0 otherwise
fullwork	employment through whole study time: 1 if true, 0 otherwise
experience	employment experience before studying
parental characteristics:	
acadmo	mother has university (or German university of applied science) degree
acadfa	father has university (or German university of applied science) degree

Table B.3: Variables of the data set

Figure B.1: Evolution of entry cohorts 1980-2011 (at the level of the German population), Data: Statistisches Bundesamt (2014)

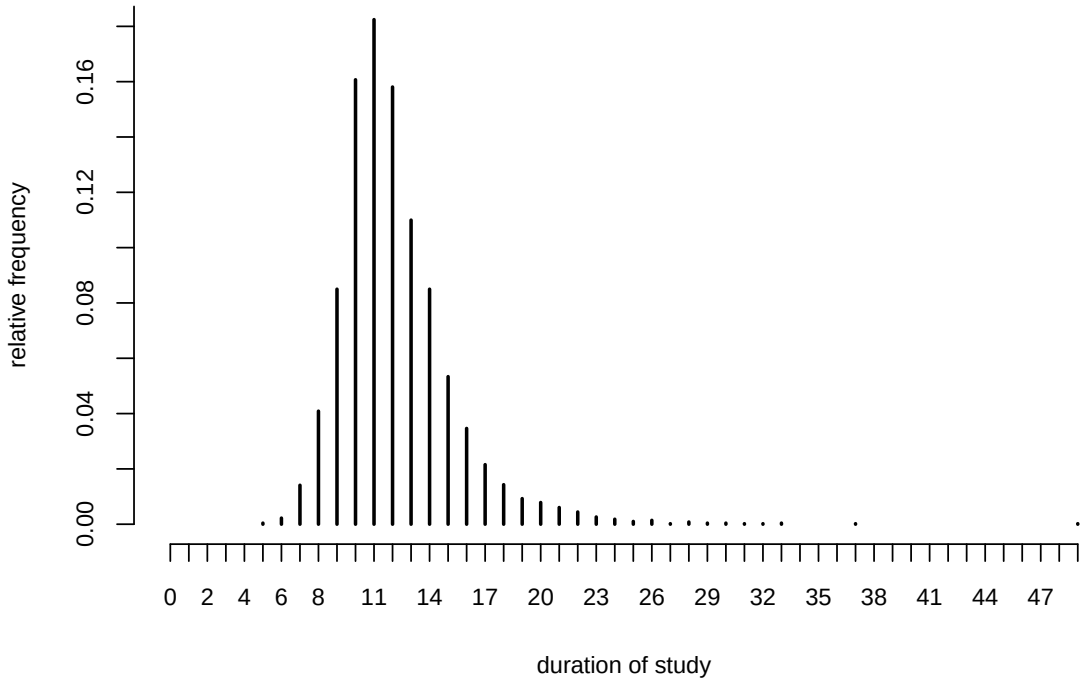

Figure B.2: Distribution of study time

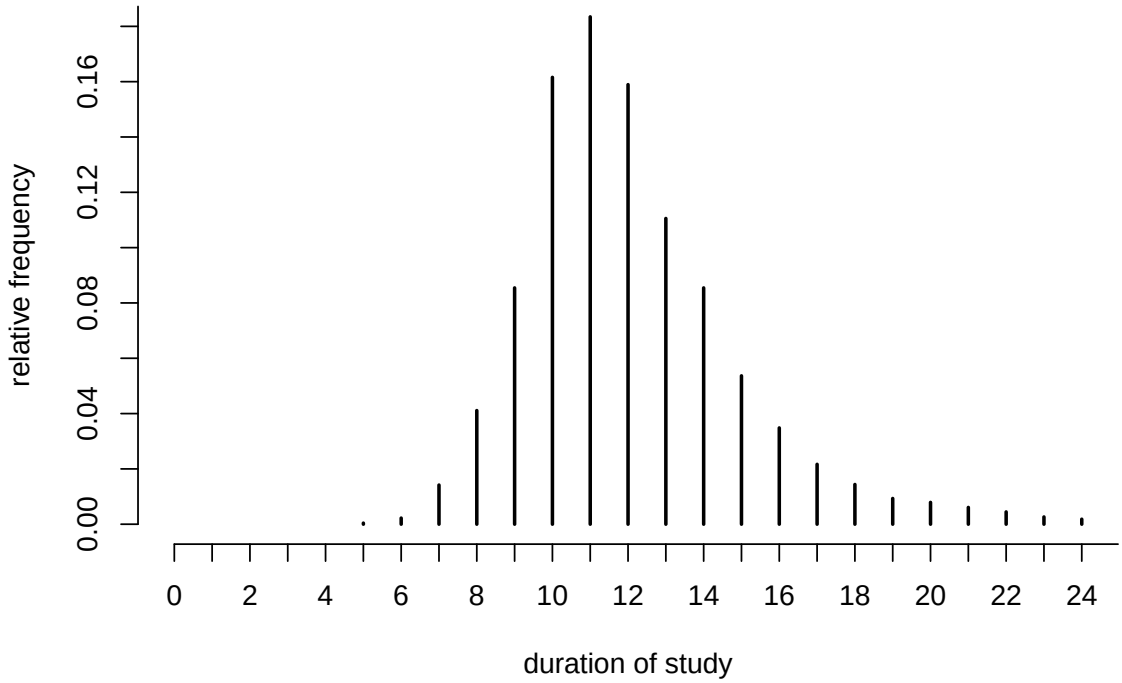

Figure B.3: Distribution of study time (without outliers)

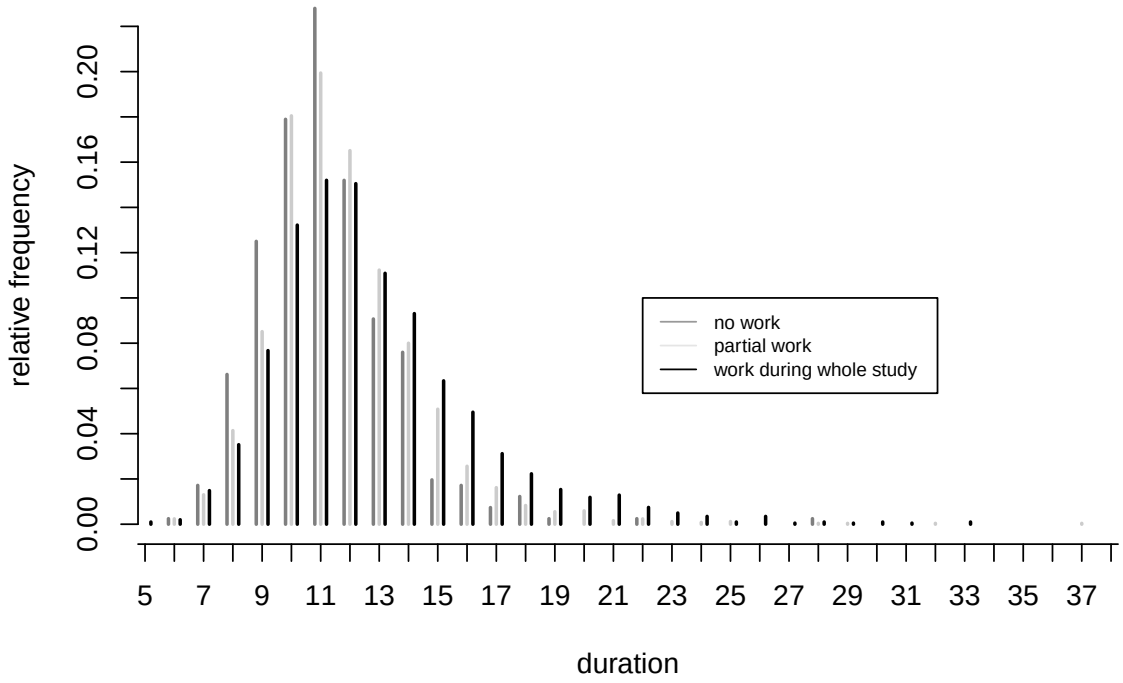

Figure B.4: Distribution of duration by work

3

The Causal Effect of Off-Campus Work on Time to Degree

The Causal Effect of Off-Campus Work on Time to Degree

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Abstract

In this paper we analyze the effect of outside university work on time to first degree at German universities. The data base is the "Absolventenpanel" 2001, a panel study conducted by the "Hochschul-Informations-System" (HIS). Aiming to estimate the causal effect correctly we apply a matching strategy based on the approach put forward by Rosenbaum and Rubin (1983). The results of the matching approach reveal that simple prima-facie results are upward biased but confirm that off-campus work has a prolonging effect on study duration.

JEL classification: I21; I22; I28
Keywords: Educational economics, Time to degree, Matching, Causality

3.1 Introduction

We analyze the duration to first university degree in Germany for ten broad fields of study and focus on the prolonging effect of off-campus work on time to degree. Because working and non-working students differ considerably with respect to personal as well as parental characteristics we apply the framework of causal analysis which is aimed to provide unbiased estimates of the treatment effect. While simple comparisons of working and non-working students hint for a substantial study prolonging effect in all ten fields of study controlling for selection effects by means of a matching approach results in more differentiated findings. Using randomization tests we find a significant prolonging effect of off-campus work for six out of ten fields. The highly significant prolonging effect for all students averages to 0.67 terms.

The German educational system is regarded as highly social selective. There is a high correlation between the parental educational and academic background and childrens' participation at upper secondary school and institutions of higher education. According to BMBF (2010) in 2007 three out of four young adults with a highly educated father (A-level) participate in higher education. On the other hand only between 20% and 25% of children from lower educated households go to university.

A-level is the typical entrance qualification for studying at a German university. However, there are also other ways, e.g. through a university of applied sciences entrance qualification, to higher education in Germany (for more details see e.g. Weiss and Steininger (2013) or Schindler and Reimer (2011)). Despite a numerus clausus for several fields of study (e.g. medicine, law, business administration), there are usually no more admission rules.

The main source of financial aid for students from low income families is provided by BAföG (Federal Education and Training Assistance Act). The eligibility for BAföG and the amount of payment is means tested (own and parental wealth and income). The maximum period of assistance is determined by the standard period of study. Only 50% of the credit has to be repaid. The maximum amount of monthly payment is about 600 Euro (without further surcharges). Furthermore, there are so called education loan programs providing low-interest financial support to students (irrespective of own or parental income). Scholarships are only awarded to students with excellent academic performance.

Recent reforms of the German university system, e.g. the reform of the student aid system, the introduction of tuition fees and the implementation of the Bologna process, are all aimed at reducing the time to degree. The supremacy of the states (Länder) in Germany in the field of education leads to different regulations. Until the introduction of tuition fees, attending a university has been free of charge (despite administrative costs/social contributions). In some federal states tuition fees only for long term students were charged (about 500 Euro per term). Since 2007 most of the western German states introduced general tuition fees (up to 500 Euro), which in almost all states are now abolished or will be abolished in the following terms. In most of the states now there are no tuition fees at all.

Traditionally Germany's tertiary education system has been characterized by long time spent to obtain the first university degree. For example, study duration for achieving a diploma at a university averages approximately at 12 terms exceeding considerably the regular study time which is 9 terms in most fields of study.

In recent years the German university system has undergone reforms in the course of the European harmonization of the higher education system (Bologna reforms). The former usual degrees (Diplom, Magister, Staatsexamen) with legal durations of 8-10 terms were substituted by the two-tier structure of bachelor's and master's degrees with legal durations of 6 and 4 terms, respectively. The bachelor's degree is aimed to provide students a fast qualification for labor market entrance. In the winter term 2013/14 approximately 87% of all study programs have by now been reformed towards the bachelor/master system.

In 1998, that is before the process of Bologna reforms started, in most fields of study the proportion of students obtaining their degree in the legal duration was below 30% and in 2003 the duration of study exceeded 11 on average and thereby exceeded the legal duration by about 2 terms. Within the new two-tiered bachelor/master structure, between 2007 and 2009 the durations for the bachelor' degree as well for the master's degree came closer to legal durations (see Wissenschaftsrat (2001),Wissenschaftsrat (2005), and Wissenschaftsrat (2011)). However, due to the considerable skewness of the duration distribution and current right censoring of long durations effects on the average duration are not possible yet.

A considerable proportion of German students is working outside the university in order to cover their costs of living. Even after the Bologna reforms with a more structured curriculum more than 60% of German students work during their studies. One of the main

motives for employment is the necessity to cover living costs, in particular for students coming from families with lower social backgrounds. The source of financing is linked to the social background of students. The importance of students' earnings increases from the "upper" to the "low" group of social background, whereas the proportion of the parental financial support decreases considerably. The socioeconomic background strongly effects students working status as students coming from an upper social group are less likely to work constantly during their studies (see e.g. BMBF (2010)).

Identifying causes of the comparatively high duration is one of the key aspects for improving efficiency of the German academic system. Shortening time to degree is regarded as important for improving national and international career entry chances of German graduates. We try to estimate the "causal" effect of work on time to degree based on observational data. Obviously, the working and non-working students have not been assigned to the groups randomly. Therefore, simple comparisons of the time to degree may be severely biased due to self-selection into the groups. We try to avoid this potential biasing effect using matching methods which are well established in medical research and lately become increasingly popular in economics, too, mainly in labor market research.

To assess the effect of outside university work during the study on time to degree we apply a matching strategy as suggested by Rosenbaum and Rubin (1983) and Rosenbaum (2002). The aim is to control as much as possible for potential selection effects using all relevant available information on the students under analysis. Throughout the analysis a random experiment with individuals assigned randomly to treatment and control groups serves as the theoretical yardstick.

The idea of the matching approach applied is to come ex post through statistical analysis as close as possible to a randomized experiment in which students would be assigned randomly towards the groups, e.g. not working or working outside the university.

We analyze ten broad fields of study separately, because we regard comparisons of durations across very different fields as inappropriate. While we conduct ten analyzes separately, we will present the analysis for one field of study (social sciences) in greater detail to discuss the method in some depth. For all other fields the analysis is carried out analogously, but the results are given in condensed form. We also provide the results for an analysis combining the students of all fields.

This paper is organized as follows: the second section provides a brief overview of the relevant literature on study duration. In section 3 we discuss the data base and the variables used in the analysis, followed by a first descriptive analysis in section 4. Section 5 contains the estimation methodology based on the matching approach in some detail. Empirical results for all fields of study are presented in section 6, section 7 concludes.

3.2 Review of the Literature

Previous international research has primarily focused on PhD students and the determinants of their time to doctorate. There is a wide range of research about different determinants of time to doctorate for several countries (see for USA Valero (2001), for Belgium Visser, Luwel, and Moed (2007), for UK Booth and Satchell (1995) or for the Netherlands Ours and Ridder (2003)).

An early study which analyzes the effect of employment on completion time for PhD students in USA is done by Abedi and Benkin (1987). They find that doctoral students who had to support themselves through off-campus earnings had longer durations of study. On-campus work seems to reduce time to degree and to reflect positive selection effects. These results are supported by Ehrenberg and Sherman (1987).

The impact of different types of financial support on completion rates is investigated by Ehrenberg and Mavros (1995). They use data of students enrolled in doctoral programs at Cornell University. Estimating a discrete time duration model they conclude that students with teaching assistantship have lower completion rates and tend to be more likely to drop out than students with fellowships requiring no work. The results for students with other forms of financial support resemble. A similar conclusion is drawn by more recent studies by Siegfried and Stock (2001) and Stock and Siegfried (2006).

There is less research conducted on time until a first university degree (e.g. for Finland by Häkkinen and Uusitalo (2003), for Italy by Garibaldi et al. (2012) and for Canada by Sheridan and Pyke (1994)). None of these studies includes variables of students' employment status to analyze their effect on duration of study.

An early study already mentioned focusing on different effects of employment on academic achievement and post-college labor market success is conducted by Ehrenberg and

Sherman (1987). Using the National Longitudinal Survey of the High School Class of 1972 they distinguish between on-campus and off-campus employment and find a positive impact of on-campus work on academic achievements while off-campus work reduces academic success.

Stinebrickner and Stinebrickner (2003) investigate the correlation between working during studying and academic performance at the Berea College. They address the problem of endogeneity concerning the students' working hours. The authors claim that academically successful individuals tend to have more motivation and thus are more involved in non-academic activities like working. As a consequence simple econometric models, which do not fully control for motivation, may underestimate the negative effect of working on academic performance.

The results of a ordinary least squares (OLS) regression indicate a positive relationship between hours worked and grade. A fixed-effects estimation, controlling for person-specific permanent attributes, leads to an insignificant effect of additional hours of work on grade performance. To control for non-permanent factors an Instrumental Variable (IV) approach is used. After controlling for endogeneity of work the results indicate that working during studies affects the academic outcome negatively. Grave (2011) studying the time allocation of undergraduate students at a German University reaches similar conclusions.

A recent paper by Aina, Baici, and Casalone (2011) analyzes different impacts on time to obtain a bachelor's degree in Italy. They identify a negative effect of work on the probability of graduating within a minimum period.

There are few studies analyzing educational outcomes for Germany and their main focus is the effect of students' financial support or tuition fees (e.g. Heineck, Kifmann, and Lorenz (2006)).

There is only little empirical evidence on the effect of employment on time-to-degree. A recent study, which focuses on the effect of student aid (BAföG) on the duration of study and the probability of graduation, is by Glocker (2011). The analysis is based on the German Socio-Economic Panel (GSOEP), an annual household panel which started in 1984. For the analysis a discrete time duration model with competing risks is estimated. A positive effect of student aid on success of tertiary education is stated as students receiving financial aid on average work less than those not receiving support. In contrast to other papers mentioned above, the author finds no effect of time spent on working on

the probability to graduate or to drop out. However, time spent on studying is found to increase the hazard to graduate and to decrease the hazard to drop out. The author concludes that part-time working only has a negative effect on graduation if it results in less time available for studying.

Amann (2005) focuses on the effects of the type of employment on time to degree in higher education. The data are also derived from the German Socio-Economic Panel. The working variable is defined as the proportion in each unit of time (during the terms) used for full- or part-time employment. A discrete time duration model with a proportional hazard and a piece-wise constant baseline hazard is specified. Amann (2005) finds that both types of employment affect the hazard for graduation negatively and full-time employment has the stronger effect. To control for possible endogeneity of the working status an IV approach is used. While full-time work has still a negative effect on graduation, the coefficient for part-time work becomes insignificant.

The review of the existing literature reveals that there is no consensus about the effect of work on academic performance. Mostly PhD students are analyzed. There are only a few studies analyzing the effect of work during studies on time to first university degree. The data sets used are often very small and rather specific, e.g. containing information for only one or a few universities or even only for one field of study. Additionally, studies for Germany are scarce.

This study contributes to the existing literature using a comprehensive data set - the Absolventenpanel for the year 2001 - including students from many different universities in Germany covering a wide variety of fields of study. The rich data set contains many variables relevant for the course of study. Students' A-level scores are very well suited to control for unobservable motivation and ability. The focus of the analysis is the effect of the working status of students on time to first university degree. The following section provides an overview of the data and variables.

3.3 Data and Variables

The empirical analysis is based on data from the German Absolventenpanel 2001 of the HIS (Hochschul-Informations-System).[1] The survey was conducted 6-18 month after graduation and includes a random sample of all graduates receiving their first

[1] Additional panels started in the years 2005 and 2009, but are not yet available.

degree in the respective year (here 2001) at a German university and is obtained as a (stratified) cluster sample. The clusters are defined by the following characteristics: field of study, type of diploma and university. The panel includes a wide range of social and demographic characteristics and detailed information about the course of study and the integration into the labor market.[2] Since only students having obtained a degree are interviewed (outflow sample), there is no information given on university dropouts.

The dependent variable is time until graduation (*duration*), measured as the number of terms until the first graduation (i.e. subject related terms). Graduation is possible at every point in time, but the usual way of measuring time to degree is in half term years.[3]

The analysis focuses on the effect of students' working status on their time to degree. We use the indicator variable Z to indicate that a student has been working off-campus during her complete study. Hence, Z takes the value 1 if the student has been working off-campus throughout and 0 in all other cases (e.g. not working, working on-campus, working only part time).

Students who work presumably have less time available for studying and this may lead to a prolongation of time to degree. Therefore, we expect to observe higher durations for working students compared to non-working students.

The final grade at school is included to approximate prior qualification. One can presume that students' ability effects time to degree. Some researchers claim that the working status may reveal unobserved motivation and ability and thus the estimated effect of work on time to degree may be biased. Here, own ability is approximated by observed final grade at school. *grade* takes values between 1.0 and 4.0[4] in steps of 0.1 and it is expected that time to degree increases with *grade*, i.e. the higher the grade the longer the time to degree.

Prior qualifications and ability is also captured by *highschool*, indicating if a student attended an academic high school (type of German school providing advanced secondary education with completion of A-level) or another type of school permitting university enrollment.

[2]For more information see Schramm and Beck (2010).

[3]terms on leave or ex-matriculated terms are subtracted from students' time to degree.

[4]The higher the value the worse the grade.

Additionally, sex (*sex*, 0 men, 1 women) and age at enrollment (*age*) are considered. For both the expected effect on time to degree is ambiguous. Especially for *age* there may be two, potentially offsetting, effects. On the one hand, the older at enrollment, the more knowledge and experience a student has attained and this may shorten the time to degree. On the other hand, older age at enrollment could hint for some waste of time and perhaps little motivation. This may result in longer time to degree.

Not only personal but also parental characteristics, especially the educational background of the parents, may have an affect on the course of study. E.g. a student from an academic household may be more encouraged to obtain his degree in a short time in contrast to a student with parents without academic background. This aspect is captured by a dummy variable (*academic*) indicating if either the mother or the father (or both) has a university degree or a degree at a German university of applied sciences. A decreasing effect on duration is expected.

The financial situation of the family is captured by the variable *subsidies* denoting the fraction of students income that is provided by its parents, hence taking values between 0 and 1.[5] Table C.1 given in the appendix provides an overview of the variables and their definitions.

An important characteristic of study is the field of study. The original data set[6] includes 33 fields which have been categorized into 10 fields: social sciences (*social*), economics (*econ*), law (*law*), humanities (*human*), engineering (*engin*), informatics and maths (*informath*), natural sciences (*science*), medicine (*medicine*), teaching (*teach*) and other fields of study (*other*).

Not surprisingly, many papers find that the field of study has an effect on the duration of study (e.g. Aina, Baici, and Casalone (2011)). However, these effects differ between different studies. Furthermore, the standard period of study is established by study regulations of the special field. To capture this intrinsic times to degree it is important to aggregate fields in a reasonable way.

The duration of study takes in some rare cases unusual high values (the maximum in our original sample was 49 terms). To prevent outliers biasing the results we drop

[5]To ease the exposition of descriptive results we also used this variable dichotomized towards low and high, indicating whether the fraction the student obtained was below or above the average fraction in the complete sample.

[6]For more details about the variables of the Absolventenpanel 2001 see Schramm and Beck (2010).

observations with durations exceeding 24 terms. The final sample with valid observations on all variables has 4709 observations.

3.4 Descriptive Statistics

Table 3.1 shows some statistics of duration and the covariates. The mean study time is 12.04 terms. 28% of the students are working off-campus during their whole study time. There are 61% female students in the sample. The final grade at school averages at 2.14. 61% of the students have a mother or father (or both one's parents) with an academic background.

	mean	min	max	std
duration	12.04	5	24	2.77
sex (1:female)	0.61	0	1	0.49
age	20.65	13	52	2.69
grade	2.14	1	4	0.63
academic	0.61	0	1	0.49
highschool	0.89	0	1	0.32
subsidies	0.56	0	1	0.32
working	0.28	0	1	0.45

Table 3.1: Some descriptive statistics: duration and covariates

For a first view of the duration in different fields of study some descriptive statistics are given in Table 3.2. According to the mean as well as the median, the shortest duration is observed in law, whereas the longest duration is found for medicine. The rather long duration of studies is also apparent if looking at the mode, which is lowest with 9 terms in law and highest in medicine (14). The largest standard deviation (3.58) is observed in informatics and maths (informath).

Table 3.3 provides an overview about how the duration of study differs within different fields of study for groups according to the covariates working/non-working, sex, academic parents, non-academic parents, attending high school or another type of school, being low or high subsidized and grades (rounded to obtain three groups).

The results reveal some very interesting facts. Firstly, for all ten different fields of study we find that the time to degree of students working off-campus throughout the whole

study exceeds the duration of their non-working counterparts. For all students the difference in average duration is 0.84 terms and in seven out of ten fields the difference exceeds a complete term.

	n	mean	median	mode	min	max	q75-q25	std
social	310	12.39	12	12	7	24	3.00	2.60
econ	390	11.33	11	10	7	23	3.00	2.28
law	288	10.52	10	9	8	17	2.00	1.65
human	600	12.54	12	11	5	23	3.00	2.80
engin	705	12.62	12	12	8	24	3.00	2.60
informath	263	13.23	12	11	5	24	4.00	3.58
science	458	11.57	11	10	6	24	2.00	2.44
medicine	354	13.42	14	14	8	23	2.00	2.66
teach	759	11.21	11	10	6	24	4.00	3.00
other	582	11.90	11	11	7	24	2.00	2.40

Table 3.2: Duration in ten fields of study

	all	social	econ	law	human	engin	inf.	science	med.	teach	other
working	12.64	12.89	12.36	10.65	13.25	13.62	14.05	12.75	14.51	11.62	12.68
non-work.	11.80	12.06	10.95	10.48	12.09	12.38	13.01	11.30	13.29	10.95	11.54
men	12.27	12.53	11.56	10.41	12.64	12.80	13.30	11.66	13.82	11.93	12.16
women	11.89	12.36	11.01	10.63	12.49	12.39	13.13	11.46	13.23	11.03	11.78
academic	11.92	12.30	11.20	10.52	12.45	12.38	12.70	11.25	13.46	11.30	11.70
non-acadamic	12.21	12.47	11.51	10.53	12.67	13.06	14.19	12.18	13.33	11.08	12.15
highschool	11.99	12.36	11.24	10.51	12.55	12.54	13.18	11.48	13.33	11.12	11.92
non-highschool	12.42	12.56	12.00	10.69	12.41	13.12	13.94	12.93	14.54	11.87	11.76
high-subs.	11.67	12.12	10.90	10.39	12.11	12.34	12.47	11.24	13.28	10.76	11.61
low-subs.	12.46	12.56	11.76	10.80	12.91	12.99	13.96	12.08	13.67	11.74	12.22
grade: 1	11.46	11.63	10.13	10.16	11.83	11.46	11.90	10.80	12.88	11.67	11.02
grade: 2	11.91	12.36	10.93	10.47	12.42	12.43	13.21	11.52	13.44	11.17	11.64
grade: ≥ 3	12.62	12.60	12.29	10.92	13.13	13.82	15.79	13.79	14.21	11.17	12.59

Table 3.3: Duration by covariates and fields of study

Secondly, the duration of studies until degree for men exceeds the duration for women in nine fields. Thirdly, the grouping according to *academic*, indicating whether at least one part of the parents obtained an academic degree, reveals mostly minor differences. In eight fields of study students with a non-academic parental background have in average a longer duration.

In eight fields the average duration for students who visited high school is below the average duration of students who did not visit high school.

Students obtaining a below average share of their income as parental subsidies have longer average durations in all ten fields and the difference for all students is 0.79 terms.

And finally, to illustrate how study duration differs with final grade at school, the variable *grade* is categorized into three groups: grades 1, 2 and 3 or worse. The differences in time to degree when splitting the sample in these three groups is noteworthy. With teaching being the only exception there is a monotone increase of duration with worsening grades in all fields of study.

In the context of the correlation between the working status of students and time to degree, it is of interest to analyze the characteristics of students working off-campus. Therefore, we have a closer look at the interplay of the working status with the covariates (Table 3.4).

	all	working	%	non-working	%
women	2849	872	31	1977	69
men	1860	458	25	1402	75
academic	2857	671	23	2186	77
non-academic	1852	659	36	1193	64
highschool	4178	1145	27	3033	73
non-highschool	531	185	35	346	65
high subsidies	2545	407	16	2138	84
low subsidies	2164	923	43	1241	57
grade: 1	691	124	18	567	82
grade: 2	2732	711	26	2021	74
grade: ≥ 3	1286	495	38	791	62

Table 3.4: Working status conditional on covariates

We find that women and non-high school students engage more often in off-campus work. 36% of students without any academic parental background work off-campus throughout their studies. Students from academic households in contrast engage considerably less in off-campus work (23%). Students whose parents provide below average financial support have to engage more often (43%) in off-campus work than their more supported fellow students (16%).

The conditional distributions of the working indicator variable on grades differ considerably. Conditional on the grade, the share of working students increases strongly with worsening

grades. In the group of students with grade 1 only 18% work throughout their studies. This share increases for grade 2 students toward 26% and is largest for students with grade 3 or worse with 38%.

In Table C.2 given in the appendix means of covariates by field of study and working status are shown. The sample contains 61% female students. The share of female students is especially high in the social sciences (81%) and teaching (80%) and low in economics (41%) and informatics and maths (41%). Women tend to engage more often in off-campus work compared to men in seven out of ten fields.

The average A-level grade is highest (worst) in social sciences and teaching and lowest (best) in natural sciences, informatics and maths, and medicine. In all fields students working off-campus have worse grades than their non-working fellow students. Students with a parental academic background and students having visited high school engage less often in off-campus work. These relations are observed in all ten fields of study. The fraction of students income provided by their parents is on average 56%. This fraction is considerably lower for working students (39%) than for non-working students (62%). This association is present in all fields of study.

In summary, we observe longer durations for working students on the one hand and a higher propensity to work for students with less favorable educational and parental background on the other hand. The objective of the following causal analysis is to disentangle the effect of off-campus work on duration from the confounding influences of the less favorable background which can be assumed to result in upward biased first sight effects when neglecting potential selection effects.

3.5 Estimating the Effect of Work on Duration for Students of the Social Sciences

3.5.1 The Aim of the Analysis

We analyze the subsample of students of the social sciences in detail and apply the analogous analysis to the other fields of study in the next section. As we are interested in the potential duration increasing effect of off-campus work (working), we regard this group as the treatment group and the non-working students as the control group (non-working). In our data we observe 124 students working throughout their studies

off-campus (treatment group) and $310 - 124 = 186$ non-working students (control group). The effect of interest is the difference in time to degree 'caused' by work during studies. We expect an increasing effect on time to degree as time spent for working might reduce the available time for studying.

We proceed in our analysis in two steps. First we counterfactually regard the working or non-working activity of students as a random assignment towards treatment (working) and control (non-working) group. Applying randomization tests we estimate the effect and its significance under the hypothesis of random assignment.

As the decision of working off-campus is probably endogenous, in the second step of our analysis we try to mimic a random assignment as close as possible using available covariates to account for the (overt) bias on observables. This analysis is based on the estimation of assignment probabilities used to construct a control group via a matching strategy.

To assess the significance, we will apply randomization tests. As in almost all cases complete enumeration of all possible permutations is computationally infeasible we approximate the true randomization distribution with $100,000$ random draws of the assignment vector.

3.5.2 Notation

We first introduce our notation. Z is a random variate which indicates whether an individual receives treatment ($Z = 1$) or not ($Z = 0$). In our analysis $Z_i = 1$ indicates that student i is working beside her studies off-campus and $Z_i = 0$ indicates that she is not working. n is the number of observed students who finished their studies with a time to degree Y. m denotes the number of students working (treatment group) and $n - m$ the number of non-working students (control group).

$$m = \sum_{i=1}^{n} Z_i = 124$$

$$0 \leq m = 124 \leq n = 310$$

The effect of interest is the difference in time to degree at the individual level, e.g. the time to degree if working (y_{iT}) minus the time to degree if not working (y_{iC})

$$y_{iT} - y_{iC}$$

3.5.3 A Simplified Analysis with Nominal Outcome

For the moment we simplify the analysis by transforming time to degree Y towards a nominal variable R indicating whether the time to degree of individual i is above average time ($\bar{y}$) to degree ($R = 1$) or not ($R = 0$):

$$\begin{aligned} r_i &= 1 \quad \text{if} \quad y_i > \bar{y} \\ r_i &= 0 \quad \text{if} \quad y_i \leq \bar{y} \end{aligned}$$

Note that the effect at the individual level is never observed as we either observe r_{iT} or r_{iC}, but never both. Here, r_{iC} is the above/below average duration indicator in the non-working group and r_{iT} is the indicator in the working group.

The assignment vector $\mathbf{Z}$ is random and indicates which individual belongs to the treatment group

$$\mathbf{Z} = \begin{bmatrix} Z_1 & Z_2 & \cdots & Z_n \end{bmatrix}'$$

We observe r_{iT} for individuals in the treatment group and r_{iC} for individuals in the control group. The vector of all observed outcomes is (here ordered according to the assignment vector)

$$\mathbf{Z}\mathbf{r}_T + (\mathbf{1} - \mathbf{Z})\mathbf{r}_C = \begin{bmatrix} r_T & r_T & \cdots & r_T & r_C & r_C & \cdots & r_C \end{bmatrix}'$$

In random experiments the treatment vector Z is randomly assigned:

$$0 < \mathrm{P}(Z_i = 1) < 1$$

Ω is the set of possible treatment assignment vectors $\mathbf{Z}$. In a randomized experiment the number of possible treatment assignments is

$$K = \binom{n}{m} = \binom{310}{124} = 1.87578 \times 10^{89}$$

Therefore, the probability for each assignment is $\mathrm{P}(\mathbf{Z} = \mathbf{z}) = 1/K$ for all $\mathbf{z} \in \Omega$.

We test the null hypothesis of no treatment effect. Under the null hypothesis the response is identical in the treatment and in the control state and the effect τ measured as the difference is 0:

$$\tau = r_{iT} - r_{iC} = 0$$

Using observed $\mathbf{Z}$ and observed $\mathbf{r}$ the treated-minus-control difference, denoted as statistic $t(\mathbf{Z}, \mathbf{r})$, is obtained as

$$t(\mathbf{Z}, \mathbf{r}) = \frac{\mathbf{Z}'\mathbf{r}}{\mathbf{Z}'\mathbf{1}} - \frac{(\mathbf{1} - \mathbf{Z})'\mathbf{r}}{(\mathbf{1} - \mathbf{Z})'\mathbf{1}}$$
$$T = \frac{54}{124} - \frac{70}{186} = 0.0591$$

The share of students with an above average time to degree in the treatment group exceeds the share in the control group by about 6%.

Now we turn to the inference for $t(\mathbf{Z}, \mathbf{r})$. Under the null hypothesis of no effect $\mathbf{r}$ is regarded as fixed. Assignment vector $\mathbf{Z}$ is randomly chosen from Ω. T is the empirical value of the test statistic $t(\mathbf{Z}, \mathbf{r})$. The $p-$value is the probability to observe T or an even higher statistic given the null hypothesis of no effect holds. In this case the $p-$value can be obtained by the probabilities for $\mathbf{z} \in \Omega$ which result in T or an even higher statistic $t(\mathbf{Z}, \mathbf{r})$:

$$\mathrm{P}\left\{t(\mathbf{Z}, \mathbf{r}) \geq T\right\} = \sum_{\mathbf{z} \in \Omega} \left[t(\mathbf{Z}, \mathbf{r}) \geq T\right] \cdot \mathrm{P}(\mathbf{Z} = \mathbf{z})$$
$$where \quad [event] = \begin{cases} 1 & if\ event\ occurs \\ 0 & otherwise \end{cases}$$

Note that Ω is a very large set and the probability therefore is difficult to obtain. In the uniform randomized experiment

$$\mathrm{P}(\mathbf{Z} = \mathbf{z}) = \frac{1}{|\Omega|} = \frac{1}{K}$$
$$\mathrm{P}\left\{t(\mathbf{Z}, \mathbf{r}) \geq T\right\} = \frac{\left|\left\{\mathbf{z} \in \Omega : t(\mathbf{Z}, \mathbf{r}) \geq T\right\}\right|}{K}$$

Using Laplace we can calculate the probability for any specific assignment vector as[7]

$$
\begin{aligned}
n = 310, \quad m = 124, \\
|\Omega| = K = \binom{310}{124} = 1.87578 \times 10^{89} \\
\mathrm{P}(\mathbf{Z} = \mathbf{z}) = \frac{1}{K} = \frac{1}{\binom{310}{124}} \quad for\ all\ \mathbf{z} \in \Omega \\
\mathbf{z}'\mathbf{1} = 124 \quad for\ all\ \mathbf{z} \in \Omega \\
\mathbf{1}'\mathbf{r} = 124
\end{aligned}
$$

We approximate the distribution of the test statistic $t(\mathbf{Z}, \mathbf{r})$ by drawing $100,000$ assignment vectors randomly and calculating the test statistic for each draw. The approximative $p-$value is 0.1786. Hence, we would not reject the hypothesis of no effect at conventional levels.

Note that in this special case with only two outcomes (below/above average time to degree) the test statistic $t(\mathbf{Z}, \mathbf{r})$ follows the hypergeometric distribution. A common notation for the hypergeometric distribution is

$$\frac{\binom{R}{r}\binom{N-R}{n-r}}{\binom{N}{n}}$$

where N is the number of balls in the urn, R is the number of red balls in the urn, n is the number of balls drawn without replacement (sample) and r is the number of red balls in the sample. This translates into our notation as follows:

$$\frac{\binom{R}{r}\binom{N-R}{n-r}}{\binom{N}{n}} = \frac{\binom{\mathbf{r}'\mathbf{e}}{\mathbf{r}'\mathbf{z}}\binom{n-\mathbf{r}'\mathbf{e}}{\mathbf{z}'\mathbf{e}-\mathbf{r}'\mathbf{z}}}{\binom{n}{\mathbf{z}'\mathbf{e}}}$$

where $\mathbf{e}$ is a column vector of length n (number of students) with ones. Using the distribution function of the hypergeometric function we obtain a $p-$value of 0.1780, confirming the result obtained from the approximation through $100,000$ draws.

The permutation distribution is discrete and this hampers the approximation using the normal distribution. Correcting for drawing without replacement and for discretionarity

[7] Note that in this case by pure coincidence the number of treated $\mathbf{z}'\mathbf{1} = 124$ equals the number of above average durations $\mathbf{1}'\mathbf{r} = 124$.

we obtain with the normal approximation

$$
\begin{aligned}
&\mathrm{P}\left(\hat{\pi} \geq \frac{54}{124} = 0.4315 | n = 124, \pi = \frac{124}{310} = 0.4\right) \\
&= \mathrm{P}\left(U \geq \frac{\hat{\pi} - \pi}{\sqrt{\frac{\pi(1-\pi)}{n}}\sqrt{\frac{N-n}{N-1}}} = \frac{\frac{53.5}{124} - \frac{124}{310}}{\sqrt{\frac{\frac{124}{310}(1-\frac{124}{310})}{124}}\sqrt{\frac{310-124}{309}}}\right) \\
&= \mathrm{P}\left(U \geq 0.9215\right) \\
&= 1 - \Phi(0.9215) = 0.1784
\end{aligned}
$$

Therefore, the normal approximation leads to the same conclusion.

3.5.4 Testing for Differences in Duration Distributions by Means of a Chi-Squared Test

To test for differences in duration distributions a χ^2-test is used. We define $\tau = 7$ duration intervals[8] indexed by $k = 1, ..., \tau$ and define the test-statistic as follows:

$$\chi^2 = n_1 \sum_{k=1}^{\tau=7} \frac{(f_{kT} - f_k)^2}{f_k}$$

where f_T is the relative frequency of duration interval k in the treatment group, f is the relative frequency for all students in duration interval k.

The null hypotheses is that the working behavior is unrelated to the length of the duration of study. To perform the χ^2-test we need to calculate the expected frequencies if the null hypotheses is true. Here, we compare the relative frequencies of duration in the treatment group with the relative frequencies of all students.

In our application the test statistic amounts to $\chi^2 = 6.459$ with a $p-$value of 0.3737 indicating no significant association at conventional levels between the working status of students and their time to degree.

[8] We use the following intervals [0,9] (9,10] (10,11] (11,12] (12,13] (13,15] (15,24] which result in similar frequencies and prevent thereby that very low expected frequencies render the test unreliable.

3.5.5 Testing for a Difference in Average Durations

Asking whether the shares of students with above average durations differ in the working and non-working group uses only part of the available information on durations. Therefore, we turn now to a comparison of average duration in the two groups. We again apply the idea of randomization and obtain the approximative distribution of the difference in means under the null hypothesis of no effect, that is identical average durations in both groups:

$$H_0 : \bar{Y}_1 - \bar{Y}_0 = 0$$

where $\bar{Y}_1$ denotes the mean duration in the working and $\bar{Y}_0$ in the non-working group.

Note that again the observed durations Y are treated fix and the assignment vector $\mathbf{Z}$ is treated as random with fixed number of treated ($Z = 1$) and controls ($Z = 0$). Assuming the null hypothesis holds, we approximate the distribution by randomly drawing $100,000$ assignment vectors and calculate the difference in means for each draw. The observed difference in average duration between $n_1 = 124$ working and $n_0 = 186$ non-working students is

$$\bar{y}_1 - \bar{y}_0 = 12.887 - 12.065 = 0.822$$

We obtain a two-sided $p-$value of 0.0062, therefore the hypothesis of identical average durations in both groups can be rejected at conventional levels of significance. Again we compare the result obtained from the approximated discrete distribution with a normal approximation.

To test $H_0 : D_0 = \mu_1 - \mu_0 = 0$ we obtain the variance of the difference in means $D = \bar{Y}_1 - \bar{Y}_0$ as

$$V(D) = \sigma_D^2 = \sigma_{\bar{Y}_1}^2 + \sigma_{\bar{Y}_0}^2$$

As we do not know σ_D^2 we estimate the variance using the observed sample based on $\hat{\sigma}_{Y_1}^2$ and $\hat{\sigma}_{Y_0}^2$:

$$\hat{\sigma}_D^2 = \frac{\hat{\sigma}_{Y_1}^2}{n_1} + \frac{\hat{\sigma}_{Y_0}^2}{n_0} = 0.0657 + 0.0300 = 0.0958$$

The test statistic is

$$\frac{d - D_0}{\hat{\sigma}_D} = \frac{0.822 - 0}{\sqrt{0.0958}} = 2.656$$

for which we find $\mathrm{P}(|U| \geq 2.656) = 2 * (1 - \Phi(2.656)) = 0.0079$. Therefore, the normal approximation would result in a rejection of the null hypothesis at conventional levels, too.

Because of the large sample size no use of the t distribution to account for the estimation of the variance is necessary.

A confidence interval can be obtained by inverting the hypothesis test. We now ask at what empirical difference the hypothesis would be rejected at a two-sided significance level of $\alpha = 0.05$. Based on the simulated distribution we obtain

$$\mathrm{P}(0.234 \leq \bar{Y}_1 - \bar{Y}_0 \leq 1.417) = 1 - \alpha = 0.95$$

Summing up, we find that the hypothesis of no effect of off-campus work during studying on time to degree has to be maintained if using a test for the dichotomized duration (above/below average study time) or the χ^2-test. When testing the hypothesis of equal average duration times, the hypothesis could be rejected almost without doubts.

3.5.6 Treatment Assignment with Unknown Probabilities

So far, we maintained the assumption that students have been randomly assigned to working or non-working groups. Of course, this assumption is unreasonable as there is self-selection into the groups. This fact may bias the analysis based on the random assignment assumption. The assumption of simple random assignment can be also expressed as constant treatment-probabilities π for all individuals.

Because of the endogeneity of the treatment probability we in fact will have individual probabilities denoted as $\pi_{[j]} = \mathrm{P}(Z_{[j]} = 1)$. The corresponding control-probability therefore is $1 - \pi_{[j]} = \mathrm{P}(Z_{[j]} = 0)$. For all varying treatment probabilities π it holds that $0 < \pi_{[j]} < 1$.

Given individual treatment probabilities the probability for assignment vector $\mathbf{Z}$ is given as

$$\mathrm{P}(Z_{[1]} = z_1, ..., Z_{[n]} = z_n) = \prod_{j=1}^{n} \pi_{[j]}^{z_j} \{1 - \pi_{[j]}\}^{1-z_j}$$

The problem we now face is that $\pi_{[j]}$ is unknown. We assume that the individual probabilities $\pi_{[j]}$ depend on observed covariates $\mathbf{x}_{[j]}$

$$\pi_{[j]} = \lambda(\mathbf{x}_{[j]}) \quad for\ j = 1, ..., n$$

where $\lambda(\mathbf{x}_{[j]})$ is the propensity score. Using the propensity scores we obtain the probability for assignment vector $\mathbf{Z}$ as

$$\mathrm{P}(Z_{[1]} = z_1, ..., Z_{[n]} = z_n) = \prod_{j=1}^{n} \lambda(\mathbf{x}_{[j]})^{z_j} \{1 - \lambda(\mathbf{x}_{[j]})\}^{1-z_j}$$

Stratifying on Sex

We stratify on sex and therefore have $S = 2$ strata. Z_{si} is the treatment indicator for individual i in stratum s. $\mathbf{x}_{si}$ denotes the vector of covariates of individual i in stratum s. In all S strata we have n assignment indicators and the assignment vector with stratification is $\mathbf{Z} = (Z_{11}, ..., Z_{S,n_s})'$ of length n. m denotes the number of treated, $m_s = \Sigma_i Z_{si}$ is the number of treated in stratum s and $\mathbf{m} = (m_s, ..., m_S)'$ is a vector containing the information of the number of treated in each stratum.

Assume that we would accomplish exact stratification, i.e. individuals would only be heterogeneous across strata but homogeneous within strata: $\mathbf{x}_{is} = \mathbf{x}_{js}$ for s, i, j. In this case stratifying on sex would result in identical propensity scores within a specific stratum $s : \lambda(\mathbf{x}_{is}) = \lambda_s$. Because all subjects in s now have identical treatment probabilities, the probability for the assignment vector is

$$\begin{aligned}\mathrm{P}(\mathbf{Z} = \mathbf{z}) &= \prod_{s=1}^{S} \prod_{i=1}^{n_s} \lambda_s^{z_{si}} (1 - \lambda_s)^{1-z_{xi}} \\ &= \prod_{s=1}^{S} \lambda_s^{m_s} (1 - \lambda_s)^{1-m_s}\end{aligned}$$

This results in constant probabilities given the number of treated in the strata for all possible assignment vectors.

$$|\Omega| = K = \prod_{s=1}^{S} \binom{n_s}{m_s}$$

$$\mathrm{P}(\mathbf{Z} = \mathbf{z}|\mathbf{m}) = \frac{1}{K}$$

Note that in this case we were allowed to use randomization methods identical to 'randomized' data. This holds even if we do not know the probability to be chosen for the different strata.

Matching on Covariates

We now use several covariates to estimate the propensity to treatment. As covariates we use sex, age, A-level grade, an indicator whether mother or father has an academic degree, the information whether the student obtained her A-level at a high school and the share of income the student obtains from parental subsidies. As we wish to estimate probabilities, we use a logit model as a natural choice because estimates are bounded towards the interval $[0; 1]$.

We observe rather similar means of the covariates in both groups, implying that both groups do not differ considerably, which hints for a small overt bias (on covariates). We apply a matching algorithm that searches for each of the $n_1 = 124$ working students a non-working student with identical or almost identical propensity for treatment, thereby restricting the search for students of identical sex (exact matching on sex).

	non-working	non-work.,contr.	working
n	186.00	124.00	124.00
mean of duration	12.06	12.62	12.89
women	0.85	0.75	0.75
mean of age	22.31	22.46	22.02
grade	2.24	2.51	2.49
acad. parents	0.47	0.30	0.40
highschool	0.84	0.79	0.82
subsidies	0.49	0.32	0.34

Table 3.5: Social sciences, characteristics in working and non-working groups

Note that the two groups, that is $n_1 = 124$ working students (treatment) and $n_{0C} = 124$ matched non-working students (controls), have very similar covariates as shown in Table 3.5. Because the 124 pairs of students now have either exact or at least very similar probabilities to be treated, the observed assignment can be hoped to resemble a pure random assignment. To judge the effect of working on time to degree we now compare the durations for each of the matched pairs making use of a paired t-test.

We find an average duration of 12.887 terms for the working students and 12.621 for the non-working control students. The difference of 0.266 term is not statistically significant at usual levels with a $p-$value of 0.4385. Note that the difference between working and non-working control students of 0.266 terms is considerably smaller than the prima facie

difference of 0.823 obtained from the simple comparison of working and non-working students.

3.6 Results for Ten Fields of Study

After having discussed our estimation methodology in some detail in section 5 for the students of social sciences, we now apply this procedure to all ten fields of study separately as well as to the pooled sample of all students. We present the results in a very condensed form in Table 3.6. In the columns we show the number of students in that field (n), the number of students working off-campus during the complete study (n_1), the number of non-working students (n_0), average time to degree for working students ($\bar{y}_1$), for non-working students ($\bar{y}_0$), the difference in time to degree (Δ_{PF}) obtained from the simple prima facie comparison, the $p-$value obtained for the null hypothesis assuming random assignment and no effect of work (p_1), the χ^2-test statistic and the corresponding $p-$value (p_2) under random assignment assumption, the mean time to degree of the $n_1 = n_{0C}$ control students obtained from the matching procedure ($\bar{y}_{0C}$), the difference in time to degree for working (treatment) and control non-working students (Δ_{TC}) and the $p-$value of the paired t-test (p_3).

The last row (all) of Table 3.6 contains the results of an encom*p*assing analysis after merging the students of all different fields. In this analysis we include dummy variables for the fields in the logit model and we match with re*p*lacement exact on sex and field based on the estimated propensity scores.

A simple analysis of mean durations between working and non-working students reveals a highly significant difference of $\Delta_{PF} = 0.841$ terms. Accounting for the overt bias on observables in the matching routine this difference decreases toward $\Delta_{TC} = 0.667$ terms but remains highly significant. Students working off-campus during their whole study time reveal a significant higher average time to degree than their non-working counterparts.

In seven out of ten fields the difference between working and non-working students Δ_{PF} exceeds one term. The smallest and insignificant difference is found for students of law. The difference in duration for informatics and maths is about one term with a $p-$value of about 5%. For the remaining eight fields the difference is significant at the 1% level under the assumption of random assignment.

	n	n_1	n_0	$\bar{y}_1$	$\bar{y}_0$	Δ_{PF}	p_1	χ^2	p_2	$\bar{y}_{0C}$	Δ_{TC}	p_3
social	310	124	186	12.887	12.065	0.823	0.006	6.459	0.374	12.621	0.266	0.439
econ	390	107	283	12.355	10.947	1.408	0.000	26.557	0.000	11.178	1.178	0.001
law	288	74	214	10.649	10.481	0.167	0.463	5.247	0.513	10.797	-0.149	0.575
human	600	233	367	13.249	12.087	1.162	0.000	14.141	0.028	12.567	0.682	0.008
engin	705	136	569	13.618	12.378	1.240	0.000	22.113	0.001	12.919	0.699	0.080
informath	263	56	207	14.054	13.010	1.044	0.053	7.873	0.248	14.196	-0.143	0.827
science	458	85	373	12.753	11.300	1.453	0.000	22.530	0.001	11.624	1.129	0.007
medicine	354	39	315	14.513	13.289	1.224	0.007	6.452	0.374	13.615	0.897	0.156
teach	759	293	466	11.625	10.946	0.678	0.002	11.306	0.079	11.038	0.587	0.022
other	582	183	399	12.678	11.544	1.134	0.000	25.927	0.000	11.765	0.913	0.001
all	4709	1330	3379	12.639	11.798	0.841	0.000	78.222	0.000	11.879	0.667	0.000

Table 3.6: Prima facie and matched comparison of duration

As the discussion of the descriptive statistics made evident, working and non-working students differ strongly with respect to their individual and parental characteristics. To take into account the non-random assignment to treatment and control group due to the self-selection process, we carry out the matching strategy explained in detail above.

The difference Δ_{TC} between working students and their matched non-working control group in duration is still positive in eight fields of study. For all fields it holds that due to the balancing effect of the matching approach the matched non-working controls have longer durations than the complete samples of non-working students. This results in treatment effects (of the treated) being lower than the simple prima facie differences in all fields, i.e. Δ_{PF} exceeds Δ_{TC}. This is reflected in higher $p-$values (p_3) for Δ_{TC} in all fields.

Hence, controlling for potential self selection into both groups (regarding the working or non-working activity of students as endogenous and not as a random assignment) seems to be very important for assessing causal effects of off-campus work on duration. Neglecting self selection results in upward biased effects.

The reduction in duration differences due to the matching approach is especially strong in informatics and maths and results in a negligible difference Δ_{TC} that is statistically insignificant different from 0. The effect of off-campus work in the matching framework is significantly duration increasing in economics, humanities, sciences, and other fields of study at the 1%-level, in teaching at the 5%-level and in engineering at the 10%-level. In economics and science the prolonging effect exceeds one term and in medicine (albeit not significant) and other fields it is just below one term. In law, informatics and maths, social sciences and medicine we found no significant effect of the working behavior of students on their time to degree.

Given these results we conclude that off-campus work has a significant prolonging effect on the average study duration. The detailed analysis for ten different fields revealed significant (10%-level) average duration increasing effects in six out of ten fields.

3.7 Conclusion

The efficiency of the academic system in Germany is an intensively discussed topic in the political arena. In this context the proportion of students achieving their degree and the time to degree is of special interest, both being key performance indicators. As Germany has traditionally been characterized by long times to degree analyzing potentially prolonging causes of time to degree is an important issue. The present situation is characterized by the fact that the regular study time is exceeded by the majority of students. Furthermore, many students work during studies, mainly to be able to cover living costs. This aspect is often neglected in investigations of the academic success of students and this study is aimed to provide evidence for the effect of work on study durations.

This paper tries to estimate the "causal" effect of off-campus work on time to degree based on observational data using matching methods suggested by Rosenbaum and Rubin (1983) and Rosenbaum (2002). The aim is to control as much as possible for potential selection effects using all relevant available information on the students under analysis like gender, age, grade and financial and social background.

A first descriptive analysis reveals a rather strong relationship between engagement in off-campus work and time to degree. Students working off-campus during their whole study time have higher durations of study compared to the non-working students. This findings holds for the complete sample as well as for the ten subsamples for different fields of study.

Looking closer at the characteristics of off-campus working students in comparison to their non-working fellow students reveals notable differences. The group of working students contain a higher share of female students and less students with academic parental background. They have on average worse grades, have less often visited high school and on average receive less financial support from their parents.

Comparing the study duration of working and non-working students (prima facie effect) reveals unequivocally that working students have longer study durations. The difference in study duration is highly significant under the assumption of random assignment for the complete sample of all students as well as in eight out of ten fields at the 1%-level. The differences in characteristics of working and non-working students hint strongly for potential biasing selection effects.

Through modeling the selection effect using a logit model and constructing a control group of non-working students by means of a matching approach we control for the potential self-selection bias.

Controlling for selection effects results in lower estimates of the effect of working on study duration thereby making evident the unreliability of simple prima facie comparisons. Nevertheless, according to the matching approach working off-campus increases average study duration significantly by 0.67 terms. For six out of ten fields a significant prolonging effect of off-campus work on the duration of study is found in the matching framework.

In summary, our study adds further evidence to the findings that the German educational system is highly socially selective. Underprivileged students face disadvantages in their educational careers in several ways. The prolonging effect of off-campus work during studies on time to degree may have several disadvantageous effects on labor market entry. These disadvantages may include forgone income during the additional study time, less favorable job offers and longer search times. One political implication may be that the reduction of tuition fees or more generous financial aid systems may reduce the detrimental effects on time to degree, in particular for educational climbers.

3.8 References

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3.9 Appendix

Variable (subset)	Definition
Z	indicator variable: 1 if working off-campus during the complete study, 0 otherwise
characteristics of study:	
duration	semesters (half term years) until first graduation
social	studying a field of social sciences
econ	studying a field of economics
law	studying a field of law
human	studying a field of humanities
engin	studying a field of engineering
informath	studying a field of informatics or maths
science	studying a field of natural sciences
medicine	studying a field of medicine
teach	studying for teachers training certificate
other	studying other fields
personal characteristics:	
sex	1 if female, 0 otherwise
age	age at enrollment
grade	final grade at school: 1.0, 1.1,..., 3.9, 4.0
highschool	having attended an academic high school (Gymnasium): 1 if true, 0 otherwise
parental characteristics:	
academic	mother or father (or both) has university (or German university of applied science) degree
subsidies	fraction of students income that is provided by parents, taking values between 0 and 1

Table C.1: Variables of the data set

	work.-stat.	all	social	econ	law	human	engin	inf.	science	med.	teach	other
duration	all	12.04	12.39	11.33	10.52	12.54	12.62	13.23	11.57	13.42	11.21	11.90
	working	12.64	12.89	12.36	10.65	13.25	13.62	14.05	12.75	14.51	11.62	12.68
	non-work.	11.80	12.06	10.95	10.48	12.09	12.38	13.01	11.30	13.29	10.95	11.54
sex (1:female)	all	0.61	0.81	0.41	0.53	0.70	0.44	0.41	0.45	0.67	0.80	0.68
	working	0.66	0.75	0.39	0.66	0.76	0.49	0.50	0.48	0.64	0.81	0.62
	non-work.	0.59	0.85	0.42	0.49	0.66	0.43	0.38	0.45	0.67	0.79	0.70
age	all	20.65	22.20	21.07	20.22	21.16	20.20	20.05	19.87	20.67	20.47	20.90
	working	20.99	22.02	20.95	20.26	21.57	20.70	20.57	19.92	21.00	20.56	21.43
	non-work.	20.52	22.31	21.11	20.20	20.90	20.08	19.91	19.86	20.63	20.42	20.66
grade	all	2.14	2.34	2.28	2.07	2.16	2.12	1.89	1.81	1.92	2.31	2.26
	working	2.30	2.49	2.38	2.15	2.30	2.33	1.97	2.03	1.97	2.41	2.32
	non-work.	2.08	2.24	2.24	2.05	2.08	2.06	1.87	1.76	1.92	2.25	2.23
academic	all	0.61	0.44	0.57	0.66	0.60	0.65	0.64	0.66	0.70	0.59	0.56
	working	0.50	0.40	0.48	0.59	0.55	0.51	0.57	0.49	0.59	0.52	0.43
	non-work.	0.65	0.47	0.60	0.68	0.63	0.68	0.66	0.69	0.72	0.63	0.62
highschool	all	0.89	0.83	0.88	0.91	0.89	0.87	0.93	0.94	0.92	0.88	0.85
	working	0.86	0.82	0.82	0.88	0.89	0.80	0.93	0.94	0.92	0.87	0.81
	non-work.	0.90	0.84	0.90	0.92	0.89	0.89	0.93	0.94	0.92	0.88	0.87
subsidies	all	0.56	0.43	0.53	0.66	0.51	0.57	0.52	0.61	0.63	0.55	0.55
	working	0.39	0.34	0.37	0.46	0.37	0.39	0.37	0.45	0.44	0.41	0.38
	non-work.	0.62	0.49	0.59	0.73	0.59	0.62	0.56	0.65	0.65	0.63	0.64

Table C.2: Means of variables by field and working status

4

The Effect of Students' Social Background and A-level Grades on University Performance

The Effect of Students' Social Background and A-level Grades on University Performance

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Abstract

This paper analyses the effect of students' social background and A-level grades on university performance of German graduates. The data base is the "Absolventenpanel" 2001. A methodological issue is whether grades have to be treated as metric or ordinal in statistical models. I treat grades as ordinal and use an ordered probit regression controlling for students' prior qualification. I find that the strong effect of academic background on A-level performance does not carry over to performance at university. After conditioning on A-level grades, the significant effect of students' social background on university grades vanishes for the lower level of parental academic background and diminishes for students from higher educated households.

JEL classification: I21; I23; I28
Keywords: Educational economics, Higher Education, A-level grades, University grades, Social background

4.1 Introduction

This paper tries to estimate the effect of students' social background and A-level grades on their academic performance, measured as final exam grades at university. University grades are of considerable importance as they serve as signals for qualification and motivation on the labour market. They reflect human capital acquisition of graduates at their entry into the labour market. From an economic point of view, worse university grades probably result in unfavourable job offers leading to lower earnings. If students' academic performance varies with social background, also later earnings may differ between graduates' social origins.

Furthermore, discussions on the selection criteria of universities raise the question if A-level grades are a reliable signal for future academic performance. The impact of students' social background is part of political debates on the social selectivity of the German academic system. Given evidence that A-level grades are affected by social origin there probably exists a disadvantage for underprivileged students to participate in higher education.

The literature on the interrelationship between social background and university grades is sparse, especially for Germany. More attention is paid to performance at school. One of the most important studies, the PISA study, reports a strong disadvantage for socially underprivileged students as they perform less well at school.

This paper analyses whether these disadvantages extend towards university. The database is the "Absolventenpanel" 2001, a panel study of graduates conducted by the "Hochschul-Informations-System" (HIS). The impact of the parental educational background is of main interest, but also other demographic and personal characteristics as age, sex, the working status and experiences before studying are taken into account. Additionally, the effect of students' own educational background, in particular A-level grades, on academic performance is analysed.

A methodological issue is whether grades should be treated as metric or ordinal in statistical models. In Germany grades for single exams are usually given on the following scale: 1.0, 1.3, 1.7, 2.0 up to 4.0. The final grade is an average of the obtained exam grades. Simple linear regression models assume that grades are metric. That means that the "interpretable" difference between e.g. the grades 1.0 and 1.3 is the same as

between 3.7 and 4.0. This assumption usually does not hold in the German grading system.

I treat grades as ordinal and use an ordered probit regression without and with controlling for students' prior qualification. As a main result, I find that the strong effect of academic background on A-level performance (as found in literature) does not carry over to performance at university in its entirety. After conditioning on A-level grades, this effect vanishes for the lower level of parental academic background and diminishes for students from higher educated households.

A-level grades seem to be a reliable predictor of future academic performance. The social background has less effect on success at a higher level in the course of education.

This paper is organised as follows: the second section provides an overview of the relevant literature on university performance. In section 3 I elucidate the data base and discuss the variables used in the analysis. Section 4 contains a descriptive analysis and the estimation methodology is discussed in section 5. Empirical results are presented in section 6, section 7 concludes.

4.2 Review of the Literature

Whereas there are numerous studies analysing educational attainment on school level (see for instance an early work by Hanushek (1987)) and the dependency between social class and school performance (see e.g. the PISA reports), less is known about the relationship between the students' social background and academic performance at university.

There are several papers focusing on other aspects of academic attainment. For instance McKenzie and Schweitzer (2001) investigate the impact of academic, psychological, cognitive, and demographic factors on performance of first year Australian university students. They find a strong dependency between previous academic performance, integration into university, self-efficacy, and students' Grade Point Average (GPA). Naylor and Smith (2004) concentrate on the effect of prior qualifications, measured as absolute and relative A-level scores, on degree performance of economics students in UK. The latter is an in-class rank of students within degree course based on their A-level scores. According to the deviation between personal score and the mean in-class

score, students are allocated into five groups (e.g. personal score more than 1.3 standard deviations away from the mean). They claim that the students' ranking within their cohort at university is also important in determining degree success. A study by Callender (2008) is aimed at quantifying the impact of students' paid work on their university degree results in UK. The results indicate a negative interrelationship between these variables.

Win and Miller (2005) concentrate on the importance of school characteristics for academic success, but also control for education and economic resources at students' home. A key finding is that school characteristics as the type of school affect university performance beyond students' background characteristics.

Betts and Morell (1999) search for an explanation of the variation in college students' performance, measured as the last observed GPA. Data base are more than 5000 undergraduates enrolled at the University of California, San Diego (UCSD) between 1991-1993. They focus on the effects of the degree program, family background (e.g. parents' income), school characteristics, and students' demographic environment.

By estimating several OLS regressions, the authors find that parental income is a highly significant predictor of GPA. Also the socio-economic environment affects grades. For instance, the proportion of (financially) supported parents in school decreases GPA, the proportion of adults with at least bachelor's degrees increases GPA. These effects are quite similar across fields. After inclusion of school grades and test scores - both highly predictive of university GPA - coefficients of students' background remain significant.

The following studies concentrate on the importance of the family background on academic success. A study by Smith and Naylor (2001) examines determinants affecting academic performance of undergraduate students in UK. Using data from University Student Records of almost 95.000 students who left university 1993, they apply ordered probit regressions, separately for men and women. The dependent variable is the university degree categorised into the classes 1-6. Explanatory variables are personal and study information, prior qualifications, and school characteristics. Of main interest is the students' social class origin based on parental occupation: professional workers, intermediate professions, skilled non-manual, skilled manual, partly skilled, unskilled, and unemployed.

The results indicate a monotonically positive effect over the social classes 1 up to 5: the more advantaged student's parental background the better academic performance. This effect remains even after controlling for school characteristics and prior qualification. There is a significantly positive effect of A-level grade on university degree. Interestingly, the social class coefficients vary strongly across different fields.

A similar conclusion is drawn by Hansen and Mastekaasa (2006) who analyse if students' social class origin affects academic performance of first-year students (58.000) and higher graduates (24.000) in Norwegian universities between 1997 and 2003. Academic performance is measured as early and final grade at the master level (relative measure from A-F). Ten social classes are defined by cultural and economic capital based on parental occupation ranging from managers and business executives over medium and lower level employees to skilled and unskilled workers[1]. Furthermore, the authors control for gender, university, degree of urbanization, parents' income, and secondary level grades.

By using an ordinal logistic regression, they find a strong positive relationship between social class and academic performance. The cultural capital seems to play an important role. Parents' income has a positive impact on performance. The inclusion of secondary level grades reduces the impact on social class considerably; the effect of income becomes insignificant. A comparison of early and final grades on the master level reveals that the class inequality in performance is maintained. The impact of social class differs strongly across fields of study.

A recent study by Katsikas and Panagiotidis (2011) focuses on the relationship between socio-economic background and students' GPA. The sample consists of 867 students enrolled at University of Macedonia, Economic and Social Studies (UoM) in 1998 and 1999. Socio-economic background is defined by students' working status and education of parents, measured as years of schooling: up to 6, up to 9, up to 12 years of schooling, higher studies and post graduate studies. Beside these explaining variables, the duration of study, department characteristics, personal characteristics (e.g. gender, age) are included in the OLS and quantile regressions.

In contrast to the other findings mentioned above the authors find no effect of students' working status (and also hours of employment) and of the parental schooling on stu-

[1]For a detailed overview of social classes see Hansen and Mastekaasa (2006, p. 282)

dents' grades. The duration of study affects grades negatively: the longer duration the lower grades. Entry exam scores are positively related to final grades.

For Germany, literature on higher education is scarce. A relevant topic is e.g. social selectivity in access to higher education (see for instance Weiss and Steininger (2013) and Schindler and Reimer (2011), also for a short description of the German higher education system). There are only very few papers analysing determinants of university performance. Jirjahn (2007) searches for factors affecting academic success in the field of economics and business administration. Data base are 458 students from three German universities (Hannover, Paderborn and Regensburg) in winter term 2002/2003. Performance indicators are the grade of and the duration until intermediate diploma, explaining variables are the own educational background (e.g. A-level grade), parental educational background, demographic characteristics (e.g. age, sex) and students' time allocation (e.g. employment). Using OLS and Poisson regression the author comes to the conclusion that grades and duration are positively affected by A-level grade and mothers academic background, and negatively affected by employment during studies.

In summary, there are only a few studies analysing the effect of social background on university performance. Some of these observe only grades of students (still studying) but not the final academic performance of graduates. Studies for Germany are very scarce. The data sets used are often very small and rather specific, e.g. containing information for only one or a few universities or even only for one field of study. The review of the existing literature reveals that there is no consensus about the effect of the social background on academic performance.

This study contributes to the existing literature using a comprehensive data set - the Absolventenpanel for the year 2001 - including students from many different universities in Germany covering a wide variety of fields of study. The rich data set contains detailed information on students' own educational background (e.g. type of school, A-level grade), which seem to be important for predicting academic success and are very well suited to control for unobservable motivation and ability. Furthermore, the data set provides relevant indicators of students' socio-economic origin, e.g. the parental academic background. The following section provides an overview of the data and variables.

4.3 Data and Variables

The empirical analysis is based on data from the German Absolventenpanel 2001 of the HIS (Hochschul-Informations-System)[2]. The first wave of the survey was conducted 6-18 month after graduation, the second wave 5 years later and a third wave 10 years after graduation. The survey includes a random sample of all graduates receiving their first degree in the respective year (here 2001) at a German university and is obtained as a (stratified) cluster sample. The clusters are defined by the following characteristics: field of study, type of diploma and university. The panel includes a wide range of social and demographic characteristics and detailed questions about the course of study and the integration into the labour market[3].

A drawback of the data is that it is a retrospective survey after graduation. University degrees are only observed for those who obtained a degree. There is no information available on students dropping out of university. However, students' social and educational background may have an effect on failure rates. E.g. if exam grades are negatively affected by students' working behaviour, worse grades possibly lead to demotivation and drop out (see e.g. Katsikas and Panagiotidis (2011)). Unfortunately, the data set does not allow to analyse this issue further.

I only use the first wave of the survey, because it contains relevant information about grades, times to degree, fields, and the course of study. The second and third waves focus on job performance and employment history which is not relevant for this analysis. The sample consists of 8117 observed individuals (first wave, response rate of 30 per cent).

The dependent variable is the final grade at university (*ugrade*) ranging from 1.0 to 4.0 (for more details see section Methodology). Note that in Germany, higher grades indicate worse academic performance.

The predictor variables are aggregated into the following three categories: characteristics of study, personal and parental characteristics. In particular, students' socio-economic status (SES) may have an effect on the course of study. As already addressed in a very early study by White (1982), the definition of SES is of great importance for the analysis and the interpretation of results. Often used types of SES measures are the parental

[2]Additional panels started in the years 2005 and 2009, but are not yet available. Also the third wave of the Absolventenpanel 2001 is not yet available.

[3]For more details about the Absolventenpanel 2001 see Schramm and Beck (2010).

occupational status and parental educational background. Following BMBF (2010) mainly the parental academic background has a dominant importance for students' own academic career. According to this study, controlling for the academic background decreases e.g. the effect of the occupational status on university participation. Furthermore, there are some uncertainties of students concerning the occupational status of their parents. Hence, only information on parental academic background seems to be a good predictor for students' university success. Many studies concentrate on the occupational status of parents instead.

It is expected that a higher level of parental educational attainments is associated with lower (better) grades. In contrast to students from non-academic households, a student from an academic household may be more encouraged to obtain a good degree. Since there is a high dependency between the academic background of mothers and fathers, a challenge is the isolation of paternal and maternal influences. Hence, referring to BMBF (2013), dummy variables indicating parental levels of educational attainments are constructed. *acad1* represents the lowest level; no more than one parent has a (non-academic) professional qualification. The next level *acad2* indicates that both parents have a (non-academic) professional qualification, followed by *acad3* characterizing that one parent has a university degree or a degree at a German university of applied science. *acad4* is the highest level of parental educational background with both parents having obtained an academic degree.

I addition, the working status of students represents their socio-economic background as students coming from an upper social group of origin are less likely to work constantly (see e.g. BMBF (2010)). Based on the information about the work intensity during studies, three dummy variables were constructed. The variable *nowork* takes the value 1, if the student did not work while studying and 0 otherwise. Working in parts during study time, that is records showing spells of work and spells of no work, is captured by the variable *partwork* and the dummy variable *fullwork* takes the value 1, if the student worked throughout the whole duration of study. Students who work presumably have less time available for studying, possibly leading to worse university grades. Therefore, the variables *partwork* and *fullwork* are expected to increase grades, with a higher quantitative effect for *fullwork*.

Students' qualifications prior to university seem to be an important predictor for university performance. At the same time, many studies report socially underprivileged students performing less well at school. A study by Sackett et al. (2009) discusses the critics that

the effect of school performance on university performance is captured by the effect of the socio-economic status at an earlier stage of education. Their results indicate that this argument is not valid. The predictive power of school performance persists even after controlling for the social background; the school-university grade relationship is only minimally affected by social background.

If disadvantages of socially underprivileged students at school extend towards university is of great importance for the underlying study. Therefore, the final grade at school, defined by the variable *sgrade*, is included in the analysis. *sgrade* takes values between 1.0 and 4.0 in steps of 0.1 and it is expected to be positively related to *ugrade* (the lower *sgrade* the lower *ugrade*). Note that higher values indicate worse grades. Prior qualifications and ability is also captured by *ahigh*, indicating if a student attended an academic high school (type of German school providing advanced secondary education) or another type of school.

Since employment experiences before studying may have an effect on academic success, the dummy variable *experience* indicates whether an individual was employed before enrolment or not. Having gained some working experience, compared to only have experienced school, might promote personal responsibility and discipline, both important for a successful study. Therefore, a negative effect on grades is expected. The same arguments hold for the variable *voctrain* indicating if a student completed a vocational training prior to attending university.

Additionally, sex (*sex*, dummy for women, males being the base category) and age at enrolment (*age*) are considered. For both the expected effect on grades is ambiguous. Two potentially opposing effects are associated with *age*. On the one hand, the older at enrolment, the more knowledge and experience a student has attained which possibly will improve grades. On the other hand, being older at enrolment could hint for some waste of time and perhaps little motivation. This may result in higher grades.

An important characteristic of study is the field of study. The original data set includes 33 fields which have been categorised into 10 fields: social sciences (*social*), economics (*econ*), law (*law*), humanities (*human*), engineering (*engin*), informatics and maths (*informath*), natural sciences (*science*), medicine (*medicine*), teaching (*teach*) and other fields of study (*other*). Not surprisingly, many studies find great differences of university performance across fields. As mean and variance of grades differ considerably between degree subjects, it is important to aggregate fields in a reasonable way.

Universities and universities of applied sciences differ considerably in the course of study and students' characteristics. Hence, the empirical analysis is based only on graduates from universities. The final sample of graduates with valid observations on all variables has 5040 observations. Table D.1 provides an overview of the variables and their definitions.

4.4 Descriptive Statistics

In Table 4.1 some statistics of university grades and the covariates are shown. The mean grade amounts approximately to 1.98. There are 60 per cent female students in the sample. The final grade at school averages at 2.15 and 88 per cent of the students attended a German academic high school before studying. 41 per cent of the students are working during their whole study time, only 8 per cent were never employed. The minority of students is coming from a household with the lowest level of parental educational attainments (9 per cent), 28 per cent are coming from a high educated background with both parents having obtained an academic degree.

	mean	min	max	std
ugrade	1.98	1	4	0.67
sex	0.60	0	1	0.49
age	20.67	13	52	2.70
sgrade	2.15	1	4	0.63
ahigh	0.88	0	1	0.32
nowork	0.08	0	1	0.28
partwork	0.51	0	1	0.50
fullwork	0.41	0	1	0.49
experience	0.32	0	1	0.47
voctrain	0.18	0	1	0.39
acad1	0.09	0	1	0.29
acad2	0.31	0	1	0.46
acad3	0.31	0	1	0.46
acad4	0.28	0	1	0.45

Table 4.1: Descriptive statistics

Table 4.2 provides an overview about how university grades differ according to the covariates. The continuous variables school grades and age at enrolment are categorised. The differences in university grades across A-level grades when splitting the sample

into three groups (A-level grades $1, 2, 3$) is noteworthy. There is a monotone increase of university grades with worsening A-level grades. Age is categorised into the following classes: age ≤ 21 (those students who are enrolled directly after school), age between $22 - 25$ (potentially students with e.g. prior vocational training who start to study subsequently), and age ≥ 26. Between these age classes and the groups of the other covariates there is only a small differences in grades with tendencies as expected for type of school (*ahigh*) and academic background. The low mean grade for *acad1* could possibly be explained by the very low group size of only 9 per cent of the whole sample size.

	mean grade
men	1.95
women	1.99
age: ≤ 21	1.96
age: 22-25	2.03
age: ≥ 26	2.02
sgrade: 1	1.62
sgrade: 2	1.96
sgrade: ≥ 3	2.20
no ahigh	2.08
ahigh	1.96
nowork	2.07
partwork	1.94
fullwork	2.00
no exp.	1.95
experience	2.02
no voctrain	1.96
voctrain	2.05
acad1	1.92
acad2	2.01
acad3	2.02
acad4	1.91

Table 4.2: Average university grade by covariates

Table 4.3 shows that grades differ considerably between fields of study. According to the means as well as the median, the lowest (best) grade is observed in science, whereas the highest (worst) grade is found for medicine and economics. The largest standard deviations are observed in medicine and humanities. In addition, Figure D.1 shows the great difference of grade distributions between fields.

	mean	median	min	max	q75-q25	std
social	1.65	1.6	1.0	3.2	0.80	0.52
econ	2.30	2.3	1.0	3.8	0.80	0.54
law	3.14	3.3	1.3	4.0	0.60	0.53
human	1.87	1.8	1.0	4.0	1.00	0.62
engin	1.96	2.0	1.0	4.0	0.80	0.54
informath	1.65	1.5	1.0	3.6	0.70	0.54
science	1.43	1.3	1.0	3.5	0.70	0.45
medicine	2.29	2.3	1.0	4.0	0.90	0.64
teach	2.00	2.0	1.0	3.8	0.80	0.57
other	1.85	1.9	1.0	4.0	0.70	0.52

Table 4.3: University grade in ten fields of study

Table 4.4 provides some information on heterogeneity in covariate effects by degree field. According to the academic background variables, there seems to be no hint for differences between fields. In the majority of fields, there is a positive relationship between grade and age (the higher age, the higher (worse) grade), exceptions are sciences and other fields of study. By far, the highest correlation ($r = 0.3$) is observed for medicine. According to school grades, there is a positive relationship to university grades for all ten fields of study, with the strongest correlation in economics, law, engineering and teaching. The dependency between these continuous variables is also presented in Figure D.2 and Figure D.3.

Another interesting fact is the relationship between school grades and parental academic background. Whereas Table 4.2 indicates that there is no or only a small difference of university grades between social origins, Table 4.5 reveals a dependency between school grades and academic background: the higher the parental level of educational attainment the better A-level grades. This is a well discussed topic in literature.

In summary, the descriptive analysis reveals some very interesting facts. I find no noteworthy differences in university grades by levels of academic origins. However, there is a high correlation between university grades and A-level grades. Furthermore, A-level grades differ considerably between levels of parental educational attainments. Students coming from a less educated household obtain on average worse school grades than students from well-educated parental backgrounds. Hence, there seem to be first hints that background effects on university success may be driven by disadvantages of socially underprivileged students on earlier levels in the course of education.

Grades differ considerably between the ten fields of study in the level but also in variation. The covariates, in particular the academic background variables, do not seem to affect university grades strongly different across fields of study.

	social	econ	law	human	engin	inf.	science	med.	teach	other
men	1.66	2.30	3.03	1.78	1.92	1.68	1.38	2.29	2.00	1.79
women	1.64	2.29	3.23	1.91	2.01	1.60	1.49	2.29	2.00	1.88
age: ≤ 21	1.63	2.27	3.12	1.84	1.96	1.65	1.43	2.18	2.00	1.85
age: 22-25	1.62	2.32	3.23	1.94	1.96	1.58	1.44	2.58	2.03	1.86
age: ≥ 26	1.71	2.65	3.29	1.95	2.02	1.86	1.18	2.79	2.06	1.77
sgrade: 1	1.33	1.98	2.69	1.60	1.62	1.36	1.20	2.02	1.61	1.55
sgrade: 2	1.61	2.20	3.16	1.82	1.93	1.71	1.49	2.31	1.89	1.82
sgrade: ≥ 3	1.75	2.54	3.35	2.10	2.24	1.88	1.70	2.62	2.25	1.97
no ahigh	1.70	2.45	3.29	2.04	2.00	1.76	1.55	2.58	2.23	1.80
ahigh	1.63	2.28	3.13	1.84	1.95	1.64	1.42	2.26	1.97	1.85
nowork	1.58	2.38	3.11	1.83	1.92	1.55	1.42	2.23	2.10	2.01
partwork	1.55	2.27	3.10	1.86	1.92	1.63	1.43	2.27	1.95	1.88
fullwork	1.71	2.31	3.23	1.88	2.03	1.70	1.44	2.34	2.04	1.78
no exp.	1.61	2.29	3.14	1.83	1.95	1.66	1.42	2.19	1.97	1.88
experience	1.70	2.31	3.15	1.93	1.99	1.64	1.47	2.46	2.06	1.79
no voctrain	1.65	2.28	3.13	1.86	1.95	1.65	1.44	2.24	1.98	1.86
voctrain	1.62	2.33	3.22	1.93	1.99	1.68	1.28	2.50	2.12	1.80
acad1	1.52	2.25	3.00	1.82	1.98	1.65	1.46	2.35	2.01	1.77
acad2	1.67	2.35	3.21	1.96	2.00	1.76	1.50	2.29	2.05	1.83
acad3	1.69	2.38	3.19	1.87	1.96	1.63	1.44	2.35	2.01	1.91
acad4	1.62	2.12	3.06	1.77	1.90	1.56	1.36	2.22	1.93	1.84

Table 4.4: Average university grade by covariates and fields of study

	mean school grade
acad1	2.26
acad2	2.27
acad3	2.16
acad4	1.96

Table 4.5: A-level by parental academic background

4.5 Methodology

A methodological issue is whether grades have to be treated as metric or ordinal in statistical models. In Germany, grades for single exams are usually given on a scale from 1.0 to 4.0 in the following manner: 1.0, 1.3, 1.7, 2.0 up to 4.0 (ten manifestations). Here, higher grades indicate worse academic performance. The final grade is an average of the obtained exam grades. Simple linear regression models assume that grades are metric. That means that the "interpretable" difference between e.g. the grades 1.0 and 1.3 is the same as between 3.7 and 4.0. However, this assumption usually does not hold in the German grading system.

Final exam grades (averages) are given in the data set on a scale from 1.0 to 4.0 in steps of 0.1 in all ten fields of study except law. In law, the grading system is based on points. For comparability, I transformed these points (and the more detailed grades for the other fields) into the usual grades mentioned above.

Because of these considerations, grades can be seen as discrete and ordinal. Thus, I use an ordered probit regression (see e.g. McKelvey and Zavoina (1975)). This model is sometimes justified by the specific assumption that there is a latent continuous metric underlying the ordinal responses observed. Thresholds partition the real line into a series of regions corresponding to the various ordinal categories. The latent continuous variable y^* is defined as:

$$y^* = \boldsymbol{\beta}'\boldsymbol{x} + \epsilon \tag{4.1}$$

We observe:

$$y = j \text{ if } u_{j-1} < y^* \leq u_j \tag{4.2}$$

with $j = 1, ..., J$, $u_0 = -\infty$ and $u_J = \infty$.

Referred to grades, the deterministic part $\boldsymbol{\beta}'\boldsymbol{x}$ reflects the linear impact of several covariates on latent students' grades y^*. These covariates are e.g. demographic characteristics as age and sex, but also the own educational and the parental background (see section Data and Variables). The stochastic part ϵ captures random influences on grades. As final

grades are an average over a number of exam grades, there might be a random process at work representing luck or bad luck for each exam.

Furthermore, in this approach latent grades y^* are seen as continuous but unobserved. The final latent grade is an average of the obtained exam grades over the whole study course, but observed are only rounded grades $y = 1.0, 1.3, 1.7, 2.0$ up to 4.0. Here, e.g. $y^* = 2.925$ but $y = 3.0$. The final observed grade y takes one of these values if a special threshold is exceeded by the unobserved metric grade y^*.

$$y = \begin{cases} 1.0, & \text{if } u_0 < y^* \leq u_1 \\ 1.3, & \text{if } u_1 < y^* \leq u_2 \\ 1.7, & \text{if } u_2 < y^* \leq u_3 \\ 2.0, & \text{if } u_3 < y^* \leq u_4 \\ \vdots & \\ 4.0, & \text{if } u_{J-1} < y^* \leq u_J \end{cases} \tag{4.3}$$

To analyse the link between several factors and each of these categories the framework of probability models is used. Since $\boldsymbol{\beta'x}$ is overlayed by an error term ϵ, assumed to be normally distributed, probabilities for each category are defined as:

$$\begin{aligned} p_j = P(y = j) &= P(u_{j-1} < y^* \leq u_j) \\ &= P(u_{j-1} < \boldsymbol{\beta'x} + \epsilon \leq u_j) \\ &= P(u_{j-1} - \boldsymbol{\beta'x} < \epsilon \leq u_j - \boldsymbol{\beta'x}) \\ &= \Phi(u_j - \boldsymbol{\beta'x}) - \Phi(u_{j-1} - \boldsymbol{\beta'x}) \end{aligned} \tag{4.4}$$

where Φ is the cumulative standard normal distribution. j takes the values 1 up to 10, indicating which grade class is under analysis (e.g. $j = 1$: grade is in the first class labelled 1.0, $j = 2$: grade is in the second class labelled 1.3 and so on).

In summary, there are 10 probabilities (because of ten grade classes) and therefore 9 thresholds u_1 up to u_9 to be estimated.

Probabilities vary with $\mathbf{x}$, hence they are often calculated at the means of covariates. Since here most of the covariates are dummy variables, an analysis of predicted probabilities only at the means is not meaningful. Therefore, average predicted probabilities are of interest:

$$\text{Avg.}(P(y_i = j)) = \frac{1}{n}\sum_i [\Phi(u_j - \boldsymbol{\beta'x_i}) - \Phi(u_{j-1} - \boldsymbol{\beta'x_i})] \tag{4.5}$$

The parameter vector and thresholds are estimated by the method of maximum likelihood. Because of an identification problem, the variance is usually fixed at one and either the first threshold or the intercept is set to zero. Which solution is chosen (here, the second alternative) does not affect the estimation of the other parameters.

For student i the probability to obtain grade $j^{'}$ is denoted by $p_{ij'}$. Note that because of $p_{ij}^0 = 1$ and

$$y_{ij} = \begin{cases} 1, & \text{if } j = j^{'} \\ 0, & \text{otherwise} \end{cases}$$

this probability can be written as: $p_{ij'} = \prod_{j=1}^{J} p_{ij}^{y_{ij}}$. The likelihood is defined as the joint probability function:

$$\text{L} = \prod_{i=1}^{N}\prod_{j=1}^{J} p_{ij}^{y_{ij}} = \prod_{i=1}^{N}\prod_{j=1}^{J} [\Phi(u_j - \boldsymbol{\beta'x}) - \Phi(u_{j-1} - \boldsymbol{\beta'x})]^{y_{ij}} \tag{4.6}$$

with $i = 1, ...N$ observed students. The log-likelihood is:

$$\ln \text{L} = \sum_{i=1}^{N}\sum_{j=1}^{J} y_{ij}\ln[\Phi(u_j - \boldsymbol{\beta'x}) - \Phi(u_{j-1} - \boldsymbol{\beta'x})] \tag{4.7}$$

The estimated coefficients are not to be interpretable directly (no partial effects), but can be used to calculate probabilities of obtaining a specific grade $P(y = j)$ for different values of $\mathbf{x}$ and marginal effects on these probabilities:

$$\frac{\partial P(y = j)}{\partial \boldsymbol{x}} = [\phi(u_{j-1} - \boldsymbol{\beta'x}) - \phi(u_j - \boldsymbol{\beta'x})]\boldsymbol{\beta} \tag{4.8}$$

where ϕ is the standard normal density function.

Again, these effects are non-linear with different effects at different values of $\mathbf{x}$. Therefore, average marginal effects are calculated:

$$\text{Avg.}\left(\frac{\partial P(y_i = j)}{\partial \boldsymbol{x}}\right) = \frac{1}{n}\sum_i [\phi(u_{j-1} - \boldsymbol{\beta'x_i}) - \phi(u_j - \boldsymbol{\beta'x_i})]\boldsymbol{\beta} \tag{4.9}$$

The effect of dummy variables is analysed by comparing the probabilities at both values 0 and 1.

4.6 Estimation Results and Discussion

The ordered probit estimation is carried out with the statistic software R and is mainly based on the package MASS (see e.g. Venables and Ripley (2002)).

To evaluate whether there is a transmission of disadvantages for students from less educated households, estimations are carried out with and without controlling for school grades. It is expected that a potentially adverse effect of *acad1* to *acad3* (in comparison to *acad4*) on university grades captures the effect of A-level grades if A-level grades are not included.

Since interpretation in ordered probit regression is not as intuitive as for linear models, an OLS regression serves as a first impression of the direction and significance of covariate effects. The included variables are coded as described in Table D.1. The dependent variable is the university grade - counterfactually treated as metric - in steps of 0.1 $(1.0, 1.1, ..., 4.0)$. A positive sign of the coefficient suggests a positive relationship between covariate and grades (the higher covariate the higher (poorer) grades). Table D.2 in the appendix shows regressions without (columns 1-3) and with controlling (columns 4-6) for A-level grades. The variables *nowork*, *acad4* and *social* serve as base categories and are omitted from the regressions. The results indicate a significantly positive effect of *acad2* and *acad3* on university grades. Students coming from less educated households obtain higher (poorer) grades in comparison to students coming from a highly educated background (*acad4*). After controlling for prior qualification (A-level grades), only the coefficient for *acad3* remains significant (at the 5 per cent level), whereas *sgrade* seems to have a high predictive power for university grades (positive relationship). Students attending a German high school before studying and male students achieve better grades than their fellow students do.

In the next step, I treat grades as discrete and ordinal. Table 4.6 shows the estimated coefficients of ordered probit regressions without (columns 1-3) and with controlling

(columns 4-6) for school grades. Again, the variables *nowork*, *acad4* and *social* serve as base categories and are omitted from the regressions. The dependent variable is the university grade categorised into ten classes as previously described. The first and fourth column of Table 4.6 (labelled value) shows the estimated coefficients for both regressions. As already mentioned, these coefficients are not to be interpretable directly. Because of the normalisation $\sigma = 1$, the magnitude of coefficients has no interpretable meaning. The effect of a change in an explanatory variable on particular probabilities depends on the magnitude of coefficients, but also on the shape of the density. The sign only shows the direction of the effect on the probability of the lowest and highest classification (see e.g. Becker and Kennedy (1992)). According to the expression of marginal effects in section 5, a positive β leads to a decline of the first probability (here, $P(Y = 1.0)$) and an increase of the last probability (here, $P(Y = 4.0)$). Notice that there is no intercept because it is set to zero for identification. The second and fifth column display the standard errors (se). Columns three and six present the associated p-values (p).

The results of the first regression indicate a negative relationship between the academic background and the probability to obtain a very good final exam grade (positive and significant coefficients for *acad2* and *acad3*). The same is true for *sex* and most of the field variables, whereas the coefficient of *ahigh* is significantly negative. A more detailed analysis of probabilities for dummy variables significantly affecting grades (except fields of study) is given in Table D.3. Predicted probabilities for obtaining one of the ten grade classes are presented. E.g. a male student, holding all other variables at their means, has a probability of 8.10 per cent to obtain a grade of 1.0 and a female student a probability of 6.07 per cent. Being a female student decreases the probabilities to obtain a grade between 1.0 and 1.7 and increases the probability of poorer grades. The situation is different for students attending an academic high school before studying; they have higher probabilities to obtain very good university grades than students from another type of school.

According to the parental educational background (with *acad4* as base category), students from less educated households obtain very good grades (1.0 up to 1.7) with a lower probability than students with both parents having obtained an academic degree. For instance, students from households with both parents having a (non-academic) professional qualification (*acad2*=1) achieve a grade of 1.0 with a probability of only 5.25 per cent in comparison to a probability of 7.65 per cent of their socially privileged fellows. For all of the ten grade classes, these differences are greater for *acad2* than

for *acad3*, indicating an increasing negative effect on educational success over social classes.

	value	se	p	value	se	p
sex	0.1501	0.0315	0.0000	0.1879	0.0317	0.0000
age	0.0065	0.0068	0.3377	-0.0089	0.0068	0.1940
sgrade				0.6378	0.0257	0.0000
ahigh	-0.2447	0.0486	0.0000	-0.3346	0.0489	0.0000
partwork	-0.0668	0.0545	0.2205	-0.0313	0.0547	0.5668
fullwork	-0.0059	0.0563	0.9167	-0.0543	0.0565	0.3372
experience	0.0624	0.0346	0.0713	0.0525	0.0347	0.1306
voctrain	-0.0605	0.0478	0.2059	-0.1135	0.0480	0.0180
acad1	0.0155	0.0564	0.7830	-0.1076	0.0568	0.0581
acad2	0.1925	0.0384	0.0000	0.0612	0.0389	0.1154
acad3	0.1719	0.0378	0.0000	0.0817	0.0381	0.0320
econ	1.2744	0.0781	0.0000	1.3859	0.0785	0.0000
law	2.6979	0.0895	0.0000	2.9920	0.0910	0.0000
human	0.4594	0.0703	0.0000	0.5699	0.0707	0.0000
engin	0.7067	0.0710	0.0000	0.8325	0.0714	0.0000
informath	0.1273	0.0855	0.1365	0.3354	0.0862	0.0001
science	-0.3614	0.0775	0.0000	-0.1231	0.0784	0.1163
medicine	1.2504	0.0803	0.0000	1.5418	0.0814	0.0000
teach	0.7104	0.0683	0.0000	0.7294	0.0685	0.0000
other	0.4522	0.0712	0.0000	0.4918	0.0714	0.0000
u1	-0.7227	0.1782	0.0001	0.2025	0.1826	0.2676
u2	-0.0391	0.1777	0.8257	0.9284	0.1825	0.0000
u3	0.5928	0.1778	0.0009	1.6061	0.1830	0.0000
u4	1.1983	0.1781	0.0000	2.2525	0.1837	0.0000
u5	1.6349	0.1784	0.0000	2.7180	0.1843	0.0000
u6	2.2104	0.1794	0.0000	3.3352	0.1858	0.0000
u7	2.7213	0.1815	0.0000	3.8831	0.1884	0.0000
u8	3.3413	0.1859	0.0000	4.5402	0.1934	0.0000
u9	4.0775	0.1990	0.0000	5.3201	0.2076	0.0000

Table 4.6: Results of ordered probit regression

Except *age* all other covariates are dummy variables. Therefore, an analysis of predicted probabilities only at the means of covariates is not meaningful. Table D.4 displays average predicted probabilities as described in section 5. The results give a similar picture as in Table D.3. On average, coming from an less educated background - with a greater effect for the lower social class - decreases probabilities of very good university grades and

increases probabilities for poorer grades[4].

Furthermore, in the regression all threshold parameters, except u_2, are significant at least at the 1 per cent level. A higher aggregation of grades does not seem to be useful.

To control for prior qualification in the second regression, the A-level grade (*sgrade*) is included. The coefficient is positive and highly significant, denoting a probability decreasing effect of obtaining very good university grades with worsening A-level grades. An illustration of probabilities for grade classes with varying school grades (everything else held constant at their means) is given in Figure D.4. As the positive coefficient already indicates, the probabilities for the lower grade classifications decrease and the probabilities for the higher classifications increase with worsening A-level grades. Average probabilities are shown in Figure D.5, which resembles the figure before.

The marginal effects at the means (of all variables) of an one unit change of A-level grade on the ten probabilities, as shown in Table 4.7, are negative for the first three probabilities and positive for the remaining probabilities.

	marginal effect
P(y=1.0)	-0.0720
P(y=1.3)	-0.1033
P(y=1.7)	-0.0748
P(y=2.0)	0.0213
P(y=2.3)	0.0631
P(y=2.7)	0.0884
P(y=3.0)	0.0487
P(y=3.3)	0.0227
P(y=3.7)	0.0053
P(y=4.0)	0.0005

Table 4.7: Marginal effects at the means

Figure D.6 presents the non-linear marginal effects of varying A-level grades (everything else held constant at their means) on the predicted probabilities. E.g. for the first grade class the negative effect on the probability decreases with worsening grades. Average marginal effects of varying A-level grades, as shown in Figure D.7, are very similar.

[4]The overall trend of the results is robust towards other specifications, i.e. calculations of the probabilities at different values of $\mathbf{x}$.

The coefficient for *acad2* becomes insignificant after controlling for A-level grades, the coefficient for *acad3* remains significant at the 5 per cent level. Differences between lower and higher social classes seem to be captured by prior qualifications on an earlier stage of the educational career. The effect of students' academic background on own academic attainments only remains important between higher levels of social origin. The predicted probabilities for *acad3* in Table D.5 indicate a diminished effect of students' social background on university grades (smaller differences between *acad3*=1 and *acad3*=0 as in Table D.3).

Table D.6 presents average predicted probabilities. The results give a similar picture as in Table D.5. On average, coming from a less educated background decreases probabilities of very good university grades and increases probabilities for poorer grades.

Now, all threshold parameters, except u_1, are significant at least at the 1 per cent level.

The descriptive analysis reveals no differences of the impact of students' social origins between degree subjects. Nevertheless, Table D.7 in the appendix presents regressions with interactions between fields and academic background variables. For the lack of space, the thresholds are omitted from the table. As expected almost none of the interaction coefficients are significant. A likelihood ratio test indicates no significant contribution of these interactions to the model either. Hence, I do not present a detailed analysis of interaction effects, which is not as intuitive as in linear models (for more details see Ai and Norton, 2003).

In summary, the probability to obtain a grade of 1.0 up to 1.7 is higher for students with a privileged social background, whereas the probability for poorer grades is higher for socially underprivileged students. After controlling for A-level grades, this effect vanishes for the lower level of parental academic background (*acad2*) and diminishes for students from higher educated households (*acad3*). A-level grades seem to have highly predictive power for university grades (positive relationship).

4.7 Conclusion

This paper examines the effect of students' social background on their academic performance, measured as final exam grades at university. University grades are of considerable importance as they serve as signals for qualification and motivation on the labour market and are part of political debates on the social selectivity of the German academic system.

The literature on the interrelationship between social background and university grades is sparse, especially for Germany. More attention is paid to performance at school. This study is aimed to at least partly fill this gap.

As one of the most important studies, the PISA study, reports a strong disadvantage for socially underprivileged students on the school level, I analyse whether these disadvantages extend towards university. Beside the educational background of parents, students' own educational background, in particular the A-level grade, is of great importance. A-level grades are more and more a topic in debates on selection criteria of universities and on their usefulness as a signal for future academic performance.

A methodological issue is whether grades should be treated as metric or ordinal in statistical models. In the German grading system, final university grades can be characterised as discrete outcomes of an underlying continuous process. Hence, I treat grades as discrete and ordinal and use an ordered probit regression without and with controlling for students' prior qualification.

A first descriptive analysis reveals a rather strong positive relationship between A-level and university grades. I find no noteworthy differences in university grades by levels of academic origins. However, A-level grades differ considerably between levels of parental educational attainments. Students coming from a less educated household obtain on average poorer school grades than students from well-educated parental backgrounds.

University grades differ considerably between the ten fields of study in the level but also in variation. The covariates, in particular the academic background variables, do not seem to affect university grades strongly different between fields of study.

The results of the ordered probit regressions confirm these descriptive findings. Without controlling for prior qualification, the probability to obtain a grade of 1.0 up to 1.7 is higher

for students with a privileged social background, whereas the probability for poorer grades is higher for socially underprivileged students. After controlling for A-level grades, this effect vanishes for the lower level of parental academic background (*acad2*) and diminishes for students from higher educated households (*acad3*).

As a main result I find that the strong effect of academic background on A-level performance does not carry over to performance at university in its entirety. One can conclude that background effects on university performance may be mainly driven by disadvantages of socially underprivileged students on earlier levels in the course of education.

4.8 References

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4.9 Appendix

Variable (subset)	Definition
characteristics of study:	
ugrade	final grade of first university degree: 1.0, 1.1, ..., 4.0
social	studying a field of social sciences
econ	studying a field of economics
law	studying a field of law
human	studying a field of humanities
engin	studying a field of engineering
informath	studying a field of informatics or maths
science	studying a field of natural sciences
medicine	studying a field of medicine
teach	studying for teachers training certificate
other	studying other fields
personal characteristics:	
sex	1 if female, 0 otherwise
age	age at enrollment
sgrade	final grade at school: 1.0, 1.1, ..., 4.0
ahigh	having attended an academic high school (Gymnasium): 1 if true, 0 otherwise
nowork	no employment during study time: 1 if true, 0 otherwise
partwork	employment during parts of study time: 1 if true, 0 otherwise
fullwork	employment through whole study time: 1 if true, 0 otherwise
experience	employment experience before studying: 1 if true, 0 otherwise
voctrain	vocational training before studying: 1 if true, 0 otherwise
parental characteristics:	
acad1	1 only one one parent has a (non-academic) professional qualification, 0 otherwise
acad2	1 if both parents have a (non-academic) professional qualification, 0 otherwise
acad3	1 if one parent has an academic degree, 0 otherwise
acad4	1 if both parents have an academic degree, 0 otherwise

Table D.1: Variables of the data set

	value	se	p	value	se	p
intercept	1.5528	0.0944	0.0000	1.0612	0.0907	0.0000
sex	0.0736	0.0167	0.0000	0.0871	0.0157	0.0000
age	0.0036	0.0036	0.3242	-0.0044	0.0034	0.1951
sgrade				0.3222	0.0124	0.0000
ahigh	-0.1266	0.0260	0.0000	-0.1636	0.0244	0.0000
partwork	-0.0409	0.0290	0.1580	-0.0219	0.0272	0.4199
fullwork	-0.0056	0.0300	0.8507	-0.0308	0.0282	0.2742
experience	0.0343	0.0184	0.0629	0.0269	0.0173	0.1195
voctrain	-0.0300	0.0255	0.2392	-0.0557	0.0240	0.0202
acad1	0.0134	0.0299	0.6535	-0.0501	0.0282	0.0760
acad2	0.1090	0.0204	0.0000	0.0361	0.0194	0.0625
acad3	0.0941	0.0201	0.0000	0.0420	0.0190	0.0268
econ	0.7037	0.0410	0.0000	0.7182	0.0385	0.0000
law	1.5459	0.0443	0.0000	1.6035	0.0416	0.0000
human	0.2492	0.0371	0.0000	0.2902	0.0349	0.0000
engin	0.3689	0.0375	0.0000	0.4098	0.0352	0.0000
informath	0.0725	0.0451	0.1078	0.1757	0.0425	0.0000
science	-0.1471	0.0404	0.0003	-0.0139	0.0383	0.7161
medicine	0.6873	0.0422	0.0000	0.7932	0.0398	0.0000
teach	0.3751	0.0360	0.0000	0.3624	0.0338	0.0000
other	0.2308	0.0377	0.0000	0.2370	0.0354	0.0000

Table D.2: Results of OLS regression

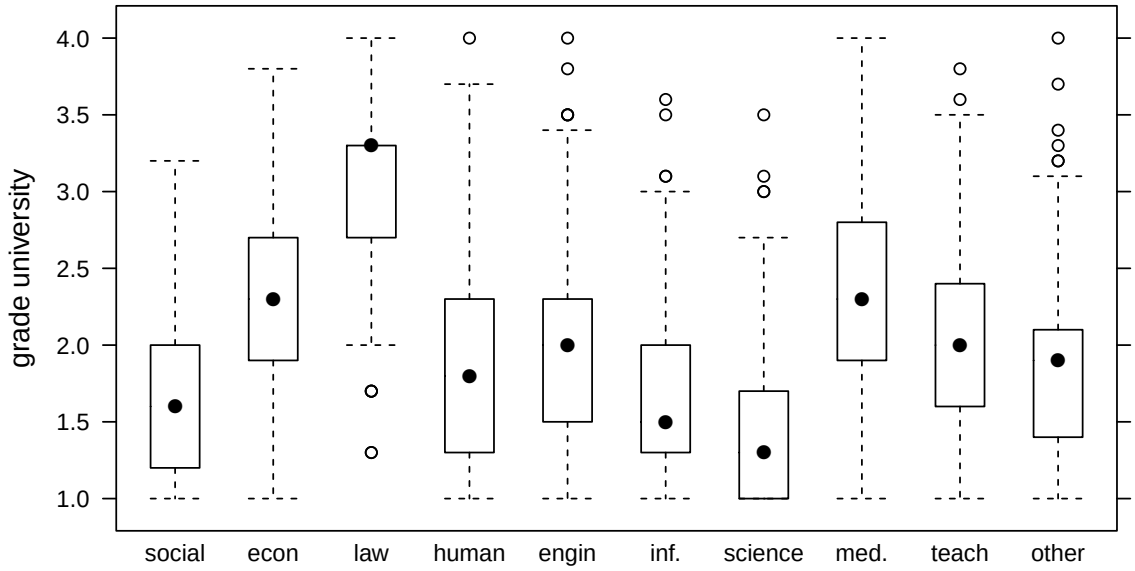

Figure D.1: Distribution of grade by fields of study

	P(y=1.0)	P(y=1.3)	P(y=1.7)	P(y=2.0)	P(y=2.3)	P(y=2.7)	P(y=3.0)	P(y=3.3)	P(y=3.7)	P(y=4.0)
male	0.0810	0.1563	0.2296	0.2324	0.1319	0.1063	0.0420	0.0166	0.0035	0.0003
female	0.0607	0.1327	0.2143	0.2374	0.1456	0.1262	0.0541	0.0231	0.0054	0.0006
ahigh=0	0.0441	0.1094	0.1949	0.2371	0.1575	0.1473	0.0687	0.0319	0.0082	0.0010
ahigh=1	0.0721	0.1465	0.2238	0.2351	0.1377	0.1144	0.0468	0.0190	0.0042	0.0004
acad2=0	0.0765	0.1515	0.2268	0.2338	0.1348	0.1102	0.0443	0.0177	0.0038	0.0004
acad2=1	0.0525	0.1217	0.2057	0.2379	0.1514	0.1360	0.0606	0.0269	0.0065	0.0007
acad3=0	0.0756	0.1505	0.2262	0.2341	0.1354	0.1111	0.0448	0.0180	0.0039	0.0004
acad3=1	0.0540	0.1238	0.2074	0.2379	0.1503	0.1341	0.0593	0.0261	0.0063	0.0007

Table D.3: Probabilities for grade classes

	P(y=1.0)	P(y=1.3)	P(y=1.7)	P(y=2.0)	P(y=2.3)	P(y=2.7)	P(y=3.0)	P(y=3.3)	P(y=3.7)	P(y=4.0)
male	0.1195	0.1609	0.2046	0.1960	0.1136	0.1016	0.0512	0.0316	0.0152	0.0057
female	0.0953	0.1429	0.1959	0.2013	0.1236	0.1157	0.0606	0.0381	0.0188	0.0076
ahigh=0	0.0740	0.1238	0.1838	0.2036	0.1329	0.1310	0.0715	0.0460	0.0232	0.0101
ahigh=1	0.1089	0.1533	0.2015	0.1989	0.1181	0.1074	0.0549	0.0340	0.0165	0.0064
acad2=0	0.1148	0.1570	0.2027	0.1971	0.1158	0.1046	0.0531	0.0328	0.0159	0.0061
acad2=1	0.0855	0.1340	0.1902	0.2024	0.1280	0.1229	0.0657	0.0417	0.0208	0.0088
acad3=0	0.1134	0.1561	0.2024	0.1977	0.1165	0.1054	0.0536	0.0330	0.0159	0.0061
acad3=1	0.0872	0.1354	0.1912	0.2025	0.1274	0.1218	0.0648	0.0410	0.0203	0.0084

Table D.4: Average probabilities for grade classes

	P(y=1.0)	P(y=1.3)	P(y=1.7)	P(y=2.0)	P(y=2.3)	P(y=2.7)	P(y=3.0)	P(y=3.3)	P(y=3.7)	P(y=4.0)
male	0.0700	0.1566	0.2445	0.2459	0.1337	0.1005	0.0351	0.0116	0.0020	0.0001
female	0.0481	0.1261	0.2232	0.2530	0.1525	0.1263	0.0491	0.0181	0.0035	0.0003
ahigh=0	0.0297	0.0935	0.1919	0.2504	0.1703	0.1581	0.0698	0.0292	0.0065	0.0006
ahigh=1	0.0605	0.1443	0.2368	0.2497	0.1414	0.1104	0.0402	0.0139	0.0025	0.0002
acad3=0	0.0589	0.1421	0.2353	0.2502	0.1428	0.1123	0.0412	0.0144	0.0026	0.0002
acad3=1	0.0499	0.1290	0.2256	0.2526	0.1508	0.1237	0.0476	0.0174	0.0033	0.0003

Table D.5: Probabilities for grade classes (contolling for A-level)

	P(y=1.0)	P(y=1.3)	P(y=1.7)	P(y=2.0)	P(y=2.3)	P(y=2.7)	P(y=3.0)	P(y=3.3)	P(y=3.7)	P(y=4.0)
male	0.1226	0.1618	0.2058	0.1949	0.1124	0.1008	0.0506	0.0308	0.0148	0.0055
female	0.0940	0.1410	0.1957	0.2011	0.1240	0.1174	0.0616	0.0384	0.0190	0.0078
ahigh=0	0.0671	0.1160	0.1786	0.2028	0.1358	0.1377	0.0765	0.0493	0.0251	0.0112
ahigh=1	0.1106	0.1532	0.2021	0.1983	0.1176	0.1075	0.0547	0.0335	0.0163	0.0062
acad3=0	0.1089	0.1515	0.2011	0.1986	0.1185	0.1089	0.0557	0.0341	0.0165	0.0063
acad3=1	0.0969	0.1425	0.1963	0.2008	0.1234	0.1162	0.0606	0.0375	0.0184	0.0074

Table D.6: Average probabilities for grade classes (controlling for A-level grade)

	value	se	p	value	se	p
sex	0.1543	0.0317	0.0000	0.1927	0.0319	0.0000
age	0.0067	0.0068	0.3250	-0.0087	0.0069	0.2031
sgrade				0.6480	0.0259	0.0000
ahigh	-0.2366	0.0489	0.0000	-0.3272	0.0492	0.0000
partwork	-0.0925	0.0548	0.0913	-0.0560	0.0550	0.3084
fullwork	-0.0188	0.0566	0.7402	-0.0668	0.0568	0.2399
experience	0.0657	0.0347	0.0585	0.0554	0.0348	0.1117
voctrain	-0.0702	0.0480	0.1436	-0.1243	0.0482	0.0099
acad1	-0.3331	0.2144	0.1202	-0.4874	0.2151	0.0234
acad2	0.0580	0.1582	0.7140	-0.0944	0.1587	0.5519
acad3	0.1115	0.1745	0.5229	0.0973	0.1749	0.5783
econ	1.0166	0.1694	0.0000	1.1698	0.1699	0.0000
law	2.6510	0.1709	0.0000	2.9456	0.1720	0.0000
human	0.2960	0.1534	0.0536	0.3972	0.1539	0.0098
engin	0.6449	0.1500	0.0000	0.7860	0.1505	0.0000
informath	-0.1061	0.1762	0.5472	0.1031	0.1771	0.5606
science	-0.5579	0.1582	0.0004	-0.2977	0.1592	0.0616
medicine	1.1309	0.1603	0.0000	1.4448	0.1613	0.0000
teach	0.5959	0.1509	0.0001	0.6095	0.1513	0.0001
other	0.4887	0.1538	0.0015	0.5596	0.1543	0.0003
acad1*econ	0.5860	0.2794	0.0360	0.6090	0.2802	0.0297
acad1*law	0.1946	0.3254	0.5498	0.2958	0.3263	0.3646
acad1*human	0.3227	0.2604	0.2152	0.3639	0.2612	0.1635
acad1*engin	0.3873	0.2662	0.1456	0.3960	0.2669	0.1379
acad1*informath	0.5559	0.3011	0.0648	0.5910	0.3022	0.0505
acad1*science	0.4875	0.2861	0.0884	0.5241	0.2873	0.0681
acad1*medicine	0.5554	0.3035	0.0672	0.5198	0.3042	0.0875
acad1*teach	0.4250	0.2532	0.0933	0.5055	0.2539	0.0465
acad1*other	0.0837	0.2638	0.7510	0.0723	0.2646	0.7848
acad2*econ	0.2920	0.2073	0.1589	0.2743	0.2078	0.1870
acad2*law	0.2314	0.2189	0.2905	0.2333	0.2195	0.2878
acad2*human	0.2739	0.1897	0.1488	0.3214	0.1903	0.0912
acad2*engin	0.0681	0.1855	0.7136	0.1118	0.1861	0.5478
acad2*informath	0.3965	0.2261	0.0795	0.4096	0.2270	0.0712
acad2*science	0.3056	0.2008	0.1281	0.3075	0.2018	0.1276
acad2*medicine	0.0791	0.2125	0.7096	0.0858	0.2131	0.6873
acad2*teach	0.1358	0.1841	0.4607	0.1902	0.1846	0.3029
acad2*other	-0.1374	0.1892	0.4677	-0.1472	0.1898	0.4379
acad3*econ	0.3196	0.2197	0.1457	0.1955	0.2203	0.3748
acad3*law	0.1228	0.2264	0.5875	0.1123	0.2271	0.6209
acad3*human	0.0737	0.2038	0.7178	0.0270	0.2044	0.8948
acad3*engin	-0.0205	0.1979	0.9175	-0.1243	0.1984	0.5311
acad3*informath	0.1231	0.2355	0.6012	0.0843	0.2365	0.7214
acad3*science	0.0978	0.2128	0.6458	-0.0007	0.2137	0.9972
acad3*medicine	0.0899	0.2166	0.6782	0.0133	0.2171	0.9511
acad3*teach	0.0179	0.1986	0.9283	-0.0642	0.1992	0.7471
acad3*other	-0.0299	0.2069	0.8850	-0.1337	0.2075	0.5195

Table D.7: Results of ordered probit regression with interactions

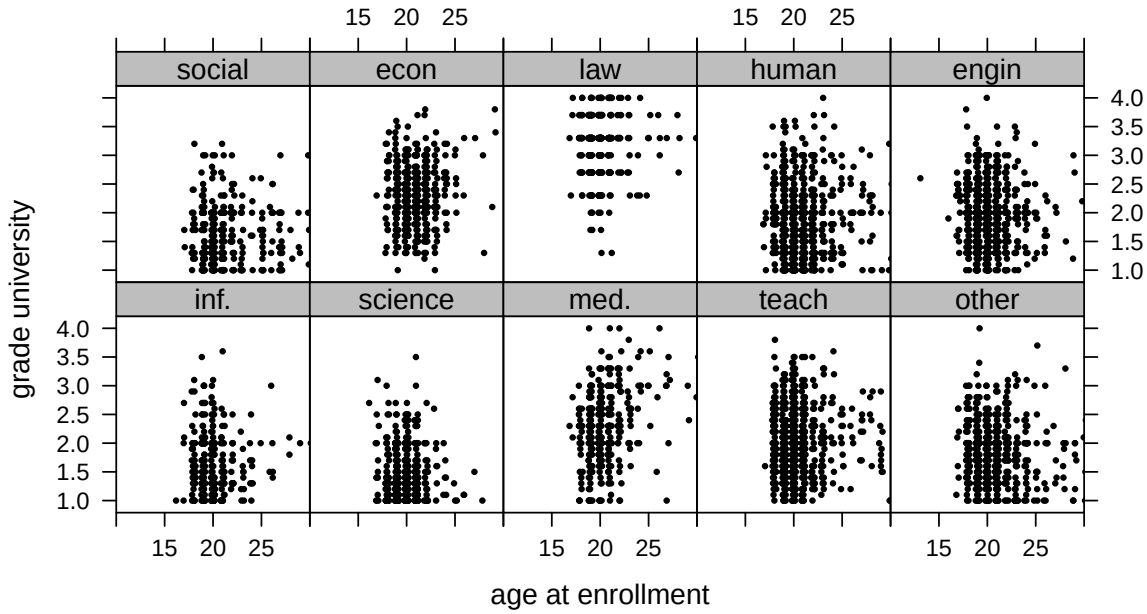

Figure D.2: Dependency age at enrollment and grade at university

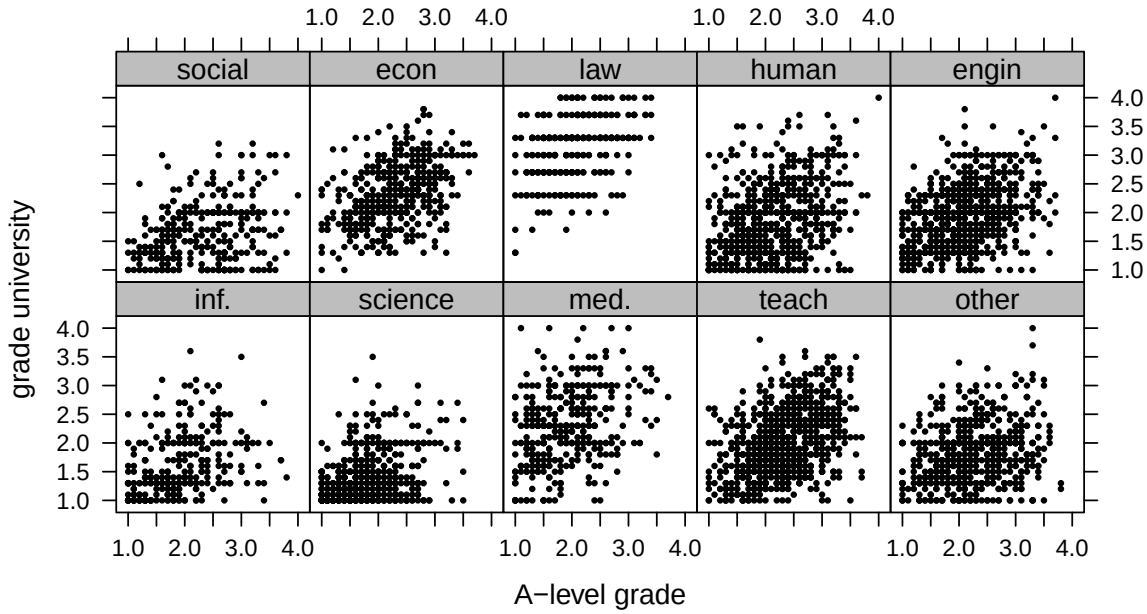

Figure D.3: Dependency A-level grade and grade at university

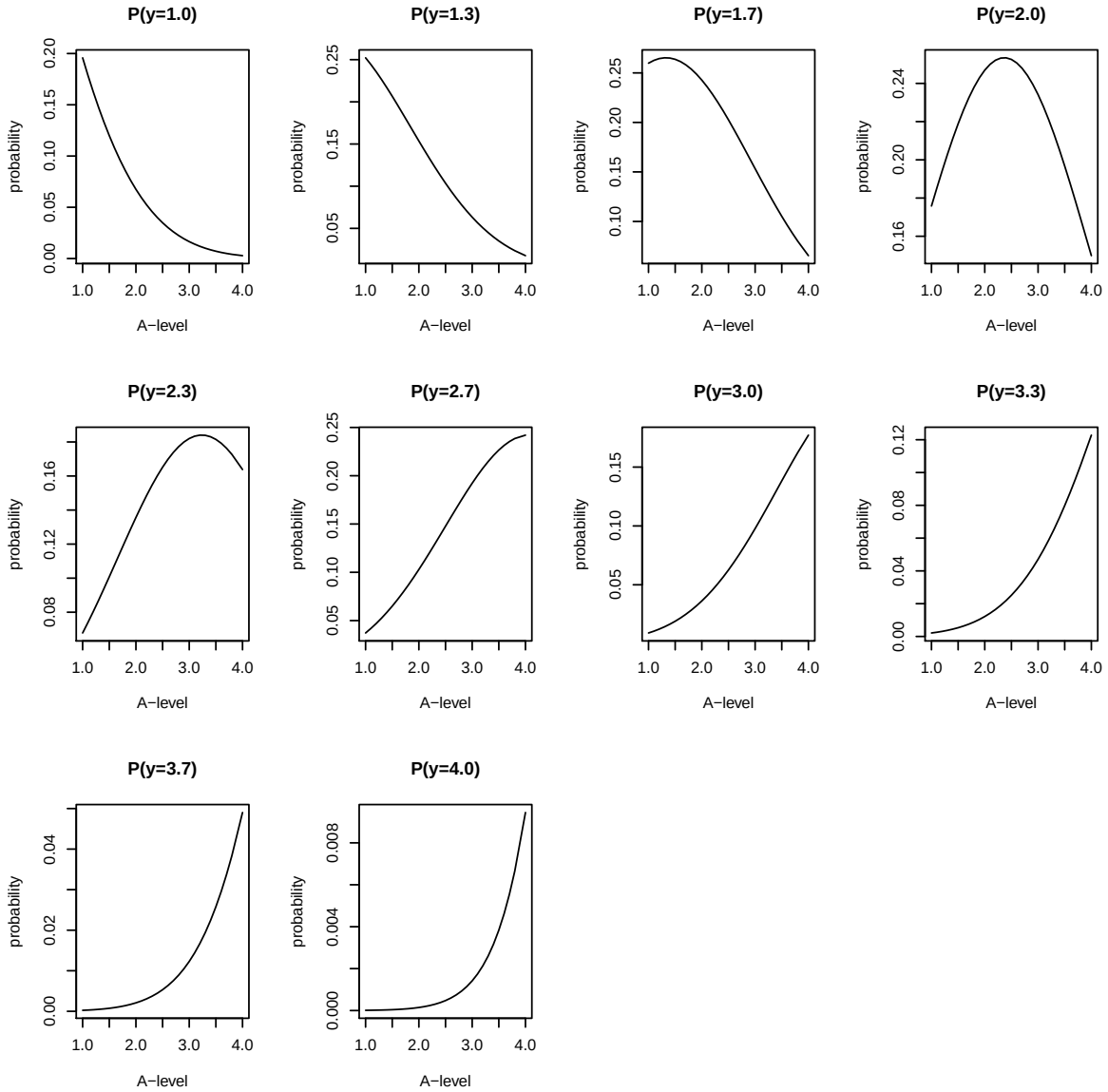

Figure D.4: Probabilities for grade classes at different A-level grades

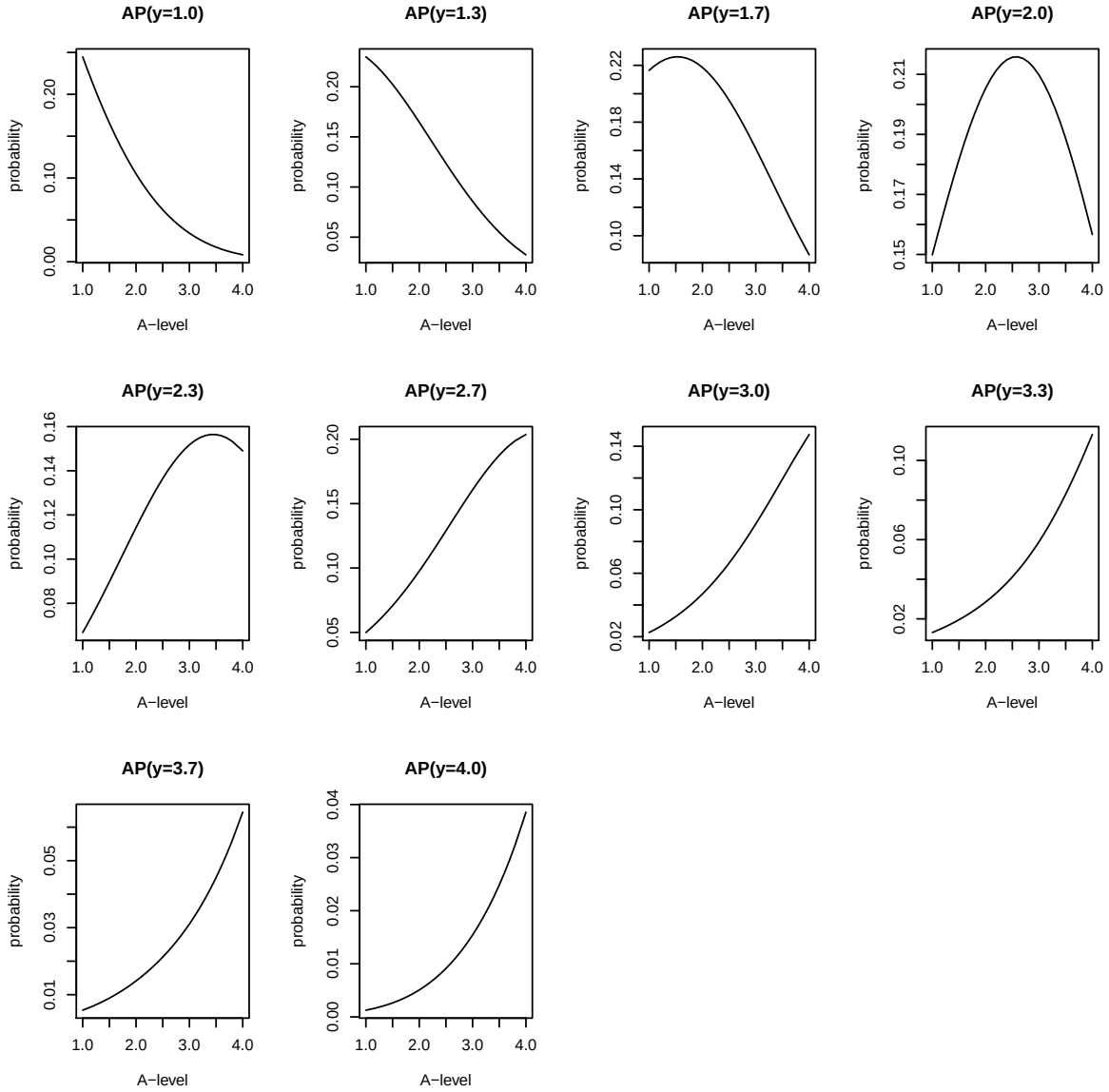

Figure D.5: Average probabilities for grade classes at different A-level grades

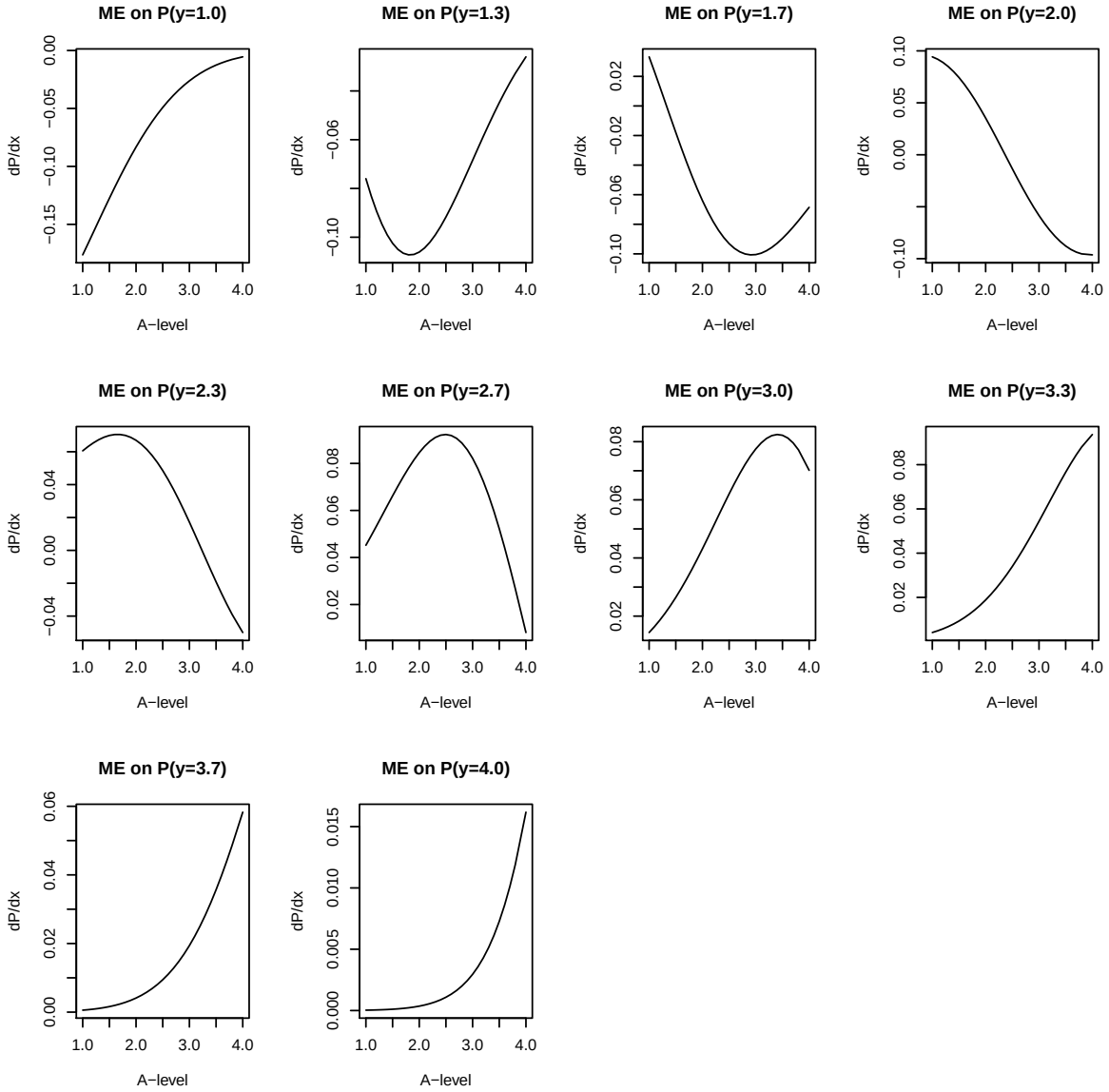

Figure D.6: Marginal effect of A-level grade on probabilities for grade classes

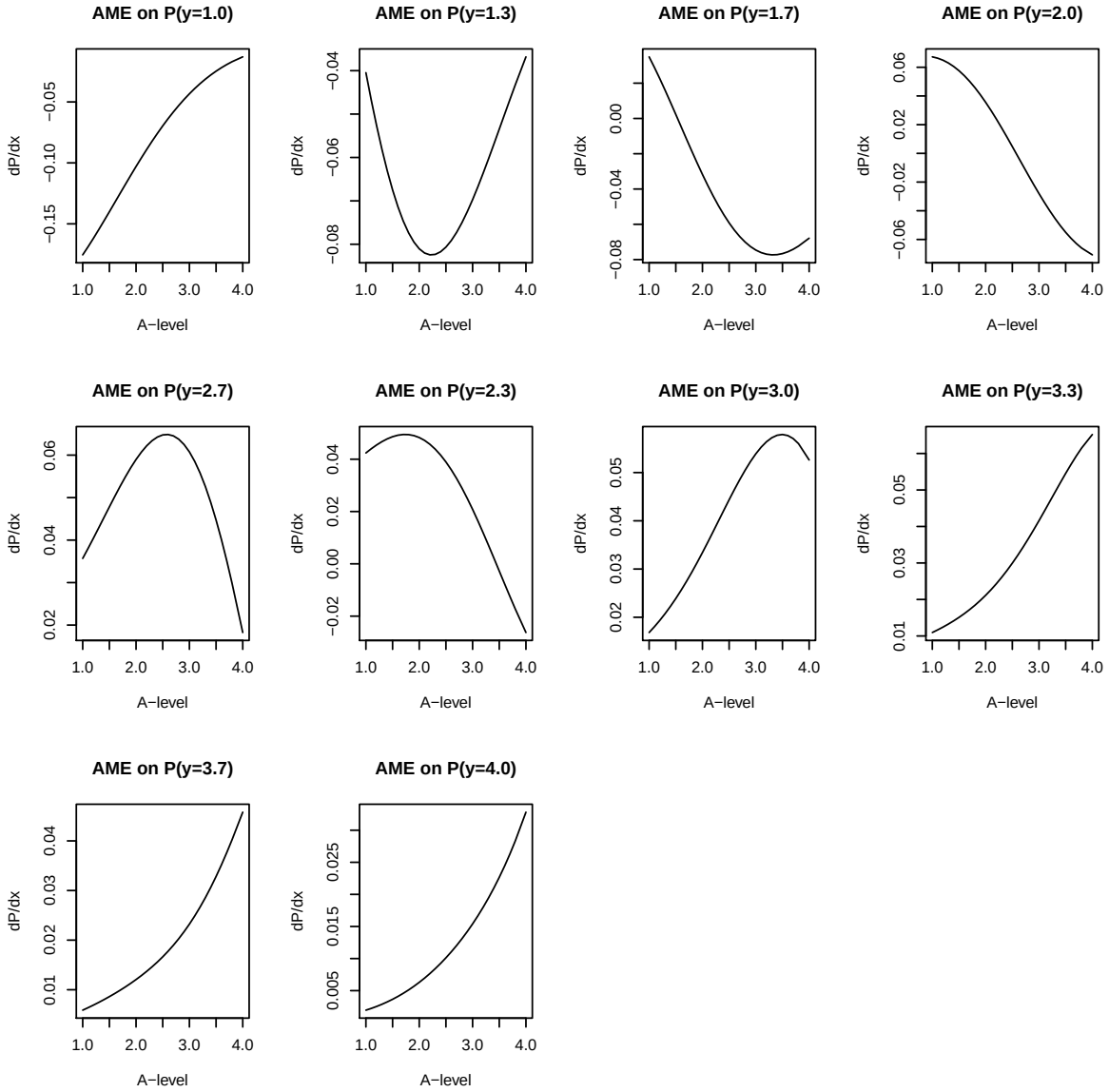

Figure D.7: Average marginal effect of A-level grade on probabilities for grade classes

5

The Gender Pay Gap at Labour Market Entrance: Evidence for Germany

The Gender Pay Gap at Labour Market Entrance: Evidence for Germany

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Abstract

The main purpose of this paper is to investigate wage differentials between German male and female graduates at labour market entrance. During the last three decades the decomposition method originally suggested to explain differences in mean wages has been considerably extended. In more recent approaches the focus has turned towards analysing complete income distributions and differences between group's incomes at all percentiles. We discuss in detail and apply a single index approach suggested by DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1998). The pay gap is decomposed in endowment, price and return-to-skill function effects. These isolated differences are calculated at all percentiles of the wage distribution. Our results reveal higher starting salaries for men at all percentiles of the income distribution, with varying magnitude of the gender pay gap. We observe the endowment and price effect to be favourable for men throughout. The effect of the difference in the return-to-skill function advantages female graduates.

JEL classification: J31; J24
Keywords: labour market entry, gender pay gap, single index model

5.1 Introduction

It is well known that in most industrialized countries wages for women are lower than those for men. While numerous studies analyse gender pay differentials in general, the literature on gender pay gaps of graduates at career entry is rather scarce and this paper tries to partly fill this gap by providing evidence for Germany.

Analysing entry wages is important for various reasons. Gerhart (1990) claims that current salary differentials are to a great extend a result of starting salary differentials. Moreover, pay rises and other forms of payment are often based on current salaries (see Graham, Hotchkiss, and Gerhart (2000)). Hence, starting wage differences between men and women can be assumed to be persistent in time.

At labour market entry, experience and human capital endowments are similar for men and women, but later in their careers women on average tend to acquire less human capital than men because e.g. of child bearing and parenting. Analysing entry wages, which are basically free of these divergences in accumulation of work experience, allows to focus on the effect of study performance, choices of field of study and further individual characteristics.

Many attempts have been made in the empirical economic literature to explain income differences between groups, e.g. men and women or between countries. This strand of literature is strongly connected to the original works of Oaxaca (1973) and Blinder (1973). In the Oaxaca-Blinder decomposition mean income differences are decomposed into differences in average characteristics and differences in prices of characteristics based on estimates of Mincerian earnings equations. During the last three decades the decomposition method originally suggested has been considerably extended. In more recent approaches the focus has turned towards analysing complete income distributions and differences between groups' incomes at all percentiles.

The approach used in this analysis has been suggested by DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1998) and can be classified as a single skill index model. Through using an ordered probit model, a flexible returns-to-skill function is estimated which transforms skills monotonically into wages. Comparing two wage distributions, single index approaches allow the estimation of isolated effects of differences in characteristics, in prices of characteristics, in skills and in the wage structure.

Suen (1997) has convincingly argued that decomposition approaches should allow to differentiate thoroughly between changes in skills and changes in the wage structure (see also Yun (2009)). Separating these effects is the main analytical gain of the applied non-parametric decomposition techniques suggested by Fortin and Lemieux (1998).[1] Additionally, these decomposition approaches lead very naturally to estimates of the isolated components of wage differences at all percentiles of the wage distribution.

The single index models can be seen as a generalization of the standard human capital-competitive markets model of wage determination. The basic assumptions are that in the labour market relevant skills are priced by means of a returns-to-skill function and that relevant skills can be measured by a skill index. The skill index itself can be thought of as a weighted aggregation of individual labour market relevant characteristics. Introducing the notion of a skill index allows to disentangle changes in the relative importance of observed characteristics, e.g. increasing importance of higher education or less importance of general working experience, from changes in the wage structure. Changes in the wage structure are defined as general shifts in the pricing function (returns-to-skill function) of skills, e.g. rising inequality through higher labour market valuation of skills, leaving worker's relative positions in the wage distribution, which are determined by the amount of skills, unchanged. Technically, introducing the notion of a skill index increases the flexibility of modeling the relation between observed characteristics and observed wages considerably through inserting a latent skill index.

A comprehensive theoretical discussion of decomposition methods in economics is provided by Fortin, Lemieux, and Firpo (2011). A detailed comparison and empirical application of four different approaches is given by Behr (2014) for the two-country case (USA and Germany).

Because of the assumed persistence of pay differentials at labour market entry, its detailed analysis can help to understand the causes and origins of observed gender pay gaps.

The paper is organized as follows: the second section provides a brief overview of the relevant literature on the gender pay gap for graduates' entry wages. In section 3 we discuss the data base and the variables used in the analysis, followed by a first descriptive analysis. Section 4 presents some basic results of wage equations and the Oaxaca-Blinder decomposition approach. In section 5 we describe the estimation methodology based on a

[1] An alternative single index approach has been suggested by Donald, Green, and Paarsch (2000).

single skill index model and the empirical implementation in some detail and present the empirical results. Section 6 concludes.

5.2 Literature Review

There exists a large body of literature on the gender pay gap. As we focus on graduates' wages at labour market entry, we present only an overview of studies closely related to this issue. While there is consensus about the existence of a pay gap in graduates' starting salaries, the empirical findings on the extent of the gap vary considerably, depending on the country analysed as well as on the specific data sets used. E.g., some studies are confined to one university or one filed of study only.

An early research work by Gerhart (1990) examines starting and current salaries of employees in the US. The data base are firm-level data of employees hired by private firms between 1976 and 1986. Annual starting and current salaries[2] are modelled using experiences, education degree, college major and year of hire as covariates. The regression for current wages additionally includes tenure, job title and job performance. Gerhart identifies a raw starting salary ratio, defined as mean wage for women divided by mean wage for men, for college graduates of 0.89. Differences in the covariates account for 58% of the observed wage gap. The adjusted ratio - i.e. ratio that would exist if men and women had equal averages for all covariates - amounts to 0.96. Wage regressions for males and females and standard decomposition techniques reveal that education degrees earn a higher premium for male graduates and that men obtain greater salary returns to potential experience than women. About 43% of the gender pay gap can be attributed towards different college majors. Current and starting pay differentials are found to be strongly correlated and the wage gap at firm entry slightly narrowed in subsequent years.

Fuller and Schoenberger (1991) investigate the impact of academic achievement, intern ship experience, and college major on the gender gap in starting salaries of 230 US business college graduates. The results suggest significant positive effects on starting salaries for a major in accountancy, higher grade point averages, and intern ship experiences. Female graduates earn on average 7% less than their male counterparts do. In contrast to

[2] As it is common to use log-wages for regression analysis, we do not explicitly refer to the logarithm in this literature review.

Gerhart (1990), Fuller and Schoenberger find the gap to widen and the significance of wage determinants to diminish over time.

Joy (2003) used data from the National Center for Education and Statistics Baccalaureate and Beyond Longitudinal Study 1993/94 to search for factors causing wage differences between recent male and female college graduates in US. The study analyses the impact of labour market variables on the gender pay gap focusing on educational factors, occupational/industrial factors, and job characteristics. The results of standard Oaxaca-Blinder decomposition techniques indicate a strong effect of differences in the occupational structure of male and female graduates on the wage gap. The ratio of average wages is 0.86 and 25% of the wage gap can be attributed towards differences in the explanatory variables, whereof labour market variables account for a larger share of the gender gap than education variables. The largest part of the gap is attributed towards differences in industry and sectoral structure. Job characteristics seem to have only negligible effects on the gender wage gap. Different majors account for only 1% of the wage gap. This finding contrasts with the findings of Gerhart (1990).

McDonald and Thornton (2007) analyse the gender gap in starting salary offers for new college graduates in US between 1969-2001, emphasizing the role of majors and job offers. They find a gender salary offer ratio of 0.9, which varies only slightly over the years. Using simulation techniques they explore what overall female-male starting pay ratios would have been observed, if women had the same distribution of offers by major as men. The results indicate an increasing ratio up to 0.99 in most years which leads the authors to conclude that the wage gap can be almost completely be attributed to gender differences in majors and number of offers.

Graham, Hotchkiss, and Gerhart (2000) try to disentangle several types of discrimination and differentiate effects between and within firms. They use a sample of 951 US bachelor graduates and find a raw starting salary ratio of 0.91. A decomposition of the gender entry wage gap reveals that 64% of the difference is due to endowment effects, mainly driven by employer characteristics. These findings correspond to the results obtained by Joy (2003). Graham, Hotchkiss, and Gerhart (2000) also find that within firms, the field of study plays an important role for wage differences between men and women. Furthermore, the authors find that 36% of the gap is due to employers paying lower entry wages to women within the same firm and with the same qualification as men (coefficient effect). Effects of different job placements of men and women within firms seem negligible.

The authors identify the differences between women and men in their choice of field of study as the main cause of the gender wage gap.

Focusing on differences in market expectations and job search strategies between male and female US university graduates, Orazem, Werbel, and McElroy (2003) find women to have considerably lower pay expectations than men before entering the labour market, which in turn leads to lower starting wages. Male graduates' starting pay exceeds female starting pay by 11%. Expected pay for men is about 7% higher than for women and explains 27% of the gender pay gap. In summary, differences in expected entry wages and in job search strategies explain 37% of the gender starting pay gap.

The development of the gender wage gap during the early career of Finnish university graduates is investigated by Napari (2008). The results suggest an increasing wage gap during the first years in the labour market, with an average wage gap of 31%. Only a small part could be explained by endowment differences between men an women, whereas the largest part is accounted for by the field of education and work experiences. The author claims the early career gender wage gap to be accountable for the lifetime wage gap increase.

For Germany, literature on gender pay gaps in entry wages among university graduates is very scarce. Bredtmann and Otten (2010) investigate gender wage differentials of business and economics graduates from one German university. They find a wage disadvantage for women of 8.7%. Depending on using male or female coefficients as weights, 15.6 and 27.9%, respectively, of the gap is related to endowment differences. Differences in the occupational structure are found to be most important for explaining the gender wage gap. Similarly, Reimer and Schröder (2006) detect a wage gap of 7%, but like Bredtmann and Otten (2010) they investigate respondents from one university graduating in one specific field of study (social sciences) and therefore, the results are difficult to generalize.

A recent study by Braakmann (2013) is aimed at identifying determinants of the gender wage gap of German graduates in their first job and 5-6 years later. Data base is the Absolventenpanel (panel survey of graduates) for the year 1997, including graduates obtaining their degrees in the respective year. Several covariates as the social background, work experience, academic achievements, attitudes towards work/life and employer characteristics are used to explain the log gross monthly income. A wage difference at labour market entry between male and female graduates of 24% is found. Applying a standard Oaxaca-Blinder decomposition, 83% of the gap could be explained by covariates.

After including employer characteristics, this proportion increases up to 96% when using male coefficients as weights. The results reveal that wage differences are mainly driven by differences in fields of study, which explains up to 70% of the wage gap. Moreover, attitudes towards life and work, e.g. differences in the importance of earning money and in the wish to take leadership position, and employer characteristics play an important role. Work experience and academic achievement are only of low importance. The wage gap is found to widen within the first 5 years after job entry and the unexplained part of the earnings gap rises over the first few career years.

In summary, there are only a few studies, mainly for the US, analysing gender wage gaps of graduates at labour market entry. Studies for Germany are very scarce. With the exception of Braakmann (2013) the data sets used are often very small and rather specific, e.g. containing information only for graduates from one university or even only students graduating in one specific field.

The review of the existing literature reveals that there is no consensus about the determinants affecting graduates' gender pay gap at labour market entry. For Germany, the empirical findings for the wage gap at career entry vary between 7% and 24%. Furthermore, the magnitude of the part that is explained by unequal endowments between men and women differs substantially.

Whereas all of the mentioned research work examine wage differentials in starting wages for graduates, the focus of the analysis and therefore the variables included vary across studies. Different results are maybe driven by these differences in modeling approaches. In particular, the contribution of fields of study varies considerably between 1% and 70%. Joy (2003) attributes these differences in findings to whether labour market determinants haven been included in the analysis whereas McDonald and Thornton (2007) hold the level of aggregation responsible for different field effects.

This study contributes to the existing literature using a comprehensive data set, the Absolventenpanel for the year 2001, including students from many different universities in Germany covering a wide variety of fields of study.[3] The rich data set contains detailed information on students' own educational background, e.g. type of school and A-level grade, which may be important for predicting entry wages and are very well suited to control for unobservable motivation and ability. Furthermore, the data set

[3]Braakmann (2013) used an older wave (1997) of this survey.

provides relevant indicators of students' socio-economic origin, e.g. the parental academic background.

Most of the mentioned studies apply standard Oaxaca-Blinder decomposition techniques to evaluate the explained and unexplained part of the gap in mean wages. We extend these approaches applying a decomposition method, which allows to analyse the complete income distribution and differences between groups' incomes at all percentiles. Applying a theoretically well-founded single-index model (DiNardo, Fortin, and Lemieux (1996), Fortin and Lemieux (1998)) the gender pay gap is decomposed in endowment, price and return-to-skill function effects thereby providing more detailed insights into the origins of the gender pay gap.

5.3 The Data Source and Descriptive Statistics

5.3.1 Data Source

The empirical analysis is based on data from the German Absolventenpanel 2001 of the HIS (Hochschul-Informations-System).[4] The survey was conducted 6-18 months after graduation and includes a random sample of all graduates receiving their first degree in the respective year (here 2001) at a German university and is obtained as a (stratified) cluster sample. The clusters are defined by the following characteristics: field of study, type of diploma and university. The panel includes a wide range of social and demographic characteristics and detailed information about the course of study and the integration into the labour market.[5]

We only use the first wave of the survey because it contains information about wages of the first job after graduation, grades, times to degree, fields and the course of study relevant for this analysis. The sample consists of 8117 observed individuals.

We present some descriptive statistics on monthly gross incomes of the first job after graduation (*wage*) and hourly wages (*wage rate*). Working hours (*hours*) are given as hours per week, therefore hourly wages are calculated as $wage/(hours*4.35)$. As exact

[4] Additional panels commenced in 2005 and 2009, but are not yet available for research.

[5] For more information see Schramm and Beck (2010).

work hours are not available in the data set, we assign to full-time workers 40 working hours per week. For the empirical decomposition analysis, we use log hourly wages throughout.

The variable *part-time* indicates if working hours per week are less than 40 (which correspond to full-time work). The time between graduation and the beginning of the first job, measured in months, is captured by *searchdur*. It is expected that longer search times decrease entry wages as they possibly signal less motivation. Furthermore, graduates who do not find a job immediately after graduation presumably accept lower salary offers.

Several covariates are included to control for prior qualification. One can presume that students' qualification obtained before studying affects entry wages as it may reveal unobserved motivation and ability. Moreover, they may also serve as a signal in the labour market. Here, prior qualification is approximated by observed A-level grades. *sgrade* takes values between 1.0 and 4.0 in steps of 0.1 and it is expected that entry wages decrease with *sgrade*, i.e. the higher the grade the lower the entry wages. Note that opposed to many other schooling systems, in Germany a higher grade indicates worse performance at school.

A similar relationship is assumed for the final grade at university (*ugrade*), also ranging from 1.0 to 4.0. As for A-level, higher grades indicate worse academic performance and we expect a negative relationship with entry wages.

Additionally, we control for time until graduation (*duration*), measured as the number of subject related terms until the first graduation. Duration is measured in half term years. One can assume that longer times to degree are related to less academic abilities or motivation, leading to lower entry wages.

A most important determinant of entry wages is the field of study. The original data set includes 33 fields which have been categorized into 4 fields: *social* (including social sciences, economics, law, humanities), *science* (including engineering, informatics and maths, natural sciences), *teach* (including all fields of teaching) and *medother* (including medicine and other fields of study). We observe different mean entry wages with varying fields.

Because employment experiences before studying may have an effect on entry wages, the dummy variable *experience* indicates whether an individual was employed before enrollment or not. Having gained some working experience, compared to only have experienced

school, may have promoted personal responsibility and discipline, both important for employers and entry wages. Therefore, a positive effect of *experience* on wages is expected. The same arguments hold for the variable *voctrain*, indicating if a student completed a vocational training prior to attending university.

Moreover, age at enrolment (*age*) is considered. The expected effect on entry wages is ambiguous. There may be two, potentially offsetting, effects. On the one hand, the older at enrolment the more knowledge and experience a student has attained and this may increase entry wages. On the other hand, older age at enrolment could hint for some waste of time and perhaps little motivation. This may result in lower wages.

To control for family background, a dummy variable (*acad*), indicating if either the mother or the father (or both) has an academic degree[6], is included. An increasing effect of *acad* on entry wages is expected.

Universities and universities of applied sciences differ considerably in the course of study and students' characteristics. Therefore, the empirical analysis is based only on graduates from universities. Furthermore, non-working graduates at the time of survey as well as self-employed persons are excluded from analysis. Individuals with less than 10 working hours per week are most likely in occasional work and have also been removed from the sample.

The hourly wages take in some rare cases unusual high and low values, respectively. To prevent outliers biasing the results we use only observations within the rather wide interval of hourly wages ranging from 2.5 up to 50 Euros. This corresponds to dropping approximately 1.14% outliers. The final sample with valid observations on all variables has 3386 observations. Table E.1, given in the appendix, provides an overview of the variables and their definitions.

5.3.2 Descriptive Statistics

Table 5.1 provides an overview about how the metric covariates differ between female and male students. The mean as well as the median, the minimum and maximum, the standard deviation and the interquartile range are presented. According to the mean as well as to the median, entry wages for men are higher than for women. The mean monthly

[6]Obtained from university or from university of applied sciences.

gross entry wage for male students amounts to 2195 Euro whereas the mean entry wage for women is only 1645 Euro. According to the standard deviation and the interquartile range, dispersion is substantially higher for men's wages.

Working hours per week range from 10h up to 70h for men and up to 60h for women, with similar mean and median hours. The average hourly wage rate for men of 14.20 Euro exceeds the average hourly wage of women of 11.21 Euro, resulting in a ratio of 0.79. Regarding the other metric covariates, there are only slight differences between male and female graduates.

	sex	mean	median	min	max	sd	iqr
wage	men	2195.21	2200.00	250.00	7000.00	1131.03	2074.00
	women	1644.75	1329.00	197.00	6300.00	947.95	1401.50
hours	men	35.60	40.00	10.00	70.00	8.80	0.00
	women	34.33	40.00	10.00	60.00	9.48	10.00
wagerate	men	14.20	15.01	2.87	43.68	6.32	9.97
	women	11.21	10.34	2.64	44.54	5.72	9.45
age	men	20.83	20.00	17.00	34.00	2.02	1.50
	women	20.34	20.00	16.00	50.00	2.75	2.00
sgrade	men	2.13	2.10	1.00	3.70	0.63	1.00
	women	2.13	2.10	1.00	3.80	0.61	0.90
ugrade	men	1.95	2.00	1.00	4.00	0.66	0.90
	women	1.99	2.00	1.00	4.00	0.65	0.90
duration	men	12.34	12.00	6.00	49.00	3.05	4.00
	women	11.95	11.00	6.00	33.00	2.93	3.00
searchdur	men	2.79	2.00	1.00	20.00	2.69	2.00
	women	3.22	2.00	0.00	24.00	2.96	3.00

Table 5.1: Descriptive statistics I: metric variables

Table 5.2 presents information on the categorical variables. 56.4% of the male and 61.5% of the female graduates come from an academic household. Women more often tend to work only part-time than men. The fraction of graduates with work experience or vocational training before studying for both groups resembles.

A closer look on the fields of study reveals interesting differences. 45.1% of the male graduates studied a field of sciences. This fraction is considerably lower for women (23.7%). For teaching, the situation is reversed: 21.6% of women obtained their degree in a field of teaching, whereas the fraction for male graduates is only 7.9%. The share of social science graduates is higher for women, too.

	men	women
acad	0.564	0.615
parttime	0.228	0.296
experience	0.310	0.321
voctrain	0.178	0.173
social	0.308	0.321
science	0.451	0.237
teach	0.079	0.216
medother	0.162	0.226

Table 5.2: Descriptive statistics II: categorical variables

Figure 5.1 displays the Kernel density estimates of the logarithmic hourly wage rate distributions. It is evident that the log-wage distribution for men has higher dispersion and is located slightly right of women‘s log-wage distribution. Up to a log hourly wage of approximately 2.6 the density of female graduates exceeds the density of their male counterparts, whereas in the region of higher hourly wages the density of men exceeds the female one.

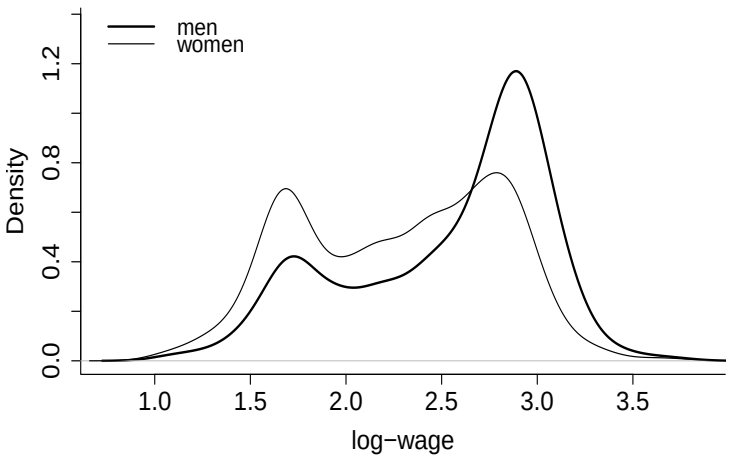

Figure 5.1: Density estimates of log-wage

Since the approach to be discussed in more detail below is concerned with differences across the complete income distribution instead of restricting the analysis on differences in mean incomes, we display in Figure 5.2 the income difference at all percentiles, that is the difference between a man and a woman having the same relative ranks in their gender specific income distributions.

At all percentiles, men have higher wages than women. In the lower positions of their respective wage distributions we observe relatively small differences between

male and female graduates. The gap widens with higher percentiles. The highest difference of 0.435 is observed at the 43%-quantile, for higher percentiles the difference declines.

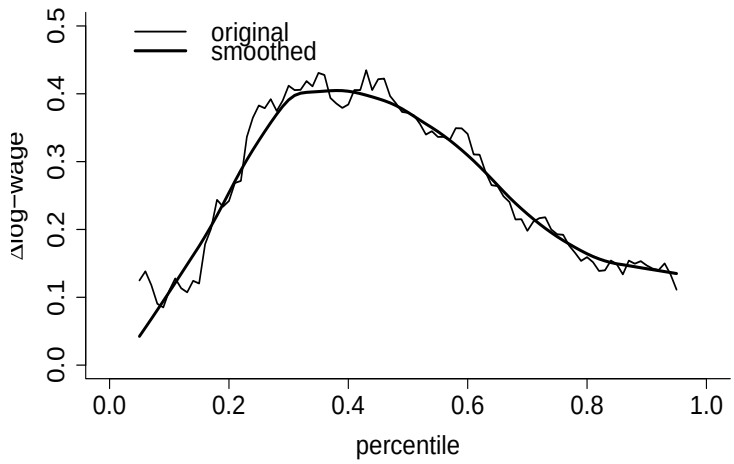

Figure 5.2: Wage differences (men-women) at percentiles

In summary, we observe that women tend to earn less than their male counterparts do at all quantiles, the difference being especially large around the centres of the gender specific income distributions. As there are only slight differences in male and female characteristics - mainly they differ in their choice of the field of study - the pay gap seems to be driven by further unobserved influences.

5.4 The Oaxaca-Blinder Decomposition Approach

To facilitate the comparison of results with previous studies that focus almost exclusively on average wages, we provide first the results of the classical Oaxaca-Blinder decomposition before turning to the analysis of the complete wage distribution.

5.4.1 Wage Equations

In the following, we use a simple linear wage equation as the starting point:

$$y_{it} = x'_{it}\beta_t + u_{it} \tag{5.1}$$

y_{it} denotes log(wage) for individual i in 'group' t ($t \in \{m, w\}$) and the vector x_{it} contains controls as the age at enrolment, the own and parental educational background, work experiences, search duration until the first job and the field of study (see section 3). In our empirical example, m denotes the sample of male and w the sample of female graduates. Therefore, $i = 1, ..., n_m$ indicates men and $i = 1, ..., n_w$ women.

According to equation 5.1 the cross section for men and the corresponding equation for women are

$$y_{im} = x'_{im}\beta_m + u_{im} \qquad y_{iw} = x'_{iw}\beta_w + u_{iw} \tag{5.2}$$

With F we refer to the distribution, e.g. $F_{y,m}$ denotes the distribution of log-wages for men. Fitted values we denote as

$$\hat{y}_{im} = x'_{im}\hat{\beta}_m$$
$$\hat{u}_{im} = y_{im} - x'_{im}\hat{\beta}_m$$

Correspondingly, $\hat{F}_{u,m}$ refers to the distribution of estimated residuals for men. The results of the two basic OLS estimations are given in Table 5.3.

We observe some covariates to differently affect male and female wages. Surprisingly, for men worse A-level grades seem to affect wages significantly positive. As expected, lower university performance decreases entry wages for male as well as for female graduates. Working only part-time, i.e. less than 40 hours a week, and age at enrolment lead to an increase of starting salaries for women, whereas male graduates' entry wages are not affected significantly. Vocational training raises wages only for men.

As expected, male and female graduates with higher search durations until the first job earn less than students finding a job immediately after graduation (for men only significant at the 10% level).

In comparison to major in *social* sciences, studying a field of *sciences* leads to higher entry wages, whereas a degree in *teaching* lowers starting salaries for both men and women. Studying medicine or other fields decreases only male graduates' entry wages in comparison with social sciences.

For both, male and female graduates, the parental academic background, time to degree and work experiences before studying seem not to affect entry wages significantly.

	all	men	women
Intercept	2.318	2.360	2.404
	(25.5)	(14.99)	(20.99)
age	0.014	0.011	0.011
	(3.48)	(1.62)	(2.14)
acad	-0.039	-0.037	-0.030
	(-2.38)	(-1.53)	(-1.37)
sgrade	0.071	0.126	0.021
	(5.02)	(5.95)	(1.15)
ugrade	-0.152	-0.177	-0.140
	(-11.28)	(-8.42)	(-8.14)
duration	-0.001	0.001	-0.002
	(-0.27)	(0.13)	(-0.62)
parttime	0.051	0.006	0.105
	(2.8)	(0.22)	(4.52)
experience	-0.013	-0.027	0.003
	(-0.68)	(-0.96)	(0.13)
voctrain	0.049	0.103	0.032
	(1.92)	(2.7)	(0.92)
searchdur	-0.011	-0.008	-0.010
	(-3.96)	(-1.84)	(-2.82)
science	0.251	0.249	0.194
	(11.89)	(7.98)	(6.61)
teach	-0.517	-0.587	-0.457
	(-20.92)	(-12.33)	(-15.39)
medother	-0.096	-0.171	-0.046
	(-4.22)	(-4.61)	(-1.62)
$r^2_{adj.}$	0.28	0.28	0.24
n	3386	1423	1963

Table 5.3: Wage equations

These simple wage equations explain only 28 (24)% of the total variation in hourly log-wages for men (women). Despite the inclusion of numerous explanatory variables, the major part of wage variation is contained in the residuals. This observation motivated Juhn, Murphy, and Pierce (1991) and Juhn, Murphy, and Pierce (1993) to try gaining insight into the distribution of residuals.[7]

In Figure 5.3 we display the distributions of estimated residuals for men and women. It is evident that the two distributions are very similar, but with a substantially higher density for estimated residuals around zero for men.

[7]Juhn et al. analysed differences in US wage distributions at different points in time.

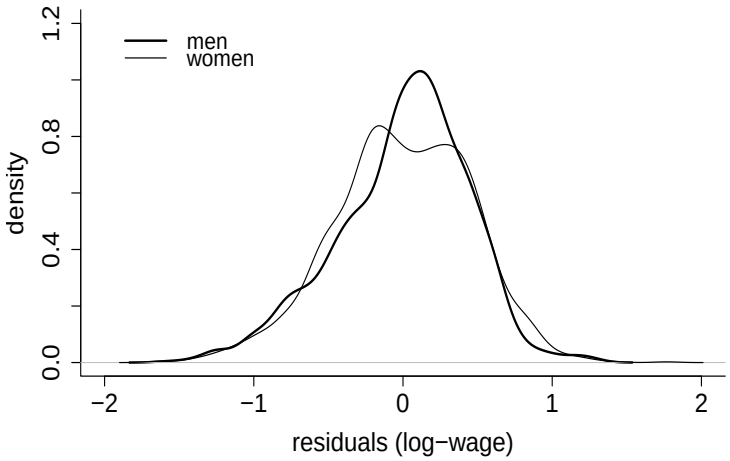

Figure 5.3: Density estimates of estimates wage residuals

5.4.2 The Oaxaca-Blinder Decompositions

The most simple decomposition for the difference in mean log-wages is given as

$$\begin{aligned} \bar{y}_m - \bar{y}_w &= \bar{x}'_m \hat{\beta}_m - \bar{x}'_w \hat{\beta}_w \\ 0.250 &= 2.533 - 2.283 \end{aligned} \tag{5.3}$$

Using men‘s coefficients and women‘s characteristics for standardization results in the following decomposition:

$$\begin{aligned} \bar{y}_m - \bar{y}_w &= \left(\bar{x}'_m - \bar{x}'_w\right) \hat{\beta}_m + \bar{x}'_w \left(\hat{\beta}_m - \hat{\beta}_w\right) \\ 0.250 &= 0.163 + 0.087 \end{aligned} \tag{5.4}$$

When using women‘s coefficients and men‘s characteristics for standardization the effect of differences in mean characteristics is smaller and the price effect is larger:

$$\begin{aligned} \bar{y}_m - \bar{y}_w &= \left(\bar{x}'_m - \bar{x}'_w\right) \hat{\beta}_w + \bar{x}'_m \left(\hat{\beta}_m - \hat{\beta}_w\right) \\ 0.250 &= 0.116 + 0.135 \end{aligned} \tag{5.5}$$

Note that the decomposition allows only a complete separation into the two effects of differences in characteristics and differences in prices of observed characteristics, when using inconsistently weights from both groups ($\hat{\beta}_m$ and $\bar{x}'_w$, or $\hat{\beta}_w$ and $\bar{x}'_m$). In the case of consistent weights ($\hat{\beta}_m$ and $\bar{x}'_m$, or $\hat{\beta}_w$ and $\bar{x}'_w$) the decomposition leads to a third component which is a joint effect of differences in characteristics and differences in prices

of observed characteristics. When using men's coefficients and men's characteristics for standardization we find:

$$\bar{y}_m - \bar{y}_w = (\bar{x}'_m - \bar{x}'_w)\,\hat{\beta}_m + \bar{x}'_m\left(\hat{\beta}_m - \hat{\beta}_w\right) - (\bar{x}'_m - \bar{x}'_w)\left(\hat{\beta}_m - \hat{\beta}_w\right) \tag{5.6}$$
$$0.250 = 0.163 + 0.135 - 0.048$$

Standardization on women's coefficients and women's characteristics leads to:

$$\bar{y}_m - \bar{y}_w = (\bar{x}'_m - \bar{x}'_w)\,\hat{\beta}_w + \bar{x}'_w\left(\hat{\beta}_m - \hat{\beta}_w\right) + (\bar{x}'_m - \bar{x}'_w)\left(\hat{\beta}_m - \hat{\beta}_w\right) \tag{5.7}$$
$$0.250 = 0.116 + 0.087 + 0.048$$

According to all decompositions, both the effect of differences in observed characteristics and in coefficients are strongly favourable for men.

5.5 A Single Skill Index Model

5.5.1 The Theoretical Model

The logarithmic wage y is assumed to result from individual latent skills r^*, which are rewarded in the market according to a flexible returns-to-skill function Λ^{-1}. Latent skills are themselves assumed to depend on characteristics X.

The logarithmic wage model in its general form is

$$\log(wage) = y = \Lambda^{-1}(r^*) = \Lambda^{-1}(f(x)) \tag{5.8}$$

The model is based on the assumption that there is an unknown monotonic transformation function between the logarithmic wages of individual i and the latent skill level r^*:

$$r_i^* = \Lambda(y_i) \tag{5.9}$$

The inverse transformation function

$$y_i = \Lambda^{-1}(r_i^*) \tag{5.10}$$

can be seen as the returns-to-skill function. Due to the monotonic transformation function, the equality of ranks in wages and skills is implied:

$$rank(y_i) = rank(r_i^*)$$

The skill level r^* is assumed to be a linear function of individual characteristics contained in X superimposed by standard normal error term ε :

$$r_i^* = X_i\beta + \varepsilon_i \qquad \varepsilon \sim N(0,1) \tag{5.11}$$

Following Fortin and Lemieux (1998) wages are grouped into K intervals $(-\infty, a_1), \ldots,$ $[a_k, a_{k+1}), \ldots, [a_{K-1}, \infty)$. Since

$$\begin{aligned} \pi_k(\Lambda, \beta, X) &:= \mathrm{P}(y \in [a_{k-1}, a_k) \,|\, X) \\ &= \mathrm{P}(\Lambda(y) \in [\Lambda(a_{k-1}), \Lambda(a_k)) \,|\, X) \\ &= \mathrm{P}(\varepsilon \in [\Lambda(a_{k-1}) - X\beta, \Lambda(a_k) - X\beta)) \end{aligned} \tag{5.12}$$

this is an ordered probit model where the constant terms are the values of the inverse returns-to-skill function.

This suggestion of Fortin and Lemieux depends on the normality assumption for ε. One could alternatively allow for different distributional assumptions or try semi-parametric estimation procedures as the ones discussed by Horowitz (2001). Another approach would try to avoid a discretization of the data altogether through the use of non-parametric transformation models as suggested by Breiman and Friedman (1985). However, these more general methods lead to very unstable estimation results for the transformation function Λ.

5.5.2 The Empirical Implementation

The empirical implementation proceeds in nine steps:

1. Choose K the number of equally densed intervals and obtain $K-1$ quantiles q of the combined wage distribution $(F(y = \{y_m, y_w\}))$ of men and women. Based on $K-1$ quantiles obtain K class centres $\tilde{q}$ to approximate class means by assuming

the two open classes (left- and rightmost) to be four times as wide as the neighbor class.

2. Transform the metric wages y towards an ordered factor variable y^c containing the number of the interval ($y^c \in \{1, 2, ..., K\}$) based on the quantiles q.

3. Estimate an ordered probit regression for y^c using the set of covariates X.

4. Obtain the vector of estimated skill indices $\hat{r}$ based on the estimated parameter vectors $\hat{\beta}$ and observed characteristics X as $\hat{r} = X\hat{\beta}$.

5. Based on the ordered probit model obtain the matrix $\hat{\Pi}$ of dimension $n \times K$ containing the interval probabilities $\hat{\pi}_{ki}$. $\hat{\pi}_{ki}$ denotes the estimated probability for individual i to belong to interval k and is obtained using the $K - 1$ estimated interval limits $\hat{a}_k$ and the normal assumption of the probit model. Summing up the probabilities within intervals over individuals results in estimated interval probabilities $\hat{\pi}_k$:

$$\hat{\pi}_k = \sum_{i=1}^{n} \hat{\pi}_{ki}$$

6. The predicted log-wage can be obtained for an individual i by $\hat{y}_i = \hat{\pi}_i' \times \tilde{q}$. The vector of predicted log-wages accordingly as $\hat{y} = \hat{\Pi} \times \tilde{q}$, with $\tilde{q}$ denoting the centres of the K wage-intervals.

7. The inverse transformation function $\Lambda^{-1}(r)$ which is regarded as the returns-to-skill function is estimated based on the estimated $\Lambda(\hat{a}_k)$ interval limits and the vector of quantiles q. The estimated function is denoted by $\hat{\Lambda}^{-1}(r) = \hat{\Lambda}^{-1}(X\beta)$.

8. The complete estimation procedure can be carried out separately for men and women. Thereby we obtain gender specific parameter vectors $\hat{\beta}_m$ and $\hat{\beta}_w$ as well as gender specific returns-to-skill functions $\hat{\Lambda}_m^{-1}$ and $\hat{\Lambda}_w^{-1}$.

9. Using $X_m, \hat{\beta}_m, \hat{\Lambda}_m^{-1}$ and $X_w, \hat{\beta}_w, \hat{\Lambda}_w^{-1}$, respectively and q, the gender specific wage distributions can be approximated almost perfectly

$$\hat{F}_m(y_m) \approx \hat{F}_m(X_m, \hat{\beta}_m, \hat{\Lambda}_m^{-1})$$
$$\hat{F}_w(y_w) \approx \hat{F}_w(X_w, \hat{\beta}_w, \hat{\Lambda}_w^{-1})$$

5.5.3 Model Estimates

In our empirical implementation, we use $K = 40$ for both genders and calculate vector q based on the quantiles of the combined log-wages of men and women.

The results of the ordered probit models are given in Table 5.4. The interpretation of coefficients is not as intuitive as for linear models, because the magnitude of coefficients has no straightforward interpretable meaning. The effect of a change in an explanatory variable on particular probabilities depends on the magnitude of coefficients, but also on the shape of the density. The sign only shows the direction of the effect on the probability of the lowest and highest wage classes. A positive β leads to a decline of the probability to belong to the lowest wage class and an increase of the probability to belong to the highest wage class.

	all	men	women
age	0.035	0.031	0.026
	(3.99)	(1.94)	(2.37)
acad	-0.091	-0.086	-0.070
	(-2.52)	(-1.55)	(-1.47)
sgrade	0.126	0.242	0.017
	(4.08)	(5.02)	(0.41)
ugrade	-0.316	-0.357	-0.307
	(-10.61)	(-7.41)	(-8.07)
duration	0.002	0.006	-0.002
	(0.38)	(0.67)	(-0.24)
parttime	0.048	-0.065	0.184
	(1.20)	(-0.99)	(3.59)
experience	-0.024	-0.052	0.012
	(-0.57)	(-0.80)	(0.23)
voctrain	0.119	0.223	0.095
	(2.10)	(2.60)	(1.25)
searchdur	-0.025	-0.018	-0.022
	(-4.02)	(-1.83)	(-2.80)
science	0.545	0.511	0.437
	(11.67)	(7.18)	(6.77)
teach	-1.013	-1.161	-0.897
	(-18.07)	(-10.48)	(-13.38)
medother	-0.193	-0.349	-0.085
	(-3.84)	(-4.12)	(-1.35)
n	3386	1423	1963

Table 5.4: Ordered probit regressions

The results point for similar directions of effects as in the OLS regression. University performance affects the probability of low wages significant positively in the combined

regression as well as in both regressions separately for men and women. Higher (worse) grades increase the probabilities of belonging to the lowest starting salary classes and decreases probabilities for the highest wage classes. The same holds true for elapsed time between graduation and the first job (for men significant only on the 10% level).

Working only part-time seems only to be relevant for women, whereas vocational training increases the probability to belong to the highest wage classes for men. The age at enrollment affects both, male (significant only on the 10% level) and female wages, positively.

In comparison to social sciences, studying a field of sciences raises probabilities of high starting salaries for both men and women. The opposite is true for the field of teaching. Studying medicine or other fields affects only male graduates' entry wages significantly. For both, male and female graduates, the parental academic background, time to degree and work experiences before studying seem not to affect entry wages significantly.

The returns-to-skill functions transform the estimated individual skills, which are calculated according to the estimated coefficients $\hat{\beta}$ of the skill function, into log-wages.

Figure 5.4: Distributions of estimated skill index

The distribution of the estimated skill indexes for men and women are given in Figure 5.4. The estimation is based on the combined regression coefficients as we assume that men and women face the same labour market conditions. Both skill distributions are slightly

skewed to the left and men's distribution is slightly located to the right of women's skill index distribution.

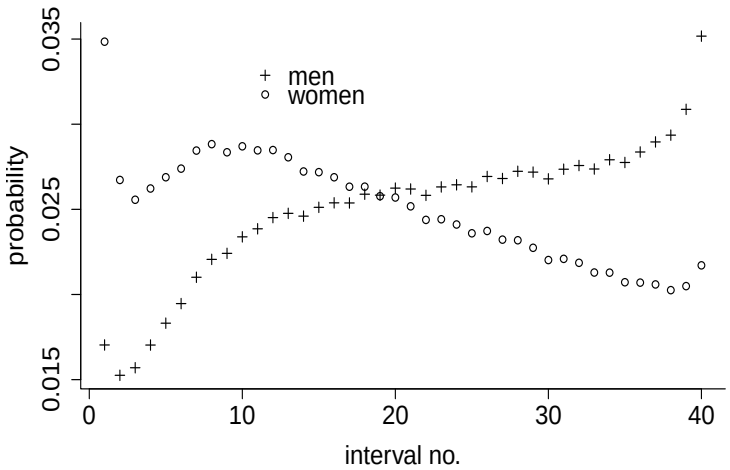

Figure 5.5: Estimated interval probabilities for men and women

Figure 5.5 presents the estimated probabilities (also based on the combined regression) for the 40 wage intervals. We observe that the probabilities of belonging to the lower wage classes are higher for women (approximately up to class 19), whereas men have higher probabilities to belong to the higher wage intervals.

Figure 5.6: Estimated returns-to-skill-function

In Figure 5.6 we show the estimated returns-to-skill function by displaying the estimated threshold values $\Lambda(\hat{a}_k)$ on the x-axis, and the corresponding quantiles q on

the y-axis [8]. The relation between skills and wages is steeper at middle skill levels. There is a smaller increase in returns to skills for the lower and higher skill indices, respectively.[9]

5.5.4 Decomposition Results Based on Counterfactual Wage Distributions

Using estimation results from the three estimated models for women, for men and for the combined sample, it is now possible to construct several counterfactual wage distributions, which highlight special features of interest. For example, applying the estimation procedure to the male sample results in estimated interval probabilities

$$\hat{\pi}_m = \hat{\pi}_m(\hat{\Lambda}_m, \hat{\beta}_m, X_m) \tag{5.13}$$

Using the matrix of women's characteristics X_w instead of X_m leads to

$$\tilde{\pi}_{m,X_w} = \hat{\pi}_m(\hat{\Lambda}_m, \hat{\beta}_m, X_w) \tag{5.14}$$

Using specific components of interest one now can easily calculate isolated differences at selected locations of the unconditional wage distribution. In particular, the π_k jointly with $\tilde{q}_k$ approximate the conditional distribution of counterfactual wages. By integrating out the distribution of X, one arrives at the marginal wage distribution. Consequently, comparisons at the quantiles of the marginal wage distributions with respect to the contributing factors, the returns-to-skill functions and prices of characteristics are possible.

In Figure 5.7 we show the differences in pay between men and women and its isolated components at all percentiles. The total pay gap and the three isolated effects behave quite differently at different percentiles of the wage distribution. This makes evident that focusing only on the mean masks important differences in wage distributions. The total

[8] One could also use e.g. class middles or mean log wages of each interval. The curse of the function remains almost the same.

[9] Estimated log-wages can be seen to have a considerable smaller variation than observed log-wages. But as the following decomposition analysis focuses on the complete wage distribution which is modelled directly, estimated individual wages will not be used in the analysis.

difference is inversely u-shaped and positive throughout the wage distribution, i.e. female graduates' starting salary is below that of male graduates.

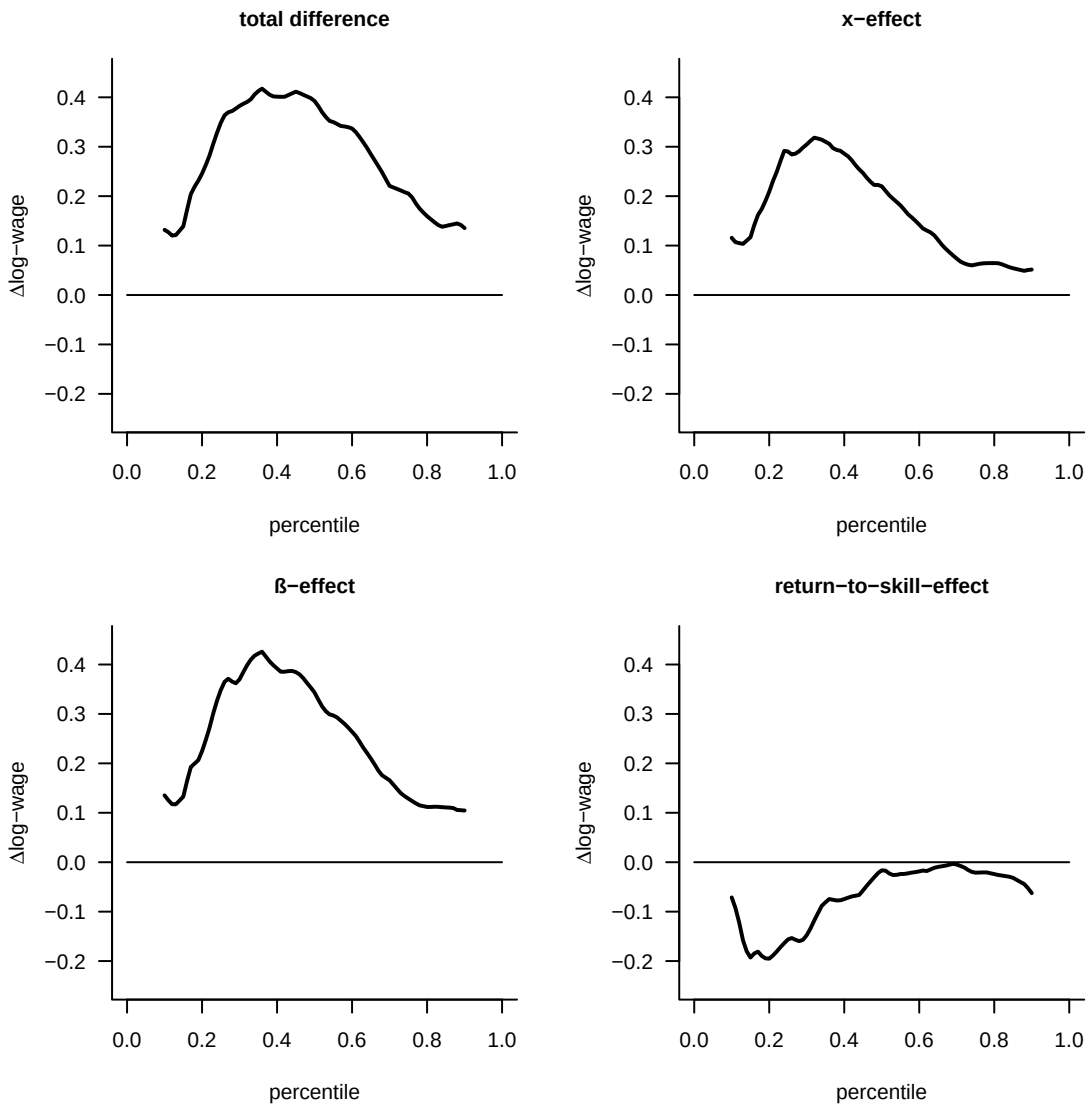

Figure 5.7: Isolated components in the Fortin-Lemieux model

The effect of differences in observed characteristics (x-effect) measures the difference that would be observed if wage differences would solely result from differences in measured characteristics. We find this effect to be positive throughout, i.e. favourable for men, and inversely u-shaped. The x-effect is increasing when moving up the income distribution up to about 0.35, and declining afterwards. Similarly, the effect of differences in prices (β-effect) is strongly advantageous for men over all percentiles, with the strongest effect found again around the 0.3 percentile.

The effect of the difference in the returns-to-skill functions is negative and advantageous for women throughout with decreasing effects at higher percentiles. In particular women in the lower part of the wage distribution benefit from gender specific differences in the returns-to-skill functions. Men would be better off if their skills would be transformed into wages according to women's returns-to-skill function. However, this effect is outweighed by both the strong x- and the strong β-effects, both being advantageous for men.

	Δ log-wage	$x-$effect	$\beta-$effect	$\Lambda-$effect	residual
q0.1	0.132	0.116	0.135	-0.071	-0.048
q0.2	0.246	0.209	0.225	-0.195	0.007
q0.3	0.383	0.305	0.370	-0.148	-0.145
q0.4	0.401	0.286	0.392	-0.075	-0.202
q0.5	0.392	0.220	0.343	-0.016	-0.154
q0.6	0.337	0.142	0.264	-0.019	-0.051
q0.7	0.221	0.074	0.166	-0.005	-0.014
q0.8	0.160	0.065	0.112	-0.024	0.007
q0.9	0.135	0.051	0.105	-0.063	0.042

Table 5.5: Decomposition results at deciles

In Table 5.5 we display the results numerically at the deciles of the wage distribution. The column of total differences reveals that there is a substantial starting wage differential between male and female graduates throughout the wage distribution, with a maximum of 0.401 at the 0.4 decile. The endowment and the price-effect are both positive throughout with the former being slightly smaller than the latter. The effect of the return-to-skills function (Λ-effect) is negative and considerable smaller (in absolute values) than both, the x- and β-effect. The residual effect, i.e. the wage difference that is not accounted for by differences in endowments, prices or in the returns-to-skill function, is highest at deciles between 0.3 and 0.5 and mostly advantageous for women.

5.6 Conclusions

We analyse wage differentials between male and female graduates at labour market entry. In recent years, several decomposition methods have been suggested which extend the classical Oaxaca-Blinder decomposition. The main characteristic of the modern approaches is the decomposition at all percentiles of the income distribution. We applied

the approach suggested by DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1998), which can be classified as a single index model and is close to the human capital theory of wage determination. By means of a returns-to-skill function individual skill levels are monotonically converted into wages maintaining the relative wage position determined by the skill index.

The gender pay gap in average hourly starting wages in our data set is 25%. This is in line with Braakmann (2013) who identified a gap of 0.24 between German male and female graduates. On the contrary, Bredtmann and Otten (2010) and also Reimer and Schröder (2006) found a much lower wage gap of about 8 and 7%, respectively. This is probably due to the fact that the sample of both studies is very homogeneous. Respondents are only from one university and obtained their degree in the same field of study.

As we used a very homogeneous sample of university graduates at labour market entry, i.e. years of education and experience are almost the same for all respondents, a gender wage gap lower than in heterogeneous samples over all educational classes was expected. However, the observed difference in mean wages is surprisingly large. E.g. Kunze (2003) detect a wage gap of only 22% for German skilled workers and the German Statistical Office reports for the last decade an overall gap between 22 and 23%. The observed wage gap of 25% is much higher than entry wage gaps of graduates found in other countries.

According to the Mincerian approach of wage determination, education and experience should be the most important covariates in wage equations. Even when using a comprehensive set of covariates the estimated wage equations explain only 28% of the total variation in hourly log-wages for men and 24% for women. Similarly to the most of the mentioned studies, wage regressions reveal university performance (here final grade) and fields of study to affect entry wages of men and women. We detect only slight differences in male and female characteristics. An exception is the field of study. A considerable fraction of 45% of male graduates obtain their degree in fields of sciences, whereas a great fraction of women major in social sciences.

We observe higher starting salaries for men at all percentiles of the income distribution. As the magnitude of the pay gap varies strongly across the income distribution, a more detailed analysis considering all percentiles of the wage distribution was carried out. Based on a single-index approach suggested by DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1998) the pay gap was decomposed in endowment-effects (x-effect),

price effects (β-effect) and effects of the returns-to-skill function (Λ-effect). By means of counterfactual wage distributions, the magnitude of the isolated effects could be obtained for all percentiles of the wage distribution.

We observe the three isolated effects to behave quite differently at different percentiles of the wage distribution. The x-effect and β-effect are inversely u-shaped and both favourable for men throughout. The effect of the difference in the returns-to-skill function is advantageous for female graduates at the lower part of the wage distribution, but this effect is outweighed by the strong x- and β-effects.

As the human capital theory of wage determination is closely reflected in the single-index skill models and these models additionally allow for a more flexible modelling of the observed wages, these approaches might be regarded as worth a more intensive study and more frequent use in the future. Our main findings, the extent of the gender pay gap at labour market entry being already of about the same magnitude as the overall pay gap in Germany and the strong effect of choice of field of study, question the present focus on equal pay politics and imply a closer look at the early processes determining the very gender specific choices of field of study. Identifying reasons motivating women to choose lower paid fields of study and to induce female students to study typically male fields are probably starting points in reducing the gender pay gap.

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5.8 Appendix

Variable (subset)	Definition
wage	monthly gross entry wage
wagerate	hourly wage
hours	working hours per week
parttime	working only part-time (less than 40h/week)
searchdur	duration until first job (in months)
sgrade	final grade at school: 1.0, 1.1, ..., 4.0
ugrade	final grade of first university degree: 1.0, 1.1, ..., 4.0
duration	semesters (half term years) until first graduation
social	studying a field of social sciences
science	studying a field of sciences
teach	studying for teachers training certificate
medother	studying medicine or other fields
experience	employment experience before studying: 1 if true, 0 otherwise
voctrain	vocational training before studying: 1 if true, 0 otherwise
age	age at enrollment
acad	parental background: 1 if at least mother or father (or both) has academic degree, 0 otherwise

Table E.1: Variables of the data set

6

Summary and General Conclusion

This thesis investigated determinants of students' academic performances, measured as time to first academic degree and final university grades, and of graduates' pay at labor market entrance in Germany. Empirical literature on students' academic performance and graduates' pay at the beginning of their career are very scarce and this thesis tries to partly fill this gap.

Figures on the German higher education system reveal a dependency between students' social background and sources of financing. The importance of personal earnings increases from the upper to the lower groups of social origin, whereas the proportion of parental financial support decreases considerably. During the last decades, there are a rising proportion of students working beside studies. Moreover, there is a linkage between social background and students' work intensities as students coming from an upper social group are less likely to work constantly during their studies.

Since tuition fees have been abolished in most federal states, students are allowed to stay at university for an unlimited amount of time without additional costs. The present situation is characterized by the fact that the regular study time is exceeded by the majority of students. Therefore, analyzing potentially prolonging causes of time to degree is an important issue. As many students work during studies, mainly to be able to cover living costs, the first paper focused on the relationship between the working status of students and their times to degree. A Cox model, a very flexible model within time to event analysis avoiding strong distributional assumptions, was applied.

As a main result, it could be stated that working and non-working students differ considerably according to their characteristics. I observed a dependency between students' work intensity and their social background. Educational climbers seem to be more likely to work throughout their studies than students coming from an academic household. In addition, students with a bad final grade at school are more likely to work intensively.

The results of the estimated Cox models revealed a negative effect of working during the whole study time on study duration in the majority of fields. In almost all fields working only in parts of study time seems not to affect study duration. Furthermore, the data base allows to include measures of students' ability and of the parental educational background in the model, information that is missing in most data sets. The results confirmed my hypothesis that good A-level grades increase the hazard of graduation. Surprisingly, the parental educational background seems not to affect time to degree significantly. This is probably due to the fact that social background effects on university performance are mainly driven by disadvantages of socially underprivileged students on earlier levels in the course of education (for example, students from low-income families tend to achieve poorer A-level grades which are found to affect time to first university degree negatively). Due to the richness of the data set, detailed insights into covariate effects on duration within different fields of study could be provided. As assumed, some covariates affect time to degree differently across fields of study. A detailed analysis of these differing effects should become a focus of further research.

As revealed in the first paper, working and non-working students differ considerably with respect to their characteristics; a random assignment to both groups could not be assumed. Therefore, in a second study we tried to mimic as closely as possible the procedure in random experiments, in which students would be assigned randomly towards the working and non-working group. The aim was to control as much as possible for potential selection effects using all relevant available information on the students under analysis.

A closer look at the characteristics of off-campus working students revealed that they contain a higher share of female students and fewer students with academic parental background than their non-working fellow students. They receive on average poorer A-level grades, have less often visited high school and on average receive less financial support from their parents. Under the assumption of a random experiment, working students unequivocally have longer study durations than non-working students. The difference in study duration is highly significant for the complete sample (0.84 terms) as well as in eight out of ten fields. Applying the matching framework, i.e. controlling for selection effects, results in lower and less significant estimates of the effect of working on study duration. The difference for the whole sample is about 0.67 terms. For six out of ten fields a significant prolonging effect of off-campus work on the duration of study was found. Controlling for potential self selection and regarding the working or non-working

activity of students as endogenous seems to be very important for assessing causal effects of work on duration.

In the third paper, the effects of students' social background on final university grades were analyzed. Since previous studies claimed a strong disadvantage for socially underprivileged students on the school level, I investigated whether these disadvantages extend towards university. Moreover, the predictive power of A-level grade for academic performance was examined. A-level grades are of particular interest in debates on university entrance restrictions.

A methodological issue was whether grades should be treated as metric or ordinal in statistical models. As in the German grading system final university grades can be characterized as discrete outcomes of an underlying continuous process, I treated grades as discrete and ordinal and applied an ordered probit regression without and with controlling for students' A-level grades.

I observed a rather strong positive relationship between A-level and university grades. I found no noteworthy differences in university grades by levels of academic origins. However, A-level grades differ considerably between levels of parental educational attainments. Educational climbers obtain on average a poorer A-level grade than students from well-educated parental backgrounds.

As a main result, I found that the strong effect of the parental academic background on A-level performance does not carry over to performance at university in its entirety. Without controlling for A-level grades, the probability to obtain good grades is higher for students with a privileged social background, whereas the probability for poorer grades is higher for socially underprivileged students. After controlling for A-level grades, this effect vanishes for the lower level of parental academic background and diminishes for students from higher educated households. Therefore, it seems that background effects on university performance may be mainly driven by disadvantages of socially underprivileged students on earlier levels in the course of education.

As academic performance is assumed to affect graduates' wages, in a next step wages and wage differentials between men and women at labor market entry were analyzed. We applied an extended decomposition approach, which can be classified as a single index model and allows analyzing the complete income distribution. By means of a returns-to-skill function, individual skill levels are monotonically converted into wages.

The pay gap was decomposed in endowment, skill-price, and returns-to-skill function effects.

The gender pay gap in average hourly starting wages in our data set is surprisingly large (25%) and of almost the same magnitude as the overall wage gap in Germany. As we used a very homogeneous sample only of university graduates at labor market entry, a gender wage gap lower than in heterogeneous samples was expected. Moreover, the observed wage gap of 25% is much higher than entry wage gaps of graduates found in other countries.

Wage regressions reveal university performance (here final grade) and fields of study to affect entry wages of men and women. Time to degree does not significantly affect entry wages. We detect only slight differences in male and female characteristics. An exception is the field of study, which seems to strongly affect wages at labor market entrance.

We observed higher starting salaries for men at all percentiles of the income distribution. The magnitude of the overall pay gap varies strongly across the income distribution. In addition, the three isolated effects behave quite differently at different percentiles. The endowment and price effects are inversely u-shaped and both favorable for men throughout. The effect of the difference in the returns-to-skill function is advantageous for female graduates at the lower part of the wage distribution. However, this effect is outweighed by the strong endowment and price effects.

In summary, the first three studies add further evidence to the findings that underprivileged students face disadvantages in their educational careers in several ways. The data allows for a detailed analysis of graduates' academic success and contributes to the existing literature on time to first university degree and on final university grades.

These results are probably useful to evaluate the German academic system, e.g. the Bologna reforms. The results are based on data for the old Diploma degrees, but could be even more relevant after the Bologna reforms. The bachelor/master system is characterized by a more structured curriculum and tighter schedules to allow for short times to degree and to provide students a fast qualification for the labor market entrance. However, as it is probably more difficult to combine work and study in a very tight curriculum, this could strengthen the detrimental effects of work on time to degree and result in even higher exceedance of regular study durations. According

to the figures listed the introduction, there is an upward trend for times to degree. The majority of students do not manage to meet the proposed time line. In 2012, only 49.4% finished with a bachelor's degree and 42.3% with a master's degree within standard duration. With the beginning of the Bologna reforms, students criticized the new bachelor/master system, in particular the structure and the feasibility of studying. In 2009, the "Kultusministerkonferenz" (Standing Conference of Education Ministers) stated to restructure bachelor's and master's degree to improve study conditions and organization, but there seems to be still a need for further improvements, probably with a manageable and more flexible workload.

The revealed dependencies between students' characteristics and academic performance should be considered in the ongoing discussion about the implementation of tuition fees and the design of the financial aid system. In particular, the high employment rates of students and even their high work intensities probably point for a weak financial aid system. A main motive for employment is to cover living expenses. Hence, there is a need to improve financial aid policies to ensure that students are not forced to work intensively to cover their living costs. Since educational climbers seem to be more likely to work intensively during their studies, an improved financial aid system is of particular importance for students from non-academic backgrounds.

The main source of financial aid for students from low income families is provided by BAföG. The maximum amount of monthly payment of about 600 Euro. A higher subsidy probably will reduce the need to cover living costs through own earnings. Currently, an increase of BAföG subsidies is part of political discussions in Germany. The maximum period of assistance is determined by the standard period of study. Therefore, after an exceedance of legal durations students face problems of financing the final period of their studies. Without additional financial aid programs they are probably forced into work with a prolongation of time until graduation as a consequence. Here, more attractive education loan programs providing low-interest financial support for finishing studies as fast as possible should be provided. Furthermore, scholarships are only awarded to students with excellent academic performance. A more generous access to study grants and more extensive information policies about such programs are probably some improvements leading to lower work intensities and therefore to shorter study durations.

Recently, the "Hochschulrektorenkonferenz" (German rectors' conference) calls for a reintroduction of tuition fees in Germany. It should be considered that higher costs of

tertiary education may well increase students' engagement in work. As the findings of this thesis suggest, this may result in longer times to degree and will be in particular relevant for students from low income families. However, there is a need to evaluate net effects of such reforms more elaborately in future research. Regarding the effect of tuition fees, there is uncertainty about the net effect. On the one hand, higher costs of studying provide incentives to shorten study time, but on the other hand, higher costs may increase employment of students in order to cover their costs.

Discussions on the selection criteria of universities raise the question if A-level grades are a reliable signal for future academic performance. The third study reveals A-level grades to be highly predictive for final university grades. Moreover, as already detected in previous research, there seems to be a high dependency between A-level grades and social background. Hence, there probably exists a disadvantage for underprivileged students to participate in higher education as they tend to receive worse grades at school. Furthermore, already enrolled at university, students with poorer A-levels tend to finish also with poorer final university grades. Since A-level grades seem to capture partly social background effects, disadvantages for socially underprivileged students' at the school level seem to extend towards university.

Moreover, academic performances may have an effect on graduates' wages at labor market entry. The fourth study revealed a dependency between university grades and entry wages, with better grades leading to higher wages. Since students' academic performance varies with A-level grades, which seem to capture partly social background effects, also later earnings may differ between graduates' social origins. Hence, disadvantages for socially underprivileged students' at the school level seem to extend even towards the labor market. Therefore, promoting skills of these pupils at the school level is maybe a starting point for higher participation rates in tertiary education and better academic performances and labor market outcomes of children with socially underprivileged backgrounds.

The main findings of the fourth paper, the extent of the gender pay gap at labor market entry being already of about the same magnitude as the overall pay gap in Germany and the strong effect of choice of field of study, question the present focus on equal pay politics. Women tend to choose lower paid fields of study than their male fellow students. As already mentioned in the introduction, average gross earnings of full-time workers vary substantially between sectors. The choice of job sectors is in turn to a great extent determined by the field of study. Therefore, analyzing the early processes determining

the very gender specific choices of field of study should become a focus of researchers and policy makers. Identifying reasons motivating women to choose lower paid fields of study and to induce female students to study typically male fields are probably starting points in reducing the gender pay gap at labor market entrance and at later stages in the career.

The German higher education system as well as the financial aid system will undergone further reforms in the future, e.g. a restructuring of the bachelor/master system, a reintroduction of tuition fees or an increase of BAföG payments. Therefore, there is a need for further research in the field of German higher education institutions. Moreover, as the results of the last paper suggest, a closer look on gender specific choices of study fields and sectors is an important topic for future research.

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Attachments

Überblick über die Einzelbeiträge der vorliegenden Dissertation:

- Katja Theune: "The Working Status of Students and Time to Degree at German Universities"
  Diese Studie wurde in *Higher Education* angenommen und befindet sich im Veröffentlichungsprozess.
- Andreas Behr, Katja Theune: "The Causal Effect of Off-Campus Work on Time to Degree"
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- Andreas Behr, Katja Theune: "The Gender Pay Gap at Labor Market Entrance: Evidence for Germany"
  Diese Studie wurde zur Veröffentlichung bei einer Zeitschrift eingereicht.