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Essays on Occupational Choice

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Dipl. rer. com. Eva Gabriele Schlenker
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Dekan: Prof Dr. Dirk Hachmeister
Prüfungsvorsitz: Prof Dr. Marion Büttgen
Erstgutachter: Prof. Dr. Gerhard Wagenhals
Zweitgutachterin: Prof. Dr. Nadine Riedel

Vorwort

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Stuttgart, Juli 2013 Eva Schlenker

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List of Abbreviations

ATS	academic secondary school track
BA	German Federal Employment Agency
BMBF	German Federal Ministry of Education and Research
CC	childcare
CEPR	Centre for Economic Policy Research
CL model	conditional logit model
DiD	difference-in-differences
DIW	German Institute for Economic Research (Berlin)
DOGEV	Dogit Ordered Generalized Extreme Value model
EFI	German Expert Commission on Research and Innovation
EGGE	European Commission's Expert Group on Gender and Employment
ESF	European Social Fund
EU	European Union
EUCOM	European Commission
Eurostat	Statistical Office of the European Union
EU-SILC	European Statistics on Income and Living Conditions
FA	family allowances
FRG	Federal Republic of Germany
GDP	gross domestic product
GDR	German Democratic Republic
IAB	Institute for Employment Research (Nuremberg)
IIA	(assumption of) the independence of irrelevant alternatives

ISCED	international standard classification of education
ISCO	international standard classification of occupation
IW	Cologne Institute for Economic Research
IZA	Institute for the Study of Labor (Bonn)
JRC	Joint Research Center of the European Commission
LR-test	Likelihood-Ratio-test
ME	marginal effect
MNL model	multinomial logit model
NL model	nested logit model
OECD	Organization for Economic Co-operation and Development
OLS	ordinary least squares
PEA	partial effect at the average
PISA	Programme for International Student Assessment
PPS	purchase power standards
RPL model	random parameters logit model/mixed logit model
RWI	Rheinisch-Westfälisches Institut
	für Wirtschaftsforschung (Essen)
SOEP	German Socio-Economic Panel
Std. Dev.	standard deviation
STEM	science, technology, engineering and mathematics
U.S.	United States
WISE	"Women into Science and Engineering"
WZB	Social Science Research Center (Berlin)
ZEW	Centre for European Economic Research (Mannheim)

List of Important Symbols

$\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ...)'$	column vector of (unknown) regression parameter
$\boldsymbol{\beta} = (\beta_1, \beta_2, ...)'$	column vector of (unknown) regression parameter
$\boldsymbol{\gamma} = (\gamma_1, \gamma_2, ...)'$	column vector of (unknown) regression parameter
δ_i	further (unknown) regression parameter
ϵ_{it}, $\hat{v}_{it}$	(estimated) error term of individual i in period t
$F_j(.)$	distribution function
I_j	inclusive value of limb j in a nested logit model
K	number of regressors
m	number of alternatives in a multinomial model
max	maximum
min	minimum
N	number of observations
p_{ij}, $P(y_i = j)$	probability that individual i chooses alternative j
$p_{k\|j}$, $P(y = k\|y = j)$	probability that alternative k is chosen given that limb j is chosen in a nested logit model
$\mathbf{R}$	correlation matrix of the error terms in a mixed logit model
σ_k	standard deviation of the kth distribution in a mixed logit model
$\mathbf{w}_i = (w_1, w_2, ...)'$	column vector of individual i' regressors not varying over alternatives in a conditional logit model
$\mathbf{x}_{it} = (x_1, x_2, ...)'$	column vector of individual i's regressors in period t

y_{it}	outcome of individual i in period t
$\mathbf{z}_i = (z_1, z_2, ...)'$	column vector of individual i's regressors varying over the limb in a nested logit model

1. Determinants and Outcomes of Occupational Choices – A Survey

1.1. Introduction and Purpose of the Study

Occupational choices have far-reaching consequences for one's life. This is a well known phenomenon. However, in times of aging populations in industralised countries occupational choices are not only a matter of individual well-being, the efficiency of labour markets is also an issue that attracts a great deal of attention nowadays. The shortage of workers in general and especially in scientific occupations and engineering is a recurrent issue. During the recent years, many member states of the European Union (EU) have hence politically debated measures to attract skilled workers and to educate more young people in high-skilled work. The European Commission (EUCOM) regards the question of occupational choice also as a matter of gender equality and social inclusion: "the European Union supports actions and projects that aim at improving career guidance with regard to non-traditional careers for both women and men; improving women's level of qualifications, particularly in the scientific and technical fields and in new technologies" (EUCOM (2006), p. 11). The member states of the EU face political pressure to follow this guideline because the European Social Fund (ESF) is bound to assist projects which strengthen economic and social cohesion, e.g., the reduction of gender segregation in the labour market (European Parliament & Commission (2006), p. 14).

The main attention in Germany is concentrated on a shortage of workers in the fields of science, technology, engineering and mathematics (STEM). Whether a significant shortage of skilled workers in these fields already exists in Germany, is hotly debated. On the one hand, industrial federations and employers stress difficulties in finding highly qualified workers in these fields. On the other hand, academic studies (see, e.g., Brenke (2010)) do not find significant effects on wages.[1] In spite of the dispute on whether skills shortage is nowadays a real threat or simply a myth, most academic observers agree that during the next decades the labour force will be shrinking dramatically due to the demographic change. The German Expert Commission on Research and Innovation (EFI) stresses the importance of a qualified workforce that matches economy's skill requirements and focusses on workers in STEM fields (see EFI (2012)). EFI reports that the problem of the match of qualified workers and job requirements becomes even more urgent because of the fact that the share of graduates in engineering has decreased from 20 to 12 % in Germany between 1998 and 2007. Compared to the average value of all member states of the Organization for Economic Co-operation and Development (OECD), Germany has lost its top position since 1998 and is average to date (see EFI (2012), p. 61). To solve this problem, the German government has already introduced many different projects encouraging especially girls to choose occupations in STEM, e.g., the "National Pact for Women in MINT Careers" guided by the Federal Ministry of Education and Research (BMBF) (see BMBF (2008)). Another project, called "Girls' day – Future Prospects for Girls", organises open days for girls in STEM industries and takes place each April since 2003.[2]

To sum up, skills shortage will be a critical issue for the stability of industralised economies as well as for the growth of companies: it is well known that, amongst

[1] For an overview of different projections, the size of estimated skills shortage and arguments on both sides see, e.g., Kappler et al. (2011), Brenke (2012a,b) and Anger et al. (2011).

[2] For further details see `http://www.girls-days.de`.

other things, the shortage of skilled workers reduces the investments in research and development. It has also been shown that a positive correlation between the share of graduates in STEM subjects and the economic welfare of states exists (see Murphy et al. (1991) and Tsai et al. (2010)). This knowledge constitutes a strong and growing interest in the determinants and outcomes of occupational choices. One reason for this can be seen in the long-term consequences of occupational choices on workers' productivity. After all the productivity of workers is best if occupation fits abilities best. This thesis contributes to the understanding of occupational choices and successive labour market behaviour. Occupational choice is considered as multi-layered process. Therefore, this thesis analyses different decisions over the (early) life-cycle because these decisions condition chances afterwards. For example schooling decisions limit the number of occupations available for an individual later in life and different occupational choices imply differences in wage premiums and labour conditions like the possibility to work in part time. Therefore, the following chapters focus on crucial decisions and their implications on the later life-cycle.

Beyond the increasing interest of politics and business, the recent years have not witnessed a boom of academic interest in occupational choice in economics, yet. Occupational choice has received rather small attention given its importance for individual well-being and the efficiency of labour markets. The analysis of occupational decisions is of prime importance because the quality of the match between individuals and occupations may decisively affect individual productivity and wages as well as other individual socioeconomic characteristics. Noteworthy exceptions are papers that investigate the impact of labour market conditions and gender on occupational choice (see, e.g., Drost (2002), Kleinjans (2010), Robertson and Symons (1990) and Sookram and Strobl (2009)). Moreover, there exists a large literature on education choices and the impact of parental background on children's schooling decision (for an overview see Haveman and Wolfe (1995)) as well as a number of studies on occupational choice conducted during the 1980s and 1990s (see Leslie et al. (1998)).

Besides the small number of studies in labour economics, an extended sociological literature on social mobility and intergenerational stratification exists. Over the last 50 years, this strand of literature has developed various theoretical concepts such as scales for socioeconomic status and prestige for different occupations (see Ganzeboom et al. (1991) for an overview). The core finding is that occupational (im)mobility is mainly driven by status. Until today a high intergenerational immobility of occupational status is observed in these studies and several factors are found to have an impact on status attainment. However, the knowledge that emerges from a review of the sociological literature concurs with the findings of the economic papers: occupational choices consist of childhood-to-employment explanations (see, e.g., Hope (1984), Erikson and Goldthorpe (1987) and Leslie et al. (1998)). Occupational choice is, on the one hand, dependent on other decisions made early in life such as education choices and is, therefore, highly influenced by parental background. On the other hand, occupational choice is of crucial importance for outcomes such as earnings, status, satisfaction and the bargaining position in the marriage market (see, e.g., Badgett and Folbre (2003)). Hence, the isolated analysis of occupational choice during adolescents has been found to leave much unexplained and a life-sequence approach is needed to fully understand occupational choice in its determinants and outcomes.

The aim of this chapter is to review the existing literature and to outline the author's own contributions in the research area of occupational choice which are presented in detail in the chapters 2 to 5. The structure of the chapters is geared to the timing of decisions during the life-cycle, starting with the decision about educational achievement moving to the decision about occupational fields and closing with the outcomes of occupational choice. The outcome of occupational choice is illustrated in detail using the example of women in the occupational field of STEM. The topic of women in STEM is brought into focus because this subarea of occupational choice is of special interest given the importance of the quantity and the quality of the science and engineering labour force for modern industries. Before turning to the analysis it seems appropriate to make clear that the author sets aside any value judgement on occupational choice. The intent is not to judge whether occupational choices of different groups (e.g., women) ought to be different, but rather to shed light on the factors that can explain different patterns in occupational choice and, as Leslie et al. (1998) state for women and minorities in science and engineering "improve the prospects of underrepresented groups entering and succeeding in [...] fields, should they choose to do so, in other words, the enhancement of free and open choices" (p. 272).

1.2. Occupational Choices in the Economic Literature

1.2.1. A Review of Related Work

As described above, occupational choice does not only affect other individual socio-economic characteristics such as earnings and status, the quality of the match between workers and occupations affects also the productivity of the labour force. Therefore, it is important to understand which determinants influence occupational choice. However, the analysis of occupational choice has received rather little attention in the economic literature during the recent decades. The existing studies segment the question of occupational choice into several problems such as the intergenerational elasticity of earnings or the gender segregation in labour markets. Labour economists are interested much more in the question of education choices. Thus, a lot of theoretical and empirical research is devoted to the question on how investments in education are influenced by different characteristics. However, it has to be kept in mind that education and occupational choices interdepend strongly, especially in highly structured labour markets like in Germany where occupations are bound to a certain level of schooling. Hence, education choices are one important component of occupational choices. Most work in the area of education choices is based on the human capital approach implemented by Becker (1964).[3] In the following, studies on education choices and their relevance for occupational choice are presented.

The Human Capital Approach and Education Choice

During the 1960s and 1970s the research topic of human capital has turned into the focus of labour economists. The labour force is not considered as homogenous any longer, but as main and diverse factor of economic growth and technological improvements. Highly skilled workers are needed in modern economies to produce welfare (see, e.g., Becker (1964)). The starting point for the research in the demand of education is the economic finding that increases in capital are not the driving force for growing earnings in modern societies. So, economists have begun to wonder on the demand for and the returns of education at that time: why do individuals invest in education and how much of the variation of earnings can be explained by different levels and fields of education?[4]

At the core of the human capital theory is the concept that education is an investment of current money and time for future (higher) earnings (see, e.g., Becker (1964), Ben-Porath (1967)). However, the notion of human capital is enhanced beyond education: "the many forms of such investments *[into human capital]* include schooling, on-the-job training, medical care, migration, and searching for information about prices and incomes" (Becker (1964), p. 1). Becker (1964) is the first to offer a pricing theory for an individual's demand for human capital and especially education. His basic idea is that an individual faces the option of either attending school for an additional year or working fulltime. On the one hand, an individual suffers foregone earnings during an additional year of schooling as well as he/she has direct costs for tuition, books, fees and others (see Becker (1964), p. 30). On the other hand, an individual can gain higher earnings because of more education

[3] Earlier contributions to the topic of human capital have been made by Schultz (1960, 1961).

[4] For an overview of early theoretical and empirical studies on the demand for education see Freeman (1986).

and, therefore, decides to attend school longer in anticipation of future earning potentials. It depends on the rate of returns of education how much time is invested in education (given the costs) (see Becker (1964), p. 46 f.). Empirical evidence for the impact of schooling on earnings is found, e.g., by Becker and Chiswick (1966). For an extensive overview of the history of the human capital theory see Becker (1993).

As described above, the human capital theory considers education (as well as occupational) choice as a rational calculation of costs and benefits. Several aspects are at the heart of the empirical research on human capital theory: for example, one strand of literature analyses the influence of family background on the demand for education. A strong positive relationship between an individual's family background and schooling is found in general (see Freeman (1986), p. 369). This effect has two different sources: first, individuals from families with higher income face lower costs during school. Second, positive family factors may effect the individual's capability to benefit from higher education, e.g., providing children with good business contacts (see Freeman (1986), p. 369). Other empirical studies show that individuals respond strongly to incentives in terms of education choices. The impact of the salaries of college workers on the number of young people enrolled is shown in several studies as well as the positive correlation between the relative salaries in specific disciplines and the share of first-year students in those fields of study (see Freeman (1986), p. 373 for an overview). McPherson (1978) reviews studies on tuition fees and finds that a $100 increase in tuition fees increases the proportion enrolled by approximately 0.8 percentage points (p. 181).

Meanwhile, the human capital approach is not only applied to education choice. Occupational choice is also brought into the focus of human capital, especially in terms of gender. Early studies of human capital explain the lower level of female education in general by the fact that women do not expect to be in the labour force for many years due to child-rearing. However, the average female education level has largely increased during the last decades, but gender differences in occupation choices maintain. The high level of occupational segregation of women and men is often referred to as gender segregation.

In the area of research on human capital, gender segregation is a research topic in several studies, too. Labour economists commonly interpret gender segregation as the result of different, but individually rational choices of women and men (see, e.g., Polachek (1981)). In contrast to men, women anticipate gaps in their employment history because of childbearing and child-raising. Hence, women choose occupations that, for example, allow to work part time, offer high starting salaries (with low increases) and re-entry opportunities after employment breaks (see, e.g., Polachek (1981)). Polachek (1981) emphasizes the low rate of atrophy of female dominated occupations (p. 62 ff.). So, women choose occupations whose specific knowledge does not loose its value during times out of the labour force. This is also found by Binder (2007) who argues that this is the main reason for women to choose jobs with low dynamics of occupation-specific knowledge, e.g., in the tertiary sector.

However, empirical studies on human capital also show contradicting evidence and find that occupational choice and experience with/knowledge about occupations are interdependent: Anker (1998) argues that girls do not choose occupations in STEM because they do not have role models. Missing role models increase girls' uncertainty and costs because of less information. This effect is self-amplifying. Additionally, the assumption of exogenous (different) preferences of women and men in the human capital theory is blisteringly criticized: for example Heintz et al. (1997) find contradicting empirical results by showing that women with children work more often in male-dominated jobs.

This review shows that much research in economics is devoted to education choices. The human capital approach explains many aspects of differences in attained educational levels. Some questions, however, are still unanswered today. One of these is the question on how family background affects schooling decisions during childhood and whether these decisions are taken rationally. The focus of labour economists has changed in this strand of literature recently and modern studies concentrate more on the question on whether the high correlation of intergenerational levels of education and earnings is caused by genetic endowment (nature) or by socialisation (nurture). Most studies find a combination of nature and nurture effects. So far, academic research does not find a clear-cut answer on the research question on which effect exceeds in the nature-nurture-debate (for an overview of studies see Black and Devereux (2011)). The author's own contribution to the research topic of parental influence on education choices can be read in chapter 2.

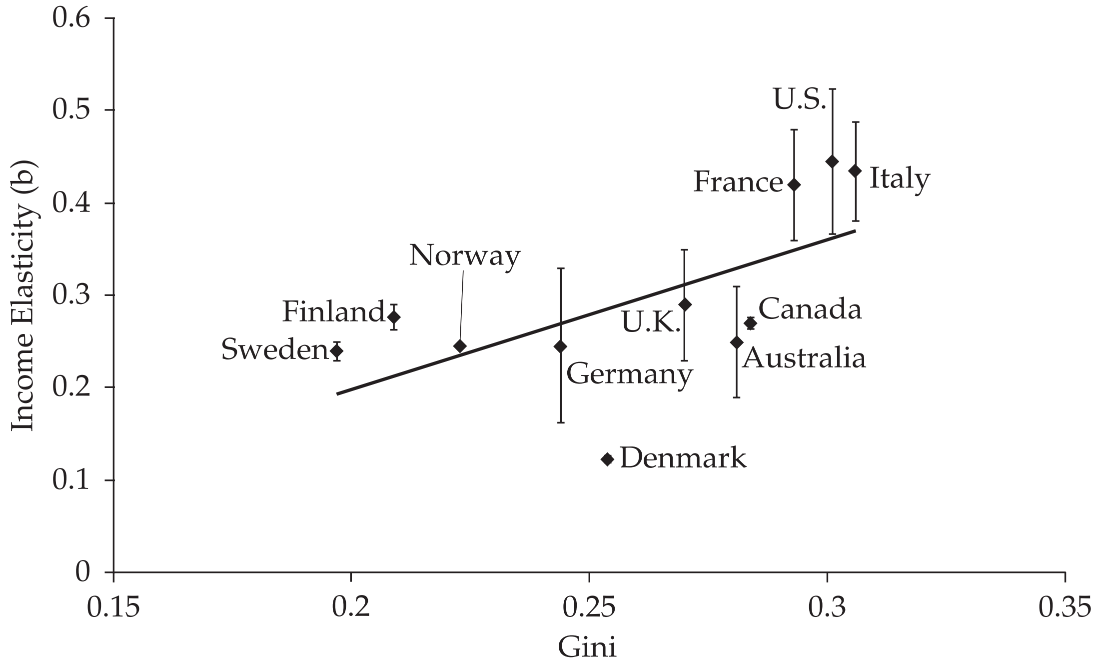
The Empirical Literature on Occupational Choices

Compared to education choices, the research question on which determinants influence occupational choice in terms of the field of study or the field of vocational training receives rather little attention by labour economists. However, many sociologists conduct research in this area. So, some general conclusions concerning occupational choice result from sociological studies on social mobility and intergenerational stratification research conducted during the last century. One of the first who have analysed social mobility is Pitirim Sorokin: Sorokin (1927) considers social dimensions to be similar to geometrical shapes: "Euclid's geometrical space is space of the three dimensions. The social space is space of many dimensions..." (Sorokin (1927), p. 7). He identifies different dimensions of mobility: horizontal versus vertical, individual versus collective and intergenerational versus intragenerational mobility. His study focuses on large social changes in the United States of America (U.S.) and finds that even during the beginning of the 20th century high social immobility between generations exists.

After World War II social mobility in Europe has become a major research topic in sociology. High immobility rates have already been found especially for farmers during these decades. Later on, the topic of status attainment has dominated sociological research (see Blau and Duncan (1967)). This strand of the literature has developed various scales for the socioeconomic status and prestige of different occupations and meanwhile finds that occupational mobility is mainly driven by socioeconomic status. Although occupational mobility raises over time, these studies still observe a high intergenerational immobility of occupational status nowadays. Several factors may have an impact on status attainment: for example, education is found to be more important than parental occupation (see Ganzeboom et al. (1991), p. 296 f.). Some sociological studies explicitly address the effect of fathers' occupational class on intragenerational mobility of sons (see Hope (1984) and Erikson and Goldthorpe (1987)), or examine how education helps to pass class attributes on to the next generation (see, e.g., Semyonov and Roberts (1989)).

Moreover, the low occupational mobility among parents and children reveals to what extend inequality is passed on and, therefore, refers to the idea of equivalent opportunities. This motivates a strand of literature in labour economics analysing the intergenerational elasticity of earnings. Corak and Piraino (2011), for example, show that 40 % of young Canadian men have worked or currently work with an employer for which their fathers also worked. They also find a positive correlation between this percentage and parental income: almost 70 % of sons whose fathers belong to the top percentile of the earnings distribution have or have had the same employer as their fathers. According to Corak and Piraino (2011), the transmission of employers increases the overall level of the intergenerational elasticity of earnings. Bentolila et al. (2008) also find some empirical evidence that social relationships and family contacts have an impact on finding a new job and especially the first permanent job more quickly. However, they also find negative consequences in terms of lower wages and a lower productivity.

Figure 1.1 shows the relationship between the intergenerational elasticity of earnings and the income equality measured by the Gini coefficient. Intergenerational elasticities of earnings are given as confidence intervals. Ermisch et al. (2012) find that inequality is negatively correlated with mobility because mobility is high if intergenerational income elasticities are low. Ermisch et al. (2012) also emphasize the differences in intergenerational mobility among countries: while mobility is highest in Scandinavia, high intergenerational immobility is found in the U.S. (p. 5 f.).



Source: Ermisch et al. (2012), p. 5.

Figure 1.1.: Estimates of Intergenerational Income Elasticities for Fathers and Sons, Early 1980s.

These findings go along with other studies. Intergenerational social links are also found to have positive effects on the material well-being of the family. Here, past economic studies have focused on certain sectors where special skills and knowledge that increase productivity are acquired during childhood (see, e.g., Laband and Lentz (1983)). Farming is a typical example since inheriting the family farm increases productivity in comparison to working on the farm of someone else. For an overview of studies concerning the agricultural sector see Corak and Piraino (2011). Lentz and Laband (1989, 1990) and Laband and Lentz (1992) also apply this model to children of doctors, lawyers and self-employed parents.

A number of economic papers assesses also the impact of labour market determinants on occupational choice. Robertson and Symons (1990) discuss the influence of relative earnings on occupational choice. They find that relative earnings have an effect on initial occupations as well as on personal job preferences. Drost (2002) sheds some light on the cyclicity of student enrollment in different academic fields and the relation to the business cycle and unemployment. Filer (1986) examines to what extend occupational choice is influenced by labour market constraints. His findings concur with Brown et al. (2008) who model supply-side as well as demand-side influences on occupational choice. The general consensus among economists is that occupational attainment is determined by labour supply-side as well as labour demand-side factors while findings on the effects on occupational choice are mixed.

As already mentioned above, other economists focus on the effect of gender on occupational choice. Occupational segregation seems to be a very robust and enduring phenomenon in labour markets all over the world.[5] According to the human capital approach, women tend to choose occupations with high entry earning levels and low growth rates over working life, i.e., Polachek (1981) shows that typical female occupations are characterized by slowly decreasing earning potentials during times out of the labour force. Apart from this point of view, much empirical research is devoted to the analysis of the effects of different cultural and institutional settings on gender segregation. Sookram and Strobl (2009) examine the gender segregation in Trinidad and Tobago in the time period between 1991 and 2004 where educational policy changes have taken place. Although these changes have reduced educational segregation, the authors find no effect on occupational segregation. Blau et al. (2012) find that gender segregation has been declining at a diminished pace between 1970 and 2009. Blau et al. (2012) confirm that gender segregation is still on a high level today. They constrain today's segregation mainly to the STEM fields, clergy and blue-collar categories (p. 22). In accordance to other studies, Blau et al. (2012) also find a negative correlation between segregation and education.

The topic of gender segregation also receive considerable political attention; EUCOM (2010) confirms a stable level of segregation for Germany and all other member states of the EU. From a European perspective the fact that most women continue to work in female dominated occupations (vice versa for men) constitutes a social

[5]For a survey of the vast empirical work on gender segregation see Anker (1997). Jonung (1996) and Blackburn et al. (2002) give an overview of theories on the origins of gender segregation and gender specifics in occupational choice.

problem because inequalities between the sexes are enforced by different wage levels in "women's" and "men's" occupations (see, e.g., EUCOM (2009)). The German level of segregation is on a medium level compared to other member states of the EU (see, e.g., Smyth and Steinmetz (2008)). Wiethölter et al. (2011) measure the level of gender segregation for Eastern and Western Germany: they find a Gini coefficient of 0.689 for Western Germany in 2009 (1993: 0.733). The level of gender segregation in Eastern Germany is slightly lower displayed by a Gini coefficient of 0.698 in 2009 and 0.743 in 1993, respectively (see Wiethölter et al. (2011), p. 25). However, both regions show a strong concentration of men and women in occupations. Detailed insight in the gender segregation in Germany is also provided by Binder (2007) and Schreyer (2008).

Closely related to the research on gender segregation are economic and pedagogic studies that focus on the gender-specific choice of different fields of study or of different fields of vocational training. The focus of these studies is often on occupations in STEM. Contrary to the declining gender gap in education in general, STEM degrees are still less pursued by women than by men. These gender differences may be explained by biological, sociological or social-psychological factors. Biological theories on the gender gap imply that the gender gap is at least partly caused by innate genetic differences between males and females (see, e.g., de Waal (1999)). Cultural factors like gender stereotypes may also be important and change rather slowly over time. However, empirical evidence shows that the local school environment can reduce the gender gap considerably (see Legewie and DiPrete (2012)).

One further reason for gender differences in occupational choice and the choice of different fields of study is seen in gender differences in preferences. For a long time, the responsibility of nature or nurture for gender differences has been a major research topic in psychology. However, there exists a growing number of contributions by economists; Croson and Gneezy (2009) review the experimental economic literature on gender differences in preferences. They find robust results in economic experiments: women tend to be more risk averse than men and dislike competitive games more (see Croson and Gneezy (2009), p. 450/464 ff.). Gender differences in social preferences seem to be more blurred (see Croson and Gneezy (2009), p. 456/459). However, Croson and Gneezy (2009) conclude that further research is needed to show whether gender differences in preference are mainly implied by genetic endowment ("nature") or socialisation ("nurture") because none of the reviewed studies can answer the nature-nurture-debate (for an overview see also Bertrand (2011)).

Furthermore, some economists extend the nature-nurture-debate on the research question on the determinants of social mobility and education: for example, are earning inequalities caused by unequal opportunities and is low social mobility of succeeding generations the result of the genetic endowment? Conlisk (1974) provides a model of intergenerational income distribution that explicitly takes into account nature-related and nurture-related factors. Taubman (1976) uses data on twins in order to find whether inequality in earnings are caused by genetic or environmental factors. He reports that up to 41 % of the variance of the logarithm of earnings is due to genetics and concludes that a substantial part of the variance can be explained by events before entry into the labour force takes place. More recently, economic researchers have broadened the scope of the nature-nurture-debate to analyse different economic labour market outcomes: for example, Behrman and Taubman (1989) use father's occupation and the number of siblings as environmental factors. According to this study, a high fraction of the variance in educational attainment can be explained by genetic differences of pupils.

Sacerdote (2002) assumes adoption to be a natural experiment. The socio-economic status and the educational level of the adoptive parents has a large effect on children's educational attainment, marital status and earnings. There seems to exist some empirical evidence for family environment being more important for economic outcomes than for children's test scores. Das and Sjogren (2002) compare income levels of biological and adopted children and conclude that parental income matters, but only through the transmission of innate abilities to offspring. An individual's educational level has a large effect on income for the subsample of adopted children while no significant effect is observed in the subsample of biological children. Similar results with respect to schooling are found by Plug and Vijverberg (2005). The author's own contribution to the nature-nurture-debate can be read in chapter 3.

Studies on occupational choice apply a broad range of econometric methods. Developments in econometrics are of core interest for occupational choice because the robustness and the consistency of estimation results are tied to econometric methods. The following section reviews the most common estimation methods and the historical development of more sophisticated identification strategies.

1.2.2. Econometric Methods of Modelling Occupational Choice

First sociological studies on intergenerational stratification research that also have focussed on occupational choice have been conducted shortly after World War II (see Ganzeboom et al. (1991) for an overview). During these times statistical methods have involved little more than the comparative inspections of frequencies into and out of occupations. The observed mobility has been displayed in mobility tables. Mobility tables contrast individuals' own status attainments with their social backgrounds and, therefore, can reveal mobility patterns. Mobility chances are derived from mobility tables. Despite the simplicity of this method, some findings are still valid today. For example Lipset and Zetterberg (1956) conclude that low intergenerational mobility is found in all industralised countries. The high persistency of farming among generations is also found in mobility tables.

Path models have been introduced into the sociological research during the 1950s and 1960s. Path models have enabled scientists to disentangle causal relationships and to differentiate intergenerational immobility into direct and indirect effects. Additionally, continuous prestige scales of occupations have been used for applying the concept of correlation during these years. Prestige scales have measured occupational status by incumbents' average education and income (see, e.g., Duncan

(1961)). For the U.S. a correlation of 0.405 has been found between son's current occupation and father's occupation in 1962. This correlation has been split into an indirect effect via education (57 %) and a direct effect, e.g., through the first job (43 %) (see Ganzeboom et al. (1991), p. 283).

Modern econometrics have enlarged estimation methods enormously since the 1970s. Since the development of discrete choice models the whole variety of these nonlinear models are applied to occupational choice. Goldthorpe (1987) motivates the use of multinomial regression models instead of correlation analysis and linear regressions by the fact that occupations as well as social classes are discrete and unordered by nature. Hence, occupational choice can be described as a choice among unordered and discrete alternatives even if occupational choice also contains a great deal of information about status and implies levels of earnings and bargaining positions in the marriage market. Specific orders of precedence are implied by different occupations, for example cleaning ladies are typically expected to have lower earnings, lower status and to be less educated compared to teachers. However, different occupations do not necessarily reflect hierarchic structures, e.g., the choice between becoming a doctor or becoming a lawyer does not necessarily imply higher earnings or status.

Therefore, researchers consider the problem as a choice among discrete alternatives and estimate discrete choice models since the beginning of the application of modern econometric methods to occupational choice. The question of occupational choice is not discussed in reference to career opportunities. Making one's career is mainly found to be highly correlated with educational attainment, not with occupational field. Some types of models for unordered multiple choices that are regularly used to examine the determinants of occupational choice are presented in the following.

In general, models for unordered discrete choices deal with dependent variables that exist of several mutually exclusive categories. The outcome y_i of individual i is one of m alternatives and equals j if the jth alternative is chosen, $j = 1, 2, ..., m$. Attention has to be paid to the fact that the alternatives $1, 2, ..., m$ are arbitrary and

– apart from ordered models – unordered (see, e.g., Cameron and Trivedi (2009a), p. 496 and Wooldridge (2010), p. 643). Multinomial models display the probability that individual i chooses alternative j, given the regressors $\mathbf{x}_i$, by

$$p_{ij} = P(y_i = j) = F_j(\mathbf{x}_i, \boldsymbol{\beta}), \quad j = 1, 2..., m, \quad i = 1, ..., N. \tag{1.1}$$

with different functional forms of the cumulative function, $F_j(.)$. $\boldsymbol{\beta}$ denotes the vector of unknown regression parameters to be estimated. Econometricians have developed different multinomial models depending on the choice of $F_j(.)$ and the vector of regressors $\mathbf{x}_i$ (see, e.g., Cameron and Trivedi (2009a) or Greene (2008)). Parameter estimation is conducted by maximum likelihood estimation (see, e.g., Cameron and Trivedi (2009a), p. 496 f.).

The estimated coefficients of multinomial models are not to be interpreted directly, but marginal effects (ME) have to be computed for estimating the size of the effect on the probability of observing the choice of alternative j. Following the notation of Cameron and Trivedi (2009b), the marginal effect of a change in regressor k on the individual i's probability to choose alternative j can be computed as

$$ME_{ijk} = \frac{\partial P(y_i = j)}{\partial x_{ik}} = \frac{\partial F_j(\mathbf{x}_i, \boldsymbol{\beta})}{\partial x_{ik}}. \tag{1.2}$$

For further details on estimation methods, for example the computation of marginal effects and different kinds of multinomial models see, e.g., Cameron and Trivedi (2009a), chapter 15, Wooldridge (2010), chapter 16.2 or Greene (2008), chapter 23. In the following the most commonly used types of multinomial models are described.

The first type of multinomial models covered in this section assumes that an individual's choice depends on individual characteristics and on alternatives' characteristics. Additionally, $F_j(.)$ is assumed to be the cumulative logistic distribution. This type of model is called conditional logit (CL) model and has been introduced by McFadden (1974).[6] The CL model implies that the vector of regressors differs across alternatives and possibly also across individuals. For taking into account that regressors vary over alternatives and over individuals, CL models are specified as

$$p_{ij} = \frac{\exp(\mathbf{x}'_{ij}\boldsymbol{\beta} + \mathbf{w}'_i\gamma_j)}{\sum_{l=1}^{m}\exp(\mathbf{x}'_{il}\boldsymbol{\beta} + \mathbf{w}'_i\gamma_l)}, \quad j = 1, 2..., m, \quad i = 1, ..., N. \tag{1.3}$$

where $\mathbf{x}_i$ varies over alternatives and $\mathbf{w}_i$ does not. $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ denote the regression parameters to be estimated (see Cameron and Trivedi (2009a), p. 500). Since $\sum_{j=1}^{m} p_{ij} = 1$, a restriction is needed for model identification which is usually $\beta_1 = 0$ (see Cameron and Trivedi (2009a), p. 500).[7] Estimating CL models is one traditional approach to model occupational choice. CL models are used to model occupational choice for example by Schmidt and Strauss (1975), Nickell (1982), Robertson and Symons (1990), Connolly et al. (1992) and Harper and Haq (1997).

However, the CL model imposes a severe restriction to the modelling of occupational choice. The CL model implies that "relative probabilities for any two alternatives depend only on the attributes of those two alternatives" (Wooldridge (2010), p. 648):

$$P(y = j|y = j \text{ or } k) = \frac{\exp(\mathbf{x}'(\beta_j - \beta_k))}{1 + \exp(\mathbf{x}'(\beta_j - \beta_k))} \tag{1.4}$$

where $P(y = j|y = j \text{ or } k)$ denotes the conditional probability of observing alternative j given that either alternative j or k is chosen (see Cameron and Trivedi (2009a), p. 502). This is called the assumption of independence of irrelevant alternatives (IIA).[8] It is obvious from 1.4 that all CL models reduce to binary logit models

[6]Multinomial models that include regressors that vary over alternatives as well as regressors that vary over individuals are sometimes also called mixed logit models (see, e.g., Cameron and Trivedi (2009a), p. 500). However, this expression is more common for quite different models of discrete choice (see Greene (2008), p. 851 f.). The author follows the standard convention and uses the expression "CL model" if some or all regressors are alternative-specific.

[7]The CL model includes the multinomial logit (MNL) model if only individual-specific regressors are included (see, e.g., Wooldridge (2010), p. 643 f. and Greene (2008), p. 843 f.). MNL models have been introduced by Luce (1959).

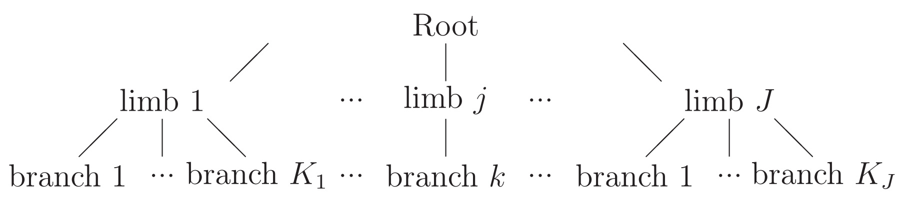
[8]For the statement and the interpretation of this assumption and the following models, it is easiest to focus on the population model instead of writing the equations for each individual i. Neglecting the index i improves the readability of the equation.

between any pair of alternatives and conditional probabilities are independent from other alternatives (see Cameron and Trivedi (2009a), p. 503).

The IIA assumption is, however, not quite plausible for occupational choice because it implies that the relative probability of the choice between two alternatives is not affected by the existence of a third alternative. So, the probability of becoming a teacher at elementary school compared to the probability of becoming a craftsmen is not affected by the opportunity to become a teacher at high school. This seems implausible.

To overcome this problem, more general multinomial models have been introduced into microeconometrics as well as into the empirical literature on occupational choice. One approach to relaxing the IIA assumption is the specification of a hierarchical model. The most popular of these, the nested logit (NL) model, has been introduced by McFadden (1978).

The NL model relaxes the IIA assumption by grouping similar alternatives into subgroups. This specification implies choices to exist of several levels. So, an individual first chooses among subgroups and then makes the choice among the alternatives in the chosen subgroup (see Greene (2008), p. 848). The IIA is maintained within subgroups. To sum up, the choice is modelled by a nested structure including error terms that are correlated within groups, but uncorrelated across groups (see Cameron and Trivedi (2009b), p. 497).



Source: Cameron and Trivedi (2009a), p. 509.

Figure 1.2.: Illustration of the Structure of a Nested Logit Model

Figure 1.2 demonstrates the structure of a NL model: there exist J limbs to choose from at the top level. Each jth limbs includes K_j branches, $j1, ..., jk, ...jK_j$ (see Cameron and Trivedi (2009a), p. 508-510). The joint probability of being on limb j and branch k can be factored as

$$p_{jk} = p_j \times p_{k|j} \tag{1.5}$$

with p_j the probability of choosing limb j and $p_{k|j}$ the probability of choosing branch k given being on limb j (see Cameron and Trivedi (2009a), p. 509). According to the assumption of the joint distribution introduced by McFadden (1978), the NL model results in

$$p_{jk} = p_j \times p_{k|j} = \frac{\exp(\mathbf{z}_j'\boldsymbol{\alpha} + \delta_j I_j)}{\sum_{m=1}^{J} \exp(\mathbf{z}_m'\boldsymbol{\alpha} + \delta_m I_m)} \times \frac{\exp(\frac{\mathbf{x}_{jk}'\beta_j}{\delta_j})}{\sum_{l=1}^{K_j} \exp(\frac{\mathbf{x}_{jl}'\beta_j}{\delta_j})} \tag{1.6}$$

with a vector of regressors $\mathbf{z}_j$ varying over the limbs only, $\mathbf{x}_{jk}$ including regressors varying over limbs and branches and the inclusive value $I_j = \ln(\sum_{l=1}^{K_j} \exp(\frac{\mathbf{x}_{jl}'\beta_j}{\delta_j}))$. For more details on the derivation of the NL model and parameter estimation see Cameron and Trivedi (2009a), chapter 15.6 and Wooldridge (2010), p. 649 ff.

NL models are used to explain occupational choice for example by Falaris (1984) and in chapter 3 of the thesis. The main limitation of the NL model – the necessity to have a nested structure – can be affirmed widely for occupational choice. The optimal nested structure can be selected based upon likelihood-ratio (LR) tests or Akaike's information criterion (see Cameron and Trivedi (2009a), p. 511).

Another type of multinomial model that has gained some popularity recently is the random parameters logit (RPL) model that is also called mixed logit model. Train (2003) implements a RPL model that modifies the MNL model by a formulation of random coefficients in the distribution of the parameters across individuals:

$$\beta_{ik} = \boldsymbol{\beta}_k + \mathbf{x}_i'\boldsymbol{\gamma}_k + \sigma_k \epsilon_{ik}, \quad k = 1, 2..., K; \quad i = 1, ..., N. \tag{1.7}$$

ϵ_{ik} is a multivariate normally distributed error term with correlation matrix $\mathbf{R}$. σ_k is the standard deviation of the kth distribution; $\beta_k + \mathbf{x}_i'\boldsymbol{\gamma}_k$ is the mean of the distribution and $\mathbf{x}_i'$ is a vector of individual i's regressors not varying over alternatives (see Greene (2008), p. 851 ff.).

The RPL model includes the earlier models as special cases. RPL models are estimated by simulating the log-likelihood function because direct integration to compute probabilities and the random part of the coefficient is unknown. Detailed information on the mixed distribution of the parameters, the implementation of the model and its interpretation are provided by Greene (2008), p. 851 ff. However, RPL models face severe technical restrictions until today because these models require huge computing capacities and, therefore, running times of several weeks. Wagenhals (2011) uses mixed logit models to estimate the effects of tax benefits on female labour supply.

Of course there exist other estimation methods, especially different models of discrete choice, that can be and, in particular cases, are applied to the research question of occupational choice (e.g., instrumental variable estimation or the Dogit Ordered Generalized Extreme Value (DOGEV) model applied by Brown et al. (2008)). However, according to the aim of this section the description above is concentrated on the most current estimation methods.

1.3. Occupational Choices and its Outcomes

The consequences of occupational choice are far-reaching. Occupations affect the socio-economic status of an individual as well as his/her earnings and bargaining positions in the marriage market. Especially in labour markets with low occupational flexibility like in Germany, job mobility is low and occupational changes are not so common compared to other labour markets like Great Britain. This is induced by high levels of employment protection and by the importance of educational credentials in Germany (see Nisic and Trübswetter (2012)). This section provides an overview of studies that analyse the effect of occupations on labour market outcomes.

Different levels of earnings – even in occupations with the same or similar levels of education – are a popular and long lasting research topic in economics. The general finding is that the differences between the returns of the field of occupational choice are larger than for example the returns of college quality (see, e.g., Daymont and Andrisani (1984), Berger (1988), Loury and Garman (1995) and Loury (1996)). James et al. (1989) even argue that " [...] while sending your child to Harvard appears to be a good investment, sending him to your local state university to major in engineering, to take lots of math, and preferably to attain a high GPA, is an even better private investment" (p. 252).

However, the question on why jobs in science pay off more than jobs in humanities cannot fully be answered until today. One possible explanation is the endogenous selection of young people into occupations due to their abilities. Arcidiacono (2004) approaches this problem by applying a dynamic model of college and major choice and, therefore, controls for selection into different majors. His findings still report large monetary premiums for natural science and business majors. Using a similar approach, Chevalier (2012) also finds that wage premiums to a degree in science come up to 10 % compared to humanities for the United Kingdom. However, Chevalier (2012) also finds that wage premiums are only partly caused by the scientific degree itself but also by the actual occupational choice. He finds that less than 50 % of the science graduates work in scientific occupations three years after graduation. Those who do not work in scientific jobs anymore report to be less satisfied than their colleagues who stay in academia. Moreover, graduates outside the scientific job market are more likely to complain that they are not employed in their most preferred job.

Görlitz and Grave (2012) present similar results concerning the wage premiums of German graduates. They find significant wage differences by fields of study, e.g., the raw wage gap of arts and humanities compared to engineering is 40 % when entering the labour market. This wage gap is persistent during work life. Furthermore, Görlitz and Grave (2012) show that wage differentials are explained to a larger extent by labour market and firm specifics than by individual or study-related characteristics. The authors hypothesize that less able students select into arts and humanities because these subjects are considered to be less challenging. Using the same data set on German graduates, Wahrenburg and Weldi (2007) conclude that studying humanities and arts is unattractive from an economic perspective, though 20 % of all first-year students are enrolled in these fields.

The topic of different levels of earnings in occupations appears in the media and in the public debate mainly in the context of the gender pay gap. Different levels of earnings of women and men are a source of social inequality implying, e.g., higher female levels of poverty among the elderly and higher risks of poverty of single mothers. According to the Statistical Office of the European Union, the unadjusted gender pay gap in Germany accounts to 23 % over the last years and is above the European mean (2010: 16 %). Finke (2011) shows that about two third of the gender pay gap can be explained by different characteristics of women and men. One third is left unexplained. The main difference between men and women in the labour force is the distribution among occupations and, therefore, gender segregation is found to explain large parts of the unadjusted gender pay gap (see, e.g., Finke (2011) for Germany, Levanon et al. (2009) for the U.S.). Hence, occupational choice has come into the focus of the public debate because occupational segregation is a driving source of the gender pay gap. Political actions aim at making especially girls enter into better paid, male-dominated jobs, for example in STEM.

In the economic literature the gender pay gap is also discussed from different moralities. Polachek (1978, 1981) shed light on gender differences in the choice of college majors and the resulting gender pay gap. He finds that women's choices of majors with lower expected earnings are correlated to their (later) times out of the labour force. According to Polachek (1981), gender-specific distributions among college majors and occupations do not need to be a topic of the political agenda if they are caused by exogenous gender-specific preferences and individuals' rational decisions. Other economists examine whether the different preferences of women and men are caused by genetic endowment or not (see Croson and Gneezy (2009)). However, a clear-cut answer to this question is not found until today.

Gender differences in career opportunities shed a different light on the gender pay gap. Many economic studies analyse the so called "glass ceiling" effect which describes the phenomenon that women do not climb the hierarchy in firms to the top (see, e.g., Judeisch and Lyness (1999), Holst and Wiemer (2010)). However, the question on why only a few women get promoted to the corporate board has yet not been answered. Different preferences and personality traits are found to influence the segregation along a firm's hierarchy (see Branson (2006), Albrecht et al. (2003)).[9]

Related to the strand of literature on female career opportunities is the study of Fossen (2012). She finds that women's higher risk aversion is one reason for women's lower activity in entrepreneurship. However: "the largest part of the lower female entry thus remains unexplained and may potentially, at least in parts, be attributed to creditor or consumer discrimination against self-employed women" (Fossen (2012), p. 25). Wichert and Pohlmeier (2003) prove the influence of non-cognitive personality traits on labour market behaviour. They find that women with higher levels of extraversion face a higher likelihood to be active in the labour force. Lower values in agreeableness have a similar effect on female labour market supply (see Wichert and Pohlmeier (2003), p. 21). Therefore, personality traits do not only influence occupational choice but also labour market behaviour.

Apart from female career opportunities, some economic studies show that occupational choice directly influence women's labour market behaviour: Jacobs (1995) analyses the German labour market and finds that segregation in the labour market is not only driven by different gender patterns in occupational choice but also

[9]The issue of more gender equity in corporate boards has also gained interest in companies recently. This is due to the finding of some economic studies that gender mixed boards perform better (see, e.g., Adams and Ferreira (2009); Adams et al. (2011)).

reinforced by job choices after childbearing. His findings imply that mothers tend to work part time and work mainly in female dominated industries like catering and caring. Rosenfeld and Birkelund (1995) show similar results for Sweden: high levels of part time working women go along with high levels of gender segregation in the labour market. So, different levels of earnings in different occupations influence female labour market behaviour. Stuth et al. (2009) show that mothers' time out of the labour force differs among occupations. Teachers stay at home with their children for more than 157 month while mothers in STEM have significantly shorter gaps in their employment history. Binder (2007) also finds that women have longer periods out of the labour force when they work in occupations with lower levels of earnings.

Recently, another strand of literature gains popularity that studies the impact of educational and occupational fields on fertility. Lappegård and Rønsen (2005) find for Norway that levels of opportunity costs differ among educational fields. Therefore, women with the same level of education, but different fields of education show different fertility behaviour. However, the authors indicate that there may be a simultaneous relationship between fertility and educational fields because the preference towards family may influence education choice (see Lappegård and Rønsen (2005)). Similar results are found for Sweden: Hoem et al. (2006a,b) conclude that the educational field is even a better indicator for fertility behaviour and childlessness as the attained educational level. In general, studies on the impact of educational field on fertility behaviour show higher numbers of children among women educated in health care and teaching (see, e.g., Neyer and Hoem (2008), Bagavos (2010) and Begall and Mills (2012)). Rønsen and Skrede (2010) additionally find higher fertility rates for women educated in a female-dominated subject and lower levels of childlessness for occupations in the public sector.

Oppermann (2012) confirms for Germany that the field of education influences women's probability of having children in Germany. Men's probability of having children does not vary among occupations. Women in Germany, however, have a higher probability of becoming mothers if they are educated in female-dominated fields like health or in male-dominated fields (see Oppermann (2012)). Similar results for men and women in Spain are found by Martín-García and Baizán (2006) and Martín-García (2009). The impact of the occupational field on fertility behaviour in Germany is shown by Maul (2012). She finds that occupational groups differ in the timing of first births. This timing effect is smaller for women in Western Germany than for men and smaller for women in the former German Democratic Republic (GDR) compared to Western Germany. According to Maul (2012), a large part of the timing effect of women's first births can also be explained by the attained educational level.

Hitherto, the discussion of the outcomes of occupational choice has concentrated on the individual level. For the society the quality of the labour force depends on aggregated occupational choices. Occupational choices that depend mainly on personal abilities and motivation increase the efficient matching of job requirements and occupational aptitude of workers and hence, foster high productivity of workers and economic growth. Especially in times of an aging society and a decreasing number of people in the labour force the productivity of workers has to be maximized in relation to their abilities.

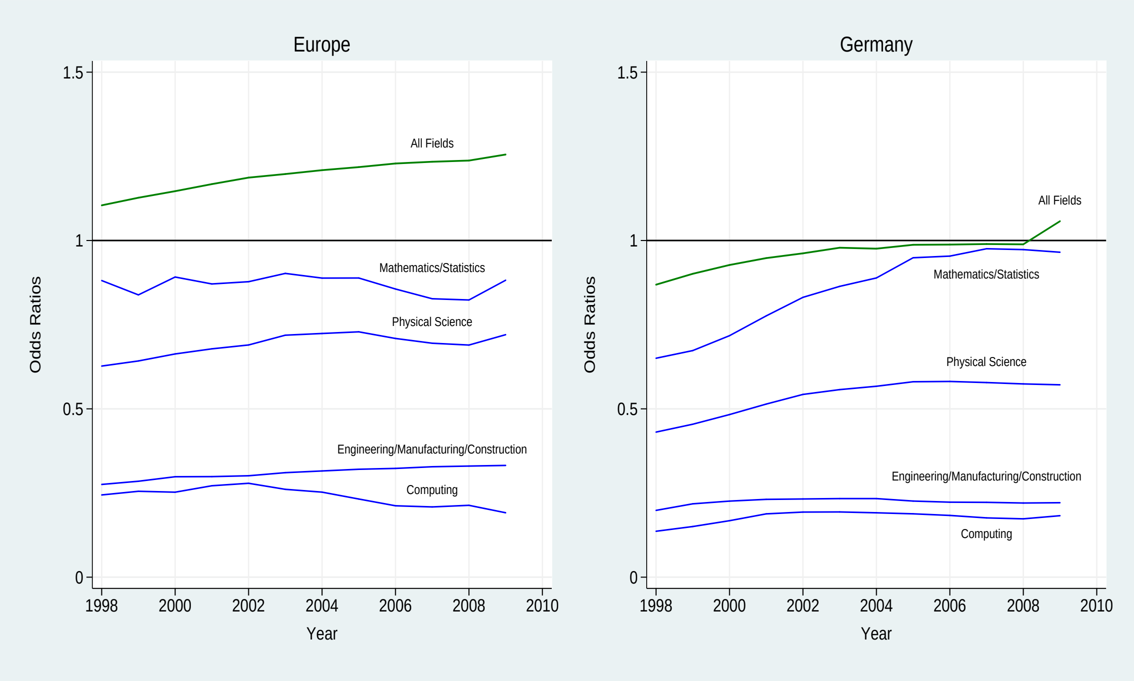
Concerning the labour force in STEM, Leslie et al. (1998) describe the importance of occupational choice as: "Not only does the lack of parity raise obvious social concerns, the quality of the science and engineering labour force is at issue, for even though the supply of scientists and engineers appears, at least for the present, to be adequate to national needs, larger labour supply pools translate into higher quality scientific workers, thereby increasing marginal labour market productivity and, in turn, the productivity of the overall economy" (p. 240).

1.4. Critical Issues in the Occupational Choice of Women in STEM

The determinants of occupational choice are considered to be highly diversified as described in section 1.2. Hence, the question of occupational choice is discussed for different subgroups. The group of women in STEM has received significant attention in the academic and political discussion. Occupations in science, technology, engineering and mathematics always have been and still are strongly dominated by men. This gender segregation has not been effected by women's educational achievements since the 1980s.

During the last thirty years there has been a striking reversal in the gender gap of educational attainment. Today girls perform better in school and receive higher school leaving certificates on average. Additionally, more university degrees are awarded to women nowadays (see Helbig (2010) for Germany, Buchmann and DiPrete (2006) for the U.S.). Girls and boys show also nearly similar performance in mathematics and science during school (see OECD (2010) for Germany, Hyde et al. (2008) for the U.S.). Despite of all these developments women keep on avoiding jobs in STEM.

Figure 1.3 illustrates the reversal of the gender gap in education as well as the ongoing segregation in STEM for Germany and for the EU. On the one hand, women outnumber men among university graduates since several years. On the other hand, the graph illustrates for several STEM subfields that women keep on lagging behind in STEM university degrees. This trend is visible for Germany as well as for the EU. However, the trend is more distinct in Germany: only about every fifth degree in the fields of engineering, manufacturing and construction is awarded to a female student in Germany. In the EU, every third graduate in STEM is female. Legewie and DiPrete (2012) find a similar pattern for the United States. The fields of mathematics and statistics have an exceptional trend in Germany: girls have nearly gained similarity to boys in this subject recently. However, the increase in the number of girls studying mathematics is not visible for the EU or in other countries.



Source: Eurostat, own calculations.
Note: The trend line for all fields shows the odds ratio that a university degree is awarded to a woman. The lines for the different subfields show these female/male odds ratios for the respective STEM field.

Figure 1.3.: Gender Gap in University Degrees Awarded by Field of Study in the EU and Germany, 1998-2010.

Similar results are found for the vocational training in the German education system. On the one hand, boys choose apprenticeship training positions in STEM like mechatronics technician, electrician or motor mechanic most frequently. Girls, on the other hand, prefer commercial apprenticeships or other apprenticeships in the tertiary sector. These patterns in occupational choice are constant over time (see Statistisches Bundesamt (2003, 2006, 2011a)).

The enduring gender gap in STEM has negative implications for the supply of highly skilled workers in these occupations as well as for the closing of the gender pay gap (see Bettio and Verashchagina (2009), EUCOM (2010)). Therefore, the ongoing debate why girls and young women do not choose occupations in STEM given the extraordinary good earning possibilities and career opportunities will remain. Reasons for this phenomenon are broadly discussed. Special focus is layed on the question whether biology or socialisation is responsible for the ongoing segregation in STEM fields in particular and the labour market in general.[10]

Several studies in educational science focus on girls' choice of college majors. Leslie and Oaxaca (1993) provide an overview of early theoretical and empirical studies on this topic conducted during the 1990s. In these studies, the focus of attention is on the United States. Several results, however, can be taken for granted by now: Leslie et al. (1998) find that having a parent who works in engineering or science increases girls' probability to choose engineering or science as a major in college. The importance of family background is also found by Jackson et al. (1993): they show that girls who have well-educated parents enter male-dominated STEM fields more often. The same is true for young women coming from intact families. Jackson et al. (1993) also point out that women who become engineers do not simply tend to have fathers who are engineers, but also tend to marry engineers themselves. So, parental background seems to be germane for young women's choice of STEM occupations.

Furthermore, some empirical work suggests that, regarding the fields of STEM, occupational choices as well as the choice of college majors can only be influenced during high school years or earlier. Legewie and DiPrete (2012) show that the attendance of a high school that supports the orientation of girls towards mathematics and science reduces the gender gap in STEM majors by one fourth. The authors observe that the gender gap in educational attainment has closed and girls perform equally well in mathematics as their male peers. However, the overall gender gap in STEM degrees still exists. Legewie and DiPrete (2012) emphasize the importance of schooling environment for gender-specific orientation towards these fields of study. The authors suggest further research in the shaping of gender stereotyping during high school for a better understanding of occupational segregation. Leslie et al. (1998) emphasize as well that the attitudes of peers have an important influence on adolescents' choices. They find that, during adolescence, girls are more mind-

[10] Chapter 4 presents the author's contribution to the reseach topic of women in STEM.

ful of what their peers think of them than boys. Girls are taught by peers during these years that childbearing and marriage are the goals to be committed to. The influence of peers seem to be one reason for a decrease in interest in science and mathematics during these years (see Leslie et al. (1998)). Similar results are found by Holland and Eisenhart (1990).

Only little research is devoted to the labour market behaviour of women in STEM. The small number of existing studies implies that women in STEM behave differently in terms of labour supply than women in general. The overall differences between women and men can also be found when analysing occupations in STEM. Minks (1996, 2001) show that women who graduate from STEM tend to search longer for their first jobs and tend to earn less than their male fellow students. Similar results are found by studies that concentrate on later-on careers (see Haffner et al. (2006)). Schlenker (2009a) shows that female engineers face employment interruptions because childbearing more often. Female engineers also tend to work part time or outside their subject area more often than their male counterparts (see Schlenker (2009a,b)).[11] However, even if differences in employment and wages exists between female and male engineers, female engineers' labour supply is larger than (highly skilled) women's labour supply on average – probably because of higher wages (see Schlenker (2009b)).

1.5. Structure and Findings of the Thesis

The main insight from this survey is that occupational choice is a widely ramified research topic. A clear-cut answer to the question on what mainly determines occupational choice is not easy to be found. The social framework of occupational choice is multi-layered and has to be interpreted in the context of childhood and adolescence as well as in the context of other important decisions taken beforehand like education choices. Furthermore, hitherto results imply that abilities are not the

[11] Similar results are found for the U.S. (see Cordero et al. (1994)).

only or even the main driving force behind occupational choice (see, e.g., Sacerdote (2002)). The following chapters contain the author's contributions to the debate on determinants and outcomes of occupational choices.[12] The chapters are in the order of their inception and can be read independently.

Chapter 2 analyses the impact of strategic parental behaviour on their offsprings' education choices. Amongst others, parents face two conflicting results if their children achieve high educational levels: first, some studies find empirical evidence for parents' desire to be visited and cared for by their children in old age. However, if individuals achieve high educational levels, their mobility increases. Second, highly educated daughters and sons have higher earning potentials and, therefore, an increased probability of being able to support their parents financially later. Depending on parents' perceptions, these scenarios can effect parents' education decisions when their children are young. By using a differences-in-differences identification strategy, some empirical evidence is found for parental influence. University foundings are exploited as exogenous variation of distances to high-level educational institutions. Combining data of university foundings and data from the German Socio-Economic Panel Study (SOEP), empirical evidence is found that the probability to graduate from academic secondary school track (ATS) increases after a university is founded closely. This positive effect is larger for girls than for boys. The difference can be interpreted as empirical evidence of parental strategic behaviour.

Chapter 3 contributes to the nature-nurture-debate. Using data from the SOEP, occupational choice is found to be persistent among generations. This phenomenon is not only driven by genetic endowments. Additionally, a nurture effect is found that reinforces occupational persistence among generations. Socialisation seems to have a significant effect on occupational choice. This effect is identified by comparing occupational choices of individuals who have grown up with their father living in the same household to those of individuals who have not grown up within their father's household. The probability to choose father's occupation decreases significantly if

[12]Note that the chapters 2 and 3 are based on joint work with Bodo Knoll and Nadine Riedel.

the father has been absent during childhood. From a labour market perspective, this finding may imply mismatches and inefficiencies because a worker's productivity is highest if he/she chooses the occupation for which his/her abilities fit best.

The author's contribution to the understanding of the labour market behaviour of women in STEM can be read in chapter 4. As already mentioned, modern societies are especially concerned about the high gender segregation in labour markets. The fact that women and men are strongly segregated into different occupations is an issue in the academic and in the political debate; gender segregation can explain a high percentage of the gender pay gap (see, e.g., Antonczyk et al. (2010)). Apart from gender equality, the issue of the quality of labour forces is concerned by high levels of gender segregation. Because the labour forces in Germany as well as in all other industrialised countries are shrinking, the quantity and the quality of workers in key industries like engineering are an issue of highest political interest. Therefore, the low rate of young women graduating from STEM is peculiarly brought into focus because the quality of a engineering and science labour force is an important issue for national welfare. Politicians of all parties are searching for actions that help to overcome the shortage of female engineers and scientists. However, a fundamental understanding of occupational choice as well as an understanding of the determinants of segregation in STEM is needed. The author contributes to the understanding of the labour supply of women in STEM and shows that women in these occupations behave differently in terms of labour supply compared to women in general. Using data from the European Statistics on Income and Living Conditions (EU-SILC), the author finds that women in STEM work more hours, but have a higher probability to be out of the labour force. These different patterns of labour supply have to be taken into account when it comes to the implementation of labour market policies that, on the one hand, aim at increasing women's share of workers in STEM and, on the other hand, at enlarging female labour supply. Finally, chapter 5 concludes.

2. Strategic Education Choices and Parents' Wish to Keep Children Close

2.1. Introduction

It is well-known that education choices have far-reaching consequences for one's future well-being. Additional years of college or university education are related to higher wages and employment propensity, increased job satisfaction, better health and a superior bargaining position in marriage markets (see, e.g., Ashenfelder and Krueger (1994) and Behrman et al. (1994)). In light of this evidence, one may expect that education and schooling choices are primarily driven by ability. The aim of this chapter is to emphasize that important schooling choices are commonly made during early childhood and are thus not (necessarily) a decision of the child him/herself; but rather, first and foremost, a decision by the child's parents.

While parental choices are likely aligned to an extent with the child's interests parents may also take their own well-being into account during decision making. In the following chapter, we will argue that parents receive rents from having their children geographically close, even after the children leave home to lead an adult life. Such rents may represent emotional benefits that parents derive from their children's visits but may also represent children acting as care-givers in the parents' old-age and sickness. In areas where the closest university is geographically distant and labour markets for workers with tertiary education are underdeveloped, parents may have an incentive to discourage their child from obtaining upper secondary education and a university entry diploma to stunt the child's geographical mobility. Moreover, this incentive is expected to rise or fall depending on the child's propensity to care for his/her parents: that is, this incentive is expected to be greater with respect to girls, younger siblings or an only child.

We empirically assess this hypothesis by utilising rich information from the SOEP that comprises individual-level data on educational attainment, geographic location and a wide array of other socio-economic characteristics. The data is used to determine the distance between the individual's childhood region of residence in Germany and German universities. Following the above hypothesis, we expect that children who live distant from university locations display a lower propensity to obtain university entry certificates. While educational costs are almost comparable between individuals living within the same distance radius around a university, our theoretical considerations predict that living close to a university exerts a heterogeneous effect on different groups of individuals. Namely, we expect a quantitatively larger impact on children who have a high propensity to care for their parents: girls, younger siblings and only children. To hedge against potential endogeneity concerns, our preferred empirical estimation strategy exploits the founding of numerous German universities from the 1970s to the 1990s as a natural experiment and determines how these universities affected the educational attainment of individuals living nearby.

The chapter is structured as follows. In section 2.2, we provide a theoretical motivation for our analysis and give a short review of the related literature. Section 2.3 describes the estimation methodology. In section 2.4 and 2.5, we present our data set and the estimation results. Finally, section 2.6 concludes.

2.2. Theoretical Background and Related Literature

This chapter contributes to a growing literature on the determinants of education choices. Since Becker (1964) and other economists have introduced the concept of human capital into economics there exists a plenty of studies that examine the economics of education. Freeman (1986) provides an overview of early theoretical and empirical studies. Black and Devereux (2011) discuss the results on causality concerning educational achievements. However, to the best of our knowledge, we are the first to emphasize that parents in areas distant from universities may have an incentive to make inferior schooling track choices to keep their children geographically close during their adult life. This result is in line with earlier descriptive evidence suggesting that, in rural Bavarian areas, 34 % of girls and 24 % of boys in primary school who qualify to attend an academic secondary school track do not pursue this option, compared to only 18 % of girls in urban areas (see Theile (2007)).

Data from the statistical agency of Baden-Württemberg shows similar results; as in Bavaria, pupils are given a secondary school track recommendation at the end of primary school in Baden-Württemberg. Limiting the survey to pupils who qualify for the academic secondary school track, this analysis indicates that the percentage of children actually attending academic secondary schools varies across counties. Three out of four children in rural areas attend secondary academic schools, given an equivalent recommendation. In larger towns and cities, nine out of ten pupils do so.[1] Using data from the German PISA 2000 extension study, Jürges and Schneider (2011) find that although girls in general perform better in school than do boys, this gender effect decreases in grade 5 because "more girls than boys are sent to tracks below the one recommended" (p. 387).

[1] This information is based on data from the "Bildungsstatistik Baden-Württemberg". We are thankful to Dr. Rainer Wolf of the Statistical Agency Baden-Württemberg who made these data available for us. A national survey of secondary school track choices is not available in Germany because schooling policies differ across states and because the statistical agencies of the states are responsible for monitoring the educational systems.

One further strand of literature, that has received considerable attention in the field of economics, deals with strategic behaviour within families. The focus of parents' strategic behaviour against their children has, however, been largely restricted to strategic bequests. Bernheim et al. (1985, 1986) show that bequests ensure children's attention (in form of visits and care) and that parents strategically exploit this fact and use bequests to receive attention. In terms of the geography of the family, the literature has thus mainly focused on the strategic behaviour of children against their parents. In particular, as visits and care for parents are considered to be burdensome (see Bernheim et al. (1985)), Konrad et al. (2002) argue that children have an incentive to shift this burden to their siblings. As firstborns have the strategic advantage of choosing their geographic location earlier than their siblings, they have an incentive to geographically move away from their parents' home. Konrad et al. (2002) confirm this effect in their analysis. Thus, location choice is found to be endogenous and to differ between the first child and younger siblings; whether one is an only child also affects location choice (see Konrad et al. (2002), Leopold et al. (2012)). One less-explored area, however, is the strategic behaviour of parents concerning the education level of their offspring. As Leopold et al. (2012) demonstrate for Germany, highly educated children tend to move further away once they leave their parental homes. The number of visits is reduced because children living far away have higher costs when visiting their parents.

As parents worry about receiving fewer visits in the future, it may be rational for them to limit their children's education to a medium level. As noted above, parents' strategic behaviour has been mainly analysed in the context of bequests (see, e.g., Bernheim et al. (1985, 1986)). There is a dearth of studies that have explored strategic parental behaviour with respect to education choices. Because longer distances increase the costs of visits and care given to parents when they grow old; a medium level of education among offspring might be of greater utility for parents than a high educational level. A high education level increases the probability that a child has a superior level of income and can offer financial support to the parents. Which of these effects dominate is theoretically indeterminate and therefore subject to empirical analysis.

We also refer to a strand of literature that addresses gender differences in educational attainment. In recent decades, girls' level of education has rapidly increased, coming to equal or exceed boys' level of education (see, e.g., Becker and Murphy (1988)). Nevertheless, parents in traditional cultures tend to value the education of sons slightly more than the education of daughters because daughters are still considered to have lower returns on education and are believed to have higher caring capabilities than sons (see, e.g., Leopold and Raab (2011) for Germany and Henretta et al. (1997) for the U.S.). Therefore, the costs of educating daughters at a higher level may outweigh the perceived marginal financial benefits.[2] Due to cultural changes, overall negative effects for daughters have vanished over time. Perceived differences in the returns on education for boys and girls have also decreased, especially if parents have several children and can pool education and caring burdens.[3] However, gender stereotyping is still observed among parents who have an only child. For only children, the burden of visits and care cannot be shared between siblings. Moreover, in rural areas, the distance to universities is larger, which also increases costs for visits to the parental home (see, e.g., Hektner (1995)).

2.3. Identification and Estimation Strategy

2.3.1. Identification of Strategic Parental Behaviour

An opportunity for strategic parental behaviour is offered by the German schooling system. At the end of primary school, pupils are given a secondary school track

[2]Dahl and Moretti (2008) show for the U.S. that parents (most likely fathers) continue to favour sons.

[3]The number of children itself is an economic decision for parents because they must decide whether to divide their budget between several children or to concentrate on one child. For details of the so called Quantity-Quality Theory, see Becker and Lewis (1973).

recommendation.[4] Based on the secondary school track recommendation, parents decide whether their children should pursue the basic ("Hauptschule"), intermediate ("Realschule") or academic ("Gymnasium") secondary school track. This choice is of crucial importance for the highest education level to be attained and later life outcomes. The academic secondary school track is the most prestigious and is the only to provide direct entry to tertiary education. There are several ways to obtain entry to tertiary education without attending the academic secondary school track, but the proportion of university students coming from basic or intermediate schools is quite small.

Apart from secondary school track recommendations, education choices – which are mainly made by parents because their children are young – are also influenced by monetary and non-monetary costs for schooling. These costs are highly affected by one's area of residence. Currently living in a rural area has a negative effect on schooling decisions because the education infrastructure is worse: universities are still concentrated in cities, distances to academic track schools are longer than to other schools and public transport is less available in rural areas. These factors result in additional educational costs for children from rural areas. Moreover, these factors add to the non-monetary costs of education and may result in well-educated children moving away from their parental home (see Konrad et al. (2002)). Locations of schools and universities, however, cannot explain why growing up in a rural area should have different effects for girls and boys. One possible explanation for this finding may be the differences in returns on education for boys and girls.

To more clearly identify strategic parental behaviour, we use a difference-in-differences (DiD) approach. We consider the founding of universities in recent decades to be exogenous. During the 1970s to 1990s 12 universities were established around Western Germany. We consider the following university foundings: Duisburg/Essen, Pader-

[4] Schooling policies differ between states. We do not refer to secondary school types that are of minor importance, such as the "Gesamtschule". Additionally, the processes for secondary school choices differ among German federal states. Secondary school track recommendations are non-binding in most states. One exception is Bavaria, where secondary school track recommendations are a binding upper limit to school choices.

born, Siegen, Wuppertal/Bielefeld (year of commission: 1971/founding year: 1972), Oldenburg, Osnabrück (1970/1973), Bayreuth (1970/1975), Passau (1972/1978), Eichstätt (1972/1980), Koblenz/Landau (1990/ 1990), Flensburg (1989/1994), Vechta (1993/1995). Please note that we only consider university foundings in cities where no university was previously located. The establishment of a university near children's residence reduces the probability that they will move away for their studies. This shift implies a reduction in the non-monetary costs for academic secondary schooling, while returns on education are not immediately altered. Therefore, we expect a generally positive effect for secondary schooling decisions near a newly founded university. Strategic parental behaviour becomes visible if the effect is different for girls than for boys.

2.3.2. Estimation Strategy

In our baseline estimations we estimate a model of the following form:

$$
\begin{aligned}
ATS_i &= \alpha_1 + \alpha_2 DISTANCE_i + \alpha_3 (DISTANCE_i \times FEMALE_i) \\
&\quad + \alpha_4 FEMALE_i + \mathbf{x}_i' \boldsymbol{\beta} + \epsilon_i
\end{aligned}
\tag{2.1}
$$

whereas ATS_i represents a dummy variable indicating whether the individual completed upper secondary education and holds a university entry degree; $DISTANCE_i$ denotes different measures for the individual's distance to universities: namely the distance in kilometres to the nearest university at age 9, a dummy variable for an individual living less than 40 kilometres from the nearest university, and a dummy variable indicating whether individuals live less than 50 kilometres from the nearest university. $FEMALE_i$ is a dummy variable indicating a female individual. The vector $\mathbf{x}_i$ indicates the father's and mother's highest level of education, the family's socioeconomic status, the 5-year birth cohort and region fixed effects.

Our theoretical considerations above suggest that a university within a short distance of the individual's location of childhood residence reduces the educational costs and, hence, increases the probability of receiving upper secondary education and a university entry certificate. While educational costs related to distance are plausibly similar for individuals living within a certain distance radius around a university, strategic parental behaviour may induce heterogeneous effects for children with differing propensities to care for their parents later in life and whom the parents attempt to keep geographically close. First and foremost, this phenomenon relates to daughters: thus, we expect that the positive effect of living close to a university on the level of secondary education is larger for girls than for boys. Thus, we expect $\alpha_2, \alpha_3 < 0$ for distances to the nearest university in kilometres and $\alpha_2, \alpha_3 > 0$ for dummy variables indicating a university located within a 40- or 50-kilometre radius.

The obvious threat to this identification strategy is that closeness to a university is not randomly assigned across individuals: rather, families that value education highly and that are simultaneously progressive in supporting the education of both their daughters and sons may tend to live close to universities, while more traditional families tend to live further away. Region fixed effects may mitigate this problem but are not plausibly instrumental in solving it. To overcome this problem, we exploit new foundings of universities in Germany between the 1970s and 1990s as exogenous natural experiments that are expected to alter education costs and the incentive for strategic parental behaviour for individuals who live close to the newly founded universities (in particular for girls). In contrast, we do not expect to observe this effect for comparable individuals in a control group in a different geographic area in which the distance and density of tertiary education institutions did not change. Thus, we exploit a restricted sample of individuals to estimate the following model:

$$\begin{aligned} ATS_i &= \beta_1 + \beta_2(FEMALE_i \times TREAT_i) + \beta_3(TREAT_i \times POST_i) \\ &\quad + \beta_4(FEMALE_i \times TREAT_i \times POST_i) + \beta_5(FEMALE_i \times TREAT_i) \\ &\quad + \beta_6 FEMALE_i + \beta_7 TREAT_i + \beta_8 POST_i + \mathbf{x}_i'\boldsymbol{\gamma} + \epsilon_i \end{aligned} \tag{2.2}$$

where the dummy variable $TREAT_i$ indicates individuals whose childhood location was close (less than 40 or 50 kilometres, respectively) to the newly founded university and who decided to pursue upper academic secondary education that led to a university entry certificate within the same time frame as the birth cohorts between 1951 and 1984.[5]

The control group ($TREAT_i = 0$) is defined as individuals who lived more than 40 kilometres away from the newly founded university at the age of 9. An individual never included in one of the treatment groups is placed in the control group of all other "natural experiments". Individuals who are in one treatment group are excluded from all control groups. We cluster on the individual level to avoid biased standard errors of our coefficients. As an additional specification, the control group is restricted to individuals living between 40 (50) and 100 kilometres of the newly founded university. $POST_i$ equals 1 if the individual reached the age of 9 at least 4 years after the final official decision to found a university.

Following our argumentation above, we expect a positive effect of the university founding on individual i's propensity to obtain upper secondary education, and this effect is predicted to be larger for female individuals. Formally, we hence presume $\beta_3, \beta_4 > 0$. To take all university foundings in Germany into account, we append the corresponding data for all 12 foundings, absorbing level effects through the inclusion of a fixed effects term for the considered experiment.

2.4. Data Set and Sample Descriptives

We use data from SOEP, a nationally representative random sample survey of each member of more than 11,000 private households. Our analysis is based on a pooled data set from 1984 to 2010. The SOEP contains detailed information on family background at the individual level, as every respondent is asked to complete a bio-

[5] Please note that this limitation of birth years implies that secondary school choices are made close in time to the university founding. For further details regarding the data set see section 2.4.

graphical questionnaire when surveyed for the first time.[6] We use individuals born in West-Germany, exclusive of Berlin. We do not include individuals from the former German Democratic Republic because school choices there have mainly been driven by policy decisions and ideology. Our sample comprises individuals born before 1985. We limit our data set to older cohorts in order to include university foundings during these decades. The oldest individuals in our data set were born after 1950. This upper age limit is set because residential information is not available in the SOEP prior to 1984 and, in addition, large social and institutional changes took place in Germany during the late 1960s ("The Revolution of 1968"). Therefore, our data set comprises 5,393 observations of which 50 % are female. Table 2.1 depicts the descriptive statistics of the data set.

Table 2.1.: Summary Statistics in the Data Set

Variable	N	Mean	Std. Dev.	min	max
ATS	5393	0.3065084	0.4610861	0	1
distance to next uni	5393	23.52063	21.41088	1	169.33
distance uni < 40km	5393	0.8240312	0.380829	0	1
distance uni < 50km	5393	0.8974597	0.3033857	0	1
FEMALE	5393	0.5013907	0.5000444	0	1
uni father	5393	0.1208975	0.3260383	0	1
uni mother	5393	0.0478398	0.2134469	0	1
SES father	5393	41.52086	12.3382	13	78
year of birth	5393	1968.551	9.818023	1951	1984

Source: own calculations.

The dependent dummy variable *Academic School Track (ATS)* equals 1 if an individual has graduated from the academic secondary school track. To test strategic parental behaviour, we focus on the distances of universities to the county where the

[6]See Wagner et al. (2007) for further details.

individual's childhood was spent.[7] County-level data is combined with geographical and founding data for all German universities during the recent decades. This regional information concerning the place of residence is available from 1984 onwards. Therefore, we can only compute these distances for older individuals if they still or again live within the county of their childhood. We employ two different measures for distances. Distance is measured in kilometres to the nearest university. Alternatively, we use a dummy variable indicating whether there is a university within a 40- or 50-kilometre radius.

Further control variables include dummy variables for 5-year birth cohorts; sex; family's socioeconomic status, measured by Treimans scale of father's occupation (*SES father*); and dummy variables indicating whether father and mother completed tertiary education (*uni father* and *uni mother*). Federal states dummy variables (*Bundeslaender*) control for region fixed effects.

2.5. Empirical Results

2.5.1. Baseline Probit Models

To identify family determinants of education choices, we regress completion of the academic secondary school track (*ATS*) on several individual characteristics and characteristics of the family structure. We limit our data set to individuals born between 1951 and 1984 in Western Germany (exclusive Berlin) to control for long-term developments and differences in education policies. All specifications include control variables for 5-year birth cohorts and region fixed effects.

Columns (1)-(3) of table 2.2 show the partial effects at the average (PEA) of probit regressions according to our baseline model. Column (1) employs minimum distance to the nearest university. Columns (2) and (3) employ dummy variables indicating

[7] County-level information in the SOEP is restricted due to data privacy regulations and is only available via remote service, called SOEPremote.

whether a university is located within a 40- or 50-kilometre radius, respectively. Full estimation results are available in table A.1 in the appendix.

Table 2.2.: Marginal Effects of Probit Baseline Regressions

ATS	(1)	(2)	(3)
female x distance	-0.00101^{+}	0.0762**	0.0818*
	(0.000652)	(0.0365)	(0.0468)
distance	-0.00115**	0.0136	0.0245
	(0.000471)	(0.0255)	(0.0313)
female	0.00860	-0.0770**	-0.0880**
	(0.0194)	(0.0328)	(0.0441)
uni father	0.176***	0.179***	0.180***
	(0.0276)	(0.0276)	(0.0276)
uni mother	0.165***	0.169***	0.169***
	(0.0392)	(0.0392)	(0.0392)
SES father	0.0102***	0.0103***	0.0103***
	(0.0006)	(0.0006)	(0.0006)
5yrs birth cohorts included	Yes	Yes	Yes
Bundeslaender included	Yes	Yes	Yes
N	5393	5393	5393
χ^2	933.4***	920.3***	918.5***
Pseudo R^2	0.140	0.138	0.138

Source: own calculations.
Notes: Standard errors in parentheses
+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Column (1) employs minimum distance to the next university
Column (2) and (3) employ dummy variables indicating
if a university is within a radius of 40 and 50km, respectively

All specifications indicate that the probability of graduating from the academic secondary school track increases if a university is located nearby. Increasing the minimum distance to the nearest university significantly decreases the probability of graduating from the academic secondary school track. Employing dummy variables for living within a 40- or 50-kilometre radius of a university increases this probability. However, the estimates for the dummy variables are not statistically significant.

Additionally, the interaction terms indicate that a university's proximity is even more important for girls. All three measures of distance show that girls' probability of graduating from the academic secondary school track significantly increases if a university is located nearby. Living within a radius of 40 (50) kilometres of a university increases girls' probability of obtaining a university entrance diploma by 7.6 (8.2) percentage points, a significant difference. This finding provides some empirical evidence for our hypothesis of strategic parental education choices: parents nurture daughters and sons differently. Daughters are more likely to be expected to give care and attention to their parents, while sons are expected to be successful in their career. As parents may wish to keep their children close, their strategic schooling decisions matter only if universities are located far from their home. Females who live near universities are more likely to obtain a university entrance diploma.

In our baseline models, girls also have a lower probability of graduating from the academic school track than boys in some specifications. Taking into account which birth cohorts are represented in our data set, these findings are in line with other studies focusing on these birth cohorts (see, e.g., Jürges and Schneider (2011)). Currently, more girls than boys complete the academic school track because of a striking reversal of the gender gap in educational attainment. However, this development has not affected the cohorts born between the 1960s and the early 1980s: men had a higher propensity to complete the academic school track until the 1990s.

Additionally, we find a highly significant positive and large effect of parents' education and socioeconomic status under all specified circumstances. Having a father (mother) who holds a degree from a university or a university of applied sciences increases the probability of graduating from the academic school track by ca. 18 (17) percentage points. This finding is in line with other studies (see, e.g., Jürges and Schneider (2011)). The high correlation between parents' and children's levels of education is a well-known characteristic of the German educational system. The estimated coefficients for birth cohort fixed effects are jointly significant. We find also a jointly significant effect of region fixed effects.

2.5.2. Difference-in-Differences Estimates

To account for potential endogeneity concerns, we focus on university foundings as an exogenous variation of distances. The data set is divided into a treatment and a control group for all specifications in table 2.3. Full estimation results are available in table A.2 in the appendix. A person is defined as treated if he/she lives within a 40-kilometre radius of a university in specifications (1) and (3). All people outside the treatment radius represent the control group in specification (1). The control group in column (3) represents non-treated individuals living within a 100-kilometre radius of the newly founded university. The same definitions apply to specifications (2) and (4): however, the treatment radius is changed to 50 kilometres. $POST_i$ indicates that individual i reaches the age of 9 at least four years after final political decision to found a university in all specifications.

To take all university foundings in Germany into account, we append the corresponding data for all 12 foundings, absorbing level effects through the inclusion of a fixed effects term for the considered experiment. As described in section 2.3.2, the number of observations shows the potential university foundings for each individual in the sample. Therefore, the data set is in a quasi long form. We cluster on the individual level to avoid biased standard errors of our coefficients.

We again find confirmation of our hypothesis: girls benefit more from close proximity to a university than do boys, and their probability of graduating from the academic secondary school track increases significantly in all four specifications. Specification (1) and (2) display that girls' probability of graduating from the academic school track increases by 20 (16) percentage points if a university is built within a radius of 40 (50) kilometres, respectively. If the control group is limited to non-treated individuals within a 100-kilometre radius in specifications (3) and (4) the estimated marginal effects show an increase in girls' probability of graduating from the academic school track by 0.14 and 0.11, respectively. We also find that empirical significance is weaker in these specifications.

Table 2.3.: Marginal Effects of DiD Models

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.199***	0.163***	0.139*	0.113+
	(0.0632)	(0.0573)	(0.0758)	(0.0709)
female x treat	-0.0558+	-0.0325	-0.0401	0.00164
	(0.0340)	(0.0328)	(0.0446)	(0.0433)
female x post	0.00814	0.00681	0.0665	0.0559
	(0.0207)	(0.0219)	(0.0468)	(0.0475)
treat x post	-0.0707**	-0.0397	-0.0840*	-0.0570
	(0.0333)	(0.0330)	(0.0454)	(0.0448)
female	-0.0273+	-0.0316*	-0.0516*	-0.0699**
	(0.0170)	(0.0181)	(0.0282)	(0.0291)
treat	0.104***	0.0818***	0.0244	0.0183
	(0.0303)	(0.0272)	(0.0345)	(0.0317)
post	-0.0131	-0.0104	-0.00745	0.00719
	(0.0152)	(0.0158)	(0.0363)	(0.0369)
uni father	0.174***	0.176***	0.210***	0.205***
	(0.0296)	(0.0306)	(0.0366)	(0.0356)
uni mother	0.154***	0.176***	0.157***	0.223***
	(0.0405)	(0.0428)	(0.0540)	(0.0483)
SES father	0.0102***	0.0101***	0.0110***	0.0109***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	607.4***	597.7***	459.3***	559.9***
Pseudo R^2	0.130	0.135	0.138	0.146

Source: own calculations.

Notes: Standard errors in parentheses

+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We cannot confirm the expected positive effect for all children in our difference-in-differences estimations. The interaction term $TREAT_i \times POST_i$ is not significant for most specifications. Additionally, we find also mixed results for the dummy variable $TREAT_i$ that indicate a higher level of graduation from academic secondary school track in specification (1) and (2). If the control group is limited to non-treated individuals within a 100-kilometre radius the significance of the effect is lost. This finding confirms our argument that the density of graduation from academic school track differs among region. The estimated effect of $POST_i$ is insignificant and small in size throughout all specifications.

Furthermore, we confirm the effects found in the baseline models: girls in the birth cohorts under analysis display a significantly lower probability of graduating from the academic school track compared to boys in all specifications. Empirical evidence is also found for the positive effects of high parental education and status on children's educational level throughout all specifications: if the father (the mother) has finished tertiary education, their children's probability of graduating from the ATS increases by approximately 17 (15) percentage points in specification (1). The estimated marginal effects in other specifications are of similar size.

2.5.3. Robustness Checks

Robustness Check 1: A Comparison of OLS and Probit Regressions

To support the empirical evidence, we conduct several robustness checks. Ai and Norton (2003) discuss estimation problems for interaction effects in probit models.[8] In contrast Puhani (2012) denies the necessity of correcting interaction terms in DiD models. To take Ai and Norton's perspective into account, we also estimate linear probability models using ordinary least squares (OLS). The estimation results are provided in table A.3 in the appendix.

[8] Ai and Norton (2003) also suggest a consistent estimator for interaction terms in probit and logit models. Because their estimates are best presented in graphical form, we cannot generate these estimates due to the restrictions of SOEPremote.

The estimated coefficients do not indicate biased marginal effects in the probit models: we again find significant and positive effects for girls within a 40- or 50-kilometres radius of a newly founded university. The probability of graduating from the academic school track increases by approximately 10 and 17 percentage points for girls in specification (1) and specification (4), respectively. The estimated OLS coefficients do not differ significantly from the estimated marginal effects in the difference-in-differences models in table 2.2.

Robustness Check 2: Definition of the Variable $POST_i$

One further robustness check refers to the definition of the variable $POST_i$. $POST_i$ defines the definitions of treatment and control group in the time frame. Alternative definitions of the variable $POST_i$ are used in tables 2.4 and 2.5. $POST_i$ is defined as 1 in tables 2.4 and 2.5 if the individual reached the age of 9 at least 3 and 5 years after the final official decision to found a university, respectively.[9] We employ the same definitions of the treatment and control group as in the specifications of the DiD approach presented in table 2.2.

Both alternative definitions of the variable $POST_i$ confirm our findings. All specifications in tables 2.4 and 2.5 show the same patterns of significance as well as the same signs as in the DiD models presented in table 2.2. We find again that the effect of a university founding on girls' probability of graduating from the academic school track is positive in alternative specifications. However, the effect is not significant anymore for both alternative definitions of $POST_i$ if the control group is reduced to non-treated individuals living within a 100-kilometre radius of a newly founded university. Again, we find mixed results concerning the interaction term $TREAT_i \times POST_i$ and the effect of $TREAT_i$. No significant influence of the variable $POST_i$ is found. The positive effect of parental education as well as the negative effect for girls are also confirmed in all specifications.

[9] Full estimation results can be found in tables A.4 and A.5 in the appendix.

Table 2.4.: Robustness Check 2a: PEA of DiD Models (+3 years)

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.142**	0.110**	0.0918	0.0551
	(0.0617)	(0.0552)	(0.0737)	(0.0678)
female x treat	-0.0392	-0.0149	-0.0234	0.0252
	(0.0364)	(0.0347)	(0.0465)	(0.0450)
female x post	0.00497	0.00497	0.0584	0.0627
	(0.0203)	(0.0215)	(0.0455)	(0.0464)
treat x post	-0.0371	-0.00480	-0.0535	-0.00873
	(0.0359)	(0.0350)	(0.0471)	(0.0462)
female	-0.0261+	-0.0310*	-0.0497*	-0.0741**
	(0.0172)	(0.0183)	(0.0284)	(0.0295)
treat	0.0873***	0.0643**	0.0124	-0.00283
	(0.0312)	(0.0277)	(0.0354)	(0.0326)
post	-0.00511	-0.00200	0.00762	-0.000476
	(0.0131)	(0.0136)	(0.0361)	(0.0363)
uni father	0.174***	0.176***	0.212***	0.206***
	(0.0296)	(0.0306)	(0.0365)	(0.0355)
uni mother	0.154***	0.176***	0.155***	0.222***
	(0.0405)	(0.0428)	(0.0539)	(0.0485)
SES father	0.0102***	0.0101***	0.0110***	0.0109***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	603.6***	594.6***	456.8***	553.5***
Pseudo R^2	0.130	0.135	0.137	0.144

Source: own calculations.

Notes: Standard errors in parentheses

+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5.: Robustness Check 2b: PEA of DiD Models (+5 years)

ATS	(1)	2	(3)	(4)
female x treat x post	0.167***	0.138**	0.0852	0.0667
	(0.0635)	(0.0575)	(0.0758)	(0.0709)
female x treat	-0.0380	-0.0185	-0.0128	0.0245
	(0.0345)	(0.0330)	(0.0447)	(0.0431)
female x post	0.0113	0.0115	0.0922*	0.0833*
	(0.0214)	(0.0227)	(0.0489)	(0.0497)
treat x post	-0.0713**	-0.0413	-0.0723+	-0.0467
	(0.0337)	(0.0333)	(0.0470)	(0.0461)
female	-0.0285*	-0.0334*	-0.0599**	-0.0788***
	(0.0169)	(0.0179)	(0.0278)	(0.0286)
treat	0.101***	0.0811***	0.0154	0.0118
	(0.0294)	(0.0266)	(0.0338)	(0.0311)
post	-0.0188	-0.0169	-0.0289	-0.0172
	(0.0154)	(0.0161)	(0.0375)	(0.0378)
uni father	0.174***	0.176***	0.210***	0.206***
	(0.0296)	(0.0306)	(0.0366)	(0.0356)
uni mother	0.154***	0.176***	0.158***	0.224***
	(0.0405)	(0.0428)	(0.0541)	(0.0482)
SES father	0.0102***	0.0101***	0.0110***	0.0109***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	605.5***	595.5***	456.3***	556.5***
Pseudo R^2	0.130	0.135	0.138	0.145

Source: own calculations.

Notes: Standard errors in parentheses

+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6. Summary of the Findings and Outlook

This chapter examines strategic parental behaviour concerning education choices. We find some empirical evidence for the hypothesis that parents pursue different strategies towards daughters and sons. This outcome indicates that parents' education decisions made for their children during childhood are also driven by parents' desire to reduce their children's probability of moving away.[10] The children's resulting levels of education, however, have far-reaching consequences. Later life outcomes are highly correlated with whether a child obtains an academic secondary school track diploma.

We present some empirical evidence that parents' educational choices during their children's childhood are partly driven by parents' desire to reduce their children's probability of moving away. Because labour market outcomes highly correlate with whether a child receives an academic secondary school track diploma, this consideration is especially important in countries like Germany that have highly regulated job markets with respect to training and educational qualifications. Furthermore, the dependence of one's level of education on parental strategic behaviour leads to an inefficient allocation of workers in the labour market, which may be problematic when the demographic change limits the number of highly skilled workers. From an economic perspective, the dependence of one's education level on parental strategic behaviour is a waste of human capital. One successful strategy to reduce this dependence has been the establishment of tertiary education institutions around Germany.

These findings can be generalised in the following manner: the establishment of educational institutions, especially in rural areas, can lead educational systems to generate more efficient results. The monetary and non-monetary costs of children's

[10] One of our readers has noted an alternative motivation for this type of parental behaviour: parents may be more worried about daughters' security and, therefore, are less willing to let daughters move away from home. We cannot eliminate this explanation. However, policy implications and children's outcome do not change if this alternative parental motivation is guiding strategic education choices.

education are decreased because the probability of move-outs decreases. Educational systems may be more productive if education choices depend less on parents' wishes for visits in their old age. Future research on this topic is needed to provide a full cost-benefit-analysis. However, children's dependence on strategic parental decisions may be an additional argument in favour of founding new education institutions, especially in rural areas, to generate more efficient educational results. Lessening children's dependence upon parents' self-interest is especially helpful for girls. Parents who are concerned about loneliness in old-age seem to be more focused on daughters. Therefore, the founding of universities not only helps to make education outcomes more efficient, but also diminishes the role of gender in educational attainment.

3. The Persistence of Occupational Choices among Generations

3.1. Introduction

The purpose of this chapter is to assess the determinants of occupational choice. The question is of utmost importance, as the quality of the match between individuals and occupations may affect productivity and wages as well as other socio-economic characteristics later in life. Astonishingly, the analysis of occupational choice has received rather little attention in the economic literature to date. Notable exceptions are papers that investigate the impact of labour market conditions and individual characteristics, such as gender, on occupational choice (see, e.g., Robertson and Symons (1990), Drost (2002), Sookram and Strobl (2009) and Kleinjans (2010)).[1]

This study analyses the intergenerational persistence of occupational choices. In particular, we are interested in the role of the family in determining individual occupational choice. Occupational decisions are made early in life, when the individual usually still lives with his/her parents, who financially support the individual's vocational education and training. Parents may therefore influence their children's

[1] However, determinants of an individual's level of educational attainment (e.g., the years of schooling) and the socio-economic status that corresponds to an individual's occupation have received considerable attention. See chapter 2 for the author's contribution to this topic.

occupational decisions. Even if parents are altruistic towards their children, strategic motives may play a role. To ensure the stability of family-owned businesses, for example, parents may want their children to choose vocational training that enables them to take over the family business later in life. Moreover, the bonding between parents and children may be closer if they work in similar occupations and can share common experiences. Furthermore, parents are a natural and important source of advice and information for children looking for information regarding potential employment at the beginning of their career. Given that the search for credible information is costly and difficult, information shared by parents may bias their children's opinions and decisions. All these aspects may increase the individual's propensity to choose the same occupation as his/her parents, although it does not necessarily improve the quality of the occupational match.

To assess whether there is a link between parental occupations and the occupational choice of their children, we exploit data from the SOEP. The data set comprises rich socio-economic information on children and their parents, including detailed information on the occupational choices of both. As a first step, we analyse whether occupational decisions are indeed persistent across generations. Estimating nested and conditional logit models, we find strong evidence in favour of persistence. The main empirical challenge is to disentangle effects related to nature and nurture. Nature effects suggest that children have an increased propensity to choose an occupation in the same (or similar) industry as their parents due to inherited genetic endowments and according similarities in talent or preferences for certain occupations. Nurture effects, in turn, suggest that parents may exert a direct influence on their children's occupational decision due to advice, educational elements, or serving as role models.

Our empirical strategy disentangles these two effects by determining the persistence separately for individuals who have grown up with their biological parents and individuals who have not. Our estimations suggest that the effect of biological fathers is significantly different between these groups. Individuals' biological fathers exert a strong and statistically significant effect on individuals' occupational choices if fathers have lived with the family during childhood. Otherwise, fathers have only a weak and quantitatively small influence. This finding underpins the importance of the nurture component in determining an individuals' occupational decision.

The chapter is structured as follows: in section 3.2, we provide a theoretical motivation for our analysis and give a short review of the existing literature. In section 3.3, we present our data set. Section 3.4 describes the estimation methodology. The estimation results are presented in 3.5. Section 3.6 concludes.

3.2. Theory and Existing Literature

As described in the introductory section, persistence in the occupational choices between parents and their children may be affected by nature and nurture components. For several decades, scientists have discussed whether individuals are defined by genetic endowment or socialisation. The answer to this question is not clear-cut. Arguments for both sides shall be presented in the following chapter. With respect to nature, a person's genetic endowment may influence his/her occupational choice for several reasons. First, job requirements differ across different economic sectors. Agriculture, craft, and many blue-collar jobs require some physical fitness and ability; cognitive abilities and social competencies are more important in the service sector. Genes, at least partly, influence these characteristics: according to psychological studies, the heritability of intelligence seems to be quite high (see, e.g., Bouchard (2004)); physical strength and body height are determined by one's genetic endowment to an even greater degree.

Additionally, recent studies find that non-cognitive skills influence occupational choice. People with high self-esteem and high self-efficacy, for example, seek more challenging occupations (see Judge and Bono (2001)), while gregarious people tend to choose jobs with more social interactions (see Krueger and Schkade (2008)). There is also some empirical evidence that "male" traits push highly educated young workers into male-dominated disciplines. Risk aversion accounts for the search for a safe job (see, e.g., DeLeire and Levy (2004), Grazier and Sloane (2008), Antecol and Cobb-Clark (2010)). Furthermore, women dislike competition more than men, which partly explains gender segregation in occupational fields (see Kleinjans (2010), Fossen (2012)). Boehm and Riedel (2012) find also that risk-averse individuals are more likely to pursue civil service, even if intrinsic motivation for these occupations is low.

With respect to nurture, families may transmit value systems from one generation to the next. People choose occupations not only to achieve high material well-being but also to enjoy high reputation in their personal environment (see Corneo and Jeanne (2009)). Parental influence on children's preference formation may be more complex. Doepke and Zilibotti (2008) argue that middle-class and upper-class families recognize different types of income and, therefore, react by imparting class-specific values to their children. Here, material incentives are the driving force of preference formation. Intergenerational social links also have positive effects on the material well-being of the family.

Past economic studies have focused on certain sectors in which special skills and knowledge that increase productivity are acquired during childhood (see, e.g., Laband and Lentz (1983)). Agriculture has often been studied as an example of intergenerational persistence in occupational choices. The intergenerational persistence of farming is a typical example of economic behaviour, as inheriting the family farm increases productivity in comparison to working on someone else's farm.[2] Lentz and Laband (1989, 1990) and Laband and Lentz (1992) also apply this model to children of doctors, lawyers and self-employed parents.

Another strand of literature focusses on the impact of parental social environments on children's job opportunities. Parents may help their children to find a job by using family and business contacts. Corak and Piraino (2011), for example, show that 40 % of young Canadian men have worked or currently work for an employer

[2]For an overview of studies describing this effect in the agricultural sector, see Corak and Piraino (2011), p. 41.

for whom their father also worked. The authors relate this phenomenon to the intergenerational elasticity of earnings. According to Corak and Piraino (2011), the intergenerational correlation of sons' and fathers' earnings is increased by the fact that many sons work for their fathers' employers. The authors hypothesise that signalling effects may explain the increased earnings of men whose father previously worked for this employer. Bentolila et al. (2008) find empirical evidence that social relationships and family contacts have an impact on finding a new job (or the first permanent job) more quickly but at the cost of lower wages and lower worker productivity. Again, these studies are conditioned upon the individual's occupational choice and thus, abstract from the family influence on the individual's occupational decision.

Most of the literature on the impact of nature versus the impact of nurture has thus focussed on economic and educational outcomes: e.g., on the duration of schooling, earnings, or the socio-economic status of jobs. At least some part of the intergenerational correlation of education and income is found to be genetically determined. Björklund et al. (2005) distinguish nature-related and nurture-related effects by using data on different types of siblings (for example biological siblings reared together or apart, twins, and adoptive siblings) and find that siblings' shared genetic endowment significantly influences the variation in earnings. However, environmental factors that are shared by siblings also explain some of the observed differences. Using data on twins or adoptees, several studies find a causal effect of parental educational attainment on children's schooling outcomes even after accounting for potential genetic factors (see Black and Devereux (2011), p. 1511 ff. and the literature cited there). However, even conditional upon the level of educational attainment, there is a wide array of occupations an individual might pursue. The quality of the match between occupation and individual appears decisive for economic productivity and the individual's socio-economic characteristics. Our chapter thus extends upon the existing literature in investigating the nature-related versus the nurture-related effects on the particular occupational choice of the individual, conditional upon his/her level of education.

Finally, it is important to remember that occupational decisions may also be influenced by demand-side factors, such as occupational opportunities in certain industries and fields. For example, Robertson and Symons (1990) explain the occupational choice of workers in professional, skilled, or unskilled occupations by relative income and personal tastes. They find that relative earnings have an effect on initial occupations as well as personal job preferences. Drost (2002) sheds some light on the cyclicity of student enrolment in different academic fields and its relationship to the business cycle and unemployment. We will not describe this strand of literature in detail. Another strand of literature we do not describe refers to gender segregation in the labour markets. Women tend to choose occupations with high entry earning levels and low growth rates over the working life. Polachek (1981) shows that typical female occupations are characterised by slowly decreasing earning potential during times taken out of the labour force. For a survey, see Anker (1997) or section 4.2 of this thesis.

3.3. Data Set and Sample Descriptives

We use data from the SOEP, a nationally representative random sample survey covering more than 11,000 private households.[3] The SOEP contains detailed information regarding the family background at the individual level, as every respondent is asked to complete a biographical questionnaire. Our analysis is based on a pooled data set from 1984 to 2010. The sample comprises individuals from Western Germany who were born before the year 1985 and who have completed their education and made their occupational decision. Our data set comprises 8,162 observations.

The variable of main interest is the occupation chosen by individuals and their parents. We use the information concerning the first job from the job biography as well as the father's occupation from the biography questionnaire. The SOEP adopts the occupational classification of the German Federal Statistical Office ("Statistisches

[3]See Wagner et al. (2007) for further details.

Bundesamt"). This classification system has been introduced in 1992 (Statistisches Bundesamt (1992)). This hierarchical classification defines 2,287 occupations. These are clustered into 6 so-called "Berufsbereiche" following the traditional concept of structural change and the three sectors: extraction of raw materials, manufacturing, and services (see Statistisches Bundesamt (1992), p. 13).

The next level defines 33 "Berufsabschnitte", which group occupations according to the tasks performed by the worker or the materials used. We prefer this occupational classification to the international ISCO classification because more-detailed occupational groups are defined and the educational level of occupations is less emphasized in the job classification of the German Federal Statistical Office. Following the classification of the German Federal Statistical Office in general, we have merged adjacent classes including only few observations due to technical reasons. We have merged (1) miners, stone workers, and workers in ceramic and glass industries; (2) workers in wood and paper manufacturing industries; and (3) workers in textile and leather industries.[4] Table 3.1 provides the descriptive statistics of the data. Table B.1 in the appendix depicts the sample statistics for the two subsamples.

Table 3.1.: Summary Statistics in the Data Set

Variable	N	Mean	St. Dev.	min	max
father's job	8162	0.143	0.350	0	1
father's sector	8162	0.214	0.410	0	1
fatherless at youth	8162	0.062	0.242	0	1
female	8162	0.520	0.500	0	1
years of education	8162	12.33	2.769	7	18
year of birth	8162	1952.27	15.543	1902	1984
northern Germany	8162	0.251	0.433	0	1

Source: own calculations.

Our empirical analysis links information on an individual's occupational choice to the occupation of his/her biological father. We focus on the father's occupation because, in our sample period, information on the mother's occupation is frequently missing (75 %). Moreover, many mothers apparently did not participate in or par-

[4] A detailed description of the occupational classification is available in table B.2 in the appendix.

ticipated to a limited extent in the labour market during their offspring's childhood. Therefore, we expect the father's occupation to be more influential in guiding children's occupational choices.

The first subsample comprises individuals who lived at least half of their childhood in a family with their biological father. As we assume that occupational choices are made after the age of 16, this definition corresponds to 8 or more years with the father present. We calculate how many years the individual has spent with a single mother, with a stepfather, with other relatives, with foster parents, or in a children's home at the age of 15. If these periods total more than 7 years, we consider nurture effects to be absent or restricted and assume that the biological father's occupation does not affect the child's career by serving as an example or by shaping his/her interests, abilities, or skills. The number of individuals whose biological father was absent for more than 7 years during their childhood is rather small in our sample: 6.2 % of individuals were raised without their father.[5]

Occupational information for individuals and their fathers is available in 8,162 cases. We compare two alternative definitions of children selecting their fathers' occupations. A strict definition implies that the same occupation is only chosen when the child's occupation is exactly the same occupational group as his/her father's (*father's job*). According to our classification, approximately 14 % of the individuals choose the same occupation as their fathers. We find that 14.5 % of children who have grown up with their fathers choose the same occupation as their fathers. If the fathers did not live with the children when children were young, this percentage drops to 10 %. Alternatively, the definition of same occupational choice implies that children work in the same or an adjacent group with respect to sector thresholds (*father's sector*). According to this definition, approximately 21 % of our observations choose the same or similar occupation as their fathers. Comparing these results, we see that children not only tend to choose the same occupation as their fathers, but also occupations in the same sector. We use also information on age,

[5]During our sample period (birth year of respondents before 1985) parental mortality and divorce rates were low on average. Therefore, most children were raised with both parents.

sex, education and residence to explain occupational choice. $female_i$ represents a dummy variable that takes a value of 1 if the individual is female and 0 if male. In our sample, 52 % of the individuals are female. Education is measured in years of education. On average, individuals attend school for 12 years, including vocational training. The average age in our sample is approximately 60 years, with most individuals born between 1940 and 1960. The dummy variable *Northern FRG*$_i$ equals 1 if an individual lives in the northern Federal Republic of Germany (FRG), namely in Schleswig-Holstein, Hamburg, Bremen or Lower Saxony.

Table 3.2.: Descriptive Statistics – Father's Job

	percentage with fathers job		
job group	whole sample	father present	father absent
Ia	.576	.598	.296
IIa/IIIa/IIIb	.320	.333	.200
IIIc	.033	.037	.000
IIId/IIIe	.076	.070	.167
IIIf	.083	.094	.000
IIIg	.171	.172	.155
IIIh	.082	.085	.000
IIIi	.143	.135	.200
IIIk/IIIl	.076	.077	.056
IIIm	.141	.148	.053
IIIn	.257	.275	.071
IIIo	.138	.149	.000
IIIp	.142	.142	.143
IIIq	.244	.253	.000
IIIr	.025	.029	.000
IIIs	.069	.066	.091
IIIt	.100	.111	.000
IVa	.139	.141	.100
IVb	.077	.077	.091
Va	.066	.068	.043
Vb	.079	.083	.000
Vc	.193	.197	.143
Vd	.195	.196	.171
Ve	.123	.130	.000
Vf	.078	.088	.000
Vg	.064	.061	.125
Vh	.096	.102	.000
Vi	.049	.044	.109
Total	.143	.145	.100

Source: own calculations.

Table 3.2 denotes the frequencies of the occupational groups in our classification. Additionally, the percentage of children with fathers in the same occupational group is presented. The relative frequencies of occupations demonstrate that occupational choices do not differ significantly between children who were raised (mainly) without their biological father and those who were raised exclusively with their biological father. Jobs in administration and the metal industry are chosen most often. Sales is also popular in our data set. However, children's transition rates differ among occupations: children are especially likely to pursue the same occupation as their fathers if the fathers work as farmers (58 %), in the masonry industry (32 %), or as house-painters (24 %). Jobs in the chemical industry and in goods issuing departments have low transmission rates (3 %).

The high rate of transmission in farming is not surprising, as bequeath motives may be important: farms are passed on to the next generation, and so both parents and children may have material incentives in the intergenerational continuity of the farm (see, e.g., Laband and Lentz (1983)). While some social classes with specific social values have worked in handicrafts, and while a tradition of small business ownership in some occupations of the salesman category exist, no such prestige or ownership has developed in, e.g., jobs in the chemical industry.

Fathers' influence also depends on the gender of their offspring. Sons pursue the same job as or a similar job to their father's more often than daughters do. With respect to the classification of jobs, approximately 18 % of men choose a job within the same group as their fathers. This proportion is much smaller for women. Only 11 % of daughters choose an occupation in the same occupational group as their fathers.

3.4. Estimation Strategy

As we are not interested in the economic performance of the employee, i.e., his/her wages or annual income, there is no natural ordering of outcomes. Therefore, using simple ordered probit models is inadequate for our research question. In our case, the outcome of the worker's choice is, e.g., "working in the service sector" or another sector of our occupational classification. Specifying multinomial logit models is a straightforward discrete choice approach in this setting. Previous empirical studies of occupational choice have employed different versions of this empirical strategy. For example, Harper and Haq (1997) use a multinomial logit selection model to correct for panel dropouts.

One major disadvantage of multinomial logit models is that the assumption of IIA must hold. Intuitively, it is difficult to justify this assumption in our setting. In our case, the IIA assumption states that the probability of becoming a doctor, given the choice between becoming either a doctor or a metal worker, is independent of whether becoming a nurse is an option. The introduction of the option "nurse" should have little impact on becoming a metal worker; however, it should reduce the probability of becoming a doctor. This choice would lead to an increase in the conditional probability of becoming a metal worker given the occupational choice between "doctor" and "metal worker".

We ran a Hausman test (not reported here) that provides weak empirical evidence that IIA does not hold. We employ an empirical strategy to account for this shortcoming: At first our baseline regressions employ McFadden's choice model (McFadden (1974)). McFadden's choice model is essentially equivalent to multinomial logit models, but it allows us to consider both the impact of individual characteristics and occupation-specific variables. However, it is important to remember that the conditional logit model implies the assumption of IIA.

We estimate a model of the following form for different subsamples:

$$job_{ij} = \alpha_1 + \alpha_2 OCC\_FATH_{ij} + \mathbf{x}_i'\boldsymbol{\beta} + \epsilon_{ij} \tag{3.1}$$

where the binary outcome variable job_{ij} indicates whether individual i has chosen occupation j,[6] OCC_FATH_{ij} represents a dummy variable indicating whether an individual has chosen his/her father's occupation; and, $\mathbf{x}_i$ is a vector of all individual specific control variables, such as age, sex, residence and education.

To disentangle nature-related and nurture-related effects, we employ this model both for the subsample of people who were raised without their biological father and for the subsample of people in "normal" family constellations with both parents. If the probability of choosing the same (or a similar) occupation differs significantly, this result indicates that there is some influence of education and parental role modellings during childhood. Otherwise, we cannot exclude that the intergenerational persistence of occupational choices is driven by genetic endowment only.

In order to test the hypothesis of significant differences between both subsamples, we estimate models that include both subsamples and interact the binary variable indicating the father's absence during childhood with all other independent variables. This approach is necessary for applying t-tests. We confirm the hypothesis of nurture-related effects if the estimated coefficient of the interaction term $OCC\_FATH_{ij} \times FATHERLESS_i$ is significantly negative.

Because more general multinomial models allow for correlated error terms, we use nested logit models as an additional robustness check, which are a tractable variant of these models. These models were introduced as an expansion of the conditional logit model by McFadden (1978). For this purpose, occupational choice is split into two career decisions, assuming independence of alternatives in each of the nested groups.

We use a hierarchical tree structure that follows the distinction of three economic sector. These three economic sectors are the extraction of raw materials, manufacturing, and services. The job group Ia belongs to the sector "extraction of raw materials". The sector "manufactoring" includes the job groups with code II, III

[6] The observations show all potential occupations for each individual in the sample. Therefore, $i * j$ observations are included.

and, IV. Job groups with coding V belong to the sector "services". Hence, we must rely on the assumption that our nested structure in the tree is correctly specified. We have tested several hierarchical tree structures and find that the estimation results, especially the estimated coefficient of the effect of father's job that is of most interest, are quite robust against changes in the nested structure of the tree.

3.5. Empirical Results

3.5.1. Estimation Results of CL and NL Regressions

Results of Conditional Logit Models

We run conditional logit regressions both for the subsample of people who did not live in same household as their biological father for many years during childhood (N=506) and for the subsample of people who grew up in family constellations with both parents living in the household (N=7,654). Tables 3.3 and 3.4 present the results of our conditional logit regressions for the subsamples of individuals raised with their fathers and raised without their father, respectively. Working in the metal industry (group IIIg) is the reference category throughout.

We find a highly significant and positive effect of father's occupation for the subsample of individuals raised with their father living in the same household (see table 3.3). This effect implies the persistence of occupational choice among generations.

A positive effect of father's occupation is found in the estimation results for the subsample of individuals who spent more than half of their childhood without their father as well. The positive coefficient of father's job is also significant in this regressions (see table 3.4). However, the effect of father's occupation becomes much smaller in size: the estimated coefficients for the subsamples differ by approximately 50 %. The 95 %-confidence intervals of both coefficients do also not overlap, indicating significant differences in the size of the effects in both subsamples.

Table 3.3.: Conditional Logit: Subsample Grown up with Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	0.954***													
	(0.038)													
female		2.546***	1.427***	2.956***	2.786***	-0.078	0.603*	2.355***	4.598***	2.121***	-2.261*	-0.581	-0.392	0.450
		(0.203)	(0.413)	(0.431)	(0.276)	(0.492)	(0.272)	(0.376)	(0.248)	(0.219)	(1.017)	(0.612)	(0.487)	(0.431)
yrs of education		-0.219***	-0.036	0.224*	0.068	-0.235**	0.125***	-0.567***	-0.165**	-0.165**	-0.146*	-0.242**	-0.145*	-0.169*
		(0.049)	(0.098)	(0.094)	(0.066)	(0.081)	(0.036)	(0.117)	(0.056)	(0.052)	(0.058)	(0.078)	(0.066)	(0.079)
time trend		-0.036***	-0.031**	0.0004	-0.008	-0.008	0.013**	0.016	-0.028***	0.003	0.006	0.015*	-0.010	0.005
		(0.005)	(0.010)	(0.013)	(0.008)	(0.007)	(0.005)	(0.011)	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)	(0.008)
northern FRG		0.338*	-0.492	-0.101	-0.107	-0.267	-0.139	0.013	-0.180	0.245	0.076	0.275	0.154	0.454^{+}
		(0.161)	(0.449)	(0.506)	(0.295)	(0.308)	(0.183)	(0.433)	(0.202)	(0.184)	(0.217)	(0.265)	(0.236)	(0.266)
constant		0.893	-2.374*	-6.354***	-3.302***	0.654	-2.357***	2.699*	-0.991	0.373	0.175	0.598	-0.039	-0.339
		(0.546)	(1.112)	(1.184)	(0.783)	(0.891)	(0.433)	(1.215)	(0.648)	(0.580)	(0.642)	(0.855)	(0.731)	(0.880)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
female	3.549***	3.117***	2.578***	2.135***	3.088***	3.912***	3.682***	1.269***	4.237***	1.940***	4.557***	5.359***	4.978***	4.963***
	(0.403)	(0.290)	(0.506)	(0.269)	(0.232)	(0.184)	(0.204)	(0.264)	(0.181)	(0.290)	(0.279)	(0.215)	(0.206)	(0.224)
yrs of education	-0.295*	-0.156^{+}	-0.142	0.782***	0.451***	0.167***	0.490***	0.036	0.440***	0.556***	0.638***	0.569***	0.833***	-0.099*
	(0.121)	(0.086)	(0.155)	(0.038)	(0.037)	(0.030)	(0.031)	(0.047)	(0.027)	(0.038)	(0.043)	(0.031)	(0.031)	(0.043)
time trend	0.047***	-0.006	0.053**	-0.023***	-0.017**	-0.002	-0.006	0.017**	-0.014***	-0.008	-0.012	0.002	-0.019***	-0.001
	(0.013)	(0.008)	(0.018)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)
northern FRG	0.113	-0.595	-1.404	-0.233	-0.249	0.111	0.191	0.369^{+}	-0.020	0.644**	0.127	0.229	0.038	0.502**
	(0.437)	(0.370)	(1.035)	(0.214)	(0.224)	(0.137)	(0.165)	(0.196)	(0.130)	(0.206)	(0.252)	(0.155)	(0.160)	(0.154)
constant	-1.079	-1.122	-2.759	-11.82***	-7.331***	-2.923***	-7.559***	-2.102***	-6.011***	-8.956***	-11.24***	-9.460***	-12.81***	-1.468**
	(1.334)	(0.959)	(1.741)	(0.569)	(0.492)	(0.363)	(0.414)	(0.551)	(0.334)	(0.537)	(0.641)	(0.418)	(0.442)	(0.506)
N	214312													
Cases	7654													
χ^2	4385.1***													

Source: own calculations.
Standard errors in parentheses; $^{+}p < 0.1$, $^{*}p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
See table B.2 for details on the job classification.

Table 3.4.: Conditional Logit: Subsample Grown up without Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	0.512**													
	(0.167)													
female		2.324**	-14.78	3.469*	2.299*	1.274	-14.32	2.493*	4.762***	2.003**	-14.45	1.122	0.977	-14.26
		(0.727)	(2438.7)	(1.373)	(1.073)	(0.985)	(1652.2)	(1.104)	(0.965)	(0.777)	(1509.8)	(1.252)	(1.240)	(2792.9)
yrs of education		-0.446*	-0.854*	-0.710	0.066	-0.246	0.151	0.013	-0.465*	-0.517**	-0.221	-0.134	-0.087	-0.709
		(0.174)	(0.352)	(0.468)	(0.202)	(0.211)	(0.136)	(0.238)	(0.223)	(0.193)	(0.179)	(0.235)	(0.217)	(0.451)
time trend		-0.038*	-0.079^{+}	0.036	-0.044	0.003	0.008	-0.019	-0.021	0.020	-0.006	-0.062^{+}	0.039	0.010
		(0.018)	(0.041)	(0.038)	(0.032)	(0.022)	(0.023)	(0.032)	(0.020)	(0.017)	(0.020)	(0.033)	(0.027)	(0.0401)
northern FRG		0.442	-0.259	-17.09	-0.319	-0.980	-1.151	-16.97	-17.14	0.106	0.359	0.958	0.355	-16.18
		(0.551)	(1.205)	(6672.3)	(1.146)	(1.099)	(1.099)	(4144.5)	(2704.4)	(0.661)	(0.676)	(0.838)	(0.906)	(3654.9)
constant		3.418^{+}	6.215^{+}	3.689	-3.467	1.168	-3.204^{+}	-2.772	2.071	4.183*	1.076	-1.314	-1.425	4.982
		(1.899)	(3.544)	(4.748)	(2.521)	(2.345)	(1.714)	(2.866)	(2.482)	(2.058)	(2.015)	(2.760)	(2.515)	(4.600)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
female	2.810*	3.845***	2.379	1.906^{+}	2.848***	3.842***	3.735***	2.700***	4.106***	1.471	3.943***	4.933***	5.081***	4.851***
	(1.128)	(0.906)	(1.626)	(1.045)	(0.865)	(0.681)	(0.803)	(0.807)	(0.666)	(1.260)	(0.867)	(0.849)	(0.797)	(0.763)
yrs of education	-0.015	-0.061	-0.434	0.584***	0.192	-0.066	0.130	-0.145	0.286**	0.474**	0.684***	0.465***	0.540***	-0.878***
	(0.263)	(0.197)	(0.532)	(0.141)	(0.140)	(0.115)	(0.134)	(0.181)	(0.088)	(0.146)	(0.129)	(0.109)	(0.102)	(0.172)
time trend	0.098*	0.018	0.143	0.016	0.008	-0.001	-0.009	0.045*	-0.019	0.012	-0.013	0.015	-0.003	0.016
	(0.044)	(0.022)	(0.090)	(0.025)	(0.022)	(0.014)	(0.019)	(0.021)	(0.014)	(0.027)	(0.023)	(0.018)	(0.017)	(0.015)
northern FRG	-17.11	0.465	-17.15	-1.179	0.289	0.289	1.709**	-0.372	-0.243	1.023	0.237	0.559	0.688	1.305*
	(4734.2)	(0.774)	(7900.3)	(1.137)	(0.761)	(0.499)	(0.614)	(0.842)	(0.490)	(0.808)	(0.730)	(0.610)	(0.559)	(0.522)
constant	-3.810	-2.326	-0.928	-9.699***	-4.608*	-0.705	-4.469*	-0.522	-4.593***	-8.729***	-11.80***	-8.940***	-9.715***	6.592***
	(3.155)	(2.332)	(5.796)	(2.142)	(1.831)	(1.362)	(1.746)	(2.062)	(1.141)	(2.175)	(2.051)	(1.623)	(1.524)	(1.765)
N	14224													
Cases	508													
χ^2	300.5***													

Source: own calculations.
Standard errors in parentheses; $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, *** $p < 0.001$.
See table B.2 for details on the job classification.

With respect to the effects of other independent variables, estimation results for individuals whose fathers were absent for more than half of their childhood do not differ significantly from the estimations of the subsample who were brought up by both parents. We find for the subsample with fathers that women make significantly different occupation choices than men (see table 3.3). Women choose a job in metal or steel industries less often than men. Compared to other occupational groups, working in the metal industry is the least probable option for women; women's probability of working in technical jobs or in agriculture is significantly higher. Women are most likely to choose occupations in administration, sales, or health and education services. Notably, nearly all occupation groups show significant differences between women and men; the only exception is the occupational group related to building industries, such as painting and architecture.

Not surprisingly, we find that the educational level has a large and significant effect on occupational choice. By controlling for educational levels, we ensure that our estimations extend beyond the effect of intergenerational educational immobility. Even if children and parents have the same level of education, they can choose between different occupational groups, e.g., after graduating from university, individuals can become engineers, teachers, or doctors. Educational level, measured by the number of years in education, has a significant effect on most occupational groups (see table 3.3). Workers in the metal and steel industry have a lower level of education compared to workers in all other occupational groups. Higher levels of education significantly increase the probability of choosing jobs in technical fields (groups IVa, IVb). People with more years in education find it, in general, more attractive to work in the tertiary sector. Fewer years of education significantly increases an individual's likelihood of being a farmer. Most other jobs in production industries do not show significant differences in education.

A linear time trend is included in the estimated models to reflect changes over time in labour market conditions. The effect implies the following expected pattern: older cohorts have a higher probability of working in the agricultural sector or as miners. This effect is significant. The time effect is, however, insignificant for most other occupational groups and indicates that all jobs in metal, chemical or paper industries have been selected more frequently over time. Additionally, jobs in the tertiary sector have increased over time; therefore, the probability of working in sales, administration, education or health does not change over time compared to group IIIg.[7]

All these effects are also visible in the subsample of individuals who grew up without fathers. However, they are not always significant due to the small sample size (N=508) (see table 3.4). Nevertheless, the results reflect similar behavioural patterns in this subsample as described above. That is, women prefer working in the tertiary sectors and tend to choose jobs in administration, sales, education and health. Jobs in the metal industry are chosen significantly less often by women. The effect of education also prevails: more years of education increases an individual's likelihood of working in technical occupations (group IVa), in education (Vh) and health (Vg) or in other jobs in the tertiary sector. Lower levels of education are more common among individuals holding blue-collar jobs. Time effects are small and nonsignificant for occupational groups in the secondary sector. However, the negative time effect remains significant for agriculture: younger cohorts are more likely to pursue occupations in production or services than in agriculture.

In both models, the results indicate that the probability of occupation choice differs broadly, independent of individual characteristics: e.g., jobs in mining are not common today compared to jobs in services. This finding is reflected by different levels of the estimated constant coefficients (see tables 3.3 and 3.4). Most occupational groups have highly significant constants. We consider these effects to be in line with past research: job-specific characteristics, such as prestige and wages, are considered before an occupational choice is made. Notably, however, real income levels may differ from young individual's wage expectations because wage expectations may be influenced by the information received in their living environment.

[7] Age group dummies are used as alternative measures of effects of economic history. However, the estimation results are not significantly altered by these specifications.

Marginal effects of the conditional logit models are shown in table B.3 in the appendix. We find that the effect of father's occupation differs significantly between occupational groups. It is lower for jobs in chemical or wood production compared to managerial positions, sales, or agriculture. We find marginal effects of, e.g., 10 percentage points for father's occupation for the occupational group "Sale of service and related occupations (Vb)", while the average marginal effect for the occupational group "Chemicals and plastic products (IIIc)" is 1 percentage point. However, even if the size of the marginal effects differs between occupational groups, we find a regular pattern for the differences between children who grew up with their fathers and those who did not: the effect of father's job is reduced by approximately 50 % if the father was absent during the individual's childhood (see table B.3).

Results of Nested Logit Models

Nested logit estimation models divide occupation choices into two levels. We define the first level as the three economic sectors (agriculture, production, services). Our classification of 28 occupational groups defines branches on the second level of individuals' decisions. Compared to the conditional logit models, the IIA assumption is relaxed and the decision between different groups of occupations within the second level may be dependent.

Tables 3.5 and 3.6 present the results of our nested logit regressions for the subsamples of individuals raised with their fathers and without their fathers, respectively. Working in the production sector is the reference category for the first-level regressions.

Table 3.5 shows the estimation for the subsample of individuals who were raised with their fathers living in the same household. We again find a large and highly significant positive effect of father's occupation. The size of the effect is similar to that for conditional logit models. However, an LR-test shows weak empirical evidence that the assumption of independence of irrelevant alternatives does not hold and that nested models increase the validity of the results.

Table 3.5.: Nested Logit: Subsample Grown up with Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.235***													
	(0.085)													
female		-0.482*	0.476	0.289	-2.644***	-2.591***	-1.949***	-0.134	2.159***	-0.398*	-4.884***	-3.158***	-2.970***	-2.098***
		(0.189)	(0.438)	(0.266)	(0.518)	(0.266)	(0.275)	(0.366)	(0.322)	(0.186)	(1.099)	(0.652)	(0.525)	(0.442)
yrs of education		0.040	0.445***	0.271***	-0.057	0.199***	0.334***	-0.418**	0.0001	0.012	0.046	-0.066	0.041	0.014
		(0.039)	(0.108)	(0.079)	(0.096)	(0.049)	(0.053)	(0.137)	(0.071)	(0.068)	(0.072)	(0.093)	(0.079)	(0.093)
time trend		0.001	0.034*	0.026**	0.027***	0.035***	0.048***	0.052***	0.007	0.038***	0.041***	0.050***	0.025***	0.040***
		(0.005)	(0.014)	(0.008)	(0.008)	(0.005)	(0.006)	(0.012)	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
northern FRG		-0.151	-0.380	-0.389	-0.536	-0.280^{+}	-0.418*	-0.245	-0.458*	-0.021	-0.196	0.015	-0.105	0.195
		(0.203)	(0.523)	(0.310)	(0.327)	(0.161)	(0.206)	(0.450)	(0.212)	(0.204)	(0.240)	(0.287)	(0.256)	(0.288)
constant		-0.945*	-7.440***	-4.145***	0.092	-0.776	-3.246***	2.403^{+}	-1.450^{+}	-0.168	-0.561	0.051	-0.694	-0.962
		(0.469)	(1.466)	(0.981)	(1.012)	(0.543)	(0.650)	(1.316)	(0.767)	(0.717)	(0.777)	(0.977)	(0.862)	(1.007)
	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
female	1.065*	0.635*	0.072	-0.256	0.650**	1.303***	0.793**	-3.431***	1.827***	-2.356***	2.346***	3.804***	3.047***	3.208***
	(0.423)	(0.289)	(0.507)	(0.260)	(0.242)	(0.173)	(0.247)	(0.595)	(0.159)	(0.577)	(0.416)	(0.324)	(0.257)	(0.325)
yrs of education	-0.143	0.024	0.035	1.045***	0.694***	0.216***	0.756***	-0.029	0.676***	0.882***	1.011***	0.886***	1.365***	-0.205*
	(0.137)	(0.099)	(0.169)	(0.082)	(0.066)	(0.058)	(0.059)	(0.094)	(0.049)	(0.076)	(0.087)	(0.061)	(0.092)	(0.088)
time trend	0.083***	0.029***	0.089***	0.008	0.015*	0.03***	0.030***	0.069***	0.014**	0.024*	0.018	0.044***	0.005	0.037***
	(0.014)	(0.008)	(0.020)	(0.007)	(0.006)	(0.005)	(0.007)	(0.010)	(0.005)	(0.011)	(0.013)	(0.007)	(0.007)	(0.006)
northern FRG	-0.149	-0.881*	-1.712	-0.522*	-0.540*	-0.215	-0.0867	0.309	-0.467**	0.718*	-0.212	-0.022	-0.380	0.502*
	(0.453)	(0.387)	(1.071)	(0.235)	(0.241)	(0.188)	(0.254)	(0.315)	(0.175)	(0.347)	(0.428)	(0.228)	(0.240)	(0.223)
constant	-1.413	-1.741	-3.368^{+}	-13.47***	-8.669***	-3.094***	-10.89***	-1.515	-8.167***	-13.52***	-17.39***	-14.17***	-20.16***	-1.140
	(1.452)	(1.084)	(1.907)	(1.260)	(0.984)	(0.607)	(0.913)	(0.947)	(0.651)	(1.260)	(1.608)	(1.103)	(1.592)	(0.811)
agricultureτ	0.396***													
	(0.064)													
craftsmenτ	1.025***													
	(0.091)													
tertiaryτ	1.813***													
	(0.168)													
N	214312													
Cases	7654													
χ^2	1463.8***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
See table B.2 for details on the job classification.

Table 3.6.: Nested Logit: Subsample Grown up without Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.052**													
	(0.372)													
female		-23.97	7.189	0.750	-6.168	-13.24*	-100.50	0.889	14.41	-2.214	-103.4	-7.471	-8.144	-96.94
		(15.26)	(8.338)	(5.647)	(5.193)	(6.473)	(11593.4)	(5.731)	(9.281)	(3.156)	(11840.4)	(7.770)	(7.311)	(7729.9)
yrs of education		-25.89^{+}	-7.237	-0.686	-2.723	-1.121	-0.466	-1.065	-3.566*	-4.737^{+}	-3.131	-2.885	-1.286	-8.798*
		(14.97)	(4.656)	(1.168)	(1.864)	(0.752)	(0.847)	(1.338)	(1.740)	(2.811)	(2.231)	(2.834)	(1.295)	(4.408)
time trend		-1.055^{+}	0.112	-0.249	-0.056	-0.036	-0.004	-0.164	-0.114^{+}	-0.005	-0.101	-0.270^{+}	0.136	-0.224
		(0.568)	(0.153)	(0.165)	(0.106)	(0.056)	(0.119)	(0.166)	(0.069)	(0.079)	(0.104)	(0.152)	(0.153)	(0.183)
northern FRG		-7.695	-117.9	-2.901	-6.325	-0.806	-6.743	-102.0	-97.53	0.488	1.227	4.490	2.343	-204.6
		(10.91)	(139065.1)	(6.908)	(6.873)	(1.733)	(6.736)	(25875.1)	(11759.9)	(3.470)	(3.615)	(5.746)	(5.045)	(348863628.2)
constant		119.0^{+}	57.52	-4.358	25.02	16.72	0.227	0.341	25.71	47.39^{+}	30.69	20.80	4.112	83.05*
		(61.48)	(39.68)	(18.90)	(20.88)	(12.55)	(14.23)	(19.54)	(17.30)	(28.41)	(23.82)	(29.31)	(18.02)	(39.84)
	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
female	3.133	11.19	1.594	-1.410	4.740	-0.618	-1.298	-3.867	0.338	-7.531	-0.767	2.408	2.803	1.907
	(5.862)	(8.063)	(8.775)	(3.399)	(4.710)	(1.639)	(2.180)	(2.871)	(1.365)	(5.584)	(2.182)	(2.166)	(2.076)	(2.233)
yrs of education	-0.419	-0.882	-2.928	1.776	0.0162	-1.916	-1.223	-2.271	-0.728	-0.058	0.560	-0.145	0.0757	-4.626^{+}
	(1.231)	(0.994)	(3.709)	(1.114)	(0.786)	(1.189)	(0.924)	(1.428)	(0.680)	(0.685)	(0.733)	(0.572)	(0.563)	(2.459)
time trend	0.400	-0.055	0.462	-0.013	-0.059	-0.061	-0.094	0.095	-0.106^{+}	-0.012	-0.068	0.006	-0.046	-0.019
	(0.262)	(0.081)	(0.425)	(0.096)	(0.093)	(0.052)	(0.072)	(0.106)	(0.055)	(0.085)	(0.067)	(0.066)	(0.052)	(0.054)
northern FRG	-95.19	5.051	-130.4	-2.175	3.142	-1.028	3.219	-3.008	-2.339	1.222	-1.433	-0.194	0.107	1.375
	(13896.9)	(4.443)	(468334.9)	(3.664)	(3.938)	(1.479)	(2.794)	(2.754)	(1.650)	(2.405)	(2.160)	(1.592)	(1.429)	(1.788)
constant	-14.32	-5.349	7.391	-33.93	-11.59	26.37	14.22	28.06	13.01	-0.662	-9.407	-0.257	-2.561	51.86^{+}
	(23.63)	(16.21)	(41.15)	(22.90)	(15.54)	(16.31)	(12.90)	(17.63)	(11.78)	(12.91)	(14.40)	(11.33)	(11.54)	(26.80)
agricultureτ	72.21													
	(52.77)													
craftsmenτ	5.961*													
	(2.938)													
tertiaryτ	2.917^{+}													
	(1.641)													
N	14224													
Cases	508													
χ^2	46.5***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
See table B.2 for details on the job classification.

The influence of other socio-demographic characteristics remains unchanged: women tend to choose jobs in steel and metal industries significantly less often than do men. Instead, they display a significantly higher probability of working in occupations concerning nutrition, health, or education, and they prefer working in sales and administration. Time effects again indicate that the selection of occupations in the secondary and tertiary sectors has increased over time. However, significant results are only found for particular occupational groups, such as Vb and, Vg. Considering different levels of education, we again find a significant and positive effect for most occupational groups in the tertiary sector.[8]

The results for the subsample of individuals whose fathers were absent for more than half of their childhood do not differ largely from the estimations described above (see table 3.6). The effect of father's occupation diminishes but is still positive and significant. However, the 95 %-confidence intervals of the estimated coefficients overlap for the nested logit models. The influence of other controls does not change significantly compared to the conditional logit estimations discussed above.

3.5.2. Robustness Checks

Conditional Logit Regressions for Sons

Gender segregation in the labour market is a much debated research topic. Although this chapter does not focus on gender segregation, we cannot deny that sons and daughters might be influenced differently by their father's absence. Therefore, we focus only on male individuals for robustness checks. The results of conditional logit estimations are displayed in tables B.4 and B.5 in the appendix.

We again find a positive and significant effect of father's occupation. The estimated effect is larger for the subsample that grew up with their father living in the same household. However, the estimated coefficient for the fatherless individuals is lower

[8] These results remain mainly unchanged for alternative specifications as well as for different tree constructions of occupations. Further results are available upon request.

than in the baseline regression for fatherless individuals. These findings imply that sons and daughters are affected differently by father's absence. Sons seem to suffer more from their father's absence in terms of occupational socialisation.[9] Further research should address the impact of mother's occupation on girls. We cannot answer this question due to missing data and historic employment patterns of mothers in Germany.

Results of CL and NL Regressions for Pooled Subsamples

Statistical test theory is a branching field of research. So, test theory states that t-tests cannot be used to test differences between coefficients that result from different estimations. To address the problem of adequate testing, we pool our two subsamples and test whether the hypothesis of the existence of considerable nurture effects holds by estimating the same models for all individuals. To disentangle nurture effects, we include interaction terms for all explanatory variables and the dummy variable indicating that the individual did not grow up with his/her biological father. We estimate these models for the full data set as well as for the subsample of boys. The relevant coefficients of the conditional logit estimations are presented in table 3.7.

Table 3.7.: Overview of Relevant CL Regression Coefficients

	conditional logit			
	full sample		only boys	
	plain model	full model	plain model	full model
father's job	1.139***	0.954***	1.389***	1.148***
	(0.035)	(0.038)	(0.046)	(0.048)
father's job x without father	-0.455**	-0.439**	-0.723**	-0.699**
	(0.157)	(0.170)	(0.228)	(0.241)
controls included?	NO	YES	NO	YES
Cases	8162	8162	3916	3916
χ^2	1051.04***	4729.12***	909.97***	1879.43***

Source: own calculations.
Standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
See tables B.6, B.7, B.8, B.9 in the appendix for full estimation results.

[9] Hellerstein and Morrill (2011) examine father's impact on girls' occupational choice. They find that daughters are also influenced by their father's occupation in terms of occupational choice.

Confirming the results of the separated estimated conditional logit models, we again find a significant and positive effect of father's occupation. Additionally, the interaction term of father's occupation and father's absence during childhood is negative and highly significant. This finding confirms that the influence of father's occupation is significantly reduced if fathers are absent for most of the individual's childhood.

This result remains valid for the whole sample as well as for sons only. However, the size of both effects – the positive effect of father's job and its decrease if the father was absent – is significantly distinct: on the one hand sons respond stronger to fathers in terms of occupational choice. The effect is, on the other hand, more decreased if fathers did not live in one household with their children during most years of childhood.

Table 3.8.: Overview of Relevant NL Regression Coefficients

	nested logit			
	full sample		only boys	
	plain	full model	plain	full model
father's job	1.932***	1.205***	2.132***	1.339***
	(0.084)	(0.085)	(0.111)	(0.102)
father's job x without father	-0.610**	-0.585**	-1.013**	-0.887***
	(0.233)	(0.195)	(0.312)	(0.245)
controls included?	NO	YES	NO	YES
Cases	8162	8162	3916	3916
χ^2	532.64***	1583.10***	369.26***	509.62***

Source: own calculations.
Standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
See tables B.10, B.11, B.12, B.13 in the appendix for full estimation results.

Table 3.8 presents the relevant coefficients for the nested logit estimation. The estimates do not differ much from the results of the conditional logit regressions. The effect of father's occupation is still positive and highly significant. A t-test again shows that the effect of father's occupation is significantly higher for the subsample of individuals raised with their fathers.

Genetic factors, therefore, do not seem to be the main driving force behind the low intergenerational mobility in the labour market. Children seem to identify themselves more with their father's occupation when he is present. Thus, nurture and socialisation within the core family, both appear to be important influences on children's occupation. Fathers not living with their children when children are young, influence children's occupational decisions less; also they do not serve as role models to the same extent that they otherwise would. In this case, children might find role models more in their mothers or other persons being close to them.[10]

3.6. Summary of the Findings and Outlook

This chapter analyses young people's occupational choices in Germany. Using data from the SOEP, we find that children are highly influenced by their father's occupation. Many individuals pursue the same occupation as or a similar occupation to their father's. Young men tend to be influenced even more than young women. This fact may also be driven by gender differences in occupational choice. Gender segregation in the German labour market is a well-documented phenomenon and might explain why daughters are less affected by father's occupation. We also find systematic differences between occupations: jobs in health and sales have high transition rates over generations, while jobs in chemical and wood industries display lower transition rates.

We divide our data set into two subsamples: one contains people who were raised in family constellations with their fathers, and the other contains individuals who were raised without their fathers. If transition rates are driven by genetic factors, no differences should arise between the two groups. Therefore, differences between the subsamples imply an additional effect of socialisation, of nurture, and of children's

[10] One of our readers has suggested to estimate mixed logit models, too. Thereby, no assumption on a nested structure of occupational choice is needed. However, we face technical restrictions and, therefore, mixed logit models can only be used as a further robustness check. In particular, the required computing capacity and the running time of several weeks per model are restrictive. The results of one mixed logit model are available in table B.14 in the appendix. We find again some weak empirical evidence that father's absence decreases the probability of choosing father's occupation also in this setting (p-value: 0.07 in a one-sided test). However, we have to estimate further mixed logit models to gain robust empirical results.

commitment towards their parents. This chapter, therefore, makes a contribution to the enduring debate over "nature versus nurture": i.e., the question of whether people are influenced most by genetics or socialisation. Occupational choices mirror this general question. Our results show that genetic factors alone cannot explain the high transition rates.

By running conditional logit models for the pooled subsamples of individuals raised with and without their fathers, we find significantly different coefficients. A t-test confirms the hypothesis of a smaller effect of father's occupation when the father does not live with his children during childhood. Thus, we find a positive effect of nurture and education and show higher influences of father's occupation for individuals raised with their fathers. When it comes to occupational choice, we conclude that children find a role model in their parents. Estimating nested logit models confirms these results and relaxes the IIA assumption.

Occupational choices that do not reflect one's personal interests and abilities induce suboptimal economic outcomes. Negative effects arise from individuals who are not employed according to their talents. These individuals suffer considerable wage losses. A lower overall productivity also yields negative effects for society. Inefficiency in the labour market is especially costly in the context of a shrinking labour force which is expected to prevail during the next decades due to demographic changes in industrialised countries.

Our analysis shows that efficiency in the labour market may be improved by increasing the influence of individual's abilities on their occupational choices. One possible approach to disentangle occupational choices from parents' wishes might be to offer children additional alternative role models: e.g., by presenting different occupations more regularly or by providing more extensive vocational guidance in schools. However, further research is needed before policy implications shall be made. Because we do not conduct a welfare analysis, further research is needed to control for costs and benefits of, e.g., introducing additional vocational guidance programs.

To develop appropriate educational policies, further research on the complex linkages between genetic and social determinants is needed. Nature and nurture should not be understood as direct influences but rather must be analysed within their context. Further analysis of these links will enable policy makers to significantly improve the efficiency of occupational choices and will help scientists to explain why some children are more affected than others by their parents.

4. The Labour Supply of Women in STEM

4.1. Introduction

This chapter analyses the determinants of female employment behaviour, focussing on science, technology, engineering and mathematics (STEM). Occupations in STEM have received special interest in academic and political discussions about occupational choice, as these occupations have always been dominated by men. Even women's educational achievements during recent decades have not effected the high gender segregation in STEM (see OECD (2012), chapters 8 and 9). However, the quantity and quality of the labour force in STEM is a key issue for economic growth, and the demand for highly skilled workers increases in technology-related occupations in modern societies from continued technological progress (see, e.g., Murphy et al. (1991) and Tsai et al. (2010)). The demand for engineers and highly skilled technicians is especially high in Germany because the German economy strongly relies on the production industries (see BA (2010, 2011)). Therefore, political discussions focus on highly skilled workers in technology-related occupations because the demand for these workers is not likely to decline, but will continue to increase in Germany as well as in other industrialised countries. The increase in demand is reinforced by the demographic change, i.e., the labour force in general will decline in all industrialised countries due to the aging of societies (see Statistisches Bundesamt (2009a)). The shortage of skilled workers in general as well as in STEM industries is, therefore, about to become a key issue of economic growth and welfare because of the demographic change and emerging globalised markets.[1]

Occupational segregation is not only an issue in terms of labour market policies, but is also an issue of gender equality. Even though girls outperform boys in educational achievement, women currently continue to earn less than men, face higher risks to live in poverty and are less likely to enter executive positions. One cause of these inequalities between women and men is the enduring occupational segregation. The report on the "OECD Gender Initiative" provides an overview of occupational segregation in industrialised countries (see OECD (2012)). The authors find that "girls are still less likely to choose scientific and technological fields of study and, even when they do, they are less likely to take up careers in those fields" (OECD (2012), p. 14). The gender gap is even more pronounced in vocational education. The authors reveal that the low number of girls choosing scientific and technological fields of study is a cause of concern. If girls do not choose these fields of study, they cannot take advantage of the promising earnings and career prospects in STEM occupations. Even women who pursue scientific or technical studies have a higher probability of not working in STEM occupations compared to men (see OECD (2012)).

Many policies have been introduced to address the issue of gender segregation in STEM occupations. For example the project "Girls' day – Future Prospects for Girls" was introduced in Germany in 2003. The project organises open house days for girls in STEM industries and is a joint initiative of both government and the private sector. Another example is the campaign "Women into Science and Engineering (WISE)" that started in 1984 in the United Kingdom. WISE has contributed to the doubling of the share of female engineering graduates to 15 % from 1984 to 2009 (see OECD (2012), p. 114). However, policymakers face a lack of reliable information as to why girls do not choose scientific and technical fields of study which

[1] Whether a skill shortage in STEM does already exist today is broadly discussed in the German media. However, scientists do not find empirical evidence for a general shortage of workers in STEM today (see Brenke (2012a)).

promise high wage premiums and career opportunities rather than health, education or administration. Additionally, the scientific understanding of the causes of increasing occupational segregation during the transition from education to employment is fragmentary. Furthermore, the knowledge about differences in the employment behaviours of women in STEM and women in other occupations must be improved. Policymakers and umbrella organisations of the business sector are interested in research concerning the labour supply in STEM (see Rukwid and Christ (2012) as an example of research projects in Germany).

This chapter contributes to the understanding of the employment behaviour of women in STEM. The focus is on the labour supply of women in different political and cultural settings, especially for the member states of the EU. How political and cultural settings influence women in STEM differently compared to women in other occupations is of prime importance because labour market policies should, in part, aim to increase the female percentage of workers in STEM. The overall increase in women's labour market attachment and their hours of work is a major topic for European and German labour market policies: e.g., the objective of Europe 2020 is to increase the employment rates of women and men to 75 % (see EUCOM (2011)). However, there exists only a small number of empirical findings that explain how different occupational groups react to labour market policies and how their employment behaviour can be influenced. So far, only little research has been devoted to analysing relations between occupation choices and labour market behaviour until now. Some studies, though, show that educational field and occupation significantly influence women's and men's fertility (see, e.g., Lappegård and Rønsen (2005) for Norway and Oppermann (2012) for Germany). Because employment behaviour and fertility are correlated, the influence of educational field and occupation on employment behaviour is likely to exist. Furthermore, a strong selection effect as well as unobserved heterogeneity between women in STEM and in other occupations can be expected.

The empirical analysis in this chapter accounts for unobserved heterogeneity as well as for selection effects by implementing the estimation methodology described by Blundell et al. (1998). They develop a grouping estimator to address identification problems caused by changing sample composition, aggregate shocks and unobserved heterogeneity. The critical issue in this estimation methodology is the definition of groups in the labour market. Blundell et al. (1998) define groups by birth cohort and educational level. I extend the number of groups by defining groups by STEM, and different regions of the EU, in addition to cohort and educational level. I apply the estimation method of Blundell et al. (1998) to data from the European Statistics on Income and Living Conditions (EU-SILC). Information on policies concerning childcare and family allowances is included. I find some crucial differences in the employment behaviour of women in STEM compared to women in other occupations; i.e., women in STEM work significantly more hours, thus reducing the labour supply significantly less, if they have young children. I find some empirical evidence that women in STEM react significantly stronger to high levels of family allowances; i.e., women in STEM reduce their labour supply more than women in other occupations if governments provide high levels of family allowance. However, this effect is small compared to the overall effect of larger levels of expenditures on family allowance and child benefits.

This chapter is structured as follows. In section 4.2, I provide a theoretical motivation for the empirical analysis and give a short review of the related literature. Section 4.3 describes my estimation methodology. In section 4.4 and 4.5, I present my data set and the estimation results. Finally, section 4.6 presents the conclusions.

4.2. Theoretical Background and Related Literature

A large number of theoretical and empirical studies exists that examine gender-specific labour market behaviour (see Altonji and Blank (1999) for an overview). However, there is a dearth of studies that analyse the differences in the employment behaviour between occupational groups. One major novelty of this chapter is, therefore, that occupation-specific labour market behaviour is enquired. This chapter relies on several strands of literature that are presented in detail in the following.

One existing strand of literature examines gender differences in occupational choice; this chapter relates to this strand of literature in terms of gender-specific behaviour. Even though occupational segregation has been analysed for several decades, economists do not agree on the determinants of occupational segregation. Traditional economic approaches explain occupational segregation either by gender differences in preferences or by taste-based and statistical discrimination. A theoretical model based on individual preferences is provided by Polachek (1981). According to his human capital approach, occupational segregation is the result of individuals' rational decisions. He shows that typical female occupations are characterised by slowly decreasing earning potential during times out of the labour force. The low rate of atrophy indicates that women anticipate times out of the labour market already at the time of occupational choice and they want to limit their loss of human capital. Following the theoretical approach of Polachek (1981), women do not choose occupations in STEM because technological progress is fast in these occupations and knowledge moves on during times out of the labour force, e.g., maternity leave. Women's preferences for housekeeping and child raising are considered to be exogenous. Blakemore and Low (1984) find empirical evidence that female students tend to choose fields of study with low atrophy rates because they assume that there will be gaps in their employment histories from childbearing and child raising. Some scientists criticize the concept of human capital for the assumption of exogenous preferences: Heintz et al. (1997) find empirical evidence that women with children work more often in male-dominated jobs with higher levels of income. That findings contradicts Polachek (1981). Moreover, Anker (1998) shows that girls lack female role models in scientific and technical-related occupations. Therefore, girls and young women face higher costs because of uncertainty if they choose these occupations.

In contrast, other economic studies consider discriminatory behaviour of employers and co-workers to be the cause of gender-specific occupational choice. Theories of discrimination regard occupational segregation as a consequence of collective discriminatory behaviour. Becker (1957) notes that employers and workers have a "taste for discrimination". That "taste" implies that employers dislike hiring minority workers and workers do not like to have minority co-workers. Becker (1957) concludes that minority workers face lower wages for equivalent productivity because minority workers on the one hand have to compensate employers and on the other hand employers compensate majority co-workers for working with minority workers. Becker (1957) shows that these tastes for discrimination create incentives in labour markets with high segregation; i.e., if minority and majority workers work together but separately, nobody has to bear the costs of distaste.

Phelps (1972) and Arrow (1972) broaden the economic understanding of discrimination and implement the concept of limited information in the context of discrimination. Their theory of statistical discrimination takes into account the fact that employers only have limited information about job candidates' skills and productivity. Therefore, employers use observable characteristics such as age, gender, or race that they expect to be correlated with productivity to infer the job candidate's expected productivity. Employers decide on hiring and wages with regard to group-specific mean productivity (see Phelps (1972)). Aigner and Cain (1977) enlarge Phelps' model to several settings with risk-averse compliances. In the context of those theories of discrimination, occupational segregation is not the result of individual decisions, but of collective discriminatory behaviour. Thus, employers dislike hiring minority workers, such as women, in STEM. Because of missing information on women's abilities to work in STEM and/or because of male employees' distaste for working with female co-workers, women face barriers to entering occupations in STEM. Critics often argue that the theory of statistical discrimination cannot be generalised for all workers because cultural settings differ among firms and countries. Therefore, employers' stereotypes have to be interpreted in their individual settings (see, e.g., Cyba (1998)).

During recent years, some concepts have been imported into economics from social psychology. One of these, the concept of gender identity, has gained popularity in the modern economic literature recently: labour economists consider gender identity as one cause of occupational segregation today. Gender identity considers the gender gap in labour market outcomes, such as labour supply, earnings and occupational segregation, as the result of prevailing social norms about what behaviour is appropriate for women and men (see Bertrand (2011) for an overview). The concept relates to experimental and empirical findings on gender differences in preferences.[2] According to Akerlof and Kranton (2000), identity is defined as one's sense of self, or one's sense of belonging to social groups. Akerlof and Kranton (2000) emphasize that having an identity comprises a clear perception of appropriate behaviour of people belonging to that group. They show that one's identity can directly influence economic behaviour by implementing one's identity into an individual's utility function. In the context of occupational segregation, Akerlof and Kranton (2000) discuss the example of a female marine. Because society sees marines as men, a female marine feels discomfort as her occupational choice is in conflict with the "typical" female occupational choice. Similar thoughts apply to a man who wants to become a nurse (see Akerlof and Kranton (2000), p. 721). This theoretical considerations can also be applied to women in STEM who are minority workers in these occupations.

[2] See Croson and Gneezy (2009) for a detailed overview on gender differences in preferences. However, scientists argue whether gender differences in preferences are caused by genetic endowment or socialisation. Gender identity mainly refers to a nurture based view of gender differences.

Some empirical studies on gender identity show that women's labour market outcomes are significantly larger in terms of labour supply and earnings if gender roles are less traditional (see, e.g., Fortin (2005, 2009) and Charles et al. (2009)). Pan (2010) finds that occupational segregation is higher in regions where men hold more sexist attitudes. However, the empirical findings on what drives gender identity are mixed. While Goldin et al. (2006) argue that women's adult identity reacts strongly to exogenous changes of career considerations, such as the introduction of the pill; Fernàndez et al. (2004) and Farre and Vella (2007) find evidence for the intergenerational transmission of gender identity. Some studies also examine the impact of schooling environment on gender identity, e.g., Lee and Marks (1990) and Dasgupta and Asgari (2004) find evidence that girls in coeducational schools held stronger stereotypes than girls in single-sex schools. In summary, scientists do not have clear-cut results on the causes of gender identity. Furthermore, Heintz et al. (1997) for example deny that gender-specific preferences are the only driving force for occupational choice; the expected career opportunities also influence an individual's occupational choice.

Apart from the vast literature on occupational segregation in general, some studies in sociology and economics focus on the high gender segregation of students in STEM subjects. The scientific interest in these occupations is rising because economies are increasingly knowledge-driven and a fierce competition exists for workers in these occupations. The main findings of these studies are similar to the research results presented above, i.e., the enduring gender gap in STEM cannot be fully explained by gender differences in abilities (see, e.g., OECD (2012)). Even in countries in which boys outperform girls in mathematics, the performance gap is small, and the findings on performance in science-based subjects are mixed (see OECD (2012), p. 84 ff.). Xie and Shauman (1997) also find that in the U.S. gender differences in college preparatory classes in mathematics and science are nearly non-existent. It is thus supposed that girls and boys choose different subjects because of personal preferences and expectations about labour market outcomes (see, e.g., OECD (2012)). However, Flabbi and Tejada (2012) find that expectations about career opportunities only marginally influence the gender-specific choice of the field of study. They conclude that gender gaps in educational fields are caused by a range of factors, such as innate preferences, gender perceptions at home and amongst peers and teachers and considerations of future family obligations.

Carrell et al. (2010) contribute to this literature by examining the impact of professor gender on the gender gap in science. Using data from the U.S. Air Force Academy, they find that girls perform better in mathematics and science classes if they are taught by a female professor. Additionally, girls' likelihood of taking further courses in science and mathematics increases. According to Carrell et al. (2010), this effect is especially pronounced for high-performing female students. Carrell et al. (2010) argue that this finding is of crucial importance because "this group of women are, arguably, the set of women most suited for entering science and engineering careers" (p. 1104). Their findings agree with Legewie and DiPrete (2012) who show that the attendance of a high school that supports the orientation of girls towards mathematics and science reduces the gender gap in STEM majors significantly. Legewie and DiPrete (2012) also observe that today girls perform equally well in mathematics as their male peers. They emphasise the importance of the schooling environment for gender-specific orientation towards these fields of study and suggest further research in the creation of gender role attitudes during high school for a better understanding of occupational segregation.

The results of these studies are in line with former findings of American educationalists like Leslie et al. (1998). They emphasize that the percentage of female graduates in STEM can only be increased by actions taken during high school years. Leslie et al. (1998) argue that the peers' attitudes have a strong influence on adolescents. Leslie et al. (1998) find that the influence of peers is the main driving force for girls' decreasing interest in science and mathematics during adolescence. Similar results are found by Holland and Eisenhart (1990). Leslie et al. (1998) analyse also the influence of family background. They show that having a father or a mother who works in engineering or science increases a girl's probability to choose engineering or science as a field of study. The importance of family background has also been found by Jackson et al. (1993). They show that women enter STEM more often in the U.S. if they have highly educated parents and if they come from intact families. Jackson et al. (1993) also note that women who become engineers do not only tend to have fathers who are engineers but also tend to marry engineers themselves. Thus, parental background seems to be germane to women's choice of STEM occupations. Leslie and Oaxaca (1993) provide an overview of early theoretical and empirical studies on women in STEM conducted in the U.S. during the 1990s.

Empirical studies on the influence of parental occupation, however, show mixed results if extended to different countries. Bergman et al. (2012) show that, in Switzerland, children tend to choose science courses if their parents' occupational status is high. However, the effect is only significant for vocational training. Using longitudinal PISA data, Fernandez et al. (2012) do not find this trend for Uruguay. They find that neither daughters nor sons are influenced in their subject choice by fathers in engineering professions. In the Czech Republic and in Australia, gender differences in the choice of the field of study contribute to the gender gap in educational achievement, i.e., boys with high grades pursue vocational training in science or in a technical field, but girls prefer to attend courses in other fields of study at a university (see Matějů et al. (2012) and Polidano and Ryan (2012)).

Apart from studies on the determinants of gender segregation in education and employment, some empirical research is conducted to examine whether labour market outcomes, especially earnings, differ among occupational groups. Focusing on scientific occupations, Chevalier (2012) finds, that it is mainly not the scientific degree itself that induces wage premiums in the United Kingdom, but the actual occupational choice. He estimates a wage premium of 18 % for scientific occupations. However, Chevalier (2012) also notes that a high percentage of science graduates does not work in scientific jobs. Those report that they are less satisfied than their colleagues who stay in academia (see Chevalier (2012)). Thus, Chevalier (2012) concludes that there is no shortage of scientists.

Görlitz and Grave (2012) present similar results using data on German university graduates. They find significant wage differences according to the fields of study in Germany; e.g., the raw wage gap of art and humanities compared to engineering is 40 % when entering the labour market. This wage gap persists throughout the employee's career. Furthermore, Görlitz and Grave (2012) show that wage differentials are explained to a larger extent by labour market and firm characteristics than by individual or study-related characteristics. Görlitz and Grave (2012) hypothesize that the least able students select art and humanities because these subjects are considered to be less challenging. Wahrenburg and Weldi (2007) obtain similar results and conclude that studying humanities and arts is unattractive from an economic perspective, even though 20 % of all first-year students are enrolled in these fields.

As already mentioned, there exists only a very small number of studies on the labour market behaviour of women in STEM. Some noteworthy exceptions are the studies of Minks (1996, 2001) that focus on young women's labour market entry after graduating from STEM. He shows that women who graduate from STEM subjects tend to search longer for their first jobs and to earn less than their male counterparts. These differences are still significant after correcting for university performance. Haffner et al. (2006) examine engineers' career paths during adult life and confirm that female engineers have worse labour market outcomes in terms of earnings and career opportunities than men. Women's lower earnings can be caused by fewer years in the labour force because of maternity leave. Using data from the German Microcensus, Schlenker (2009a) shows that female engineers face employment interruptions from child-rearing more often than their male colleagues. Female engineers also tend to work part-time or avoid STEM occupations more often than their male counterparts (see Schlenker (2009a,b)). Both, part time work and working outside one's area, causes a loss in earnings. However, even if a gender gap in engineers' employment and earnings exists, female engineers supply more labour than highly skilled women in other occupations, most likely because of the wage premiums in STEM occupations (see Schlenker (2009b)). Similar results are found for the employment behaviour of female engineers in the U.S. (see Cordero et al.

(1994)). In summary, the few existing studies indicate that women in STEM behave differently in terms of labour supply than men. Some differences in employment behaviour may be attributed to overall differences in male and female labour supply. However, women in STEM display some specific characteristics in terms of labour market behaviour.

The empirical analysis in this chapter relates to these strands of literature. However, one major novelty of the analysis is the focus on how European women in STEM react to different institutional settings. All empirical studies presented in the literature review face the problem of selection effects. The question on why some women choose occupations in STEM whereas many do not remains unanswered. Therefore, unobserved heterogeneity and selection effects cannot be denied. Inconsistent estimation results may be the consequence. This study takes these issues into account by implementing a special type of grouping estimator proposed by Blundell et al. (1998). The technical details of this estimation strategy are explained in the following section.

4.3. Identification and Estimation Strategy

4.3.1. A Specification of Labour Supply

Following the method introduced by Blundell et al. (1998), I specify the equation for women's number of hours worked per week (h) as follows

$$h = \alpha + \beta \log(w) + \gamma\mu \tag{4.1}$$

where w is hourly net wages and α, β and γ are the regression parameter to be estimated. μ represents non-wife income, defined as the difference between the net household income (c) and woman's net wage (wh), i.e., $\mu = c - wh$. This definition of non-wife income is consistent with Wagenhals (2000). Because consumption is not reported in my data set I cannot apply the definition used by Blundell et al.

(1998), which defines non-wife income as the difference between consumption and a woman's net wage. This specification of labour supply supposes that the following equation is valid for every woman i in every year t:

$$h_{it} = \alpha + \beta \log(w_{it}) + \gamma \mu_{it} + \epsilon_{it}$$

where h is again the weekly hours of work, w and μ are hourly net wage and non-wife income, and ϵ_{it} is the error term. α, β and γ denote again the regression parameters to be estimated. Technical problems in the estimation of this equation can occur because the error terms ϵ_{it} are expected to be serially correlated, correlated with the explanatory variables and may also be dependent across individuals, reflecting some macroeconomic developments (see Blundell et al. (1998)). Mroz (1987) describes other reasons why labour supply effects are difficult to estimate, e.g., (nonlinear) tax schedules and differences in individuals' tastes for work and consumption are some of the typical problems which researchers face. Therefore, traditional estimation methods such as the tobit model overestimate earning effects (see Mroz (1987)).

To counter these identification problems, Blundell et al. (1998) propose a grouping estimator that uses pooled cross-sectional data. The key issue in their estimation strategy is the definition of groups whose hourly net wages and other net income develop differently over time. Blundell et al. (1998) assume that unobserved differences in the average labour supply of the defined groups can be fully accounted for by additive group and time effects. They also add the assumption of linear conditional expectations. According to these assumptions, Blundell et al. (1998) implement a generalised Wald estimator.[3] This estimator is the difference-in-differences estimator in the case of only two groups and two time periods and can, therefore, be considered as a generalised difference-in-differences approach.

Following the method of Blundell et al. (1998), I define groups who face different variations in their net wages and other types of income. Therefore, the data are

[3]For technical details in regard to the derivation and characteristics of the estimator see Blundell et al. (1998), p. 835 ff. Heckman and Robb (1985) provide a general discussion of grouping estimators.

divided by the year of the survey, 10-year birth cohort, educational level, geographical area and working in STEM. There must be a sufficient number of individuals per group in the data set. Because of that limitation, I use only two educational groups and six groups of member states of the EU. Concerning educational attainment, the first group comprises women who attained (upper) secondary education or less (attained ISCED level 0-3). The second educational group includes women with post-secondary education or tertiary education (attained ISCED level 4-6). The EU is divided into six groups of member states in accordance to similarities in culture, history and institutional setting. These groups refer to the classification of countries introduced by Esping-Andersen (1990, 1999). I form the following groups of member states of the EU: (1) Scandinavia (Denmark, Finland, Sweden), (2) German-speaking countries (Austria, Germany), (3) Western European countries (Belgium, France, Luxembourg, the Netherlands), (4) Anglo-Saxon countries (Ireland, United Kingdom), (5) Southern European countries (Cyprus, Greece, Italy, Spain, Portugal) and (6) Eastern European countries, including countries that were formerly part of the Union of Soviet Socialist Republics (Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia, Slovak Republic). Using these definitions, I form 72 groups for every survey year. Applying the estimation strategy to a pooled data set of three survey years (2007, 2008, 2009) the estimates include 216 groups.

I expect that the characteristics by which I have specified my groups are affected differently by institutional settings and labour market environments. The distribution and changes in group average net wages and group average non-wife income (especially partner's income) differ across groups; e.g., technical progress affects labour demand and, therefore, wages differently for different groups. The interaction of group and time effects are excluded from the estimation function of weekly hours of work h. This is implied by the assumption that the average difference in labour supply between groups is time-invariant (see Blundell et al. (1998), p. 838). More details on the implementation of the estimator are provided in the next subsection.

4.3.2. Implementation of the Estimator

The estimator is implemented using a control function approach (see Blundell et al. (1998)). Initially, I estimate three reduced forms using labour participation, log wages and non-wife income as dependent variables. A Heckman selection model[4] is applied to regress labour participation on a complete set of time and group interactions and demographic variables. The participation equation is estimated for the whole sample. Non-working women are excluded from the estimation sample of log wages and non-wife income. I perform a regression of log wages and non-wife income on a complete set of time and group interactions and demographic variables using ordinary least squares (OLS). I then compute the residuals for both regressions.[5]

The parameters of the labour supply equation can be estimated consistently using OLS. The estimation equation is of the following form:

$$h_{it} = a_g + m_t + \mathbf{x}_{it}'\boldsymbol{\alpha} + \beta \log(w_{it}) + \gamma\mu_{it} + \delta^p \hat{v}_{it}^p + \delta^w \hat{v}_{it}^w + \delta^\mu \hat{v}_{it}^\mu + \epsilon_{it} \tag{4.2}$$

where a_g and m_t represent group and time effects, respectively, $\mathbf{x}_{it}$ is a vector containing socio-demographic variables, w is hourly net wage and μ is non-wife income. The $\hat{v}$'s are the residuals from the reduced forms. More precisely, $\hat{v}_{it}^p$ is the estimated inverse Mill's ratio from labour participation, $\hat{v}_{it}^w$ and $\hat{v}_{it}^\mu$ correspond to estimated residuals from log wages and other income, respectively. ϵ_{it} is the error term. I want to estimate the regression parameters $\boldsymbol{\alpha}$, β, γ and δ^i.

This computational approach gives numerically identically results to grouping estimators. Furthermore, the t statistics of the estimated coefficients δ^p, δ^w and δ^μ can be used to test for exogeneity (see Smith and Blundell (1986)). I group my data set according to several characteristics. As described above, 216 groups are used in the data set. Three groups are excluded from the estimation because they comprise

[4]See Heckman (1979) for details on estimation techniques.

[5]See Blundell et al. (1998) for further details on the implementation of the estimator (p. 841 f.). Wagenhals (2000) applies the estimator to data from Germany.

less than 50 individuals. The average cell size for the other groups is approximately 1,042 individuals.

4.4. Data Set and Sample Descriptives

I use data from the EU-SILC, an official survey designed to describe and to explain living conditions in all EU member states. EU-SILC collects data at the individual level and has been conducted on an annual basis since the first test wave in 2004. Every year, approximately 130,000 households in the EU member states are surveyed. Although the Statistical Office of the European Union (Eurostat) is responsible for providing the EU-SILC data at the European level, the collection and preparation of the data is conducted by the individual countries' statistical offices.[6] The main focus of EU-SILC is to provide data on social inclusion, poverty and living standards. Therefore, the survey design is based on the multidimensional Laeken indicators. EU-SILC contains detailed information, at the individual level, on the family and education background in addition to the current living environment.

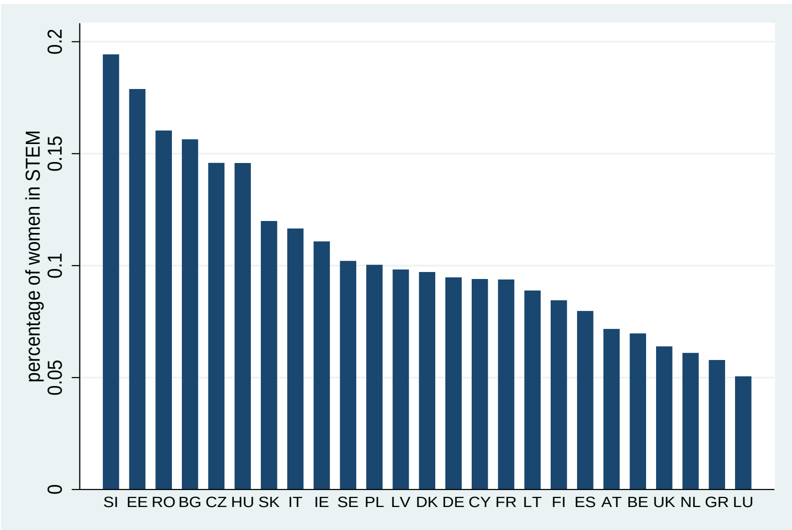
For my analysis, the cross sectional data sets of the waves 2007, 2008 and 2009 are pooled. My data set comprises females who were born between 1960 and 1990. I limit the analysis to these birth cohorts because it can be expected that most of these women have finished their education but are not yet retired. Women who are in fulltime education are excluded from the data set. The data set is also limited to women who are neither in military and social services nor retired. The data set comprises approximately 205,000 individuals.

The variable of main interest is the weekly number of working hours. Women in this data set work 36 hours per week on average. Approximately 20 % of all individuals do not participate in the labour market. Sample descriptives show, furthermore,

[6] Serious concerns about the data quality in the first waves of EU-SILC between 2004 and 2006 exist (see, e.g., Hauser (2007)). These waves are not included in my empirical analysis. For further details on the design of EU-SILC and the data quality of the waves used in this chapter see Statistisches Bundesamt (2009b, 2011b,c).

that the individuals in the data set have 1.3 children on average and approximately 15 % of them have a child three years old or younger. Table C.1 in the appendix depicts the summary statistics of the data set.

For a comparison of labour market behaviour between women in STEM and other occupations, the dummy variable *stem* is introduced that equals 1 if a woman works or has worked in the fields of science, technology, engineering or mathematics. I isolate women in STEM using the 2-digit ISCO88 classification available in EU-SILC.[7] Hence, a woman is classified as working in STEM if she indicates one of the following ISCO-88 codes: 21, 31, 71-73, 82, 93. Approximately 11 % of the individuals in the data set are indicated as women in STEM.



Source: own calculations.

Figure 4.1.: Percentage of Women in STEM per Country in the Data Set.

Figure 4.1 illustrates the percentage of women in STEM per country. The percentage of German women in STEM is close to the European mean. However, the percentage of women in STEM varies between countries. The lowest percentage of women in STEM is found in Luxembourg, Greece, and the Netherland according to my data set. The levels are especially distinct between Eastern European countries and other

[7]The occupation of the individuals' current main job, or individuals' last job if they are not currently working is coded via ISCO-88 on a two-digit-level in EU-SILC. Because individuals are not asked to name their educational fields I cannot measure whether the women have a degree in STEM, but do not work in a related job.

EU member states. Eastern European countries display relatively high percentages of women in STEM compared to other European countries.

Similar results are found by OECD (2012); under a communist government, policies have promoted young women's studies of STEM subjects. After the breakdown of the Soviet regime, however, the percentage of women in STEM has again decreased (OECD (2012), p. 155). The percentage of women in STEM in the data set is slightly lower than reported by other sources. This may be because the classification of occupations is only available at the 2-digit level in EU-SILC. Therefore, some differences in the definition of STEM occupations can occur compared to more detailed occupational classifications. Table 4.1 depicts the summary statistics of the data set for women in STEM and women in other occupations.

Table 4.1.: Summary Statistics of Women in STEM and in other Occupations

Variable	Mean	Std. Dev.	min	max	N
Women in STEM					
labour participation	0.747	0.435	0	1	22692
hours worked per week	38.351	6.890	1	84	16877
hourly wage in PPS	7.743	9.432	0.001	320.11	16877
non-wife income in 1000 PPS	20.19	25.407	0	487.7	22692
year of birth	1971.031	7.504	1960	1990	22692
high educational level	0.260	0.439	0	1	22692
youngest child 0-3 years	0.143	0.35	0	1	22692
youngest child 4-6 years	0.101	0.301	0	1	22692
youngest child 7-10 years	0.122	0.327	0	1	22692
Women in other occupations					
labour participation	0.801	0.399	0	1	181918
hours worked per week	35.66	9.499	1	99	145002
hourly wage in PPS	9.696	10.402	0.002	706.526	145002
non-wife income in 1000 PPS	25.472	31.111	0	2410.095	181918
year of birth	1971.351	7.624	1960	1990	181918
high educational level	0.379	0.485	0	1	181918
youngest child 0-3 years	0.157	0.364	0	1	181918
youngest child 4-6 years	0.11	0.312	0	1	181918
youngest child 7-10 years	0.125	0.331	0	1	181918

Source: own calculation.

Sample descriptives display some differences in the labour market behaviour between women in STEM and women in other occupations: table 4.1 shows that the weekly hours of work differ between these two groups: women in STEM work on average more hours per week than women in other occupations (38.4 versus 35.7). However, labour participation of women in STEM is lower: a woman's likelihood to participate in the labour market increases by approximately 5 percentage points if the woman works in another occupation compared to working in STEM. These findings indicate that once women are in the STEM labour force, they work more. I adjust the data to account for the number of children, including dummy variables to indicate a child younger than 3, between 4 and 6 years, and between 7 and 10 years.[8] I do not find relevant differences between women in STEM and in other occupations concerning the percentage of individuals with small children. The differences in ISCED educational levels attained as well as birth years are not large in size between women in STEM and women in other occupations. To account for tertiary education, a dummy variable *high educational level* is defined that equals 1 if the ISCED level attained is 4 or 5.

The level of wages and non-wife income are important economic predictors of labour supply. I employ hourly net wages and household's non-wife income to account for income effects. However, several specifics of EU-SILC must be taken into account when using income variables. On the one hand, all income variables are measured in national currency and refer to the year before the survey. On the other hand, the weekly hours of work and the employment status refer to the date of the interview. This can cause measurement errors if the employment status and/or the job have changed (see Engel and Schaffner (2012)). However, many empirical studies use the available information on wages and earnings as proxies to calculate (actual) hourly wages (see, e.g., Badescu et al. (2010) and Glocker and Steiner (2011)). I also follow this approach.[9] The non-wife income is calculated as the difference between the net household income and the woman's net wage. At first, all wage and income

[8] Only children living in the same household can be taken into account when using data from EU-SILC. There is no variable included in EU-SILC that indicate an individual's number of biological children. However, children living in the same household require the most care in terms of childcare and housework.

[9] Engel and Schaffner (2012) propose a correction for this problem that I have tried to apply. However, the correction implemented economically implausible results such as a negative correlation between hourly wages and hours worked or a correlation of approximately zero between

variables are converted into Euros and then they are converted into purchase power standards (PPS) taking the countries' different price levels into account. The rates of exchange are provided by Eurostat via an online database.[10]

The average hourly wage is approximately 9.5 Euro. However, the distribution of wages is right-skewed and scattered. Astonishingly, I find that the average hourly wages of women in STEM are lower on average in the data set (see table 4.1). This is surprising because occupations in STEM are known to have high wage premiums. This contradiction in the sample is caused by different wage patterns in Eastern European countries. Occupations in STEM reflect lower educational levels and wages in these countries because of specifics in these countries' histories (see OECD (2012), p. 155 f.). If Eastern European countries are excluded, the data set shows the expected right-skewed distribution of wages with higher wages on average for occupations in STEM. Additionally, higher levels of education show higher levels of wages than lower and middle levels of education. Figure C.1 in the appendix shows the wage distributions for different educational levels as well as for occupational groups excluding Eastern European countries.

To sum up, the descriptives show some differences between women in STEM and women in other occupations. Working in part-time jobs seems to occur less often in STEM while labour participation is higher in other occupations. Whether socio-demographic variables or selection effects can explain these differences is analysed in the following section that discusses the estimation results.

wages (referring to the past year) and corrected hourly wages. This is most likely caused by the large number of dropped individuals following the approach of Engel and Schaffner (2012).

[10] Access to the data used is available via `http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database`.

4.5. Empirical Results

4.5.1. Estimation Results of the Reduced Forms

Tables 4.2, 4.3, and 4.4 present the estimation results of the reduced forms for labour participation, log hourly wages and other non-wife income. As described in section 4.3, the estimation results of the three reduced forms are used to compute residuals which are included in the final estimation of labour supply, presented in section 4.5.2.

Table 4.2.: Reduced Form: Labour Participation

	labour participation
youngest child 0-3 years	-0.851***
	(0.00867)
youngest child 4-6 years	-0.384***
	(0.00978)
youngest child 7-10 years	-0.233***
	(0.00928)

Source: own calculations.
Standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group effects and time effects as well as a full set of interactions is included.
Additionally, country fixed effects are controlled for.

Table 4.2 presents the estimation results of a probit regression for labour participation. The estimates agree with economic theory, i.e., I find that having small children significantly reduces women's likelihood of labour participation. The estimation results show that the younger a woman's children are the lower is her likelihood to participate in the labour market. The reduced form also includes dummy variables for groups and time as well as a full set of interactions. The interaction effects of groups which are excluded because of multicollinearity are set to zero. Additionally, I account for country-specific fixed effects.

Table 4.3.: Reduced Form: log Wage (in PPS)

	log wage
youngest child 0-3 years	-0.255^{***}
	(0.0247)
youngest child 4-6 years	-0.0866^{***}
	(0.0120)
youngest child 7-10 years	-0.0541^{***}
	(0.00836)
hazard rate	0.388^{***}
	(0.0579)

Source: own calculations.
Standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group effects and time effects as well as a full set of interactions is included.
Additionally, country fixed effects are controlled for.

Table 4.3 shows the estimated coefficients of the reduced form for log hourly wages. The estimation equation includes group and time effects and a full set of interaction terms and country fixed effects. Additionally, the estimated inverse Mills' ratio of the Heckman selection model is included.

The estimated coefficient of the inverse Mill's ratio is significantly positive (p-value: 0.000). This finding implies selection effects. From this result follows that women with higher wages are more likely to work and therefore, a positive selection into the workforce exists. The interactions of time and group effects are also jointly significant in the reduced form. The interaction effects of groups which are excluded due to multicollinearity are again set to zero. The other estimation coefficients are again in line with economic theory, i.e., having young children significantly reduces a woman's hourly wage because mothers of young children often work in part-time jobs as mini-jobbers with low levels of earnings.

The last reduced form regresses non-wife income on demographic variables, group and time effects and their interactions. Country fixed effects are also included. The estimation results are presented in table 4.4.

Table 4.4.: Reduced Form: Non-Wife Income (in PPS)

	non-wife income
youngest child 0-3 years	4.165***
	(0.244)
youngest child 4-6 years	2.299***
	(0.273)
youngest child 7-10 years	1.659***
	(0.255)

Source: own calculations.
Standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group effects and time effects as well as a full set of interactions is included.
Additionally, country fixed effects are controlled for.

I find again that the estimation results agree with economic theory, showing a significant increase in non-wife income if women have small children. This is caused by the lower labour participation of young mothers and the provision of family allowances for (young) children by all EU member states. The interactions of time and group effects are again jointly significant. The interaction effects of groups which are excluded because of multicollinearity are also set to zero in this reduced form.

4.5.2. Baseline Models for Labour Supply

After the estimation of the reduced forms their residuals are included in the final estimation of labour supply measured by the number of weekly hours of work. Table 4.5 presents the estimation results. I estimate four different models that differ in respect of the control variables included.

All four models include dummy variables for group and time effects as well as fixed effects for countries and fixed effects for 10-year birth cohorts. The effects of time and groups are jointly significant for all specifications; country fixed effects are also jointly significant in all specifications.

Table 4.5.: Regression Results for Hours Worked

	(1)	(2)	(3)	(4)
youngest child 0-3 years	-3.473***	-3.565***	-3.271***	-3.516***
	(0.239)	(0.240)	(0.245)	(0.246)
youngest child 4-6 years	-3.237***	-3.349***	-3.154***	-3.327***
	(0.121)	(0.123)	(0.123)	(0.125)
youngest child 7-10 years	-2.655***	-2.775***	-2.595***	-2.751***
	(0.0876)	(0.0903)	(0.0889)	(0.0916)
high education	1.295***	1.295***	1.298***	1.334***
	(0.0464)	(0.0464)	(0.0464)	(0.0465)
log wage	0.0215	0.0202	0.743***	0.542*
	(0.165)	(0.165)	(0.218)	(0.218)
non-wife income	-0.0140	-0.0137	-0.0400**	-0.0389**
	(0.0115)	(0.0115)	(0.0132)	(0.0132)
hazard rate	-1.112*	-1.126*	-1.173*	-0.871
	(0.530)	(0.530)	(0.532)	(0.532)
residuals of log wage	-1.179***	-1.177***	-1.907***	-1.794***
	(0.168)	(0.168)	(0.219)	(0.220)
residuals of non-wife income	0.00877	0.00853	0.0346**	0.0334*
	(0.0115)	(0.0115)	(0.0132)	(0.0132)
working in STEM		7.082***		8.040***
		(0.965)		(1.021)
STEM x youngest child 0-3 years		1.016***		1.005***
		(0.243)		(0.243)
STEM x youngest child 4-6 years		1.151***		1.142***
		(0.239)		(0.239)
STEM x youngest child 7-10 years		1.174***		1.174***
		(0.214)		(0.214)
% of GDP spent in family allowance (FA)			-1379.5***	-2016.1***
			(284.6)	(289.4)
% of GDP spent in childcare (CC)			291.9+	405.4**
			(156.5)	(156.7)
% in part-time x CC			-791.0**	-1052.4***
			(295.9)	(296.5)
% in employment x FA			2346.8***	3369.2***
			(455.0)	(462.7)
% in part-time			-34.68***	-38.30***
			(4.404)	(4.412)
% in employment			-15.36**	-10.20+
			(5.231)	(5.247)
STEM x % of GDP spent in FA				-38.53+
				(20.50)
STEM x % of GDP spent in CC				-138.5***
				(33.54)
% in STEM				-39.45***
				(3.335)
Adj. R^2	0.226	0.226	0.227	0.228
F	470.7***	457.7***	446.0***	424.8***
N	161879	161879	161879	161879

Source: own calculations. Wage and non-wife income in PPS.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group and time effects, country and birth-cohort effects included.

The estimations indicate that wages are endogenous for the parameters of the equation of labour supply. This finding is highly significant throughout all specifications (p-value of *residuals of log wage*: 0.000). Empirical findings concerning the exogeneity of labour participation are mixed: the residuals of the reduced forms for labour participation (*hazard rate*) are only significant in three out of four specification. Other non-wife income seems to be exogenous for the equation of labour supply. The estimated coefficient of *residuals of non-wife income* are insignificant for the baseline specifications (1) and (2).

Column (1) presents a baseline model for all women. The signs as well as the sizes of the estimated coefficients are not surprising. If a woman has (young) children, she works significantly fewer hours per week. The number of weekly hours worked is also reduced if a woman faces lower hourly wages or if a woman has higher income from other sources. However, these coefficients are not significant. I find a significant effect of a high level of education: women who have attained an ISCED level of 4 or 5 work approximately 1.3 hours more per week.

Column (2) represents an extension of the baseline model and compares the labour supply of women in STEM with the female labour supply in other occupations. I find significant differences in the labour supply of women in STEM compared to women in other occupations. Women in STEM work approximately 7 hours more per week. This finding is highly significant. The estimated model also shows that women in STEM react less to having children. The overall negative effect of young children in terms of labour supply is less pronounced if a woman works in STEM: women in STEM reduce their weekly working hours approximately 30 to 40 % less than women in other occupations if their youngest child is younger than 3, 6 and 10 years.

My empirical analysis not only shows differences in the employment patterns of women in STEM and women in other occupations but also examines whether women in STEM and women in other occupations react differently to policies concerning family allowances and childcare. These macro variables are included in the specifications (3) and (4). I have included the percentage of gross domestic product (GDP) spent on family allowances (FA) and the percentage of GDP spent on daily childcare (CC). Additionally, the percentage of women in employment and their percentage in part-time jobs are inserted into the estimations. Finally, I account for the country's percentage of women in STEM.[11]

Column (3) refers to all women and does not differentiate between occupations. I find effects of similar size as in specification (1) for the socio-demographic variables. However, the positive effect of wages as well as the negative effect of non-wife income are significant in specification (3). Policies also significantly effect female labour supply; there is a significant increase in weekly working hours if the expenditures on childcare are increased. High ratios of expenditures on childcare correspond to a high percentage of women in part-time employment. Higher ratios of expenditures on family allowance and child benefits significantly reduce the number of women's weekly working hours.

I test for differences between STEM and other occupations in terms of reaction to the discussed policies in column (4) and find some empirical evidence that women in STEM react slightly differently in terms of labour supply to expenditures on family allowances and childcare. If governments spend more money on family allowance, women in STEM reverse their weekly working hours even more than women in other occupations. They react significantly weaker to higher levels of the spending on childcare than women in other occupations. However, the estimated coefficients for both these effects are small compared to the overall effects.

[11] The macro variables are taken from the online database of Eurostat. The percentages of GDP spent on family allowance and the percentage of GDP spent on childcare are available via the codes "STTCPALLOW" and "STTKCHILD". Both data belong to the category "spr_exp_ffa". The information on the percentage of women in employment and on the percentage of women working part-time is coded "lfsa_argan" and "lfsa_eppga", respectively. The country's percentage of women in STEM is computed from the data set.

4.5.3. Robustness Checks

The Labour Supply of Women with ISCED Level 2 or Higher

It is a hotly debated topic whether economies face a future lack of workers in STEM. However, the public debate refers to highly educated workers in STEM with vocational or even tertiary education. This is the context for the empirical findings of this chapter. Therefore, I conduct a robustness check by excluding women with pre-primary or primary education (attained ISCED level of 0 or 1). The results for women with at least lower secondary education are presented in table 4.6.

The empirical results show again that wages are endogenous for the parameters of labour supply (p-value of *residuals of log wage*: 0.000). Additionally, some empirical evidence for the endogeneity of labour participation is found in the subsample of women who have attained at least ISCED level 2 (*hazard rate*). The results for non-wife income are not clear-cut: there is no empirical evidence for the endogeneity of non-wife income in the first two specifications. However, the residuals of non-wife income are significant in the models (3) and (4).

The estimation results reflect similar findings as in the baseline models. The estimated coefficients display a similar pattern of significance and of signs. The sizes of the estimates are also similar. The only exception is the size of the estimated coefficient of the variable $STEM$. The positive effect of working in STEM is more pronounced for the sample of women who attained an ISCED level of 2 or higher. Working in STEM increases labour supply by approximately 8 and 9 hours in specification (2) and (4), compared to 7 and 8 hours in the same specifications of the baseline regressions (see table 4.5).

However, only a small number of women is excluded from the robustness check. The percentage of women who did not attain an ISCED level of 2 or higher is really small (approximately 3 %). Therefore, the robustness check indicates also that only a small percentage of women does not achieve lower secondary education in the EU.

Table 4.6.: Robustness Check 1: Women with ISCED Level of 2 or higher

	(1)	(2)	(3)	(4)
youngest child 0-3 years	-3.273***	-3.363***	-3.132***	-3.391***
	(0.243)	(0.243)	(0.248)	(0.249)
youngest child 4-6 years	-3.176***	-3.280***	-3.119***	-3.290***
	(0.122)	(0.124)	(0.124)	(0.126)
youngest child 7-10 years	-2.611***	-2.725***	-2.569***	-2.723***
	(0.0882)	(0.0910)	(0.0896)	(0.0923)
high education	1.278***	1.278***	1.282***	1.318***
	(0.0460)	(0.0460)	(0.0460)	(0.0461)
log wage	0.0623	0.0613	0.738***	0.541*
	(0.165)	(0.165)	(0.219)	(0.219)
non-wife income	-0.0185	-0.0183	-0.0418**	-0.0402**
	(0.0115)	(0.0115)	(0.0133)	(0.0133)
hazard rate	-1.554**	-1.566**	-1.503**	-1.162*
	(0.542)	(0.542)	(0.544)	(0.544)
residuals of log wage	-1.182***	-1.180***	-1.864***	-1.757***
	(0.167)	(0.167)	(0.220)	(0.220)
residuals of non-wife income	0.0136	0.0134	0.0367**	0.0350**
	(0.0115)	(0.0115)	(0.0133)	(0.0133)
working in STEM		7.741***		9.123***
		(0.836)		(0.899)
STEM x youngest child 0-3 years		0.980***		0.966***
		(0.242)		(0.242)
STEM x youngest child 4-6 years		1.065***		1.056***
		(0.240)		(0.240)
STEM x youngest child 7-10 years		1.106***		1.111***
		(0.214)		(0.214)
% of GDP spent in family allowance (FA)			-1541.6***	-2207.1***
			(291.8)	(297.0)
% of GDP spent in childcare (CC)			284.9+	395.4*
			(156.9)	(157.0)
% in part-time x CC			-827.7**	-1099.7***
			(294.9)	(295.6)
% in employment x FA			2583.9***	3655.9***
			(464.9)	(473.3)
% in parttime			-34.47***	-38.32***
			(4.420)	(4.430)
% in employment			-15.99**	-10.99*
			(5.294)	(5.308)
STEM x % of GDP spent in FA				-42.33*
				(20.73)
STEM x % of GDP spent in CC				-131.4***
				(33.66)
% in STEM				-39.25***
				(3.327)
Adj. R^2	0.228	0.228	0.229	0.230
F	460.0***	456.1***	436.1***	422.9***
N	158071	158071	158071	158071

Source: own calculations. Wage and non-wife income in PPS.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group and time effects, country and birth-cohort effects included.

The Labour Supply of Cohabiting Women

Many empirical studies that examine female labour supply concentrate on married or women cohabiting with a partner (see, e.g., Blundell et al. (1998) and Wagenhals (2000, 2011)). Married women are of special interest because some tax systems judge married couples' earnings differently from unmarried couples. Additionally, the elasticity of a woman's labour supply has been found to be larger if she lives with a partner. This is explained by the fact that a cohabiting and/or married woman faces less financial constraints if she does not work or reduces her weekly working hours because a couple can pool their earnings and take advantage of economies of scale (see, e.g., Bick and Fuchs-Schündeln (2012)). Therefore, I use cohabiting women for a further robustness check and test whether cohabiting women react in accordance to the empirical results of the baseline regressions. I do not only refer to married women because marriage has become a less popular family model in many European countries during the last 20 years. Therefore, many women who live with a partner and can pool their earnings would be excluded because of the missing legal status.

The estimation results for cohabiting women are presented in table 4.7. The estimates show some differences in comparison to the baseline models for all women. The main findings for socio-demographic variables, however, remain unchanged. The empirical results indicate a stronger influence of non-wife income for cohabiting women. The negative effect of non-wife income is significant for all specifications in table 4.7. The size of the effect seems also to be larger compared to the full sample.

Additionally, some empirical evidence for the endogeneity of non-wife income for the labour supply equation is found in the subsample of cohabiting women (p-value of *residuals of non-wife income*: 0.005). These findings agree with economic theory and constrain the importance of partner's earnings on the labour supply of cohabiting women.

Table 4.7.: Robustness Check 2: Cohabiting Women

	(1)	(2)	(3)	(4)
youngest child 0-3 years	-3.194***	-3.277***	-3.096***	-3.339***
	(0.277)	(0.277)	(0.284)	(0.285)
youngest child 4-6 years	-3.021***	-3.117***	-2.987***	-3.146***
	(0.138)	(0.141)	(0.141)	(0.143)
youngest child 7-10 years	-2.429***	-2.527***	-2.401***	-2.536***
	(0.0996)	(0.103)	(0.102)	(0.105)
high education	1.453***	1.452***	1.458***	1.496***
	(0.0563)	(0.0563)	(0.0563)	(0.0564)
log wage	0.0715	0.0717	0.566*	0.377
	(0.205)	(0.205)	(0.273)	(0.273)
non-wife income	-0.0333*	-0.0333*	-0.0463**	-0.0451**
	(0.0138)	(0.0138)	(0.0160)	(0.0160)
hazard rate	-1.052+	-1.060+	-1.042+	-0.718
	(0.616)	(0.616)	(0.618)	(0.618)
residuals of log wage	-1.315***	-1.314***	-1.814***	-1.719***
	(0.207)	(0.207)	(0.274)	(0.274)
residuals of non-wife income	0.0397**	0.0397**	0.0525**	0.0512**
	(0.0139)	(0.0139)	(0.0160)	(0.0160)
working in STEM		-1.274		-12.44
		(25489.5)		(25465.3)
STEM x youngest child 0-3 years		0.895***		0.881**
		(0.271)		(0.271)
STEM x youngest child 4-6 years		0.987***		0.976***
		(0.268)		(0.268)
STEM x youngest child 7-10 years		0.959***		0.965***
		(0.239)		(0.239)
% of GDP spent in family allowance (FA)			-1116.7**	-1785.2***
			(346.6)	(351.8)
% of GDP spent in childcare (CC)			178.5	309.3+
			(180.0)	(180.2)
% in part-time x CC			-797.1*	-1080.7**
			(338.4)	(339.2)
% in employment x FA			1984.7***	3054.9***
			(555.2)	(563.5)
% in parttime			-28.25***	-32.56***
			(5.326)	(5.339)
% in employment			-10.09	-4.049
			(6.521)	(6.542)
STEM x % of GDP spent in FA				-46.89+
				(25.15)
STEM x % of GDP spent in CC				-144.2***
				(39.49)
% in STEM				-44.56***
				(4.158)
Adj. R^2	0.257	0.257	0.257	0.258
F	391.3***	380.4***	370.5***	352.7***
N	113949	113949	113949	113949

Source: own calculations. Wage and non-wife income in PPS.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Complete set of group and time effects, country and birth-cohort effects included.

Another more surprising difference between the full sample and the subsample of cohabiting women is found: the positive effect of working in STEM in terms of labour supply is not evident for cohabiting women. The estimated coefficient turns insignificant and negative. This may be explained by the fact that women in STEM are often married or living with men who also work in STEM (see, e.g., Leslie et al. (1998)). Because these men have also higher earning potentials because of their occupational fields in most countries, their female partners face less financial pressure to contribute to the income of the household. Whether this is the correct explanation has to be analysed in further studies. Another effect of the baseline regressions can be confirmed for the subsample of cohabiting women. Women in STEM reduce their weekly working hours significantly less if they have young children. However, the size of the estimated coefficient is smaller for cohabiting women compared to the baseline models. Similar motivation as mentioned for the overall effect of working in STEM may apply to this variable also.

4.6. Summary of the Findings and Outlook

This chapter analyses the determinants of the labour supply of women in STEM. Using data from EU-SILC, I find that women in STEM are less likely to participate in the labour force but that women in STEM work significantly more hours per week. Additionally, the empirical analysis shows that women in STEM decrease their labour supply significantly less if they have small children. The effect of having a child of age 3 or younger is dampened by approximately one third for women in STEM compared to women in other occupations.

Labour supply effects are difficult to estimate consistently (see Mroz (1987) for an overview). The estimation method developed by Blundell et al. (1998) controls for unobserved heterogeneity and selection effects in occupations and employment. Blundell et al. (1998) have designed a special type of grouping estimator. They have shown that consistent estimation results can be obtained in settings with selection effects by accounting for group effects. I apply their method to my research question and find empirical evidence for the endogeneity of wages and of labour participation. The empirical results indicate additionally that other (non-wife) income is exogenous for the labour supply equation. Therefore, grouping estimator is necessary to ensure consistent estimates of the coefficients.

The empirical analysis focusses on different institutional settings. To test the effect of policies I compare women in different member states of the EU. I find empirical evidence for an increase in weekly working hours if governments increase expenditures on childcare. A significantly negative effect is found for the percentage of GDP spent on family allowance. Women in STEM work fewer hours in countries with higher percentages of family allowances compared to other women. However, this effect is only weakly significant and small compared to the overall effects of higher percentages of expenditures on family allowance and child benefits.

This chapter contributes to the scientific understanding of differences in the employment behaviour between occupational groups. The focus on STEM is chosen because of the high relevance of these occupations for industrialised economies. Policymakers and business people would like to increase the quantity of young women choosing occupations in STEM, partly because of the demographic change. In times of aging societies and shrinking labour forces, the quantity and the quality of workers in key industries such as STEM are critical issues for the economy's future growth and welfare. Because of these developments, many policies and political campaigns in the EU and in Germany address attracting women into occupations in STEM. However, a better understanding of occupational choices and later life outcomes is urgently needed to make these initiatives work. This understanding is necessary to ensure that women who graduate in STEM fields remain workers in STEM occupations and take advantage of high earnings and career possibilities. I contribute to this understanding by exploring differences in the employment behaviour of women in STEM and women in general.

In summary, more studies are needed that focus on differences in the female employment behaviour between occupations. One aspect that needs to be examined in future studies is the impact of tax benfit and social security systems on women's labour supply with respect to their occupations. A solid scientific understanding is needed to design policies and campaigns that meet the needs of the occupational group in focus. Group specific employment behaviour must be taken into account if policies are to produce the desired outcomes.

5. Conclusion

Occupational choices have far-reaching consequences for young adults. Occupations do not only influence career opportunities and earnings. They also have an impact on status and reputation in society. Badgett and Folbre (2003) find also that occupations influence one's bargaining position in the marriage market. The importance of occupational choice is reinforced because occupational choice is hardly reversible and, therefore, creates path dependencies in one's life. This issue is especially crucial if job mobility is low, as is the case in Germany. Changes in occupations are less common in Germany in comparison to labour markets that are characterised by lower levels of employment protection, such as Great Britain. Additionally, the importance of educational credentials is high in Germany compared to Great Britain (see Nisic and Trübswetter (2012)). Therefore, occupational choices are hardly revisable and, if at all, at high monetary and non-monetary costs such as student fees and a loss of leisure time while participating in adult education. However, in times of aging societies and shrinking labour forces, occupational choices are not only a matter of an individual's well-being. The match of individuals and their occupations is also of crucial importance for the efficiency of labour markets because a worker's productivity is increased if the job requirements match the worker's skills.

The shortage of workers in general and especially in scientific occupations is hotly debated in all member states of the EU. This debate focusses on the fields of science, technology, engineering and mathematics in Germany and other European countries (see, e.g., BMBF (2008) for Germany). Interest groups such as "The Association of German Engineers" argue that, already today, there exists a lack of engineers and other scientists in Germany and in the EU as a whole (see Anger et al. (2011)). However, scientists cannot find empirical evidence for a comprehensive lack of highly skilled workers in STEM in Germany (see, e.g., Brenke (2012a)).

Apart from the controversial debate of whether a lack of highly skilled workers already exists, scientists commonly agree that a skill shortage will become a key issue in all industrialised countries during the next decades (see, e.g., EFI (2012)). Hence, many policies are being introduced to attenuate the shortage of workers either in terms of attracting workers from abroad or increasing female labour supply. Meanwhile, it is of utmost importance that the available workers increase their productivity by improving the match of individual abilities and job requirements. This match can be improved through a better scientific understanding of education and occupational choices. Knowing about how individuals choose their occupation can help to find policies that enhance the match of worker's abilities and job requirements.

This thesis addresses the question of how occupational choices are affected by exogenous circumstances and social environments. When analysing occupational choices, it is crucial to recognise that occupational choices are highly ramified and cannot be modelled by a single self-contained decision process. Occupational choices must be understood as the result of decisions during childhood and adolescence because these decisions condition individual opportunities afterwards. Thus, education choices during childhood affect occupational choices to a large extent because the access to occupations depends on educational credentials; e.g., young people with low levels of education can choose fewer occupations than young people who graduate from academic secondary school track.

This thesis considers the described multi-layered structure of occupational choice by analysing different decisions made during childhood and adolescence and their implication on occupational outcomes. On the one hand, the thesis examines whether parents influence their children's education and occupational choices. One hypothesis is that parental influence can decrease the efficiency of these choices because choices do not simply present the child's abilities and interests but also parental interests. On the other hand, the consequences of occupational choices on labour market outcomes are analysed in terms of labour supply in this thesis. The effect of institutional settings on the labour market behaviour of different occupation groups is tested conditionally with respect to selection effects. The author shows different patterns of behaviour in terms of labour supply using the example of women in STEM.

For this purpose the author starts by presenting the current state of research on occupational choice. Beyond the increasing interest of business and politics, the academic interest in occupational choice in economics has not yet gained significance within the discipline. The analysis of occupational choice is of prime importance as the quality of the match between individuals and occupations may decisively affect individual productivity as well as the efficiency of the labour market. Noteworthy exceptions are empirical studies that examine the elasticity of earnings among generations (see for example Corak and Piraino (2011) or Sookram and Strobl (2009)). An increasing number of economic studies on the persistence of education and earnings among generations investigate whether low intergenerational mobility is caused by genetic endowment or by socialisation. Black and Devereux (2011) provide an overview of the existing studies. Additionally, numerous studies address occupational gender segregation. Occupational segregation has been found to explain large proportions of the gender wage gap, women's labour supply when having a family and different career opportunities for women and men. This thesis enlarges the existing strands of literature by empirically testing further research questions.

The author's own contributions to the scientific understanding of occupational choice are presented in the second part of the thesis. These contributions consist of the analyses of three research questions. The first study concentrates on strategic parental behaviour. The author examines whether parents strategically influence their children's education choices. Amongst others, parents face two conflicting results if their children achieve high educational levels. Some studies find empirical evidence for parents' desire to be visited and cared for by their children in old age (see Bernheim et al. (1985, 1986)). However, if individuals achieve high educational levels, their mobility increases, as does the probability of moving far from their parents (see Leopold et al. (2012)). Hence, long distances between parents' and adult children's homes limit the number of visits. In contrast, highly educated daughters and sons have higher earning potentials and therefore an increased probability of being able to support their parents financially during old age. It is not clear which effect dominates and it may also depend on parents' characteristics. Depending on parents' perceptions, however, these scenarios can effect parents' education decisions when their children are young. These scenarios may especially influence the decision about the secondary school track; a decision which is mainly made by the parents, not by the (young) children themselves.

It is additionally assumed that parents evaluate the presented scenarios differently for boys and girls because daughters have a higher probability of providing care for older parents (see Leopold and Raab (2011)). The author uses difference-in-differences estimations to test whether strategic parental behaviour influences their children's schooling decisions. The author exploits the founding of numerous universities in Western Germany between the 1970s and the 1990s as quasi-experiments. If a university is founded, the distance to the nearest university is changed exogenously for children living in the area. Additionally, the founding of a university has long-term consequences for regional labour markets and increases the labour demand for academic workers in this area. For these reasons, a newly founded university decreases the probability of young adults of moving far away at the beginning of their studies or after graduation from university.

The founding data of universities is merged with pooled cross-sectional data from the SOEP. Regional information on the residences of SOEP respondents is used to calculate their distances to the nearest university as well as changes after new universities are built. The author uses the data to estimate probit models explaining whether an individual achieves a university entrance diploma. These probit estimations show that a university founding that is close to the family residence increases children's probability of achieving a university entrance diploma. The size of this effect, however, differs between boys and girls. Girls benefit significantly more in terms of schooling if a university is nearby. In producing these results the parents' educational level, the family's socioeconomic status, gender, birth cohorts and region fixed effects are accounted for. The estimation results show some empirical evidence for the hypothesis that parents pursue different strategies towards daughters and sons and that, among other reasons, educational decisions are also influenced by parental strategic behaviour.

The second study contributes to the "nature versus nurture" debate and enhances the literature on occupational immobility among generations. In contrast to past studies, the author focusses on occupational choice instead of income elasticity or educational achievement. Again, the rich data of the SOEP is exploited. The author pools cross-sectional data of the SOEP and finds that approximately 14 % of individuals have indicated the same occupation as their first job and as their father's occupation. The author concentrates on father's occupation because information on mother's occupation is scarce. This can be explained by the fact that maternal labour supply has been low for recent decades (information on mother's occupation is given as "not employed"). Hence, fathers have mainly shaped the occupational desires and beliefs for the birth cohorts (born 1985 or earlier) analysed.

To differentiate between the influence of genetic endowment and socialisation the author uses the information whether the individual has grown up with or without his/her father; i.e., whether they shared one household with their father when being a child. An individual is defined as having grown up without his/her father if he/she has not lived in the same household as the biological father for more than seven years at the age of 15. To test the effect of father's occupation on the children's occupational choice, the author estimates conditional logit and nested logit models. These models are applied because conditional logit and nested logit models can estimate effects on dependent variables that exist in several mutually exclusive and unordered categories.

The SOEP adopts the occupational classification of the German Federal Statistical Office, introduced in 1992. For technical reasons, this classification is slightly modified and adjacent occupational groups with very few observations are merged (e.g., miners, stone workers, and workers in ceramic and glass industries are merged). A significant effect of father's occupation is found, as the probability of choosing an occupation increases if the father has worked in this occupation. Additionally, the estimation results show that genetic endowment is not the only driving force for the persistence of occupations among generations. The author finds a reinforcing effect of socialisation; individuals who have not lived in the same household as their biological father are affected significantly by their father's occupation, too. However, the effect is significantly smaller compared to individuals who have lived in the same household as their biological father. The estimated coefficients of the effect of the father's occupation is approximately twice the size for individuals who have grown up with their fathers compared to "fatherless" individuals. From a labour market perspective the effect of socialisation may imply less efficient occupational choices. This can be the case if individuals choose an occupation only because their father has worked in it and not because their abilities and interests meet the job requirements best. If individuals choose occupations that do not fit their abilities best, the productivity of these workers is reduced and labour markets fail to ensure the best match of workers' abilities and job requirements.

In contrast, the third study does not concentrate on the determinants of occupational choice, but rather on its consequences. The study focusses on the determinants of the labour supply of women in STEM. To test the effect of different institutional settings, the author compares women in different member states of the EU. During recent years, there has been a hot debate in the EU about the effects of occupational segregation on gender equality (see, e.g., EUCOM (2006)). Occupational segregation has been found to explain a large proportion of the gender wage gap in all member states. The public has mainly focussed on occupations in STEM, especially in engineering. Occupations in STEM are considered to be an example for occupations that are mainly chosen by men and that offer high wage premiums. Furthermore, many scientific studies examine the roots of occupational segregation. However, they have not found clear-cut results to show that gender differences in occupational choice are caused by differences in genetic endowment or cultural settings (see Fossen (2012) as an example).

Apart from the debate on gender equality, government and business have a special interest in increasing the quantity of young women choosing occupations in STEM because of the demographic change. When labour forces start shrinking, the quantity and quality of workers in key industries, such as the automotive industry in Germany, are critical issues for the economy's growth and welfare. Because of these developments, many policies and political campaigns in the EU and in Germany aim at making STEM occupations more attractive for women. However, a better understanding of occupational choices and later life outcomes is urgently needed to make these initiatives work. This thesis contributes to the understanding by exploring differences in the employment behaviour between women in STEM and women in general. Special focus is given to institutional settings and their impacts on female employment behaviour in STEM.

To compare different institutional settings, data from the EU-SILC is used. The survey EU-SILC is conducted by the European Statistical Office in all member states of the EU. The empirical analysis is based the pooled cross-sectional data sets from the years 2007, 2008 and 2009. The empirical analysis, furthermore, applies the estimation method developed by Blundell et al. (1998) to account for unobserved heterogeneity and selection effects. Blundell et al. (1998) design a special type of grouping estimator. They show that unbiased and consistent estimation results can be obtained in settings with selection effects by accounting for group fixed effects. The data set is divided into 72 groups per year based on birth cohorts, educational level, country of residence and whether a woman works in STEM or not. Fixed effects are estimated for each group with regard to labour force participation, wage and non-wife income.

Finally, the effects of different determinants on labour supply, measured by the number of hours worked per week, are estimated. The empirical results show that women in STEM work significantly more hours than women in general. Additionally, empirical evidence is found that maternal employment in STEM is also significantly more pronounced. Women in STEM work less hours in countries with higher levels of family allowances. However, this effect is only weakly significant and small compared to the overall effects of larger levels of expenditures on family allowance and child benefits.

Shortcomings exist in the economic understanding of occupational choice. This thesis contributes to the improvement of this understanding and fills some of the existing knowledge gaps. The author's empirical findings show that parents substantially influence their children's education and occupational choices. It is not certain that parental influence improves the efficiency of these choices, however. Further research would answer this question by measuring costs and benefits. Additionally, further research is needed to improve the understanding of differences in labour supply between occupational groups. This thesis shows that significant differences in the labour supply of women in STEM exist compared to women in other occupations. Future studies are required to answer the research question of how other occupational groups, such as sales or education, react to different institutional settings. These scientific results are crucial to develop policies that meet the needs of the occupational groups in focus and that take into account group-specific employment patterns.

A. Appendix of Chapter 2

Table A.1.: Estimated Coefficients of Baseline Probit Regressions

ATS	(1)	(2)	(3)
female x distance	-0.00296^{+}	0.221**	0.239*
	(0.00191)	(0.105)	(0.136)
distance	-0.00338**	0.0403	0.0731
	(0.00138)	(0.0758)	(0.0951)
female	0.0252	-0.226**	-0.259**
	(0.0569)	(0.0967)	(0.130)
uni father	0.478***	0.486***	0.488***
	(0.0712)	(0.0711)	(0.0711)
uni mother	0.443***	0.455***	0.455***
	(0.0998)	(0.0997)	(0.0998)
SES father	0.0300***	0.0301***	0.0301***
	(0.00190)	(0.00189)	(0.00189)
constant	-1.706***	-1.857***	-1.877***
	(0.151)	(0.154)	(0.162)
5yrs birth cohorts included	Yes	Yes	Yes
Bundeslaender included	Yes	Yes	Yes
N	5393	5393	5393
χ^2	933.4***	920.3***	918.5***
Pseudo R^2	0.140	0.138	0.138

Source: own calculations. Standard errors in parentheses.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Column (1): minimum distance to the next university.

Column (2)/(3): dummy variable (1=a university within a radius of 40/50km).

Table A.2.: Estimated Coefficients of DiD Models

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.531***	0.441***	0.366*	0.302*
	(0.159)	(0.146)	(0.193)	(0.183)
female x treat	-0.176+	-0.100	-0.113	0.00457
	(0.114)	(0.104)	(0.128)	(0.121)
female x post	0.0242	0.0203	0.181+	0.153
	(0.0614)	(0.0650)	(0.125)	(0.128)
treat x post	-0.227*	-0.123	-0.242*	-0.162
	(0.116)	(0.106)	(0.137)	(0.131)
female	-0.0816+	-0.0945*	-0.143*	-0.195**
	(0.0508)	(0.0540)	(0.0782)	(0.0812)
treat	0.290***	0.232***	0.0673	0.0508
	(0.0807)	(0.0742)	(0.0947)	(0.0881)
post	-0.0391	-0.0311	-0.0206	0.0200
	(0.0456)	(0.0474)	(0.101)	(0.102)
uni father	0.479***	0.484***	0.549***	0.538***
	(0.0768)	(0.0793)	(0.0930)	(0.0905)
uni mother	0.421***	0.479***	0.410***	0.578***
	(0.104)	(0.109)	(0.136)	(0.122)
SES father	0.0304***	0.0301***	0.0305***	0.0304***
	(0.00216)	(0.00225)	(0.00261)	(0.00247)
constant	-1.970***	-1.974***	-1.957***	-1.966***
	(0.106)	(0.111)	(0.188)	(0.185)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	607.4***	597.7***	459.3***	559.9***
Pseudo R^2	0.130	0.135	0.138	0.146

Source: own calculations.
Notes: Standard errors in parentheses
+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns (1) and (3): treat indicates living within a radius of 40km.
Columns (2) and (4): treat indicates living within a radius of 50km.
The control group in (1) and (2) are all people outside the treatment radius.
The control group in (3) and (4) are the non-treated inside a radius of 100km.
Post indicates age 9 at least 4 years after final political decision.

Table A.3.: Robustness Check 1: OLS Estimation of DiD Models

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.173***	0.142***	0.120*	0.0980*
	(0.0514)	(0.0468)	(0.0622)	(0.0580)
female x treat	-0.0582+	-0.0343	-0.0391	-0.00390
	(0.0361)	(0.0324)	(0.0405)	(0.0371)
female x post	0.00527	0.00439	0.0546	0.0448
	(0.0184)	(0.0193)	(0.0396)	(0.0393)
treat x post	-0.0696*	-0.0339	-0.0754*	-0.0456
	(0.0376)	(0.0343)	(0.0445)	(0.0418)
female	-0.0228+	-0.0260*	-0.0414*	-0.0547**
	(0.0149)	(0.0157)	(0.0238)	(0.0240)
treat	0.0899***	0.0700***	0.0204	0.0144
	(0.0268)	(0.0239)	(0.0313)	(0.0281)
post	-0.0121	-0.00983	-0.00816	0.00329
	(0.0134)	(0.0139)	(0.0315)	(0.0315)
uni father	0.200***	0.201***	0.214***	0.210***
	(0.0272)	(0.0281)	(0.0316)	(0.0308)
uni mother	0.144***	0.163***	0.125***	0.171***
	(0.0333)	(0.0345)	(0.0394)	(0.0347)
SES father	0.00937***	0.00922***	0.00992***	0.00975***
	(0.000630)	(0.000652)	(0.000805)	(0.000756)
constant	-0.103***	-0.106***	-0.126**	-0.106*
	(0.0342)	(0.0323)	(0.0575)	(0.0587)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
Adj. R^2	0.162	0.167	0.173	0.181

Source: own calculations.
Notes: Standard errors in parentheses
+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns (1) and (3): treat indicates living within a radius of 40km.
Columns (2) and (4): treat indicates living within a radius of 50km.
The control group in (1) and (2) are all people outside the treatment radius.
The control group in (3) and (4) are the non-treated inside a radius of 100km.
Post indicates age 9 at least 4 years after final political decision.

Table A.4.: Robustness Check 2a: Estimated Coefficients of DiD Models (+3 years)

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.387**	0.305**	0.245	0.150
	(0.158)	(0.145)	(0.191)	(0.180)
female x treat	-0.121	-0.0450	-0.0655	0.0695
	(0.117)	(0.106)	(0.131)	(0.123)
female x post	0.0148	0.0148	0.159	0.171
	(0.0602)	(0.0639)	(0.122)	(0.125)
treat x post	-0.115	-0.0144	-0.152	-0.0244
	(0.115)	(0.106)	(0.137)	(0.129)
female	-0.0779+	-0.0926*	-0.138*	-0.206**
	(0.0514)	(0.0546)	(0.0789)	(0.0823)
treat	0.246***	0.184**	0.0342	-0.00787
	(0.0842)	(0.0768)	(0.0976)	(0.0907)
post	-0.0153	-0.00597	0.0211	-0.00132
	(0.0390)	(0.0408)	(0.0998)	(0.101)
uni father	0.479***	0.484***	0.552***	0.540***
	(0.0768)	(0.0793)	(0.0928)	(0.0904)
uni mother	0.421***	0.479***	0.405***	0.575***
	(0.104)	(0.109)	(0.136)	(0.123)
SES father	0.0304***	0.0301***	0.0304***	0.0303***
	(0.00216)	(0.00225)	(0.00260)	(0.00247)
constant	-1.978***	-1.982***	-1.967***	-1.955***
	(0.106)	(0.111)	(0.188)	(0.185)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	603.6***	594.6***	456.8***	553.5***
Pseudo R^2	0.130	0.135	0.137	0.144

Source: own calculations.
Notes: Standard errors in parentheses
+ p < 0.15, * p < 0.10, ** p < 0.05, *** p < 0.01
Columns (1) and (3): treat indicates living within a radius of 40km.
Columns (2) and (4): treat indicates living within a radius of 50km.
The control group in (1) and (2) are all people outside the treatment radius.
The control group in (3) and (4) are the non-treated inside a radius of 100km.
Post indicates age 9 at least 3 years after final political decision.

Table A.5.: Robustness Check 2b: Estimated Coefficients of DiD Models (+5 years)

ATS	(1)	(2)	(3)	(4)
female x treat x post	0.452***	0.379**	0.227	0.180
	(0.161)	(0.148)	(0.197)	(0.187)
female x treat	-0.118	-0.0561	-0.0357	0.0677
	(0.111)	(0.102)	(0.125)	(0.118)
female x post	0.0337	0.0341	0.248*	0.226*
	(0.0632)	(0.0670)	(0.129)	(0.132)
treat x post	-0.229*	-0.128	-0.208+	-0.133
	(0.117)	(0.108)	(0.140)	(0.134)
female	-0.0849*	-0.0997*	-0.166**	-0.220***
	(0.0504)	(0.0536)	(0.0773)	(0.0799)
treat	0.282***	0.230***	0.0426	0.0330
	(0.0787)	(0.0726)	(0.0930)	(0.0866)
post	-0.0564	-0.0508	-0.0802	-0.0479
	(0.0462)	(0.0483)	(0.105)	(0.106)
uni father	0.479***	0.484***	0.549***	0.540***
	(0.0768)	(0.0793)	(0.0931)	(0.0907)
uni mother	0.421***	0.479***	0.413***	0.580***
	(0.104)	(0.109)	(0.136)	(0.122)
SES father	0.0304***	0.0301***	0.0305***	0.0304***
	(0.00216)	(0.00225)	(0.00261)	(0.00247)
constant	-1.963***	-1.965***	-1.932***	-1.938***
	(0.106)	(0.111)	(0.188)	(0.185)
5yrs birth cohorts included	Yes	Yes	Yes	Yes
University foundation fixed effects included	Yes	Yes	Yes	Yes
N	62495	56872	8229	8008
N cluster	5592	5592	4385	4385
χ^2	605.5***	595.5***	456.3***	556.5***
Pseudo R^2	0.130	0.135	0.138	0.145

Source: own calculations.
Notes: Standard errors in parentheses
+ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns (1) and (3): treat indicates living within a radius of 40km.
Columns (2) and (4): treat indicates living within a radius of 50km.
The control group in (1) and (2) are all people outside the treatment radius.
The control group in (3) and (4) are the non-treated inside a radius of 100km.
Post indicates age 5 at least 4 years after final political decision.

B. Appendix of Chapter 3

Table B.1.: Summary Statistics of Individuals Grown up with and without Father

Variable	Mean	Std. Dev.	min	max	N
Individuals grown up with their father					
father's job	0.145	0.353	0	1	7654
father's sector	0.216	0.412	0	1	7654
female	0.52	0.5	0	1	7654
year of birth	1952.333	15.505	1902	1984	7654
years of education	12.358	2.773	7	18	7654
northern Germany	0.221	0.41	0	1	7654
Individuals grown up without their father					
father's occupation	0.1	0.301	0	1	508
father's sector	0.177	0.382	0	1	508
female	0.52	0.5	0	1	508
year of birth	1951.244	16.077	1913	1984	508
years of education	11.944	2.694	7	18	508
northern Germany	0.246	0.431	0	1	7654

Source: own calculation.

Table B.2.: Occupational Classification

job code	group	group code	description of job group
110/629	1	Ia	Agriculture, animal agriculture, forestry and horticulture
700/1359	2	IIa/IIIa/IIIb	Mining, stone cutting and ceramics
1410/1539	3	IIIc	Chemicals and plastic products
1610/1859	4	IIId/IIIe	Paper and wood industries
1910/2459	5	IIIf	Metal processing and metal working
2500/3099	6	IIIg	Metal fabrication, technical engineering and related jobs (smiths, industry mechanics, tool makers)
3100/3187	7	IIIh	Electrical occupations (electricians, telecommunication,etc)
3211/3239	8	IIIi	Assemblers and metal workers
3310/3789	9	IIIk/IIIl	Textile, garment, leather and fur
3910/4359	10	IIIm	Food careers (cooks, brewers, bakers)
4401/4729	11	IIIn	Civil engineering (scaffolding, road building, brickwork)
4801/4929	12	IIIo	Building finishers and upholsterers (plasterers, roofers, mattress manufacturers)
5010/5069	13	IIIp	Wood and plastic processing (joiners, wood technicians, boat builders, construction of sports equipment)
5101/5149	14	IIIq	Painters, varnishers and related occupations (furniture varnishing, gilding, glass painting)
5210/5233	15	IIIr	Goods inspectors (outgoing goods inspection, sorting of goods and materials, marking of goods)
5311/5319	16	IIIs	Elementary occupations (labourer, assembly line workers)
5400/5509	17	IIIt	Machinists and related occupations (machine setter, crane operator , hydropower plant machinist)
6000/6129	18	IVa	Occupations in engineering, chemical, physical, mathematic science professionals
6200/6529	19	IVb	Technicians and special technical personals (research technology, technical draftsmen, industry foreman)
6600/6899	20	Va	Sale of goods (retail dealers, pharmaceutical consultants, gas station attendants)
6910/7064	21	Vb	Sale of service and related occupations (banking professionals, advertising specialists, ticket clippers)
7110/7449	22	Vc	Traffic (Locomotive engine drivers, bridge guards, post-office employees)
7501/7899	23	Vd	Organization, administration and office clerks (consulting, ministers and delegates, computer scientists and administrative staff)
7910/8142	24	Ve	Law and security (personal security, detectives, soldiers, police, judges)
8211/8399	25	Vf	Creating and ordering of writing and creative or performing artists (journalists, interpreters, librarians, musicians, interior decorators)
8410/8599	26	Vg	Health services (doctors, pharmacists, masseurs, nurses, dieticians)
8610/8944	27	Vh	Social work, education and other natural science and humanities occupations (geriatric nurses, teachers, economists, pastoral care)
9010/9379	28	Vi	Miscellaneous service occupations (body care, hotels and restaurants, waste disposal, domestic economy)
9711/9971	.e	VIa	Miscellaneous workers (helping family members excluding agriculture, workers (yet) without specified job such as interns, workers without specified area of occupation)

Table B.3.: Marginal Effects of Conditional Logit Models

	marginal effect grown up			marginal effect grown up	
job	with father	without father	job	with father	without father
Ia	.042***	.030	IIIr	.005**	.000
	(.005)	(.020)		(.002)	(.095)
IIa/IIIa/b	.008***	.000	IIIs	.0149***	.023
	(.002)	(.001)		(.003)	(.016)
IIIc	.009***	.000	IIIt	.003*	.000
	(.002)	(.078)		(.001)	(.016)
IIId/e	.025***	.012	IVa	.023***	.008
	(.003)	(.010)		(.003)	(.007)
IIIf	.007***	.015	IVb	.053***	.027
	(.002)	(.012)		(.005)	(.018)
IIIg	.066***	.052	Va	.167***	.082+
	(.006)	(.033)		(.009)	(.044)
IIIh	.042***	.000	Vb	.096***	.0317
	(.005)	(.006)		(.007)	(.022)
IIIi	.003**	.000	Vc	.029***	.024
	(.001)	(.247)		(.004)	(.017)
IIIk/l	.033***	.000	Vd	.209***	.10**
	(.004)	(.211)		(.009)	(.048)
IIIm	.042***	.023	Ve	.027***	.008
	(.005)	(.017)		(.004)	(.007)
IIIn	.005+	.000	Vf	.0264***	.013
	(.002)	(.006)		(.004)	(.010)
IIIo	.005**	.007	Vg	.0932***	.029
	(.002)	(.007)		(.007)	(.020)
IIIp	.010***	.010	Vh	.068***	.035
	(.002)	(.009)		(.006)	(.023)
IIIq	.009***	.000	Vi	.066***	.020
	(.002)	(.000)		(.006)	(.015)

Source: own calculations.

Standard errors in parentheses.

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4.: Robustness Check 1a: Boys Grown up with Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.148^{***}													
	(0.048)													
yrs of education		-0.081	-0.107	0.275^{*}	-0.069	-0.189^{*}	0.140^{***}	-0.495^{**}	-0.135	-0.131^{*}	-0.129^{*}	-0.234^{**}	-0.146^{*}	-0.166^{*}
		(0.054)	(0.117)	(0.107)	(0.095)	(0.082)	(0.037)	(0.152)	(0.120)	(0.058)	(0.057)	(0.079)	(0.067)	(0.082)
time trend		-0.028^{***}	-0.035^{**}	0.044^{*}	-0.010	-0.009	0.015^{**}	0.018	-0.031^{**}	0.005	0.007	0.016^{*}	-0.009	0.006
		(0.006)	(0.012)	(0.021)	(0.010)	(0.008)	(0.005)	(0.015)	(0.012)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)
northern FRG		0.314	-0.225	-14.34	-0.084	-0.205	-0.099	-0.037	-0.060	0.156	0.080	0.319	0.210	0.509^{+}
		(0.197)	(0.459)	(659.6)	(0.386)	(0.311)	(0.188)	(0.567)	(0.435)	(0.220)	(0.219)	(0.268)	(0.239)	(0.275)
Constant		-0.599	-1.672	-7.081^{***}	-1.716	0.152	-2.525^{***}	1.969	-1.370	0.026	-0.031	0.506	-0.038	-0.371
		(0.612)	(1.306)	(1.405)	(1.069)	(0.898)	(0.443)	(1.579)	(1.329)	(0.652)	(0.640)	(0.862)	(0.746)	(0.909)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
yrs of education	0.085	-0.0002	0.059	0.760^{***}	0.388^{***}	0.192^{***}	0.471^{***}	0.022	0.433^{***}	0.543^{***}	0.487^{***}	0.822^{***}	0.976^{***}	0.037
	(0.148)	(0.102)	(0.160)	(0.041)	(0.042)	(0.036)	(0.037)	(0.051)	(0.030)	(0.041)	(0.064)	(0.060)	(0.055)	(0.077)
time trend	0.056^{*}	0.014	0.064^{*}	-0.028^{***}	-0.018^{*}	-0.002	-0.009	0.017^{**}	-0.012^{**}	-0.010	0.007	-0.007	-0.026^{***}	0.042^{***}
	(0.024)	(0.012)	(0.026)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)	(0.007)	(0.012)	(0.009)	(0.007)	(0.011)
northern FRG	0.331	-0.906	-0.908	-0.377	-0.391	0.059	0.034	0.480^{*}	-0.086	0.543^{*}	0.335	0.400	-0.102	0.814^{**}
	(0.686)	(0.616)	(1.060)	(0.238)	(0.286)	(0.185)	(0.219)	(0.208)	(0.166)	(0.225)	(0.391)	(0.284)	(0.238)	(0.309)
Constant	-5.462^{**}	-2.886^{*}	-5.196^{**}	-11.35^{***}	-6.382^{***}	-3.195^{***}	-7.190^{***}	-1.972^{***}	-5.898^{***}	-8.692^{***}	-9.044^{***}	-13.44^{***}	-15.13^{***}	-3.401^{***}
	(1.792)	(1.170)	(1.925)	(0.600)	(0.556)	(0.438)	(0.492)	(0.590)	(0.380)	(0.565)	(0.915)	(0.960)	(0.882)	(0.904)
N	102816													
Cases	3672													
χ^2	1735.5													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.5.: Robustness Check 1b: Boys Grown up without Fathers

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	0.443^{+}													
	(0.238)													
yrs of education		-0.733^{**}	-0.899^{*}	-0.287	0.186	-0.214	0.157	0.175	-0.124	-0.481^{*}	-0.224	-0.222	-0.0602	-0.747
		(0.241)	(0.368)	(0.662)	(0.201)	(0.226)	(0.138)	(0.233)	(0.420)	(0.233)	(0.186)	(0.284)	(0.226)	(0.466)
time trend		-0.055^{*}	-0.081^{+}	0.226	-0.026	0.004	0.010	-0.038	-0.015	0.050^{*}	-0.004	-0.070^{+}	0.029	0.013
		(0.024)	(0.042)	(0.165)	(0.039)	(0.025)	(0.023)	(0.047)	(0.053)	(0.023)	(0.021)	(0.037)	(0.030)	(0.041)
northern FRG		0.324	-0.273	-14.71	0.136	-0.767	-1.082	-14.42	-14.42	-0.251	0.395	0.510	0.590	-14.49
		(0.680)	(1.212)	(2860.8)	(1.204)	(1.113)	(1.102)	(1452.2)	(1794.9)	(0.862)	(0.681)	(0.943)	(0.933)	(1620.0)
constant		6.271^{*}	6.643^{+}	-4.364	-4.939^{+}	0.788	-3.297^{+}	-4.871	-1.627	3.670	1.091	-0.278	-1.712	5.363
		(2.533)	(3.711)	(8.410)	(2.618)	(2.527)	(1.734)	(3.000)	(4.778)	(2.502)	(2.090)	(3.219)	(2.631)	(4.761)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
yrs of education	-0.050	0.132	-1.342	0.482^{***}	0.191	-0.043	0.175	0.071	0.244^{*}	0.527^{***}	0.532^{***}	0.867^{**}	0.613^{***}	-0.889^{*}
	(0.384)	(0.248)	(0.893)	(0.146)	(0.172)	(0.157)	(0.172)	(0.187)	(0.106)	(0.158)	(0.159)	(0.321)	(0.181)	(0.346)
time trend	0.120	0.0163	0.109	0.004	0.025	-0.005	-0.028	0.065^{*}	-0.019	-0.002	-0.007	0.006	-0.024	0.058^{+}
	(0.075)	(0.041)	(0.112)	(0.029)	(0.030)	(0.022)	(0.033)	(0.030)	(0.020)	(0.031)	(0.032)	(0.044)	(0.036)	(0.032)
northern FRG	-14.58	1.911	-15.06	-0.845	0.477	-0.462	1.926^{*}	0.291	0.315	0.816	0.801	1.120	-0.413	1.550
	(1873.5)	(1.273)	(3145.4)	(1.152)	(0.937)	(0.837)	(0.931)	(0.923)	(0.602)	(0.883)	(0.888)	(1.147)	(1.201)	(0.977)
constant	-3.777	-5.323^{+}	8.620	-8.128^{***}	-4.701^{*}	-0.821	-5.222^{*}	-3.351	-4.146^{**}	-9.381^{***}	-9.463^{***}	-15.70^{**}	-10.60^{***}	6.295^{+}
	(4.671)	(3.190)	(8.108)	(2.130)	(2.226)	(1.845)	(2.299)	(2.299)	(1.378)	(2.392)	(2.424)	(5.488)	(2.838)	(3.488)
N	6832													
Cases	244													
χ^2	115.0													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.6.: Robustness Check 2a: CL plain Model, full Sample

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.139***													
	(0.035)													
x fatherless	-0.455**													
	(0.157)													
constant		-0.744***	-2.597***	-3.054***	-1.945***	-1.937***	-0.844***	-2.719***	-0.864***	-1.014***	-1.443***	-1.946***	-1.661***	-2.066***
		(0.0643)	(0.146)	(0.186)	(0.111)	(0.109)	(0.070)	(0.159)	(0.071)	(0.075)	(0.086)	(0.110)	(0.096)	(0.117)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
Constant	-2.761***	-2.046***	-3.476***	-1.032***	-1.239***	0.252***	-0.548***	-1.367***	0.615***	-1.488***	-1.608***	-0.137*	-0.064	-0.201***
	(0.163)	(0.114)	(0.227)	(0.074)	(0.081)	(0.050)	(0.064)	(0.082)	(0.046)	(0.089)	(0.096)	(0.057)	(0.055)	(0.058)
N	228536													
Cases	8162													
χ^2	1051.0***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.7.: Robustness Check 2b: CL full Model, full Sample

		Ia	IIa/IIIa/b	IIIc	IIId/e	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	0.954***													
	(0.038)													
x fatherless	-0.439**													
	(0.170)													
female		2.537***	1.369***	2.876***	2.787***	-0.074	0.601*	2.419***	4.585***	2.105***	-2.264*	-0.569	-0.385	0.437
		(0.202)	(0.412)	(0.425)	(0.276)	(0.491)	(0.272)	(0.376)	(0.247)	(0.219)	(1.017)	(0.611)	(0.487)	(0.431)
x fatherless		-0.153	-14.70	1.114	-0.578	1.324	-14.59	-0.389	0.256	-0.0156	-14.59	1.492	1.344	-14.19
		(0.742)	(1474.8)	(1.537)	(1.058)	(1.090)	(1359.0)	(1.115)	(0.944)	(0.800)	(5085.0)	(1.374)	(1.321)	(2269.1)
yrs of education		-0.234***	-0.103	0.173+	0.066	-0.231**	0.122***	-0.491***	-0.183***	-0.189***	-0.151**	-0.224**	-0.136*	-0.189*
		(0.047)	(0.097)	(0.093)	(0.063)	(0.075)	(0.035)	(0.112)	(0.054)	(0.050)	(0.054)	(0.074)	(0.062)	(0.078)
x fatherless		-0.005	-0.037	-0.053	-0.009	0.029	-0.037	0.091	-0.029	-0.010	0.0001	-0.060	-0.0648	-0.049
		(0.032)	(0.074)	(0.108)	(0.051)	(0.036)	(0.030)	(0.057)	(0.066)	(0.034)	(0.033)	(0.057)	(0.049)	(0.060)
time trend		-0.036***	-0.030**	0.001	-0.008	-0.008	0.013**	0.017	-0.027***	0.003	0.006	0.015*	-0.010	0.005
		(0.005)	(0.010)	(0.013)	(0.008)	(0.007)	(0.005)	(0.011)	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)	(0.008)
x fatherless		-0.002	-0.055	0.032	-0.032	0.012	-0.006	-0.031	0.005	0.018	-0.011	-0.070*	0.046+	0.012
		(0.018)	(0.043)	(0.043)	(0.032)	(0.023)	(0.022)	(0.032)	(0.020)	(0.018)	(0.021)	(0.032)	(0.027)	(0.042)
northern FRG		0.334*	-0.503	-0.120	-0.109	-0.268	-0.140	0.021	-0.185	0.240	0.074	0.275	0.154	0.450+
		(0.161)	(0.449)	(0.505)	(0.295)	(0.308)	(0.183)	(0.434)	(0.202)	(0.184)	(0.217)	(0.265)	(0.236)	(0.266)
x fatherless		0.154	0.475	-14.47	-0.200	-0.717	-1.002	-14.55	-14.48	-0.124	0.259	0.581	0.174	-14.43
		(0.568)	(1.270)	(1965.2)	(1.177)	(1.139)	(1.107)	(1203.1)	(817.6)	(0.680)	(0.704)	(0.862)	(0.924)	(1225.1)
constant		1.068*	-1.607	-5.709***	-3.282***	0.617	-2.326***	1.888	-0.782	0.645	0.227	0.410	-0.140	-0.114
		(0.520)	(1.092)	(1.154)	(0.744)	(0.822)	(0.416)	(1.175)	(0.623)	(0.554)	(0.605)	(0.812)	(0.694)	(0.861)
	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
female	3.599***	3.149***	2.574***	2.102***	3.053***	3.894***	3.649***	1.260***	4.217***	1.926***	4.577***	5.349***	4.934***	4.884***
	(0.405)	(0.289)	(0.505)	(0.268)	(0.231)	(0.184)	(0.203)	(0.264)	(0.181)	(0.290)	(0.276)	(0.214)	(0.204)	(0.221)
x fatherless	-0.813	0.553	-0.229	0.170	0.184	0.125	0.568	1.513+	0.0743	-0.313	-0.562	-0.389	0.817	0.546
	(1.146)	(0.899)	(1.679)	(1.065)	(0.866)	(0.690)	(0.791)	(0.839)	(0.664)	(1.257)	(0.826)	(0.774)	(0.770)	(0.823)
yrs of education	-0.250*	-0.127	-0.152	0.767***	0.434***	0.152***	0.474***	0.027	0.427***	0.547***	0.637***	0.558***	0.814***	-0.148***
	(0.113)	(0.079)	(0.148)	(0.037)	(0.035)	(0.029)	(0.030)	(0.045)	(0.026)	(0.037)	(0.040)	(0.029)	(0.030)	(0.042)
x fatherless	0.057	-0.005	-0.129	-0.049	-0.057	-0.051+	-0.136**	-0.046	-0.041+	-0.047	0.041	-0.041	-0.099**	-0.071
	(0.092)	(0.056)	(0.209)	(0.030)	(0.038)	(0.029)	(0.042)	(0.042)	(0.023)	(0.038)	(0.033)	(0.036)	(0.034)	(0.055)
time trend	0.047***	-0.006	0.053**	-0.022***	-0.017**	-0.002	-0.005	0.017**	-0.014***	-0.008	-0.012	0.002	-0.018***	-0.001
	(0.013)	(0.008)	(0.018)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)
x fatherless	0.042	0.027	0.091	0.040	0.026	0.002	-0.005	0.028	-0.003	0.020	0.001	0.014	0.016	0.011
	(0.041)	(0.022)	(0.089)	(0.026)	(0.023)	(0.015)	(0.020)	(0.021)	(0.014)	(0.027)	(0.023)	(0.018)	(0.018)	(0.015)
northern FRG	0.120	-0.594	-1.407	-0.240	-0.257	0.105	0.183	0.366+	-0.026	0.641**	0.126	0.223	0.0311	0.491**
	(0.438)	(0.370)	(1.035)	(0.214)	(0.223)	(0.137)	(0.164)	(0.196)	(0.130)	(0.206)	(0.252)	(0.155)	(0.159)	(0.154)
x fatherless	-14.60	1.118	-14.73	-0.788	0.698	0.298	1.751**	-0.697	-0.087	0.441	0.184	0.429	0.938	0.838
	(1267.8)	(0.852)	(4574.9)	(1.166)	(0.802)	(0.519)	(0.640)	(0.863)	(0.509)	(0.812)	(0.756)	(0.618)	(0.593)	(0.540)
constant	-1.606	-1.449+	-2.651	-11.61***	-7.102***	-2.744***	-7.344***	-1.993***	-5.852***	-8.861***	-11.29***	-9.340***	-12.55***	-0.862+
	(1.245)	(0.881)	(1.656)	(0.547)	(0.472)	(0.348)	(0.398)	(0.528)	(0.318)	(0.518)	(0.608)	(0.402)	(0.423)	(0.485)
N	228536													
Cases	8162													
χ^2	4729.1***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.8.: Robustness Check 2c: CL plain Model, only Boys

		Ia	IIa/IIIa/b	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/l	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.389***													
	(0.046)													
x fatherless	-0.723**													
	(0.228)													
constant		-1.373***	-2.748***	-3.673***	-2.495***	-1.951***	-0.869***	-3.207***	-2.837***	-1.368***	-1.410***	-1.928***	-1.638***	-2.091***
		(0.082)	(0.161)	(0.261)	(0.148)	(0.113)	(0.074)	(0.208)	(0.169)	(0.089)	(0.087)	(0.113)	(0.099)	(0.122)
	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
constant	-3.806***	-2.934***	-4.010***	-1.112***	-1.746***	-0.961***	-1.309***	-1.547***	-0.592***	-1.621***	-2.650***	-1.983***	-1.199***	-2.381***
	(0.280)	(0.176)	(0.304)	(0.079)	(0.103)	(0.075)	(0.087)	(0.091)	(0.063)	(0.096)	(0.159)	(0.117)	(0.083)	(0.139)
N	109648													
Cases	3916													
χ^2	910.0***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.9.: Robustness Check 2d: CL full Model, only Boys

		Ia	IIa/IIIa/IIIb	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/IIIl	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.148***													
	(0.048)													
x fatherless	-0.699**													
	(0.241)													
yrs of education		-0.120*	-0.182	0.262*	-0.031	-0.188*	0.137***	-0.363*	-0.134	-0.151**	-0.134*	-0.226**	-0.135*	-0.186*
		(0.053)	(0.115)	(0.106)	(0.085)	(0.076)	(0.036)	(0.142)	(0.114)	(0.056)	(0.054)	(0.075)	(0.064)	(0.081)
x fatherless		-0.031	-0.029	-0.357	-0.002	0.026	-0.040	0.076	-0.017	-0.025	-0.0003	-0.060	-0.063	-0.051
		(0.039)	(0.077)	(0.338)	(0.052)	(0.037)	(0.030)	(0.062)	(0.069)	(0.038)	(0.033)	(0.061)	(0.049)	(0.061)
time trend		-0.027***	-0.034**	0.044*	-0.010	-0.009	0.015**	0.019	-0.032**	0.006	0.007	0.016*	-0.009	0.006
		(0.006)	(0.011)	(0.021)	(0.010)	(0.008)	(0.005)	(0.015)	(0.012)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)
x fatherless		-0.033	-0.052	0.197	-0.012	0.014	-0.006	-0.053	0.016	0.048*	-0.010	-0.084*	0.036	0.013
		(0.026)	(0.044)	(0.139)	(0.038)	(0.026)	(0.023)	(0.044)	(0.053)	(0.023)	(0.022)	(0.037)	(0.029)	(0.043)
northern FRG		0.307	-0.233	-14.22	-0.0769	-0.206	-0.099	-0.030	-0.061	0.153	0.079	0.319	0.210	0.506+
		(0.197)	(0.459)	(621.4)	(0.386)	(0.311)	(0.188)	(0.568)	(0.436)	(0.220)	(0.219)	(0.268)	(0.239)	(0.275)
x fatherless		0.214	0.172	-0.260	0.086	-0.570	-0.982	-14.26	-14.22	-0.463	0.306	0.106	0.345	-14.24
		(0.680)	(1.275)	(2557.0)	(1.238)	(1.152)	(1.112)	(1237.4)	(1656.4)	(0.883)	(0.710)	(0.966)	(0.948)	(1121.7)
constant		-0.157	-0.827	-6.930***	-2.157*	0.153	-2.498***	0.573	-1.375	0.260	0.032	0.422	-0.148	-0.150
		(0.592)	(1.261)	(1.379)	(0.972)	(0.833)	(0.425)	(1.510)	(1.269)	(0.623)	(0.604)	(0.824)	(0.710)	(0.889)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
yrs of education	0.069	0.025	0.005	0.740***	0.374***	0.177***	0.458***	0.025	0.419***	0.537***	0.488***	0.817***	0.952***	-0.024
	(0.138)	(0.093)	(0.161)	(0.039)	(0.041)	(0.035)	(0.036)	(0.049)	(0.029)	(0.039)	(0.059)	(0.059)	(0.052)	(0.076)
x fatherless	0.0002	-0.055	-0.139	-0.060+	-0.065	-0.040	-0.151**	-0.060	-0.056*	-0.042	0.036	-0.063	-0.077*	-0.058
	(0.141)	(0.079)	(0.277)	(0.031)	(0.043)	(0.030)	(0.057)	(0.049)	(0.026)	(0.037)	(0.039)	(0.046)	(0.037)	(0.078)
time trend	0.056*	0.014	0.062*	-0.028***	-0.018*	-0.002	-0.009	0.017**	-0.012**	-0.010	0.007	-0.007	-0.026***	0.042***
	(0.024)	(0.012)	(0.026)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.004)	(0.007)	(0.012)	(0.009)	(0.007)	(0.011)
x fatherless	0.069	0.003	0.094	0.033	0.045	-0.002	-0.022	0.042	-0.008	0.007	-0.015	0.010	0.001	0.034
	(0.075)	(0.040)	(0.128)	(0.031)	(0.031)	(0.023)	(0.035)	(0.029)	(0.021)	(0.031)	(0.034)	(0.043)	(0.040)	(0.037)
northern FRG	0.327	-0.901	-0.917	-0.382	-0.396	0.054	0.028	0.482*	-0.091	0.543*	0.340	0.400	-0.107	0.797**
	(0.685)	(0.616)	(1.059)	(0.237)	(0.286)	(0.185)	(0.218)	(0.208)	(0.165)	(0.226)	(0.391)	(0.284)	(0.237)	(0.308)
x fatherless	-14.35	2.642*	-14.50	-0.403	0.928	-0.457	2.049*	-0.165	0.479	0.239	0.447	0.671	-0.247	0.848
	(1423.2)	(1.315)	(4384.9)	(1.203)	(0.989)	(0.859)	(0.956)	(0.930)	(0.634)	(0.879)	(0.947)	(1.139)	(1.260)	(1.029)
constant	-5.274**	-3.179**	-4.527*	-11.07***	-6.211***	-3.012***	-7.021***	-2.009***	-5.723***	-8.634***	-9.091***	-13.41***	-14.77***	-2.670**
	(1.660)	(1.077)	(1.904)	(0.575)	(0.535)	(0.421)	(0.475)	(0.565)	(0.363)	(0.546)	(0.851)	(0.941)	(0.841)	(0.881)
N	109648													
Cases	3916													
χ^2	1879.4***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.10.: Robustness Check 2e: NL plain Model, full Sample

		Ia	IIa/IIIa/IIIb	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/IIIl	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.932***													
	(0.084)													
x fatherless	-0.610**													
	(0.233)													
constant		-1.042***	-4.908***	-3.116***	-3.093***	-0.050	-1.333***	-4.359***	-1.363***	-1.608***	-2.292***	-3.102***	-2.662***	-3.300***
		(0.163)	(0.610)	(0.432)	(0.423)	(0.173)	(0.279)	(0.551)	(0.280)	(0.299)	(0.344)	(0.425)	(0.386)	(0.446)
	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
constant	-4.434***	-3.283***	-5.597***	-1.680***	-1.984***	-2.187***	-4.597***	-6.903***	-0.989**	-7.343***	-7.810***	-3.411***	-3.124***	-3.611***
	(0.561)	(0.439)	(0.687)	(0.304)	(0.329)	(0.489)	(0.734)	(0.954)	(0.357)	(1.009)	(1.067)	(0.618)	(0.584)	(0.638)
agricultureτ	0.601***													
	(0.084)													
craftsmenτ	1.626***													
	(0.123)													
tertiaryτ	2.979***													
	(0.290)													
N	228536													
Cases	8162													
χ^2	532.6***													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.11.: Robustness Check 2f: NL full Model, full Sample

		Ia	IIa/IIIa/IIIb	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/IIIl	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.205***													
	(0.085)													
x fatherless	-0.585**													
	(0.195)													
female		-0.483**	0.380	0.286	-2.575***	-2.527***	-1.903***	-0.069	2.099***	-0.402*	-4.771***	-3.070***	-2.890***	-2.059***
		(0.186)	(0.419)	(0.261)	(0.507)	(0.262)	(0.270)	(0.359)	(0.317)	(0.182)	(1.076)	(0.638)	(0.514)	(0.433)
x fatherless		-14.06	1.324	-0.340	1.540	0.246	-14.23	-0.174	0.476	0.205	-11.77	1.768	1.562	-12.92
		(28709526.4)	(1.487)	(0.948)	(0.996)	(0.738)	(1249.6)	(1.013)	(0.824)	(0.661)	(1394.0)	(1.291)	(1.252)	(1323.7)
yrs of education		0.031	0.409***	0.294***	-0.021	0.225***	0.354***	-0.299*	0.012	0.017	0.071	-0.015	0.081	0.024
		(0.036)	(0.104)	(0.074)	(0.087)	(0.046)	(0.051)	(0.128)	(0.068)	(0.065)	(0.068)	(0.086)	(0.074)	(0.089)
fatherless		-0.002	-0.054	-0.010	0.031	0.002	-0.037	0.092	-0.028	-0.009	0.003	-0.059	-0.064	-0.048
		(0.031)	(0.112)	(0.057)	(0.044)	(0.031)	(0.039)	(0.063)	(0.071)	(0.042)	(0.04)	(0.062)	(0.055)	(0.065)
time trend		0.002	0.035**	0.026**	0.027***	0.034***	0.047***	0.052***	0.007	0.038***	0.040***	0.050***	0.025***	0.040***
		(0.005)	(0.013)	(0.008)	(0.008)	(0.004)	(0.006)	(0.012)	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
fatherless		-0.013	0.041	-0.023	0.021	0.009	0.003	-0.022	0.012	0.027	-0.002	-0.062+	0.055+	0.021
		(0.018)	(0.045)	(0.034)	(0.026)	(0.018)	(0.026)	(0.034)	(0.023)	(0.022)	(0.024)	(0.034)	(0.030)	(0.044)
northern FRG		-0.156	-0.395	-0.386	-0.529+	-0.278+	-0.412*	-0.238	-0.457*	-0.030	-0.196	0.011	-0.107	0.183
		(0.200)	(0.511)	(0.304)	(0.320)	(0.159)	(0.203)	(0.440)	(0.209)	(0.201)	(0.236)	(0.281)	(0.252)	(0.283)
fatherless		0.035	-15.14	-0.373	-0.911	-0.190	-1.211	-15.87	-16.58	-0.299	0.070	0.403	-0.023	-15.69
		(0.543)	(2543.8)	(1.207)	(1.178)	(0.554)	(1.156)	(2112.2)	(2190.1)	(0.738)	(0.764)	(0.900)	(0.978)	(2070.4)
constant		-0.829+	-6.841***	-4.323***	-0.244	-1.053*	-3.433***	1.219	-1.492*	-0.169	-0.782	-0.450	-1.074	-1.001
		(0.431)	(1.383)	(0.929)	(0.922)	(0.514)	(0.626)	(1.244)	(0.725)	(0.675)	(0.725)	(0.913)	(0.809)	(0.963)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
female	1.092**	0.652*	0.070	-0.305	0.590*	1.323***	0.813***	-3.151***	1.813***	-2.145***	2.365***	3.704***	2.932***	3.023***
	(0.419)	(0.284)	(0.495)	(0.254)	(0.236)	(0.167)	(0.236)	(0.559)	(0.155)	(0.545)	(0.392)	(0.308)	(0.242)	(0.298)
x fatherless	-0.625	0.793	-0.063	0.403	0.422	0.210	1.005	2.521*	0.201	-0.405	-0.859	-0.535	1.590+	0.910
	(1.076)	(0.781)	(1.641)	(0.977)	(0.741)	(0.629)	(0.911)	(1.035)	(0.551)	(1.912)	(1.013)	(0.889)	(0.882)	(0.951)
yrs of education	-0.059	0.082	0.053	1.034***	0.687***	0.243***	0.753***	0.022	0.682***	0.883***	1.019***	0.886***	1.325***	-0.211*
	(0.125)	(0.089)	(0.158)	(0.080)	(0.064)	(0.055)	(0.056)	(0.087)	(0.047)	(0.072)	(0.081)	(0.058)	(0.086)	(0.085)
x fatherless	0.058	-0.006	-0.132	-0.049	-0.058	-0.045	-0.195**	-0.041	-0.036	-0.050	0.107+	-0.035	-0.141*	-0.076
	(0.096)	(0.062)	(0.214)	(0.040)	(0.046)	(0.047)	(0.072)	(0.069)	(0.038)	(0.065)	(0.056)	(0.061)	(0.058)	(0.088)
time trend	0.082***	0.028***	0.088***	0.009	0.016*	0.034***	0.030***	0.067***	0.015**	0.024*	0.018	0.043***	0.007	0.038***
	(0.014)	(0.008)	(0.019)	(0.006)	(0.006)	(0.005)	(0.007)	(0.010)	(0.005)	(0.010)	(0.012)	(0.007)	(0.007)	(0.006)
x fatherless	0.051	0.036	0.102	0.049+	0.034	0.007	-0.007	0.057	-0.002	0.03	0.004	0.027	0.030	0.023
	(0.043)	(0.025)	(0.091)	(0.030)	(0.026)	(0.021)	(0.032)	(0.035)	(0.020)	(0.045)	(0.036)	(0.028)	(0.028)	(0.022)
northern FRG	-0.146	-0.866*	-1.679	-0.524*	-0.541*	-0.211	-0.092	0.286	-0.450**	0.678*	-0.201	-0.027	-0.368	0.461*
	(0.444)	(0.379)	(1.046)	(0.231)	(0.237)	(0.183)	(0.245)	(0.304)	(0.172)	(0.332)	(0.408)	(0.220)	(0.232)	(0.215)
x fatherless	-15.62	0.990	-12.84	-1.026	0.516	0.0927	2.536*	-1.583	-0.627	0.340	-0.282	0.157	0.942	1.037
	(1941.9)	(0.900)	(1639.7)	(1.217)	(0.863)	(0.709)	(0.994)	(1.364)	(0.703)	(1.318)	(1.194)	(0.926)	(0.872)	(0.722)
constant	-2.243+	-2.318*	-3.452+	-13.21***	-8.480***	-3.276***	-10.61***	-1.913*	-8.122***	-13.26***	-17.17***	-13.87***	-19.29***	-0.738
	(1.341)	(0.991)	(1.771)	(1.240)	(0.956)	(0.572)	(0.856)	(0.874)	(0.619)	(1.183)	(1.504)	(1.043)	(1.475)	(0.762)
agricultureτ	0.391***													
	(0.063)													
craftsmenτ	1.001***													
	(0.090)													
tertiaryτ	1.718***													
	(0.157)													
N	228536													
Cases	8162													
χ^2	1583.1***													

Source: own calculations. Standard errors in parentheses; $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.12.: Robustness Check 2g: NL plain Model, only Boys

		Ia	IIa/IIIa/IIIb	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/IIIl	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	2.132^{***}													
	(0.111)													
x fatherless	-1.013^{**}													
	(0.312)													
constant		-0.698^{***}	-5.099^{***}	-3.205^{***}	-2.310^{***}	0.785^{***}	-0.580^{*}	-4.342^{***}	-3.746^{***}	-1.371^{***}	-1.432^{***}	-2.273^{***}	-1.811^{***}	-2.539^{***}
		(0.160)	(0.748)	(0.520)	(0.422)	(0.155)	(0.270)	(0.648)	(0.569)	(0.336)	(0.331)	(0.420)	(0.377)	(0.448)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
constant	-5.314^{***}	-3.898^{***}	-5.638^{***}	-1.006^{**}	-2.000^{***}	-2.053^{***}	-2.924^{***}	-3.502^{***}	-1.021^{**}	-3.644^{***}	-6.338^{***}	-4.656^{***}	-2.610^{***}	-5.647^{***}
	(0.782)	(0.583)	(0.822)	(0.306)	(0.393)	(0.503)	(0.612)	(0.668)	(0.359)	(0.690)	(1.050)	(0.829)	(0.570)	(0.955)
agricultureτ	0.554^{***}													
	(0.103)													
craftsmenτ	1.612^{***}													
	(0.134)													
tertiaryτ	2.488^{***}													
	(0.283)													
N	109648													
Cases	3916													
χ^2	369.3^{***}													

Source: own calculations.
Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.13.: Robustness Check 2h: NL full Model, only Boys

		Ia	IIa/IIIa/IIIb	IIIc	IIId/IIIe	IIIf	IIIh	IIIi	IIIk/IIIl	IIIm	IIIn	IIIo	IIIp	IIIq
father's job	1.339***													
	(0.102)													
x fatherless	-0.887***													
	(0.245)													
yrs of education		0.0001	0.403***	0.092	-0.081	0.122*	0.270***	-0.263+	-0.017	-0.044	-0.020	-0.123	-0.025	-0.079
		(0.035)	(0.120)	(0.099)	(0.092)	(0.052)	(0.057)	(0.156)	(0.127)	(0.074)	(0.073)	(0.092)	(0.081)	(0.097)
x fatherless		0.006	-0.369	0.022	0.052	0.026	-0.017	0.102	0.009	-0.002	0.027	-0.036	-0.039	-0.026
		(0.026)	(0.354)	(0.061)	(0.048)	(0.036)	(0.043)	(0.070)	(0.076)	(0.050)	(0.045)	(0.068)	(0.059)	(0.069)
time trend		-0.002	0.070**	0.017	0.018*	0.027***	0.041***	0.047**	-0.005	0.033***	0.034***	0.044***	0.018*	0.033***
		(0.005)	(0.022)	(0.011)	(0.009)	(0.005)	(0.007)	(0.016)	(0.013)	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)
x fatherless		-0.004	0.257+	0.027	0.054	0.040+	0.034	-0.014	0.056	0.091**	0.030	-0.046	0.078*	0.055
		(0.015)	(0.148)	(0.043)	(0.033)	(0.024)	(0.031)	(0.048)	(0.057)	(0.032)	(0.030)	(0.042)	(0.036)	(0.048)
northern FRG		0.036	-14.78	-0.323	-0.441	-0.248	-0.347	-0.253	-0.298	-0.079	-0.158	0.091	-0.020	0.275
		(0.180)	(688.7)	(0.411)	(0.340)	(0.192)	(0.233)	(0.588)	(0.457)	(0.258)	(0.258)	(0.303)	(0.275)	(0.311)
x fatherless		-0.126	0.560	-0.108	-0.776	-0.194	-1.191	-15.83	-15.33	-0.644	0.113	-0.010	0.164	-16.09
		(0.460)	(1825.9)	(1.313)	(1.238)	(0.645)	(1.209)	(2291.6)	(2473.0)	(1.008)	(0.828)	(1.036)	(1.057)	(2420.4)
constant		-0.461	-7.099***	-2.106+	0.356	0.0452	-2.563***	0.857	-1.288	0.478	0.150	0.679	0.023	0.070
		(0.406)	(1.643)	(1.133)	(0.975)	(0.580)	(0.685)	(1.607)	(1.403)	(0.789)	(0.771)	(0.964)	(0.866)	(1.027)

	IIIr	IIIs	IIIt	IVa	IVb	Va	Vb	Vc	Vd	Ve	Vf	Vg	Vh	Vi
father's job														
x fatherless														
yrs of education	0.187	0.150	0.120	0.924***	0.530***	0.138+	0.630***	-0.145	0.571***	0.777***	0.679***	1.310***	1.575***	-0.242
	(0.151)	(0.106)	(0.174)	(0.086)	(0.068)	(0.075)	(0.071)	(0.106)	(0.057)	(0.081)	(0.115)	(0.145)	(0.159)	(0.156)
x fatherless	0.017	-0.031	-0.128	-0.041	-0.044	-0.002	-0.223*	-0.048	-0.043	-0.013	0.146+	-0.049	-0.079	-0.036
	(0.150)	(0.087)	(0.291)	(0.045)	(0.054)	(0.056)	(0.112)	(0.095)	(0.050)	(0.072)	(0.079)	(0.089)	(0.070)	(0.147)
time trend	0.083***	0.041**	0.090***	-0.006	0.006	0.022*	0.016	0.060***	0.007	0.012	0.047+	0.023	-0.013	0.109***
	(0.025)	(0.013)	(0.027)	(0.008)	(0.009)	(0.009)	(0.011)	(0.012)	(0.008)	(0.013)	(0.024)	(0.017)	(0.012)	(0.022)
x fatherless	0.114	0.044	0.143	0.071+	0.086*	0.031	-0.017	0.115*	0.020	0.042	0.002	0.053	0.038	0.010
	(0.081)	(0.046)	(0.136)	(0.039)	(0.039)	(0.040)	(0.060)	(0.056)	(0.036)	(0.056)	(0.061)	(0.078)	(0.070)	(0.074)
NG	0.0967	-1.147+	-1.161	-0.670*	-0.667*	-0.325	-0.338	0.562	-0.550*	0.643	0.251	0.309	-0.604	1.202*
	(0.706)	(0.642)	(1.082)	(0.285)	(0.321)	(0.321)	(0.394)	(0.369)	(0.280)	(0.413)	(0.749)	(0.520)	(0.416)	(0.581)
x fatherless	-15.36	2.475+	-13.10	-0.588	0.749	-1.462	3.498*	-1.160	0.426	-0.0980	0.307	0.629	-1.278	0.746
	(1999.8)	(1.428)	(1920.5)	(1.319)	(1.109)	(1.552)	(1.743)	(1.669)	(1.049)	(1.608)	(1.747)	(2.105)	(2.343)	(1.824)
constant	-5.181**	-3.188*	-4.427*	-11.85***	-6.569***	-2.425**	-9.561***	-0.601	-7.109***	-12.56***	-13.51***	-21.75***	-24.37***	-1.953
	(1.855)	(1.251)	(2.074)	(1.296)	(0.953)	(0.778)	(1.091)	(1.021)	(0.762)	(1.404)	(1.936)	(2.705)	(2.840)	(1.598)
agricultureτ	0.327***													
	(0.067)													
craftsmenτ	1.009***													
	(0.096)													
tertiaryτ	1.959***													
	(0.235)													
N	109648													
Cases	3916													
χ^2	509.6***													

Source: own calculations. Standard errors in parentheses; $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.14.: Estimation Results of a Mixed Logit Model

	Mean	Std. Dev.
father's job	-0.0527	2.536***
	(0.715)	(0.000)
father's job x fatherless	-1.672	2.331
	(0.136)	(0.115)
controls included?	YES	
interactions of controls and job groups included?	YES	
N	228536	
Cases	8162	
χ^2	6570.7***	

Source: own calculations.

p-values in parentheses.

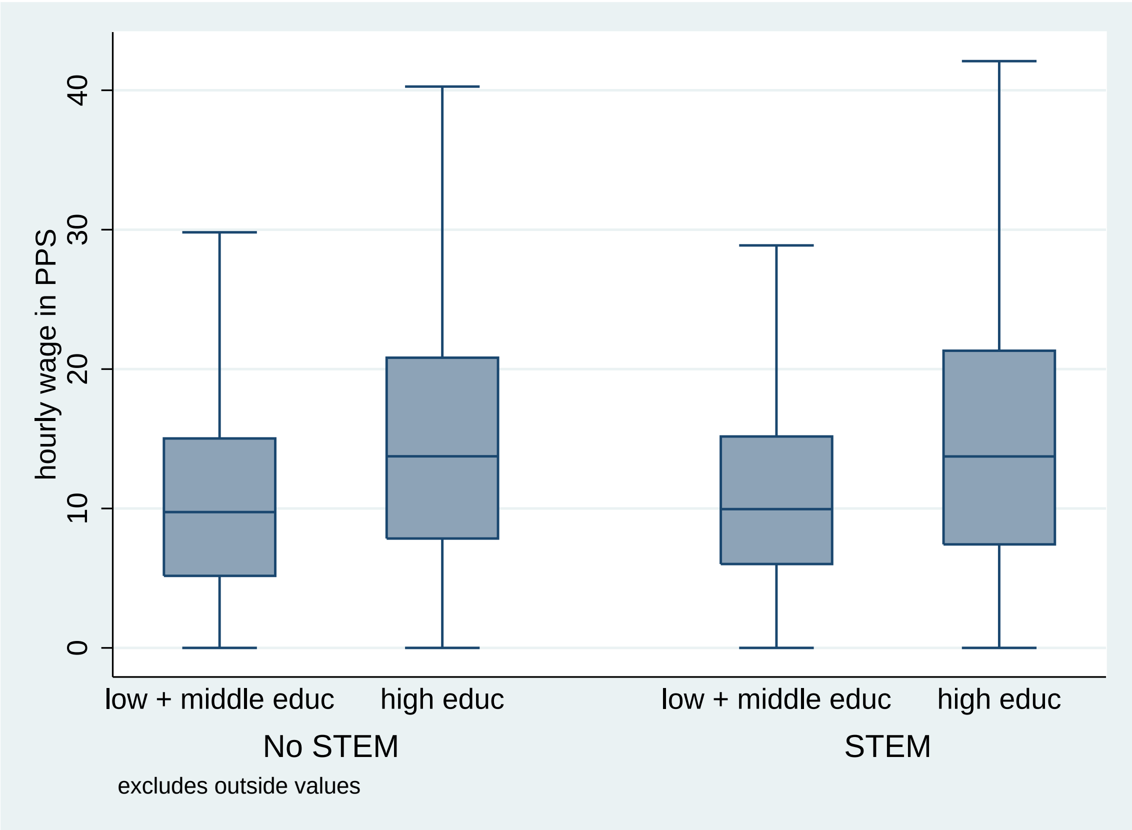
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C. Appendix of Chapter 4

Table C.1.: Summary Statistics in the Data Set

Variable	Mean	Std. Dev.	min	max	N
labour participation	0.795	0.403	0	1	204610
hours worked per week	35.94	9.298	1	99	161879
hourly wage in PPS	9.492	10.323	0.001	706.526	161879
non-wife income in 1000 PPS	24.886	30.576	0	2410.095	204610
year of birth	1971.316	7.611	1960	1990	204610
highest ISED level attained	3.487	1.149	0	5	204610
youngest child 0-3 years	0.155	0.362	0	1	204610
youngest child 4-6 years	0.109	0.311	0	1	204610
youngest child 7-10 years	0.125	0.33	0	1	204610

Source: own calculations.



Source: own calculations.
Eastern Europe excluded.

Figure C.1.: Wage Distributions of Women in the Data Set.

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