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Essays on Overqualification, Work Organisation, and Technology: Empirical Evidence for Germany

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Chapter 1

Introduction

Human capital is deemed to be an important determinant of long-term economic growth.[1] As emphasised by endogenous growth theory, the initial stock of human capital as well as improvements in human capital might promote growth through several channels. Human capital accumulation might not only increase individual productivity but also accelerate growth through positive externalities that increase the production capacity of the economy (Lucas, 1988). Human capital might also increase the innovative capacity of the economy promoting growth by the introduction of new ideas, goods, and technologies (Romer, 1990). Furthermore, a high stock of human capital might facilitate the adoption and implementation of superior technologies that have been developed in another country (Nelson and Phelps, 1966). Empirical evidence supporting the notion of growth-enhancing effects of human capital is provided by an extensive macroeconomic literature measuring human capital in terms of the quantity and quality of education (Barro, 2001; Hanushek and Woessmann, 2008). A central policy implication emerging from the economic growth literature is the provision of subsidised education. Since the social rate of return of human capital is likely to exceed its private rate of return, even a well-functioning market economy is unlikely to ensure an optimal level of education without public subsidies (Lange and Topel, 2006). As a consequence, the (tertiary) education sector in many developed countries has increased substantially in the last decades (OECD, 2014). In Germany, between 2005 and 2013 public expenditures for tertiary education have increased by 45% and the number of beginning students has increased by 43% (Destatis, 2014). Likewise, to promote human capital formation is one of the main pillars of the European strategy for economic growth (European Commission, 2010).

However, it is unlikely that human capital *per se* facilitates economic growth. In order to increase output, the stock of skills and knowledge inherent in an economy's workforce has to be put into efficient use. Given that workers differ in accumulated skills and jobs differ in skill requirements, workers have to hold adequate jobs in order to fully deploy their human capital in the execution of tasks. As opposed to human capital theory (Becker, 1964), assignment models suggest that the workers' productivity will depend on the match between their acquired skills and their jobs' skill requirements (Roy, 1951; Sattinger, 1993). Similarly, the "task-based approach" literature follows a conceptual framework that links the tasks performed by workers on the job to the skills required to execute these tasks (Autor et al., 2003). Focusing on the varying task-content of occupations, these studies assume that educated workers differ in their comparative advantage for jobs of different complexity (Acemoglu and Autor, 2011). If matching quality determines productivity, reaping the benefits of human capital investments requires that the increasing supply of high-skilled labour will meet with a sufficient shift in the demand for skills. As a vast literature documents, labour markets in many countries have been characterised by a large increase in the demand for skills in recent decades (Katz and Autor, 1999). Shifts in the relative demand for high-skilled labour are considered to largely result from skill-biased technical change, i.e. changes in production processes favouring the employment of high-skilled workers. Skill demand may rise due to technical change embodied in capital goods, such as

[1] See, e.g., Aghion and Howitt (1998) and Barro and Sala-i-Martin (1995).

information and communication technologies (Michaels et al., 2014), or due to disembodied forms of technical change, such as organisational change (Caroli and Van Reenen, 2001).[2] To some extent, a rapid increase in the supply of high-skilled workers may have promoted the development of skill-complementary technologies (Acemoglu, 1998). Therefore, the shift in the supply of high-skilled workers seems to have been compensated by the shift in demand for skills (or even overcompensated in some countries, see e.g. Katz and Autor, 1999). However, even in the absence of aggregate imbalances between supply and demand for skills, worker-job mismatches may arise at the individual level as a consequence of labour market frictions such as asymmetric information and costly job search (Sattinger, 2012). In this case, a suboptimal allocation of skills in the labour market can lead to an underutilisation of the available human capital which yields less than the maximum productivity.

The present cumulative dissertation focuses on the question which factors contribute to an efficient utilisation of the available human capital in the German labour market. Two relevant aspects for answering this question are analysed in the related parts of the dissertation. First, the effective use of the available human capital depends on the allocation of skills in the labour market. Second, over time technological advances may change the way how employers can fully utilise their employees' skills.

In the context of skill allocation, many studies show that labour markets of industrialised countries share the common feature that substantial shares of workers are holding jobs which are not commensurate to their educational attainment. Summarising studies for various industrialised countries, Leuven and Oosterbeek (2011) find that an average share of 30% of workers acquired a level of qualification exceeding the educational requirement of their current job. Consequently, these workers are formally overqualified for their job, i.e. they experience a vertical educational mismatch. This suboptimal allocation of workers across jobs may signal an inefficient allocation of skills in the labour market because available skills are not fully exploited. A real underutilisation of skills, however, will not arise if overqualified workers lack the necessary skills to hold a formally matching job because they are less able than equally educated workers. Given that education is subsidised in most developed countries, there is a concern of a possible overinvestment in education. Educational investments into skills which remain untapped by overqualified workers may be partly wasted because of reduced returns in terms of wages or tax revenues. As outlined by Tinbergen (1975), the evolution of the skill premium for highly-educated workers will depend on the joint trends of skill supply and skill demand where the former is promoted by public investments and the latter is a results of skill-biased technical change. In the 1970s, several authors reported a decrease in the returns to tertiary education in the US in response to a strong increase in the number of graduates. Great attention was especially raised by the book *The Overeducated American* by Freeman (1976), in which the author claims the presence of an oversupply of college graduates resulting in a long lasting decrease in returns to college education. Although the persistence of such an

[2] Other potential sources for rising skill demand include international trade (Feenstra and Hanson, 1999) or capital-skill complementarity (Krusell et al., 2000).

imbalance between overall supply and demand of education was proven to be wrong (Smith and Welch, 1978), Freeman's analysis gave rise to an extensive set of studies analysing educational mismatches at the individual level.[3]

An important strand of the literature on overqualification focuses on potential detrimental effects of the underutilisation of skills on productivity at the individual, firm, or economy level. At the individual level, many studies infer the costs of overqualification from its effect on wages which are assumed to represent the marginal productivity of workers (Becker, 1964). Cross-sectional analyses consistently find that overqualified workers earn more than their coworkers in the same low-requirement job but less than equally educated individuals in adequate jobs (Duncan and Hoffman, 1981; Hartog, 2000). Panel studies accounting for skill-heterogeneity among equally educated workers provide mixed results. While some studies conclude that wage penalties only represent spurious correlations because overqualified workers have lower ability (Leuven and Oosterbeek, 2011; Tsai, 2010), other studies find that wage penalties diminish but remain significant after controlling for skill-heterogeneity (Kleibrink, 2015; Korpi and Tåhlin, 2009). Further studies have shown that overqualification is associated with a lower job satisfaction of workers (Hersch, 1991). A reduced job satisfaction may lead to lower motivation and effort which ultimately will reduce the workers' productivity. At the firm level, hiring overqualified candidates might induce productivity losses due to this lower job satisfaction, a higher incidence of shirking and absenteeism, or a higher turnover (Büchel, 2001). However, recent studies employing firm-level panel data for Belgium find that firm productivity is positively affected by the level of required education as well as by additional years of overeducation (Kampelmann and Rycx, 2012; Mahy et al., 2015).[4] Mahy et al. (2015) conclude that the positive effect of overqualification on firm productivity seems to indicate that additional skills and capabilities acquired in school outweigh potential effects of job dissatisfaction.

At the economy level, however, aggregate productivity may be adversely affected by overqualification even if some firms might benefit from it. The reason is that, in contrast to the firm-level perspective, the perspective of the economy as a whole takes the role of allocative efficiency into account. Therefore, overqualification could affect aggregate productivity through the allocation of workers across firms with different productivity levels (McGowan and Andrews, 2015). An adverse effect could emerge if overqualified workers are employed by low-productivity firms and can not be hired by relatively more productive firms that would more efficiently utilise these workers' skills. Consequently, firms with a high productivity level may not be able to grow and to increase their market share due to a lack of adequately skilled labour. Therefore, reallocating mismatched workers to firms deploying their skills optimally could increase aggregate labour

[3] See, e.g., the reviews provided by Hartog (2000) and Leuven and Oosterbeek (2011).

[4] These studies employ the ORU model introduced by Duncan and Hoffman (1981). It divides the workers' years of schooling into the number of years of overeducation (O) exceeding the number of years of schooling required for the job (R). If workers obtain lower levels of schooling than required for the job, U depicts the number of years of undereducation. Furthermore, the result of these firm-level studies are in line with the literature on individual wage effects employing the ORU model and finding significant returns to surplus years of education that, however, are lower than the returns to required schooling for the job.

productivity given that the economy is characterised by varying productivity levels of firms.[5] A number of recent empirical and theoretical studies focus on the implications of resource allocation if workers as well as jobs are assumed to be heterogenous. For instance, Hsieh et al. (2013) attribute a substantial share of the US economic growth between 1960 and 2010 to an improved allocation of talent inherent in female and black workers. Jovanovic (2014) provides a model implying that long-run growth is negatively affected by a misallocation of workers to jobs because of assignment frictions. Focusing on search frictions, Gautier and Teulings (2015) argue that output losses induced by mismatches may be particularly high if productivity is highly contingent on the precision of job matches and if different types of workers are poor substitutes.

Due to the outlined consequences for various economic actors, understanding which forces lead to a mismatch of (high-skilled) workers seems to be highly relevant from a policy perspective. The first two essays of this dissertation aim to contribute to the growing literature on the determinants of overqualification at the individual level. One general contribution stems from the data set employed for the empirical analyses. Both essays are based on data from a cohort study of tertiary graduates in Germany conducted over the early career cycle of the respondents (HIS-Graduate Panel).[6] Focusing on the group of tertiary graduates at the transition to the labour market allows to analyse the factors affecting the early misallocation of skills as well as the potential long-lasting effects of an initial mismatch. Comparable studies are scarce since studies for the German labour market often rely on samples drawn from the entire working population observed at different stages of individual career cycles. Furthermore, my data set has the advantage to include a rich set of explanatory variables of particular importance in the context of overqualification. For instance, it provides school leaving examination grades and university grades as proxy variables for differences in general ability and occupation-specific skills. In addition, detailed study characteristics are included such as the field of study or university type.

The first essay explores which factors are relevant determinants of overqualification at the start of the career, i.e. one year after graduation. As a further contribution, the study focuses on the question whether and how the family background of German graduates affects the probability to be overqualified. This question seems relevant because policies that improve the access to higher education aim to promote both economic growth and intergenerational social mobility. A higher social mobility might in turn enhance growth through a better allocation of human capital resources inherent in individuals from disadvantaged family backgrounds (OECD, 2010). The main aim of the study is to uncover potential transmission channels mediating the link between family background and overqualification. Depending on the family background, graduates might differ in various characteristics that are potential determinants of overqualification. For instance, (innate) ability and cognitive skills are transmitted within families (Black et al., 2009) and

[5] Bartelsman et al. (2013) provide evidence for a large within-industry variation of firms' labour productivity for the US and several European countries including Germany.

[6] The data stems from three interviews conducted 1, 5, and 10 years after graduation among individuals who have completed their study programme in 1997 and 2001, respectively. For further information on the study design see Fabian et al. (2013).

decrease the probability of being overqualified (Büchel and Pollmann-Schult, 2004). Measuring family background in terms of parental education, I find that graduates from high status families are less likely to be overqualified. The unconditional social overqualification gap amounts to 7.4 percentage points. Blinder-Oaxaca decompositions of the overqualification gap show that differences in ability and skills, study characteristics, and social capital are important mediators of the family background effect.

The second essay focuses on the persistence of overqualification and the long-run effects of an initial mismatch. From a policy perspective, it is relevant whether overqualification is a transitory or permanent phenomenon during the career of graduates. To what extent overqualification is detrimental at the economy or the individual level will strongly depend on its longevity. If overqualification occurs just transitorily at the start of the career before workers find suitable jobs, losses may only arise in the short-run until available skills are optimally allocated. In contrast, if workers are permanently overqualified, long-term losses may arise because of a continuous underutilisation of their human capital. In this case, private and public educational investments into skills which are permanently untapped, i.e. unproductive, may be wasted to a higher degree because of reduced returns in terms of wages or tax revenues. Based on panel data gathered 1, 5, and 10 years after graduation, I find that overqualification is highly persistent for a substantial share of tertiary graduates over the first ten years of their career. The main aim of the study is to disentangle true state dependence of overqualification from persistence arising due to differences in individual characteristics that are observed or unobserved, i.e. spurious state dependence. Employing dynamic random-effects probit models, I find that a moderate share of the observed persistence can be attributed to a true state dependence effect. In particular, the behavioural effect of past overqualification on the probability of future overqualification amounts to 3 percentage points. In addition, the estimation results indicate that unobserved factors driving the selection into initial overqualification are highly important for the persistence of overqualification at the individual level. However, persistence of overqualification is to some extent attributable to observed heterogeneity. Employing a rich set of explanatory variables, I find that overqualification transitions are related to ability, field of study, occupational mobility, and preferences for adequate job matches.

While the first part of the dissertation focuses on the determinants and consequences of an efficient allocation of skills in the labour market, the second part is concerned with the efficient use of human capital from a firm perspective once the match between workers and firms has been formed. How firms can efficiently use their workers' human capital might change due to technological advances and the increasing digitisation of working processes. The development of the personal computer has relocated computing power from large mainframe computers to the workers' desktops in the 1980s and the diffusion of the internet has granted connectivity in the 1990s. In recent years, mobile information and communication technologies (ICT) connecting to the internet, such as notebooks, tablets and smartphones, have been rapidly diffusing into the workplace. This expansion of mobile ICT marks the next step in the decentralisation of computing technologies. The firms' adoption of mobile ICT is driven by dramatically declining prices for mobile ICT and improvements in the wireless infrastructure granting mobile connectivity. Moreover, wireless digital connectivity is continuously improved allowing employees to access internal documents and information, or to communicate with customers and business partners from virtually everywhere at any time. As digital communication and information processing is becoming ubiquitous, mobile ICT are widely expected to change how work will be organised in the future, dissolving its temporal and spatial boundaries. From a firm perspective, the use of mobile ICT and appropriate flexible organisational practices might exhibit productivity-enhancing effects.

The third essay, co-authored by Steffen Viete, investigates the role of mobile ICT for labour productivity with a special focus on organisational complements. As previous studies have shown, the returns to ICT investments depend heavily on organisational complements, such as decentralised work organisation (Bresnahan et al., 2002). A complementary relationship between generic ICT and decentralised work organisation is founded in the difficulties to convey specific knowledge and the constraints to information processing abilities of 'bounded rational' individuals within the firm. As ICT have the capacity to mitigate both by reducing informational frictions and communication costs, these properties are deemed valuable especially when accompanied with respective changes in organisational practices and decision authority (Bloom et al., 2014; Hitt and Brynjolfsson, 1997). Ubiquitous digital information processing and wireless connectivity are novel features of mobile ICT bearing the potential for enhanced labor productivity due to an efficient use of the workers' human capital. Building on the ICT productivity literature, we hypothesise that mobile ICT can create value if organisational practices grant employees with appropriate decision rights and autonomy over when and where to perform work-related tasks. Within a production function framework, we find that the use of mobile ICT is associated with a productivity premium only in firms granting workplace flexibility by means of trust-based working time. As trust-based working time implies a step towards greater self-management and autonomy, our findings suggest that a high degree of workplace flexibility is crucial for the effective use of mobile ICT. The analysis poses a first step in attaining a better understanding of the effective use of these rapidly diffusing technologies and how they might shape our working environment in the future.

The present dissertation provides new policy-relevant insights in the light of two related public debates on fundamental labour market developments. The first debate revolves around the opposing assertions that on the one hand publicly funded education may result in an oversupply of high-skilled workers, while on the other hand employers often claim to face increasing difficulties to find suitable workers because of skill shortages in specific fields. Given the trends of rising global competition, inevitable demographic changes, and rapid technical changes, policies reconciling these concerns and facilitating an efficient allocation of skills and public resources gain importance in many countries including Germany. The second debate revolves around the ongoing digitisation of working processes which may favour the employment of high-skilled workers and, at the same time, dissolve the temporal and spatial boundaries of work. As reaping the benefits of ubiquitous digital connectivity may be contingent on firms' work organisation, the adoption of recently diffusing new mobile technologies could change how work will be organised in the future.

The dissertation consists of the following three empirical essays concerned with the allocation and the utilisation of human capital in the German labour market which is characterised by an increasing skill supply and the recent diffusion of new mobile ICT:

1. Erdsiek, Daniel (forthcoming), Overqualification of Graduates: Assessing the Role of Family Background, *Journal for Labour Market Research*.

2. Erdsiek, Daniel (2016), Dynamics of Overqualification: Evidence from the Early Career of Graduates, Mimeo.

3. Viete, Steffen and Daniel Erdsiek (2015), Mobile Information and Communication Technologies, Flexible Work Organisation and Labour Productivity: Firm-Level Evidence, ZEW Discussion Paper No. 15-087, Mannheim.

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Chapter 2

Overqualification of Graduates: Assessing the Role of Family Background

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Abstract

Overqualification signals a mismatch between jobs' educational requirements and workers' qualifications implying potential productivity losses at the macro and the micro level. This study explores how the family background of German graduates affects the probability to hold a job that does not require tertiary education, i.e. to be overqualified. Potential pathways of the family background effects are discussed and proxy variables for the mediating factors ability and skills, study characteristics, social capital, financial capital, and aspiration are incorporated into the empirical analysis. Graduates from high status families are found to be less likely to be overqualified. The unconditional social overqualification gap amounts to 7.4 percentage points. Blinder-Oaxaca decompositions of the overqualification gap show that differences in ability and skills, study characteristics, and social capital are important mediators of the family background effect.

2.1 Introduction

A large number of theoretical and empirical studies show that human capital is an important determinant of economic growth. Human capital captures the aggregate amount of skills and knowledge inherent in an economy's workforce. It is one of the main pillars of the European strategy for economic growth to promote human capital formation (EU2020). One related target is that a share of 40% of the population aged 30-34 will hold a tertiary degree by the year 2020 (European Commission, 2010). However, human capital *per se* does not facilitate growth. In order to increase output, the stock of skills and knowledge has to be deployed by workers in the execution of tasks. Reaping the benefits of human capital investments requires that workers hold adequate jobs that make efficient use of their skills. Otherwise, imbalances between employer needs and skills of the workforce can lead to an underutilisation of the available human capital hampering economic growth. According to assignment theory, high-skilled workers holding jobs with low skill requirements underutilise their human capital and do not reach their individual production capacity (Sattinger, 1993). In the literature, such vertical mismatches are commonly identified in terms of overqualification arising if individuals' current qualification exceeds the educational requirement of their job.

Overqualification entails productivity-related implications for both economies and individuals. At the aggregate level, reallocating mismatched workers to appropriate jobs could increase productivity and GDP (Gautier and Teulings, 2015; McGowan and Andrews, 2015). Thus, overqualification implies a potential waste and misallocation of scarce public resources, in particular those public funds invested into education (Chevalier, 2003). At the individual level, mainly productivity-related outcomes, such as job satisfaction or wages, have been analysed (Hartog, 2000). These studies commonly find that overqualified workers are less satisfied with their job which could reduce workers' motivation and effort leading to lower productivity (Hersch, 1991; Korpi and Tåhlin, 2009). Concerning the effects on wages, overqualified workers are found to earn more than their well-matched co-workers because surplus schooling is rewarded (Duncan and Hoffman, 1981). However, the return on surplus schooling is commonly found to be lower than the return on years of schooling required for a job (Hartog, 2000). Therefore, overqualified workers are found to earn less than equally educated workers holding a matching job (Büchel and Mertens, 2004; Daly et al., 2000). Further studies also indicate that overqualification comes along with significant wage penalties for the subgroup of graduates (Chevalier, 2003; Diem and Wolter, 2014). As discussed by Tsai (2010) and others, negative wage effects might partly arise from a selection of less able individuals into overqualification because individuals holding the same qualification might differ in (innate) ability. In this case, overqualification would not represent an underutilisation of available skills. Recent studies controlling for the skill-heterogeneity between equally educated individuals produced mixed results concerning the causal interpretation of the wage penalty for overqualification. In some studies the negative wage effect of overqualification vanishes once skill-heterogeneity is accounted for (Bauer, 2002; Tsai, 2010), while other studies find robust wage penalties (Kleibrink, 2015; Korpi and Tåhlin, 2009). Since previous findings suggest that overqualification is detrimental at the macro and the micro level, understanding the causes for the occurrence of mismatches is highly relevant from a policy perspective.

This study explores which factors are relevant determinants of overqualification among university graduates. Concentrating on the subgroup of graduates is meaningful from a policy perspective since increasing the share of high-skilled workers is an important strategy to promote economic growth. A further aim of policies that improve the access to higher education is to increase intergenerational social mobility. A higher social mobility might in turn enhance growth through a better allocation of human capital resources inherent in individuals from disadvantaged family backgrounds (OECD, 2010). In order to promote growth through social mobility, these human capital resources have to be put into productive use in the labour market. It is a special focus of this study to assess the importance of family background as a potential determinant of overqualification. In this context, the outcome variable of overqualification can be interpreted in two ways that are closely related. First, from a growth perspective, overqualification can be interpreted as an indication for putting the skills and knowledge acquired during tertiary education into productive use in the job. This interpretation depicts whether graduates from disadvantaged family backgrounds utilise their human capital efficiently in order to promote economic growth. Second, overqualification can be interpreted as an alternative indicator for individual labour market success since it is related to lower job satisfaction and lower wages. This interpretation is relevant from a social mobility perspective in order to assess whether graduates from disadvantaged family backgrounds reap the benefits of higher education to the same extent as graduates from high status families.

This study contributes to the literature on the determinants of overqualification. Family background has been included in few studies on overqualification determinants, however only as additional control variable (Boll and Leppin, 2013; Fehse and Kerst, 2007). In the present study, this relationship is the focal point of the analysis. The main aim is to uncover potential transmission channels mediating the link between family background and overqualification. Depending on the family background, graduates might differ in various characteristics that are potential determinants of overqualification. For instance, (innate) ability and cognitive skills are transmitted within families (Black et al., 2009) and decrease the probability of being overqualified (Büchel and Pollmann-Schult, 2004). Similarly, the choice of field of study is affected by family background (Jonsson et al., 2009) and is a crucial determinant of overqualification (Dolton and Vignoles, 2000). Using data of the HIS-Graduate Panel 1997, I include a set of proxy variables which account for potential factors mediating the link between social origin and overqualification. These factors include ability and skills, study characteristics, financial capital, social capital, and aspiration. Employing a Blinder-Oaxaca decomposition approach, I then analyse which share of the social overqualification gap can be attributed to differences in these factors. The relative importance of the mediating factors is evaluated by conducting a detailed decomposition of the overqualification gap.

The empirical analysis shows that the risk of overqualification depends on the family background of graduates. Based on parental education (PE), graduates are divided into two groups: They either originate from a family with at least one parent holding a tertiary degree (high PE) or from a family with neither of the parents holding a tertiary degree (low PE). As compared to graduates from low PE families, graduates from high PE families are found to be less likely to hold a job that does not require a tertiary degree, i.e. to be overqualified. The unconditional overqualification gap between graduates from low PE families and graduates from high PE families amounts to 7.4 percentage points. The effect of family background is reduced but remains highly significant if the potential pathways are accounted for in a probit regression. Blinder-Oaxaca decompositions show that roughly 60% of the social overqualification gap can be attributed to the fact that graduates differ in observable characteristics, i.e. the endowments effect. I find that differences in ability and skills, study characteristics, and social capital are significant mediators of the link between family background and overqualification. The most important pathway is the social difference in the choice of university type and subject pointing to the importance of the horizontal dimension of higher education. In contrast, I find little evidence that financial support or aspiration mediate family background effects on overqualification. However, this result might be influenced by the imprecise measures for these factors.

The remainder of the chapter is organised as follows. Section 2.2 presents the related literature and elaborates on potential pathways for family background affecting the risk of overqualification. In Section 2.3 the data are introduced and in Section 2.4 the econometric methodology is described. In Section 2.5 the results are presented and the conclusion is provided in Section 2.6.

2.2 Pathways for Family Background Effects

This section discusses why family background might influence the risk of overqualification and presents potential pathways for the family background effect. Empirical evidence on both the relevant determinants of overqualification as well as their relation to family background is reviewed.

2.2.1 Ability and Skills

Skill heterogeneities among workers with the same educational background are likely since human capital also comprises ability and skills that are not acquired during education. Workers could compensate a lack in ability and skills with a higher educational attainment in order to meet their jobs' requirements (Korpi and Tåhlin, 2009). Several studies find that individuals with relatively low ability have a higher probability to be overqualified (Chevalier and Lindley, 2009). In general, these studies consistently suggest that cognitive skills are an important determinant of overqualification (Green et al., 1999; Quintini, 2011). In Germany, individuals with worse school leaving grades or university grades face a higher risk of being overqualified (Büchel and Pollmann-Schult, 2004; Fehse and Kerst, 2007). Although non-cognitive skills have been found to predict various labour market outcomes (Heckman et al., 2006), studies focusing on non-cognitive skills as determinants of overqualification are scarce. Blázquez and Budría (2012) show that non-cognitive skills significantly reduce the probability of becoming overqualified in Germany. In contrast, Sohn (2010) finds no significant effect for the US.

Family background is a crucial determinant of an individual's ability and skills (Feinstein, 2003). Several studies find that cognitive skills of parents and their offspring in adulthood are significantly correlated (Anger and Heineck, 2010; Björklund et al., 2010; Black et al., 2009). The same holds for the intergenerational transmission of non-cognitive skills within families (Anger, 2012; Grönqvist et al., 2011). The amount of financial resources invested in an individual's human capital is also likely to depend on the social origin (Bourdieu, 1983).

Social differences in (innate) ability and skills could maintain a correlation between social origin and overqualification since the probability of being mismatched seems to be affected by cognitive skills and non-cognitive skills.

2.2.2 Study Characteristics

The risk of overqualification has been found to be related to the characteristics of the individual's education. For university graduates, the overqualification rates differ strongly across fields of study (Dolton and Vignoles, 2000; Green and McIntosh, 2007). Klein (2011) provides evidence that the occupational specificity of a field of study reduces the risk of overqualification. In Germany, the lowest rates of overqualification are observed for the subjects Medicine, Law, and Teaching (Berlingieri and Erdsiek, 2012). As shown by Arcidiacono (2004), ability sorting and individual preferences are important drivers of subject choices. Differences in overqualification rates across subjects, therefore, might arise due to self-selection and are not interpretable in a causal manner (Berlingieri and Zierahn, 2014). The risk of overqualification also differs across educational institutions. The quality or prestige of the university a worker graduated from has been found to affect the risk of overqualification (McGuinness, 2003; Robst, 1995). In Germany, individuals who obtained the university entrance certificate can choose between two tracks of tertiary education. They can either enrol at a traditional university or at a university of applied sciences. In general, traditional universities are academically more demanding than the practically oriented study programmes at universities of applied sciences. At the early stage of the career cycle, German graduates from universities of applied sciences face a higher risk of overqualification than graduates from universities (Klein, 2011).

Many studies provide empirical evidence that family background is crucially important for educational choices such as the decision to enrol in tertiary education (Lucas, 2001). Recently, a growing number of sociological studies analyse how social origin affects the choice of field of study. The results indicate that the subject choice is related to the family's socioeconomic status and parental occupations (Becker et al., 2010; Jonsson et al., 2009). In Germany, the offspring from high status families more often enrol in subjects promising high levels of prestige or economic payoff such as Medicine or Law (Lörz, 2012). Social differences tend to be less pronounced in the fields of Engineering or Business & Economics. The literature has pointed out several pathways for the family background effects on subject choice. In order to avoid downward social mobility, members of the privileged group might be more inclined to choose more promising subjects. Subject choices are also based on considerations on costs and benefits which might depend on the social origin. Furthermore, differences in the school leaving examination grades might contribute to the social stratification in fields of study. Enrollment in some prestigious subjects is restricted by the requirement of school grades better than a certain threshold. In addition, some studies focus on the relevance of occupational reproduction in the context of subject choices (Jonsson et al., 2009; Van de Werfhorst and Luijkx, 2010). The intergenerational transmission of occupation-specific knowledge seems to affect the offspring's preferences and interests which are crucial for the subject choice. Family background also might influence the decision whether to enrol in traditional universities or in the more practically oriented universities of applied sciences. Studying at a university of applied sciences might be more appealing for members of the less privileged group for the same reasons that affect the subject choice (Reimer and Pollak, 2009). The quality or prestige of the chosen university also might depend on the available financial capital transmitted within families.

Since the risk of overqualification strongly differs across subjects and university type, social stratification in the study programme characteristics might contribute to the association between social origin and overqualification.

2.2.3 Capital Transmitted Within Families

A social gap in the risk of overqualification could also be mediated by the different kinds of capital transmitted within families. The process of finding a job could be directly influenced through the social capital of the parents. Based on their social networks, parents may provide contacts to potential employers. These social connections could be more advantageous for graduates from high status families. For instance, Corak and Piraino (2011) provide evidence for the intergenerational transmission of employers between Canadian fathers and their sons. The probability that sons are working for the same employer as their father increases with the father's earnings and is particularly high among the top income families. Weiss and Klein (2011) analyse how the probability of overqualification is affected by different types of social networks that helped graduates to find their job. Graduates who found their jobs through the agency of their professors or previous internships during the study programme obtain a lower risk of overqualification. In contrast, finding the job through the agency of parents or friends is associated with a higher probability of overqualification.

Furthermore, a family's financial capital might influence the risk of overqualification. Graduates from wealthy families might have the opportunity to search longer for an adequate job than graduates with an adverse family background. Less privileged graduates might be obliged to start working shortly after graduation due to financial constraints resulting in a higher probability to accept an inadequate job. As shown by Berlingieri and Erdsiek (2012), overqualified graduates more often accepted a job in order to avoid unemployment than matched graduates. Baert et al. (2013) point out that being overqualified shortly after graduation delays the transition into an adequate job. One explanation could be that overqualification sends an even more negative productivity signal to potential employers than unemployment (McCormick, 1990). How familiar graduates are with the high-skilled labour market might also be influenced by the cultural capital provided by the family. The knowledge about job tasks and the functionality of the high-skilled labour market could be more profound among children from high status families. More accurate expectations about the selection procedure for high-skilled jobs could improve the performance in recruitment processes and increase the probability to get a job offer.

Social differences in aspiration might affect occupational choices after tertiary education has been completed. Graduates from high status families might try to prevent downward mobility by only accepting jobs requiring tertiary education. In contrast, graduates from low status families already reached the goal of social advancement by obtaining a tertiary degree. They might be less motivated to be in leading positions or to get a high status job (Jacob and Klein, 2013). Due to occupational reproduction, graduates might also end up in similar occupations as their parents. For graduates from low status families these jobs are less likely to require a tertiary degree.

2.2.4 Discrimination

Graduates from low status families could be prevented from accessing adequate jobs due to discrimination. A crucial source for discrimination is favouritism which occurs if persons are favoured not because of relevant characteristics but rather because of being a member of a preferred group. In the context of this study, favouritism would occur if recruiters are less likely to pick graduates from low status families out of a group of equally eligible candidates for a high-skilled job. It is important to point out that this behaviour only pictures discrimination if the recruiter's decision is only based on favouring members of high status families but is not due to productivity signals associated with family background. Potential employers could incorporate family background into their selection process of new workers as a signal related to productivity (Jacob and Klein, 2013). As pointed out by Erikson and Jonsson (1998), the difference between favouritism and the productivity mechanism is rather subtle.

2.3 Data

2.3.1 Data Set

For the empirical analysis data from the first wave of the HIS-Graduate Panel 1997 are employed covering graduates who completed their tertiary education in 1997.[1] It is a representative nationwide study of tertiary graduates in Germany which surveys individuals one year after graduation. This data set has several advantageous features for my analysis. In comparison to survey data covering the entire work population, focusing the analysis on the policy-relevant group of graduates does not produce small sample sizes. In addition, graduates are observed at the same early stage of the career cycle and face the same overall economic situation. In order to further increase the comparability of graduates, I exclude individuals who were older than 35 years at the time of graduation or who obtained the university entrance certificate abroad. The size of the remaining sample amounts to 3,706 graduates.

Overqualification is the main outcome variable in this analysis. I employ a subjective measure for overqualification that is based on self-assessments of the graduates. Graduates were directly asked whether their job usually requires a tertiary education. They are defined to be overqualified if they indicate that their job usually does not require a tertiary degree. Since this measure relies on the workers' self-assessment, it is sensitive to potential differences in the individuals' perception of job requirements (Barone and Ortiz, 2011). Estimates of the family background effect on overqualification would be biased if actually identical job requirements were assessed differently by graduates who originate from either low or high status families. Therefore, I have to assume that the assessment of job requirements does not systematically differ between both groups of graduates. As pointed out in the literature, the subjective measure of overqualification has the main advantage that it captures specific job characteristics that only the job holder

[1] Hochschul-Informations-System (HIS), Hannover (2007): HIS-Graduate Panel 1997. GESIS Data Archive, Köln. ZA4272 Data File Version 1.0.0, `dx.doi.org/10.4232/1.4272`.

can assess and, thus, is not based on information aggregated at any occupational level (Hartog, 2000).[2]

The central explanatory variable of this study is the social origin of graduates which is measured in terms of parental education (PE). In particular, I use the information whether at least one parent has completed tertiary education. Graduates are divided into two groups: They either originate from a family with at least one parent holding a tertiary degree (high PE) or from a family with neither of the parents holding a tertiary degree (low PE). An education-based measure of family background is likely to be correlated with other, unobserved aspects of social origin, such as parents' ability, preferences or support. Therefore, parental education serves as a general proxy for the educational, social and economic background of graduates.

The aim of this study is to uncover which channels contribute to the social gap in the risk of overqualification. Employing a rich data set, I thus include the following proxy variables for the aforementioned potential mediators. The potential mediating channel of social differences in ability and skills is accounted for by including school leaving examination grades and university grades.[3] Grades can take decimal values within the range of 1 to 4, with higher grades indicating better achievements. Since the procedures of the school leaving examination differ across the 16 federal states in Germany, school grades are standardised within federal states. University grades are standardised within fields of study and university types in order to account for differences in the distribution of grades.

Differences in the study programme characteristics are observed in terms of field of study, university type and study duration. The subject groups Medicine & Law, and Teaching can solely be studied at universities, whereas the remaining subjects can be studied at either universities or universities of applied sciences. The latter subjects are divided into three groups, namely Science, Technology, Engineering, and Mathematics (STEM subjects), Business & Economics, and Social & Cultural Sciences. Dummy variables are generated for each combination of subject group and type of university (university vs. university of applied sciences). Study duration (in semesters) is standardised within subjects and university types since average study durations vary across subjects and university types.

Information on job search channels is employed to account for differences in social capital. Respondents indicated whether they found their current job through the guidance of their parents or friends. If high-skilled parents have better connections to potential employers, this search channel could be more profitable for graduates from high PE families. Further search

[2] In addition to the subjective indicator, two objective methods for measuring required education have been employed in the literature. First, the assignment of required education to occupations based on the evaluation of job analysts (JA approach). Second, the realized matches (RM) approach focusing on the distribution of educational qualifications possessed by workers within an occupation. The main drawback of the RM approach is that it measures the endogenous allocation of workers to jobs driven by demand and supply forces rather than the genuine job requirements. In contrast, the measures of the JA approach are based on the technology of the job yielding an objective evaluation of requirements. However, heterogeneities of jobs within occupational codes are ignored and JA indicators are not available for most countries, e.g. Germany. Hartog (2000) provides a detailed discussion on overqualification measures.

[3] Although grades are surely an imperfect proxy for ability, previous research shows that cognitive as well as non-cognitive skills are relevant predictors of grades (Almlund et al., 2011; Poropat, 2009).

channels include connections that have been established during a previous internship or other jobs the graduate has had before or during the study.

Financial capital is a crucial part of the properties that characterise high status families. Unfortunately, the data set does not contain a direct question concerning a family's financial capital such as parental earnings. Therefore, a set of 3 proxy variables are employed. First, I include the information to what extent graduates financed their costs of living during the study by own work or by parental support. Although the observed shares result from graduates' choices, they could proxy for parental financial capital. The offspring from poorer families, for instance, are expected to be more often constrained to work during the study. This is also the rationale of the second proxy variable, where respondents indicate if their job during study was related or unrelated to their subject. If working is necessary for financing the study, it may be more likely that jobs are taken that are unrelated to the subject. The third proxy for financial capital covers information on the graduates' regional mobility. The respondents indicate the distance between working place and native place. The rationale of this proxy is that moving or commuting over a long distance could be encouraged by parental financial support.

Graduates whose parents are not highly educated already achieved social advancement in terms of educational attainment. Low PE graduates, therefore, might have lower aspirations concerning subsequent labour market success than high PE graduates. In order to control for social differences in aspiration and career orientation, I employ two sets of questions. First, respondents were asked about their future career goals. They had to indicate whether they plan to perform better than the average, to fully exploit their own potential, or to fill a leading position. Second, respondents were asked which actions they have already undertaken to improve their career prospects. The items include showing a high commitment to the job, taking additional courses during the study programme, gaining experiences abroad, being regionally mobile, and establishing social networks.[4]

Finally, I include a gender dummy and control variables for age, marriage, and parenthood at the time of the survey (one year after graduation).

2.3.2 Descriptive Statistics

Descriptive statistics for the estimation sample are provided in Table 2.1. One year after graduation 20% of the respondents are overqualified, i.e. they hold jobs that usually do not require a tertiary education. 46% of the graduates originate from a high PE family, i.e. at least one parent holds a tertiary degree. With a share of 25%, most respondents graduated in STEM subjects at traditional universities.

Table 2.2 presents the differences in the mean values depending on the family background. Column 1 presents the means for graduates from low PE families, whose parents do not hold a tertiary degree, and column 2 presents the means for graduates from high PE families. A share

[4] The two items concerning experiences abroad and mobility may not only proxy for career orientation but also depend on the financial capital of the parents.

of 16.1% of the high PE graduates is overqualified whereas 23.5% of the graduates from low PE families are overqualified.[5] Column 3 shows that the mean difference of 7.4 percentage points is significantly different from zero at the 1 percent level.

The two groups of graduates are highly heterogenous with respect to observable characteristics. Graduates from high PE families have better school leaving examination grades and finished their study programme with better university grades than low PE graduates.[6] The choice of the university type and field of study also differs strongly between both groups of graduates. While 34% of the respondents from low PE families graduated from a university of applied science, the share for high PE graduates amounts to only 15%. Social differences in the choice of university type remain significant if subjects are presented separately. Except for the subject group Business & Economics, low PE graduates study significantly less often at traditional universities than high PE graduates. For instance, Medicine & Law is studied nearly twice as often by high PE graduates (15%) than by low PE graduates (8%).

The job search channels differ in some aspects. Low PE graduates more often found their job through jobs they had before studying (6%) or during the study (14%). This finding corresponds to the fact that the share of respondents who completed a vocational education before entering the study programme is higher among low PE graduates. There are no significant differences in the share of graduates finding a job through the agency of parents/friends (8%) or an internship (16%).

Concerning the proxies for the families' financial capital, I find that during the study programme low PE graduates more often worked in jobs not related to their subject (22%). Low PE graduates financed a share of 32% of their costs of living during the study programme by own work. In contrast, earnings from own work covered only 24% for high PE graduates. The share of costs of living financed by parental support was significantly higher for high PE graduates (57%) than for low PE graduates (34%). High PE graduates have been more mobile than low PE graduates since they are more likely to work more than 100 kilometers away from the native place (43%).

I find little evidence for social differences in the proxy variables for career orientation and aspiration. For instance, 43% of both groups of graduates indicated that they have shown high commitment to the job in order to improve career prospects and 55% indicated that they have the future goal of filling a leading position. However, the share of graduates who gained experiences abroad is significantly higher among high PE graduates (38%) than among low PE graduates (25%).

[5] With the data at hand, little evidence for social differences concerning the selection into employment is found. At the time of the survey, 2.8% of high PE graduates and 3.0% of graduates from low PE families have been unemployed.

[6] Social differences in university grades cannot be driven by self-selection into subjects with a higher level of average grades since university grades are standardised within university type and subject.

Table 2.1: Descriptive Statistics

	Mean	SD	Min	Max
Overqualification	0.201	0.401	0	1
High PE[a]	0.461	0.499	0	1
(Pre-)Study characteristics:				
Vocational education	0.373	0.484	0	1
School grade[b]	0.000	0.998	-3.16	2.53
University grade[c]	0.000	0.998	-4.12	2.42
Duration of study[c]	0.000	0.998	-2.54	6.29
Univ. of applied sciences (UAS)	0.253	0.435	0	1
University types, Subjects:				
Univ.: Medicine & Law	0.111	0.314	0	1
Univ.: Teaching	0.112	0.315	0	1
Univ.: STEM Subjects	0.247	0.431	0	1
UAS: STEM Subjects	0.172	0.377	0	1
Univ.: Business & Economics	0.145	0.352	0	1
UAS: Business & Economics	0.046	0.209	0	1
Univ.: Social & Cultural Sciences	0.133	0.340	0	1
UAS: Social & Cultural Sciences	0.035	0.184	0	1
Job found through:				
Agency of parents/friends	0.077	0.267	0	1
Job before studying	0.048	0.214	0	1
Job while studying	0.126	0.332	0	1
Internship	0.162	0.369	0	1
Worked during study:				
Yes: related to subject	0.569	0.495	0	1
Yes: not related to subject	0.189	0.392	0	1
Not worked during study	0.242	0.428	0	1
Study was financed by:				
Own work (in %)	28.453	22.538	0	99
Parental support (in %)	44.766	31.489	0	99
Distance work and native place:				
Less than 50 km	0.470	0.499	0	1
Between 50 km and 100 km	0.146	0.353	0	1
More than 100 km	0.385	0.487	0	1
Improve career prospects:				
Commitment to the job	0.433	0.496	0	1
Gained experience abroad	0.313	0.464	0	1
Established social networks	0.406	0.491	0	1
Have been mobile	0.300	0.458	0	1
Attended additional courses	0.415	0.493	0	1
Future goals:				
Above-average performance	0.685	0.465	0	1
Fully exploit own potential	0.801	0.399	0	1
Fill a leading position	0.547	0.498	0	1
Observations	3706			

Note: [a] High Parental Education (PE) takes value one if at least one parent has a tertiary degree and zero otherwise; [b] Standardised within federal states; [c] Standardised within subjects and university types. *Source:* HIS-Graduate Panel 1997.

Table 2.2: Descriptive Statistics by Family Background

	Low PE[a]	High PE[b]	
	Mean	Mean	Diff.
Dependent variable:			
Overqualification	0.235	0.161	0.074***
(Pre-)Study characteristics:			
Vocational education	0.468	0.263	0.205***
School grade[c]	-0.116	0.136	-0.252***
University grade[d]	-0.038	0.044	-0.082**
Duration of study[d]	-0.009	0.011	-0.020
Univ. of applied sciences (UAS)	0.342	0.148	0.194***
University types, Subjects:			
Univ.: Medicine & Law	0.078	0.149	-0.071***
Univ.: Teaching	0.101	0.124	-0.023**
Univ.: STEM Subjects	0.207	0.293	-0.086***
UAS: STEM Subjects	0.237	0.095	0.143***
Univ.: Business & Economics	0.150	0.139	0.012
UAS: Business & Economics	0.063	0.026	0.037***
Univ.: Social & Cultural Sciences	0.121	0.147	-0.026**
UAS: Social & Cultural Sciences	0.042	0.028	0.014**
Job found through:			
Agency of parents/friends	0.076	0.079	-0.003
Job before studying	0.063	0.030	0.033***
Job while studying	0.136	0.115	0.020*
Internship	0.160	0.164	-0.004
Worked during study:			
Yes: related to subject	0.560	0.580	-0.020
Yes: not related to subject	0.223	0.150	0.073***
Not worked during study	0.217	0.270	-0.053***
Study was financed by:			
Own work (in %)	32.243	24.025	8.218***
Parental support (in %)	33.948	57.407	-23.46***
Distance work and native place:			
Less than 50 km	0.492	0.444	0.048***
Between 50 km and 100 km	0.162	0.126	0.036***
More than 100 km	0.346	0.430	-0.084***
Improve career prospects:			
Commitment to the job	0.435	0.431	0.004
Gained experience abroad	0.254	0.381	-0.127***
Established social networks	0.393	0.422	-0.030*
Have been mobile	0.295	0.305	-0.011
Attended additional courses	0.409	0.422	-0.013
Future goals			
Above-average performance	0.686	0.685	0.001
Fully exploit own potential	0.798	0.804	-0.006
Fill a leading position	0.553	0.541	0.013
Observations	1997	1709	3706

Note: [a] Low Parental Education (PE): neither of the parents holds a tertiary degree; [b] High PE: at least one parent has a tertiary degree; [c] Standardised within federal states; [d] Standardised within subjects and university types; Significant at 1% ***, significant at 5% **, significant at 10% *. *Source:* HIS-Graduate Panel 1997.

2.4 Methodology

As shown in the descriptive statistics, overqualification is more prevalent among graduates from low PE families than among graduates from high PE families. The empirical analysis now focuses on the question which of the aforementioned pathways contribute to the social overqualification gap.

In a first step, it is tested whether the family background effect is robust against the inclusion of the potential mediating variables. Conducting probit regressions, the effects of family background and the mediating factors on the probability to be overqualified one year after graduation are estimated. For graduate i, the relationship is specified as:

$$\Pr[Overqualification_i = 1 | High\_PE_i, \mathbf{X_i}] = \Phi(\alpha + \beta_{High\_PE} High\_PE_i + \boldsymbol{\beta}_{\mathbf{X}} \mathbf{X_i}) \tag{2.1}$$

with $\Phi(\cdot)$ representing the cumulative normal distribution function. The binary variable *Overqualification* takes the value one if a graduate works in a job that does not require a tertiary education and zero otherwise. Family background is measured by the binary variable *High PE* taking the value one if at least one parent holds a tertiary degree and zero if parents do not hold a tertiary degree. All aforementioned control variables are included in matrix **X**.

In the second step, a decomposition analysis is applied to reveal how differences in observable characteristics contribute to the social overqualification gap. For this purpose, I employ the Blinder-Oaxaca decomposition method for mean outcome differences (Blinder, 1973; Oaxaca, 1973). In a linear model, the raw differential in the continuous outcome variable Y between two groups L and H can be expressed in two ways:

$$\overline{Y}_L - \overline{Y}_H = (\overline{X}_L - \overline{X}_H)\beta_L + \overline{X}_H(\beta_L - \beta_H), \tag{2.2}$$

$$\overline{Y}_L - \overline{Y}_H = (\overline{X}_L - \overline{X}_H)\beta_H + \overline{X}_L(\beta_L - \beta_H), \tag{2.3}$$

where $\overline{X}_j$ is a row vector comprising average values of the independent variables and β_j is a vector of coefficient estimates obtained by OLS regressions for group $j = L, H$.[7] The first part on the right hand side of both equations is the explained part of the raw gap that can be attributed to differences in observable characteristics, i.e. the endowments effects. The second term on the right hand side indicates which share of the gap is due to group differences in the estimated coefficients. This unexplained part also picks up the share of the raw differential due to differences in unobservable characteristics, i.e. unobserved heterogeneity between groups L and H. The unexplained part can thus not be interpreted as a single measure for discrimination such that the same bundle of characteristics is less valuable for one group only because of group membership.

Equations (2.2) and (2.3) differ in terms of the weights used for the evaluation of the endowments effect. The selection of the weighting scheme hinges on the expectation whether members

[7] The auxiliary regressions for groups L and H are: $Y_L = F(X_L\beta_L)$ and $Y_H = F(X_H\beta_H)$

of group L or members of group H are being discriminated. Optimally, the nondiscriminatory coefficients should be used but these are unknown and have to be approximated. If it is assumed, for instance, that group H is being discriminated, the endowments effect is evaluated by the coefficients of group L (β_L) (Equation 2.2).[8]

Since the outcome variable in the present study is binary, I employ the methodology by Yun (2004) enabling Blinder-Oaxaca decompositions for non-linear models. Using this methodology, the social overqualification gap can be decomposed into the endowments effect and coefficients effect at the aggregate level. Furthermore, the methodology is suited to indicate the contribution of each variable to the raw differential, i.e. to compute the detailed decomposition. I will use the detailed decomposition to analyse which pathways are particularly relevant for generating the social overqualification gap.

2.5 Results

2.5.1 Probit Results

Results from probit estimations of overqualification on family background and relevant control variables are provided in Table 2.3. The marginal effect of originating from a high PE family is significant if socio-demographic controls and proxies for ability are included in the probit model (specification 1). The likelihood of being overqualified is 6.2 percentage points lower for graduates whose parents obtained higher education than for graduates from low PE families. Better school leaving examination grades and university grades significantly reduce the probability of being overqualified. Since university grades are standardised within subjects and university types, the results suggest that the probability to be overqualified reduces by 5 percentage points if university grades increase by one standard deviation.

In specification 2, further study characteristics are included in the model. The coefficient of family background decreases but remains highly significant. While the effect of university grades hardly changes, the effect of school grades diminishes. The favourable effect of good school grades on the risk of overqualification, therefore, might work through the selection into subjects promising a good transition into the labour market. University grades seem to be more important to potential employers who might use this information as a signal for job related skills. Similarly, the significant and positive coefficient of standardised study duration could indicate that an above-average study duration sends a negative signal regarding a graduate's ability or motivation. The incidence of overqualification is found to strongly differ across subjects. Compared to the reference group of Social & Cultural Sciences at traditional universities, graduates in Medicine & Law obtain a 20.5 percentage points lower probability to be overqualified. Only Business & Economics graduates from universities of applied sciences do not obtain a significantly lower

[8] In many cases, it remains unclear which group is solely discriminated leading to an "index-number problem" (Oaxaca, 1973). Since the choice of the weight influences the segmentation into the explained and unexplained part, researchers often present decomposition results for both weighting schemes or use coefficients from a pooled regression (Neumark, 1988).

Table 2.3: Probit Regressions, Overqualification

	Dependent Variable: Overqualification					
	(1)		(2)		(3)	
High PE[a]	-0.062***	(0.013)	-0.041***	(0.013)	-0.033**	(0.014)
(Pre-)Study characteristics:						
Vocational education			0.021	(0.017)	0.011	(0.017)
School grade	-0.023***	(0.007)	-0.010	(0.007)	-0.004	(0.007)
University grade	-0.050***	(0.007)	-0.053***	(0.007)	-0.041***	(0.007)
Duration of study			0.017**	(0.007)	0.014**	(0.007)
University types, Subjects:[b]						
Univ.: Medicine & Law			-0.205***	(0.008)	-0.194***	(0.008)
Univ.: Teaching			-0.136***	(0.013)	-0.134***	(0.012)
Univ.: STEM Subjects			-0.164***	(0.014)	-0.146***	(0.014)
UAS: STEM Subjects			-0.103***	(0.017)	-0.091***	(0.017)
Univ.: Business & Economics			-0.038**	(0.019)	-0.020	(0.020)
UAS: Business & Economics			0.019	(0.032)	0.031	(0.033)
UAS: Social & Cultural Sciences			-0.085***	(0.023)	-0.078***	(0.023)
Job found through:						
Agency of parents/friends					0.143***	(0.029)
Job before studying					0.109***	(0.035)
Job while studying					0.086***	(0.022)
Internship					-0.069***	(0.015)
Worked during study:[c]						
Yes: related to subject					-0.042**	(0.018)
Yes: not related to subject					-0.012	(0.019)
Study was financed by:						
Own work (in %)					0.001*	(0.000)
Parental support (in %)					0.000	(0.000)
Distance work and native place:[d]						
Between 50 km and 100 km					-0.034**	(0.016)
More than 100 km					-0.051***	(0.014)
Improve career prospects:						
Commitment to the job					-0.031**	(0.013)
Gained experience abroad					-0.035***	(0.014)
Established social networks					0.006	(0.013)
Have been mobile					-0.027*	(0.014)
Attended additional courses					0.011	(0.013)
Future goals:						
Above-average performance					-0.029**	(0.014)
Fully exploit own potential					0.019	(0.015)
Fill a leading position					-0.002	(0.013)
Socio-demographics[e]	Yes		Yes		Yes	
Pseudo R^2	0.047		0.126		0.166	
Observations	3706		3706		3706	

Note: Probit estimations; Marginal effects (at the average); Standard errors in parentheses; [a] Takes value one if at least one parent has a tertiary degree and zero otherwise; [b] Reference: Univ: Social & Cultural Sciences; [c] Reference: Not worked during study; [d] Reference: Less than 50 km; [e] Socio-demographic controls include age and dummies for gender, being married, and having children; Significant at 1% ***, significant at 5% **, significant at 10% *.

probability of overqualification than the reference group. Due to self-selection into subjects, however, these effects can not be interpreted in a causal manner.

Specification 3 includes the full set of observable characteristics that could mediate the relationship between family background and overqualification. The family background effect reduces but remains significant. The results indicate that the probability to be overqualified is 3.3 percentage points lower for graduates from high PE families even if grades, study characteristics and the following mediating factors are accounted for.

Information on a graduate's social capital is included in terms of job search channels. Finding the current job through the agency of parents/friends, a job before studying, or a job while studying increases the probability to be overqualified. Since jobs held before or during the study usually do not require tertiary education, these social networks seem to hamper the transition into a matching job. In contrast, social connections based on internships support a good start of the career. Finding a job through an internship is associated with a reduction in overqualification by 6.9 percentage points.

The financial capital of families is measured through working experience during the study, the parents' financial support and regional mobility. Graduates who worked in a subject-related job during the study are significantly less likely to be overqualified than graduates who did not work during the study. No favourable effect is found for working in jobs unrelated to the subject. The probability to be overqualified increases with the share of costs of living during the study that was financed by own work. But no significant effect is found for the share that was covered by parental support. Regional mobility is related to a lower risk of overqualification. Graduates whose working place is more than 50 kilometers away from their native place are significantly less likely to be overqualified. Of course, this effect cannot be interpreted in a causal way since the decision to move or commute itself is probably determined by the job quality. With respect to the focus of the analysis, however, it could be relevant if social differences in the graduates' regional mobility contribute to the overqualification gap.

Some of the proxies for career orientation and aspiration are significantly related to overqualification. The probability to be overqualified is roughly 3 percentage points lower for graduates who indicated that they showed commitment to the job, gained experiences abroad, or were regionally mobile in order to improve their career prospects. Moreover, the share of overqualification is 2.9 percentage points lower among graduates who have the future goal to perform above-average in their job.

The robust family background effect in specification 3 could be the result of both unobserved heterogeneity and discrimination. An important source for unobserved heterogeneity might be that the available proxy variables measure the mediating factors for family background effects imprecisely. For instance, school grades and university grades are used as proxies for ability and skills. However, social differences in specific skills like numeracy or literacy are not observed. A further important component of an individual's human capital are non-cognitive skills which predict various labour market outcomes. The literature on human capital acquisition generally concludes that the offspring of wealthy families have higher non-cognitive skills. Therefore, including a proxy for non-cognitive skills could reduce the conditional correlation between social origin and overqualification. The present study, however, focuses on a highly selective group of individuals who completed tertiary education. Whether social differences in non-cognitive skills exist among the highly educated respondents in the sample is unclear. Graduates originating from low PE families might only have been able to complete higher education because they compensated the less favourable parental support by higher non-cognitive skills.

Proxy variables for the different kinds of capital transmitted within families might also be imprecise. For instance, I cannot observe whether graduates accepted a job offer because of financial constraints due to low financial capital of the parents. Furthermore, I cannot control for social differences in cultural capital. Graduates from high PE families might be more familiar with hiring procedures and the functionality of the high-skilled labour market. Graduates might also differ in terms of transmitted preferences and opinions that lower the risk of overqualification. Finally, it is likely that my measures for career orientation and aspiration cannot account for the entirety of this phenomena. For instance, some career choices might be the result of unconscious decision processes related to innate aspiration.

The family background effect could also be attributed to preferences of potential employers. Recruiters could use the family background as a signal for ability and skills. Furthermore, they could value individual characteristics differently depending on social origin of the applicants. The latter case implies discrimination if recruiters favour applicants from high PE families without any other reason than group membership. As a consequence, graduates exhibiting the same characteristics could differ in the number and quality of jobs they get offered.

2.5.2 Decomposition Results

Employing a decomposition analysis, individual characteristics are identified that mediate the effect of family background on the probability to be overqualified.[9] In a first step, the group specific coefficients are estimated by running probit regressions separately for graduates from low PE families (specification 1) and high PE families (specification 2) as presented in Table 2.4. The results show similar effects of university grades, study characteristics and job search channels for both groups of graduates. The significant increase in the overqualification risk due to finding the job through the guidance of parents/friends is not statistically different between low PE graduates (13 percentage points) and high PE graduates (15 percentage points).

Holding a subject-related job during study and financing the study through own work is significantly correlated with overqualification solely for low PE graduates. Gaining experiences abroad reduces the risk of overqualification for both groups, while the effects of the remaining strategies to improve career prospects depend on social origin. High PE graduates who have the future goal of above-average performance obtain a lower overqualification risk, while

[9] Decomposition results were computed in Stata employing the "Oaxaca" command (Jann, 2008) incorporating the non-linear decomposition proposed by Yun (2004). As a robustness test, the analysis has also been conducted using the non-linear extension proposed by Fairlie (2005). The results are not qualitatively sensitive to the choice of methodology.

Table 2.4: Probit Regressions by Family Background, Overqualification

	Dependent Variable: Overqualification			
	Low PE		High PE	
	(1)		(2)	
(Pre-)Study characteristics:				
Vocational education	0.003	(0.025)	0.019	(0.022)
School grade	-0.012	(0.011)	0.006	(0.009)
University grade	-0.041***	(0.010)	-0.037***	(0.008)
Duration of study	0.020*	(0.011)	0.007	(0.009)
University types, Subjects:[a]				
Univ.: Medicine & Law	-0.216***	(0.013)	-0.163***	(0.012)
Univ.: Teaching	-0.144***	(0.022)	-0.111***	(0.012)
Univ.: STEM Subjects	-0.147***	(0.024)	-0.131***	(0.017)
UAS: STEM Subjects	-0.081***	(0.030)	-0.086***	(0.016)
Univ.: Business & Economics	0.024	(0.035)	-0.045**	(0.020)
UAS: Business & Economics	0.085	(0.052)	-0.025	(0.035)
UAS: Social & Cultural Sciences	-0.117***	(0.032)	-0.021	(0.036)
Job found through:				
Agency of parents/friends	0.129***	(0.041)	0.151***	(0.041)
Job before studying	0.086*	(0.045)	0.175***	(0.065)
Job while studying	0.102***	(0.033)	0.070**	(0.029)
Internship	-0.088***	(0.024)	-0.050***	(0.018)
Worked during study:[b]				
Yes: related to subject	-0.081***	(0.027)	-0.001	(0.021)
Yes: not related to subject	-0.043	(0.028)	0.028	(0.028)
Study was financed by:				
Own work (in %)	0.001**	(0.000)	-0.000	(0.000)
Parental support (in %)	0.000	(0.000)	-0.000	(0.000)
Distance work and native place:[c]				
Between 50 km and 100 km	-0.073***	(0.022)	0.017	(0.025)
More than 100 km	-0.073***	(0.021)	-0.035**	(0.017)
Improve career prospects:				
Commitment to the job	-0.016	(0.020)	-0.041**	(0.016)
Gained experience abroad	-0.038*	(0.022)	-0.030*	(0.016)
Established social networks	-0.012	(0.020)	0.030*	(0.016)
Have been mobile	-0.044**	(0.022)	-0.009	(0.018)
Attended additional courses	0.008	(0.020)	0.017	(0.016)
Future goals:				
Above-average performance	-0.023	(0.021)	-0.041**	(0.018)
Fully exploit own potential	0.001	(0.024)	0.034*	(0.018)
Fill a leading position	0.007	(0.020)	-0.013	(0.017)
Socio-demographics[d]	Yes		Yes	
Pseudo R^2	0.150		0.202	
Observations	1997		1709	

Note: Probit estimations; Marginal effects (at the average); Standard errors in parentheses; [a] Reference: Univ: Social & Cultural Sciences; [b] Reference: Not worked during study; [c] Reference: Less than 50 km; [d] Socio-demographic controls include age and dummies for gender, being married, and having children; Significant at 1% ***, significant at 5% **, significant at 10% *.

overqualification is more likely among those who plan to fully exploit their own potential. The latter effect may result from reversed simultaneity because overqualified workers might set this future goal as a reaction to the current underutilization of skills.

Based on the presented auxiliary probit regressions, the social overqualification gap can be decomposed into two parts that are explained or unexplained by differences in observable characteristics. The explained part, i.e. the endowments effect, can be either evaluated with the coefficients estimated in specification (1) or (2) of Table 2.4. The results of the non-linear Blinder-Oaxaca decomposition when the low PE graduate coefficients are used for evaluating the endowments effect are presented in Table 2.5. A share of 23.5% of the graduates from low PE families are overqualified, while only 16.1% of the graduates from high PE families are overqualified. The difference in these percentages, i.e. the total overqualification gap, amounts to 7.4 percentage points. A share of 60.6% of the overqualification gap can be attributed to the fact that graduates differ in observable characteristics depending on family background. This endowments effect can be interpreted in the following way: If high PE graduates had the same average observable characteristics as low PE graduates, the overqualification gap would be reduced by 4.5 percentage points.

In order to identify through which pathways family background affects the risk of overqualification, I carry out a detailed decomposition of the endowments effect. Social differences in university grades explain a significant share of 6.1% of the endowments effect. This result is in line with the previous findings that university grades are better among graduates from high PE families and that better grades reduce the risk of overqualification.

The most important contributor to the endowments effect is the choice of university type and subjects. A share of 66.4% of the endowments effect can be attributed to social differences in these study characteristics. High PE graduates study more often at traditional universities and are more likely to choose subjects with a lower risk of overqualification. If graduates studied the same subjects at the same university type, the social overqualification gap would decrease by 3 percentage points.

Differences in the usage of job search channels significantly account for 8.1% of the endowments effect. The main cause for this contribution is that low PE graduates more often find their job through a job they had before studying.[10] The decomposition results do not indicate that graduates from high PE families obtain a lower risk of overqualification because they profit from parental networks in terms of job placement.

A significant part of the endowments effect can be attributed to differences in actions undertaken to improve career prospects. In particular, the higher share of high PE graduates who gained experiences abroad contributes to the endowments effect.

The previous decomposition results are strongly robust against changing the weighting scheme, i.e. using the coefficients for high PE graduates (Table 2.6). Social differences in university grades, subject choices, and job search channels remain significant contributors to the

[10]The detailed decomposition results presenting each variable separately are not shown in this chapter but are available upon request.

Table 2.5: Decomposition of the Overqualification Gap, Weighted by Coefficients of Low PE Graduates (β_L)

	Coef.	Std. Err.	$P > \|z\|$	% of Total gap	% of Explained part
Low PE	0.235	0.009	0.000		
High PE	0.161	0.009	0.000		
Total overqualification gap	0.074	0.013	0.000		
Explained part	0.045	0.009	0.000	*60.6*	
Unexplained part	0.029	0.013	0.026	*39.4*	
Contribution to explained part					
Vocational education	0.001	0.004	0.893		*1.2*
School grade	0.002	0.002	0.280		*5.4*
University grade	0.003	0.001	0.035		*6.1*
Study duration	0.000	0.001	0.556		*-0.7*
University types, Subjects	0.030	0.006	0.000		*66.4*
How job was found	0.004	0.002	0.051		*8.1*
Worked during study	-0.001	0.002	0.442		*-3.0*
Financing of study	0.000	0.007	0.983		*-0.3*
Dist work, native place	0.003	0.002	0.119		*6.4*
Improve career prospects	0.005	0.002	0.063		*10.2*
Future goals	0.000	0.000	0.885		*0.1*
Socio-demographics	0.000	0.003	0.986		*0.1*

Note: Probit decomposition computed in Stata employing the procedure by Jann (2008); Explained part evaluated by coefficients of graduates from low PE families.

Table 2.6: Decomposition of the Overqualification Gap, Weighted by Coefficients of High PE Graduates (β_H)

	Coef.	Std. Err.	$P > \|z\|$	% of Total gap	% of Explained part
Low PE	0.235	0.009	0.000		
High PE	0.161	0.009	0.000		
Total overqualification gap	0.074	0.013	0.000		
Explained part	0.044	0.011	0.000	*58.9*	
Unexplained part	0.030	0.016	0.058	*41.1*	
Contribution to explained part					
Vocational education	0.004	0.004	0.364		*9.2*
School grade	-0.002	0.002	0.504		*-3.5*
University grade	0.003	0.001	0.032		*7.2*
Study duration	0.000	0.000	0.621		*-0.3*
University types, Subjects	0.023	0.007	0.000		*53.0*
How job was found	0.005	0.002	0.016		*12.2*
Worked during study	0.002	0.002	0.247		*4.6*
Financing of study	0.001	0.007	0.902		*2.0*
Dist work, native place	0.004	0.002	0.027		*8.4*
Improve career prospects	0.003	0.002	0.228		*6.5*
Future goals	0.000	0.001	0.579		*-1.0*
Socio-demographics	0.001	0.003	0.813		*1.6*

Note: Probit decomposition computed in Stata employing the procedure by Jann (2008); Explained part evaluated by coefficients of graduates from high PE families.

endowments effect. The overall contribution of the strategies to improve career prospects becomes insignificant but social differences in gaining experiences abroad remain a significant mediator. Since for high PE graduates the risk of overqualification decreases only if the distance between work and native place exceeds 100 kilometers, the regional mobility significantly contributes to the endowments effect if the high PE coefficients are used as weights. Independently of the weighting scheme, I find no indication that the other proxy variables accounting for financial support and aspiration significantly contribute to the endowments effect. This result might be driven by the lack of precision of the measures for these mediating factors.

Differences in endowments are an important force behind the overqualification gap but a substantial part of approximately 40% of the gap remains unexplained.[11] This unexplained part captures how differences in the coefficients of observable characteristics as well as group differences in unobserved characteristics contribute to the overqualification gap. The bulk of the unexplained part can be attributed to the group difference in the constant reflecting unobserved heterogeneity.[12] Unobserved heterogeneity could arise because of missing proxies for relevant characteristics, such as non-cognitive skills, or because of imprecise measurement of mediators included in the analysis.

Discrimination could be a further reason for the significant unexplained part. Employers could value individual characteristics differently for graduates from high PE or low PE families. However, I find no indication that the overqualification gap widens because employers value the graduates' characteristics differently. Differences in the group specific coefficients only play a minor role for the social overqualification gap in my analysis. Individual characteristics, such as university grades, seem to be equally evaluated by the labour market. However, it is possible that employers discriminate applicants on the basis of characteristics that I cannot observe with the data at hand.

2.6 Conclusion

This study finds that family background, as measured by parental education (PE), is a crucial determinant of overqualification at the start of graduates' careers. One year after graduation, the unconditional overqualification gap between graduates from low PE families and high PE families amounts to 7.4 percentage points. The main aim of this study was to uncover which pathways mediate the link between family background and overqualification. In order to account for potential mediators, proxy variables for ability and skills, study characteristics, social capital, financial capital, and aspirations are included in the empirical analysis. Graduates are found to strongly differ in these potential mediators. The effect of family background is reduced but remains highly significant if the potential pathways are accounted for in a probit regression.

[11] The size of the unexplained part nearly equals the marginal family background effect estimated in the probit regression including all observable mediators.

[12] The detailed decomposition of the unexplained part is available upon request.

Employing a Blinder-Oaxaca approach, I show that roughly 60% of the overqualification gap can be attributed to the fact that graduates differ in observable characteristics, i.e. the endowments effect. Concerning social differences in ability and skills, I find that differences in university grades significantly contribute to the overqualification gap. In contrast, social differences in school leaving examination grades are found to primarily affect overqualification through the selection into promising subjects. The most important mediator of the family background effect is the social difference in the choice of university type and subjects. This result points to the importance of the horizontal dimension of higher education in the context of parental influences on the risk of overqualification.

A substantial part of approximately 40% of the overqualification gap remains unexplained by differences in observable mediators. Most of the unexplained part can be attributed to unobserved heterogeneity between graduates from low PE families and graduates from high PE families. An important source for unobserved heterogeneity might be that the proxy variables employed are imprecise measures of mediating factors. Other potentially important factors, such as non-cognitive skills, are not observed. The unexplained family background effect could also arise because of discrimination based on preferences of potential employers. Concerning the individual characteristics included in the present analysis, I find no indication that the overqualification gap widens because employers value characteristics differently. However, it is possible that employers discriminate applicants on the basis of characteristics that are not included in the analysis.

It is difficult to infer policy implications from the findings since it is crucial to disentangle the effect of parental education on overqualification from other potential effects of inherited ability or disposition. However, the result that the incidence of overqualification strongly differs across university types and subjects is striking. In particular, the subjects Medicine & Law, Teaching, and STEM at traditional universities exhibit considerably low overqualification rates. This finding holds for both types of graduates from low PE and high PE families. Since low PE graduates are significantly less likely to choose these subjects, I find that the social difference in the choice of university type and subject is the most relevant pathway for the social overqualification gap. Therefore, selective measures aiming to inform and motivate students from low PE families to choose promising subjects at traditional universities might reduce their overqualification risk, even though the estimated effects of studying in a particular subject might partly arise due to self-selection.

As this study focuses on graduates observed one year after graduation, no conclusions can be drawn on the correlation between family background and overqualification at later stages of the career cycle. It is a question for further research to what extent initial overqualification affects the long-run career prospects of graduates in Germany. If overqualification is permanent at the individual level, the offspring of low PE families can get trapped in bad matches and underutilise their human capital in the long-run.

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Chapter 3

Dynamics of Overqualification: Evidence from the Early Career of Graduates

Abstract

This study analyses the persistence and true state dependence of overqualification because the size of potential detrimental effects strongly depends on whether it represents a transitory or a permanent phenomenon. Employing individual-level panel data for Germany, I find that overqualification is highly persistent for a substantial share of tertiary graduates over the first ten years of their career cycle. Accounting for unobserved heterogeneity, results from dynamic random-effects probit models suggest that a moderate share of the observed persistence can be attributed to a true state dependence effect. Unobserved factors are found to be the main driver of the high persistence of overqualification and selection into initial overqualification at the start of the career seems to be highly important. Persistence is also partly attributable to observed heterogeneity. Employing a rich set of explanatory variables, I find that overqualification transitions are related to ability, field of study, occupational mobility, and preferences for adequate job matches.

3.1 Introduction

Labour markets of industrialised countries share the common feature that substantial shares of workers are holding jobs which are not commensurate to their educational attainment. Summarising previous studies, Leuven and Oosterbeek (2011) find that an average share of 30% of workers acquired a level of qualification exceeding the educational requirement of their current job. Consequently, these workers are formally overqualified for their job, i.e. they experience a vertical educational mismatch. This suboptimal allocation of workers across jobs may signal an inefficient allocation of skills in the labour market because available skills are not fully exploited. According to assignment theory allowing for skill-heterogeneity among workers and jobs (Sattinger, 1993), workers holding jobs below their qualification level cannot fully utilise their human capital and thus do not reach their individual production capacity. At the economy level, misallocations in the form of overqualification may imply significant productivity losses (McGowan and Andrews, 2015). Output losses may be particularly high if productivity is highly contingent on the precision of job matches and if different types of workers are poor substitutes (Gautier and Teulings, 2015). At the individual level, many studies infer the costs of overqualification from its effect on wages which are assumed to represent the marginal productivity of workers (Becker, 1964). Cross-sectional analyses consistently find that overqualified workers earn more than their co-workers in the same low-requirement job but less than equally educated individuals in adequate jobs (Duncan and Hoffman, 1981; Hartog, 2000). Panel studies accounting for skill-heterogeneity among equally educated workers provide mixed results. While some studies conclude that wage penalties only represent spurious correlations because overqualified workers have lower ability (Leuven and Oosterbeek, 2011; Tsai, 2010), other studies find that wage penalties diminish but remain significant after controlling for skill-heterogeneity (Kleibrink, 2015; Korpi and Tåhlin, 2009).

To what extent overqualification is detrimental at the economy or the individual level will strongly depend on its longevity. If overqualification occurs just transitorily at the start of the career before workers find suitable jobs, losses may only arise in the short-run until available skills are optimally allocated. In contrast, if workers are permanently overqualified, long-term losses may arise because of an continuous underutilisation of their human capital. In this case, private and public educational investments into skills which are permanently untapped, i.e. unproductive, may be partly wasted because of reduced returns in terms of wages or tax revenues. This is of particular relevance in the context of the publicly subsidised expansion of tertiary education induced by a strong increase in the demand for skills and the notion that human capital promotes economic growth. Shifts in the relative demand for high-skilled labour are considered to largely result from skill-biased technical change, i.e. changes in production processes favouring the employment of high-skilled workers. Skill demand may rise due to technical change embodied in capital goods, such as information and communication technologies (Michaels et al., 2014), or due to disembodied forms of technical change, such as organisational change (Caroli and Van Reenen, 2001).[1] In order to meet the rising demand for skills, it is one of the main pillars of the European strategy for economic growth (EU2020) to ensure a steady increase in the supply of tertiary graduates (European Commission, 2010). At the aggregate level, overqualification of graduates may occur if the shift in supply is not balanced by the shift in demand for high-skilled labour. However, even in the absence of aggregate imbalances, overqualification at the individual level may arise as a consequence of worker and job skill-heterogeneity in conjunction with asymmetric information and labour market frictions inducing costly job search (Sattinger, 2012).

Predictions on the duration and, ultimately, the costs of overqualification at the individual level differ across related theories. According to career mobility theory (Sicherman, 1991), overqualification is only a short-term phenomenon and part of a human capital investment strategy of new labour market entrants. Workers deliberately choose jobs below their own level of education in order to acquire relevant on-the-job training and experience promoting upward mobility and a fast career progression. In contrast, further theories focus on labour market frictions and suggest that overqualification will be highly persistent at the individual level, e.g. because of segmented labour markets (Doeringer and Piore, 1971; Scherer, 2004). Descriptive findings based on panel data for graduates entering the labour market confirm a high persistence of overqualification and show that previously overqualified graduates are much more likely to be overqualified in the future (Verhaest and Velden, 2012). The observed persistence may partly arise as a consequence of constant individual-specific characteristics affecting the probability to be overqualified in every observation period, i.e. spurious state dependence. For instance, individuals may permanently hold low-requirement jobs because of an inferior level of human capital relative to equally educated individuals. In contrast, the persistence could be partly attributed to a behavioural effect such that past overqualification

[1] Other potential sources for rising skill demand include international trade (Feenstra and Hanson, 1999) or capital-skill complementarity (Krusell et al., 2000).

causally increases the probability of future overqualification, i.e. true state dependence. For instance, true state dependence of overqualification may arise because workers get trapped in a mismatch due to cognitive decline (De Grip et al., 2008), investments in specific human capital (Pissarides, 1994), or reduced job search effort on-the-job (Holzer, 1987). In terms of policy implications, it is crucial to detect whether overqualification arises due to differences in individual characteristics or because of true state dependence. If overqualification causally increases the probability of future overqualification, i.e. true state dependence is present, policy measures that prevent entry into or promote exits out of overqualification can induce a lasting reduction in the rate of overqualification. In contrast, if persistence arises solely due to constant individual characteristics, policies facilitating exits out of overqualification have little impact on future overqualification unless the factors causing overqualification are addressed directly.

The current study analyses the dynamic features of overqualification for the policy-relevant group of tertiary graduates. The main aim is to disentangle true state dependence from persistence arising due to differences in individual characteristics that are observed or unobserved. Dynamic models of labour market state choice which account for unobserved individual-specific effects face the problem of endogenous initial conditions. The “initial conditions problem” can be considered as an endogenous selection problem because individual-specific unobserved factors may affect both the persistence of a labour market state and the initial state in the first period available in the data (Heckman, 1981b). True state dependence is likely to be overestimated if potential endogeneity of the outcome in the first period is ignored (Chay and Hyslop, 2014). Therefore, I employ the dynamic random-effects probit model proposed by Wooldridge (2005). In order to integrate out the individual-specific effect, this estimator models the unobserved heterogeneity as a function of the initial condition, individual-specific explanatory variables, and a new random error that is uncorrelated with the initial condition.

The empirical analysis is based on panel data covering the first ten years of individual careers for university graduates in Germany (HIS-Graduate Panel). Interviews were conducted 1, 5, and 10 years after graduation and provide information on current overqualification and a rich set of explanatory variables such as university and school grades, field of study, or previous unemployment. Graduate overqualification is found to be considerably high over the observed time span. While 53% of the graduates who were overqualified in the previous interview remain overqualified in the next period, only 8% of previously well-matched graduates enter overqualification. Therefore, the raw state dependence observed in the data, i.e. the difference in the conditional probabilities to be overqualified, amounts to 45 percentage points. The dynamic effect of previous overqualification reduces to 34 percentage points when the set of observed characteristics is accounted for.

Accounting for unobserved heterogeneity, the results of the Wooldridge estimator suggest that a moderate share of the observed persistence can be attributed to a true state dependence effect. Previous overqualification experience is found to have a significant behavioural effect on future overqualification amounting to 3 percentage points. Furthermore, the results suggest that unobserved factors are the main driver of the high persistence of overqualification over the early career of graduates. In particular, unobserved characteristics driving the selection into the initial state of overqualification observed one year after graduation are strongly related to the probability to remain overqualified later on. Relevant unobserved factors might include preferences for particular job characteristics found in low-requirement jobs or labour market frictions such as regional immobility (Büchel and Van Ham, 2003).

Sensitivity analyses show that the findings on true state dependence are robust to the choice of the econometric model and the measure for educational mismatch. First, the estimations are replicated employing the estimator proposed by Heckman (1981b). The Heckman estimator differs from the Wooldridge estimator in the way how unobserved heterogeneity and the initial conditions are treated. Second, the baseline estimations are replicated using a measure for the mismatch in the *field* of education instead of the *level* of education. Since the main results emphasise the importance of the initial overqualification experience, a third sensitivity analysis examines a potential explanation for the selection into early overqualification. In particular, I test the prediction of the career mobility theory that overqualification may occur because new labour market entrants voluntarily choose jobs below their own qualification anticipating that on-the-job training and experience will facilitate a higher wage growth (Sicherman, 1991).

The contribution to the existing literature is twofold. First, the study complements the scarce literature on true state dependence of overqualification. A common feature of previous studies is that they rely on samples drawn from the entire working population observed at different stages of individual career cycles. Consequently, as opposed to the present study, they do not provide evidence for equally educated workers who enter the labour market and are observed over the early career cycle. Focussing on a sample of workers at the onset of their career is of particular relevance for testing theories hypothesising that overqualification is a short-term phenomenon among new labour market entrants, e.g. career mobility theory. The first available information on overqualification is observed much more closely to the real start of the labour market experience in the present study than in the few previous studies accounting for endogenous initial conditions. Furthermore, previous studies focus on rather short-term transitions between consecutive years, while the present study analyses dynamics of overqualification between observations approximately 5 years apart. This eases a problem studies based on annual data often face, i.e. one single spell of overqualification may span two consecutive years inducing spurious state dependence.

As a second contribution, the study examines the role of observed characteristics that have been analysed only scarcely, if at all, in the dynamic context of overqualification so far. In particular, I show that ability as measured by university and school grades is significantly associated with a lower probability to remain or to become overqualified.[2] Similarly, study characteristics such as university type and field of study affect overqualification transitions. Furthermore, the role of occupational mobility and the dynamic interdependence between vertical and horizontal educational mismatches are analysed. Finally, direct information on

[2] These findings stem from an econometric model that does not account for the selection into the previous overqualification status.

individual preferences for a future job match are employed. While high preferences are positively associated with a lower probability to experience overqualification in the future, a substantial share of graduates with high preferences will still be overqualified pointing to potential labour market frictions inducing involuntary overqualification.

The remainder of this chapter is organised as follows. Section 3.2 provides a review of the related theoretical and empirical literature. Section 3.3 introduces the data and provides descriptive statistics. In Section 3.4 the role of observed heterogeneity for the dynamics of overqualification is analysed. Section 3.5 describes the econometric model employed to analyse the true state dependence of overqualification. Section 3.6 provides the main results and sensitivity analyses are provided in Section 3.7. Section 3.8 discusses the results and concludes.

3.2 Background Discussion

This section provides a review of the related literature. First, an overview on the theoretical explanations for the existence and, in particular, the longevity of overqualification is provided. Second, the results of previous empirical studies on the dynamics of overqualification are summarised and discussed.

3.2.1 Theoretical Background

Several labour market theories suggest that overqualification is only a temporary phenomenon. *Human capital theory* predicts that workers will always earn their marginal product because production processes are continuously adapted to available input factors (Becker, 1964; Mincer, 1974). Therefore, underutilisation of human capital should not occur in the labour market and overqualification will not exist in equilibrium. However, overqualification could temporarily arise if the labour market is in disequilibrium because of a sudden increase in the supply of better educated workers inducing a decline in their relative wages. In this situation, employers could hire more qualified, i.e. more productive, workers into positions previously held by individuals with lower educational levels (Borghans and Grip, 2000). However, overqualification will disappear once individuals respond to lower returns to education by reducing their investments into education and firms adjust their production processes in order to make use of the higher supply of skilled workers. According to human capital theory, prolonged overqualification can only be explained as representing a statistical artifact arising from the fact that human capital is observed only incompletely.[3]

According to *matching theory*, the job match quality cannot be foreseen by workers and firms because of imperfect information (Jovanovic, 1979). Because job match quality is an "experience good", workers might accept jobs that turn out to not match their skills. As a consequence, mismatched workers will start to search for new positions and improve their job matches until they find an appropriate position. In a similar vein, search theories stress the

[3] This argument will be discussed in more detail below.

costly and time-intensive nature of job search activities (Burdett, 1978). Workers might accept a job offer below their educational level temporarily while pursuing their search on-the-job. Therefore, overqualification is only transitory within these frameworks and will predominantly occur at the beginning of the workers' careers.

As suggested by the *career mobility theory*, overqualification might also be a part of a planned career path (Sicherman and Galor, 1990; Sicherman, 1991). Workers might deliberately enter jobs for which they are overqualified in order to acquire further skills through on-the-job training which promote a rapid career development. From this point of view, overqualification at the start of the career is short-lived and might serve as a stepping-stone to better jobs in the future within or outside the firm. The career mobility theory provides explanations for both the employee's as well as the employer's motivation for accepting a transitory phase of overqualification. In addition to higher starting wages, potential returns to investments in high levels of education include better prospects of promotion within firms or an upward move to other firms. Employees maximizing their earnings over their career cycle might accept a lower pay at the start of their contract in exchange for a favourable position in the firm's promotion queue assuring higher future earnings. In case promotions fail to appear as planned, workers will move to another firm. From a firm perspective, employers might be willing to accept this agreement since they have the opportunity to test whether the new workers are eligible for higher and more demanding positions within the firm at lower costs during the overqualification period. According to the theory, mismatches are resolved by either the employee or the employer in the long-run.

On the contrary, other theories focus on labour market frictions and suggest that overqualification may be persistent at the individual level. In the *job-competition model* (Thurow, 1972), an applicant's place in the queue for a promising job is largely determined by his education. Under imperfect information, employers use education as a proxy for future job performance and trainability. From the employer's perspective, a higher level of an applicant's education implies lower training costs. Based on the employer's preference to hire those applicants who are likely to be the cheapest to train, overqualified candidates have a head start in the job queue because they raise the highest expectations in terms of returns to further educational investments. This model, thus, gives an explanation for the employer's motivation for preferring job candidates with schooling exceeding the job requirements. Concerning the supply-side, the model does not directly explain the motivation of workers to accept a job offer below their educational attainment since overqualified workers cannot realise a wage premium. The formal qualification only determines the position in the job queue, but does not affect the wage offer. However, the job-competition model suggests another potential supply-side explanation for enduring overqualification. Individuals might acquire the highest level of education in order to secure the best possible position in the job queue. If consequently the educational attainment of workers increases, a reduction in the returns to schooling contributes to a crowding-out of less qualified workers into low wage jobs or entirely out of the labour market. Since investments are not reduced despite of lower returns to education in order to retain the position in the job queue, a higher share of high-skilled individuals will end up in jobs below their skill level.

Furthermore, according to the model, most actual required skills are learned through experience or on-the-job training. Therefore, workers in low-level occupations cannot compete for more demanding positions suggesting that the state of overqualification is likely to be permanent.

The effect of geographic restrictions on the probability to be overqualified is emphasised by the *spatial mobility theory* (Büchel and Van Ham, 2003). Due to costs of commuting and migration, individuals are assumed to search for jobs in their local (regional) labour market. Since the number of suitable jobs will be lower in smaller, regional labour markets than in the global market, the probability of overqualification is assumed to depend on the spatial mobility of job seekers. Empirical support for the spatial mobility theory is provided by the finding that overqualification is less likely in larger and thicker local labour markets (Abel and Deitz, 2015; Büchel and Van Ham, 2003). As a consequence, overqualification caused by geographic restrictions could persist as long as spatial flexibility of workers or job opportunities in a given local labour market are not improved.

The *assignment model* is concerned with the problem of allocating individuals with different skill levels to jobs with varying complexity (Sattinger, 1993). In practice, mismatches are likely to occur because the distribution of workers and their skill levels will not fully match the distribution of available jobs and their skill requirements. Furthermore, workers might accept a job offer above their reservation wage before finding the optimal match because of imperfect information. In the same vein, employers might hire an applicant before finding the optimal one. Therefore, the phenomenon of overqualification will be an inevitable outcome of such a complex allocation process. According to the assignment theory, the workers' productivity does not only depend on the individual human capital, but also on the match quality between the individual characteristics and job tasks. Better skilled workers have a comparative advantage in more complex jobs. Mismatches occur if workers are not assigned to a job type where their comparative advantages are best utilised. Consequently, high-skilled workers holding a job with low skill requirements will not reach their individual productive capacity. The assignment model therefore contradicts both the job-competition model suggesting that solely the job characteristics determine productivity and the human capital model suggesting that solely the worker's skills predict productivity (Hartog, 1986). Concerning the longevity of overqualification, models combining assignment with costly search have shown that job mismatch might be a long-lasting phenomenon at the individual level (Albrecht and Vroman, 2002; Dolado et al., 2009; Teulings and Gautier, 2004).

Hiring decisions of employers will be governed by productivity-based considerations. From a *firm perspective*, hiring overqualified candidates might induce productivity losses due to lower job satisfaction and motivation, or a higher incidence of shirking and absenteeism (Büchel, 2001). Furthermore, a higher probability of frequent job changes could result in a loss of company-specific human capital and induce transaction costs for finding new job candidates. Recent studies employing firm-level panel data, however, find that firm productivity is positively affected by the level of required education as well as by additional years of overeducation (Kampelmann and Rycx, 2012; Mahy et al., 2015). Therefore, overqualified workers seem to be more productive than their well-matched colleagues. This result is in line with the literature on wage effects of overqualification finding significant returns to surplus years of education that, however, are lower than the returns to required schooling. Taken together, these findings support the hypothesis that overqualified workers earn more than their well-matched job colleagues because they are more productive than the latter. Mahy et al. (2015) conclude that the significant positive effect of overqualification on firm productivity seems to indicate that additional skills and capabilities acquired in school outweigh potential effects of job dissatisfaction. Hiring applicants with higher skills than necessary for the job could also be used as a form of insurance strategy in order to ensure a continuous and uninterrupted supply of high-skilled labour to the firm (Cedefop, 2012; Desjardins and Rubenson, 2011). These findings suggest that employers might have an incentive to hire and retain overqualified employees. This demand side effect might contribute to the persistence of overqualification (Büchel, 2002).

As frequently discussed in the literature, overqualification may also arise due to individual heterogeneity among workers who attained the same level of education (Hartog, 2000). If the relevant individual-specific factors are persistent over time, they could lead to a high degree of overqualification persistence. Since this does not imply a causal dependence between previous and future overqualification experience, this mechanism is referred to as spurious state dependence (Heckman, 1981a). In line with the human capital theory, individuals might be overqualified because of low ability for their level of qualification. This situation then might be consistent with a well-functioning labour market rather than indicating a form of market failure. Since skill formation also depends on other factors than formal education, the measure of overqualification might neglect other important components of the workers' human capital required for demanding job tasks. In line with this human capital compensation hypothesis, several studies have shown that individuals with an inferior level of ability and skills are more likely to be overqualified (Büchel and Pollmann-Schult, 2004; Chevalier and Lindley, 2009). Consequently, a share of the overqualified workers might just be "apparently mismatched" such that observed overqualification does not come along with a significant underutilisation of skills (Chevalier, 2003; Green and McIntosh, 2007; Green and Zhu, 2010). The fact that a transition into a formally adequate job might not be an option for this group of workers might translate into highly persistent overqualification and, thus, into spurious state dependence.

Another reason for enduring overqualification may be that workers voluntarily choose positions below their own level of education. They might have preferences for non-pecuniary job characteristics available in low-requirement positions. For instance, these workers might prefer an easier workload than they can find in jobs which they are adequately educated for. Employing data on UK graduates, McGuinness and Sloane (2011) find that overqualified male workers are more likely to value and to opt for jobs which offer a greater balance with family life. This group is also found to place a lower emphasis on high earnings. This suggests the occurrence of compensating wage effects, i.e. a lower wage for an overqualified worker could be explained by better non-wage characteristics provided by the job (Sattinger, 2012). As long as the workers' preferences for low-requirement jobs remain unchanged over time, this could induce another source for spurious state dependence of overqualification.

Alternatively, overqualification persistence could arise because of a causal effect of previous overqualification experience implying true state dependence. Being overqualified in one period may in itself increase the probability to be overqualified in the next period, even if compared to another identical individual who was not overqualified in the base period. Several mechanisms could explain such a state dependence effect of overqualification. Most of these mechanisms have been discussed in the literature on state dependence in low wage and unemployment but seem to be similarly relevant for overqualification which is often associated with wage penalties and the underutilisation of skills.[4] Overqualification may alter the process of human capital acquisition and job-specific human capital investments may lock overqualified workers into low-requirement positions (Pissarides, 1994). Workers' productivity may also be negatively affected by enduring overqualification for another reason. Knowledge and skills untapped during longer periods of overqualification may depreciate or become devalued because of changing skill requirements in jobs matching the educational level of workers (Heckman and Borjas, 1980). De Grip et al. (2008) find a significant relationship between overqualification and cognitive decline. Therefore, job mismatch may send negative signals to potential future employers who use previous overqualification experience as a screening device for the applicants' future productivity. According to McCormick (1990), the signal may be even more negative for overqualification than for unemployment.[5] In his model, unemployed high productive individuals will specialise in job search for high-skilled jobs rather than take an interim low-requirement position, while employers may use the individuals' job search strategy as a productivity signal if individual differences in productivity are unknown to them. Finally, overqualification spells may change the individuals' preferences or motivation to hold adequate jobs. Experiencing overqualification may lead to a lower perception of the own market value discouraging workers to apply for more adequate jobs in the future (Stewart and Swaffield, 1999). Overqualified workers may also be locked in low-quality jobs because of a reduced job search effort on-the-job (Holzer, 1987) or segmented labour markets (Doeringer and Piore, 1971).

3.2.2 Empirical Evidence

The longevity of mismatches is the focus of a growing strand of the empirical overqualification literature. Several studies have tried to assess the validity of the career mobility hypothesis stating that overqualification serves as a stepping-stone to better future jobs. In favour of the career mobility theory, early studies using simple cross-sectional data sets often found that experience and tenure are negatively correlated with the probability to be overqualified

[4] In this related literature, scarring effects of low pay and unemployment are well-documented (Arulampalam et al., 2000; Stewart and Swaffield, 1999).

[5] Kroft et al. (2013) provide experimental evidence for negative duration dependence of unemployment in the US. Sending fictitious job applications varying in past unemployment experience to real job postings, they find that the likelihood of receiving a callback for an interview significantly decreases with the length of the unemployment spell.

(Alba-Ramirez, 1993; Sicherman, 1991). Following studies, however, have found no evidence for a significant difference between promotion prospects of overqualified employees and adequately educated employees in similar jobs (Büchel, 2001). Employing wage growth as a more direct measure of upward mobility, Büchel and Mertens (2004) provide a test of the career mobility theory for Germany. Contrary to the theoretical prediction, they find that overqualified employees experience less wage growth than workers with the same level of qualification holding adequate jobs. In a similar study for Sweden, Korpi and Tåhlin (2009) also find no evidence for a higher wage growth among overqualified workers relative to well-matched workers in similar low-requirement jobs.

In recent years, cohort studies of school leavers offer new empirical tests on the career mobility at the time of labour market entry. Focusing on unemployed Flemish school leavers, Baert et al. (2013) show that taking up a job below the educational attainment significantly delays the transition into adequate employment. Based on a multi-national survey of college graduates in 13 European countries and Japan, Verhaest and Velden (2012) analysed the persistence of overqualification over the first five years of the career cycle. Among those graduates who were overqualified in their initial employment in the year 2000 between 30% (the Netherlands) and 58% (Switzerland) have remained overqualified in the year 2005. In contrast, on average only 5% of the graduates with a matching initial job have been found to be overqualified after five years. Similarly, Frenette (2004) finds that a share of 74% of Canadian graduates who were overqualified two years after graduation remained in that state three years later. Battu et al. (1999) make use of survey data collected 1, 5, and 11 years after graduation for a sample of UK graduates who completed their study programme in 1985. They find that approximately 30% of the graduates never had a job that required a tertiary degree during the observed time span. Finding a substantial rate of raw state dependence in the data sets employed, these studies suggest that overqualification is a persistent phenomenon rather than a transitory state for a substantial share of workers at the start of the career. However, these studies do not provide evidence whether the observed persistence arises because of time-invariant unobserved heterogeneity, i.e. spurious state dependence, or a genuine behavioural effect of previous overqualification, i.e. true state dependence.

A few recent studies employ more advanced panel estimation models in order to evaluate the size of true state dependence of overqualification by controlling for unobserved individual heterogeneity. Employing annual German data from 2000 to 2008, Blázquez and Budría (2012) find a very high persistence rate of overqualification. While 86% of previously overqualified workers remain overqualified in the next year, only 2% of previously well-matched workers enter overqualification. Therefore, the difference in the conditional probabilities to be overqualified, i.e. the raw state dependence, amounts to 84 percentage points. Estimating a trivariate probit model, the authors show that a share of 18% of this raw state dependence can be attributed to a true state dependence effect. Employing the dynamic random-effects model proposed by Wooldridge (2005), the study by Boll et al. (forthcoming) also finds significant state dependence of overqualification in the German labour market for the time period from 1984 to 2011. The results are robust to the inclusion of two different measures for overqualification. Using the same estimation approach, Kiersztyn (2013) provides evidence for overqualification being a self-perpetuating state in Poland from 1988 to 2008. The risk of being overqualified is found to be four times higher for those workers who have been overqualified in the preceding wave relative to previously well-matched workers. Furthermore, Mavromaras and McGuinness (2012) find that skill mismatch, i.e. a situation where workers report that their skills are not fully utilised in their job, exhibits true state dependence in Australia.[6]

Only few studies have analysed which characteristics affect transitions into and out of overqualification over the path of individual careers. Using a panel data set for American workers, Clark et al. (2014) find that cognitive ability is a relevant factor for overqualification dynamics. Higher scores in a cognitive ability test have a positive and significant effect on the hazard rate out of overqualification. The authors also provide evidence for considerable differences in the dynamics of overqualification with respect to race, gender, and unemployment history. A higher rate of overqualification persistence is more prevalent among black workers and female workers. Furthermore, longer duration of previous unemployment delays the transition into a matching job. For Germany, Blázquez and Budría (2012) have shown that the probability to remain mismatched is significantly affected by the workers' personality traits. For instance, high scores in the Big Five personality dimensions conscientiousness and extraversion decrease the probability to remain overqualified.

A common feature of these studies on stated dependence of overqualification is that their results rely on samples of workers drawn from the entire working population observed at different stages of individual career cycles. Consequently, they do not measure state dependence for cohorts of equally educated workers who enter the labour market and are observed over the early years of the career cycle. It is the main aim of the present study to contribute to the reviewed literature by providing evidence on the extent of true state dependence of overqualification over the early career cycle of university graduates in Germany.

3.3 Data

The empirical analysis is based on two cohorts of the HIS-Graduate Panel covering university graduates who completed their study programme in 1997 and 2001, respectively.[7] It is a longitudinal nationwide study of tertiary graduates in Germany which surveys individuals of each cohort 1 year, 5 years, and 10 years after graduation.[8] This data set has several

[6] The skill mismatch variable is constructed using the individuals' responses to the following question: "To what extent do you agree with the following statement: I use many of my skills and abilities in my current job" (Mavromaras and McGuinness, 2012).

[7] Hochschul-Informations-System (2007): HIS-Graduate Panel 1997. GESIS Data Archive, Köln. ZA4272, `dx.doi.org/10.4232/1.4272`;
Hochschul-Informations-System (2010): HIS-Graduate Panel 2001. GESIS Data Archive, Köln. ZA5186, `doi:10.4232/1.5186`

[8] I thank the staff of the German Centre for Higher Education Research and Science Studies (DZHW) for the opportunity to access the data from the third interview not included in the scientific use files.

advantageous features with respect to my analysis. In comparison to survey data covering the entire working population, focusing the analysis on the policy-relevant group of graduates does not produce small sample sizes. This is of particular relevance in the context of the study since it focuses on the dynamics of overqualification which is a labour market outcome only a rather small share of graduates will be affected by. Only a large sample size allows to adequately analyse the subsequent labour market progression for the group of initially overqualified individuals. In addition, the individuals are jointly observed over the first ten years of their career cycles after entering the labour market as tertiary graduates and they face the same overall economic situation. In order to further increase the comparability of graduates, I exclude individuals who were older than 35 years at the time of graduation or who obtained the university entrance certificate abroad. After deleting observations with missing values in the relevant variables, the size of the remaining sample amounts to 5,987 graduates.[9] In order to test for systematic differences in sample attrition, I tested whether characteristics observed in the first interview significantly differ between individuals who dropped out of the survey and individuals who participated in all three interviews. Unfortunately, I find that stayers have significantly better grades than drop-outs so that a selection of more able graduates into the sample might be present. In contrast, I find no significant difference in the hourly wage rate at the time of the first interview between stayers and drop-outs. Since the incidence of overqualification at the time of the first interview is slightly lower for stayers than for drop-outs, however, the results on overqualification rates and persistence over the observed time span might be downward biased. Potential biases caused by sample attrition are not accounted for in the present analysis.

3.3.1 Dependent Variable

The focal dependent variable in this analysis is graduate overqualification. Overqualification indicates the occurrence of a vertical educational mismatch, such that workers hold a higher qualification than is required by their job or position. Three different measures for overqualification have been employed in the literature. They differ in the way how they evaluate the level of qualification that is needed for a job and are based on either the respondents' subjective assessments, realized matches within occupational classifications, or job analysts' ratings (see e.g. Hartog, 2000, for an overview). The present study employs a subjective measure of overqualification which is based on the respondents' self-assessment of the level of educational attainment required for their job. In particular, the graduates were asked whether they hold a position for which a tertiary degree is a conventional requirement. Graduates are defined to be overqualified if they indicate that their job usually does not require a tertiary degree. An indicator variable takes the value 1 for overqualified graduates and 0, otherwise. The binary overqualification

[9] According to the survey reports, the following number of interviews have been conducted in the respective waves for cohort 1997 (2001): wave 1: 9,582 (8,103); wave 2: 6,220 (5,427); wave 3: 5,477 (4,734) (Fabian and Briedis, 2009; Fabian et al., 2013). The reduction in sample size in the present study is mostly driven by missing values in control variables. The raw dynamics of overqualification based on all available observations do not significantly differ from those based on the estimation sample.

status is observed at each of the three survey waves conducted 1 year, 5 years, and 10 years after graduation for both cohorts.[10] The subjective measure of overqualification has one main advantage that is of particular relevance in the dynamic context of the study. As Hartog (2000) and others pointed out, the subjective measure captures specific job characteristics that only the job holder can assess and, thus, is not based on information aggregated at any occupational level. Therefore, in contrast to the objective measures defined for occupational classifications, a change in the overqualification status is possible within occupations because the tasks that have to be performed by the respondent have changed. However, since this measure relies on the workers' self-assessment, it is sensitive to potential differences in the individuals' perception of job requirements. Therefore, I have to assume that the assessment of job requirements does not systematically change over time at the individual level. Overall, the longitudinal cohort study design allows to analyse the dynamic features of overqualification over the first ten years of individual career cycles.

3.3.2 Explanatory Variables

Since this study focuses on the underlying mechanisms of overqualification persistence, it is important to include relevant characteristics that may determine mismatches and could contribute to spurious state dependence. Based on the vast empirical literature concerned with potential determinants of overqualification, this study incorporates a rich set of explanatory variables.

Individuals holding the same level of qualification may differ in (innate) ability and skills. In line with the human capital compensation hypothesis, several studies have shown that individuals with an inferior level of ability and skills are more likely to be overqualified (Büchel and Pollmann-Schult, 2004; Chevalier and Lindley, 2009). Low-ability graduates lacking the skills required for graduate jobs may contribute to a high persistence of overqualification because of their high probability to stay in their formally inadequate position. In order to account for differences in ability and skills among the graduates in the sample, this study incorporates school leaving examination grades and university grades as proxy variables. Although grades are surely an imperfect proxy for ability, previous research shows that cognitive as well as non-cognitive skills are relevant predictors of grades (Almlund et al., 2011; Poropat, 2009). School leaving examination grades may proxy primarily for differences in general skills and ability. Since the procedures of the school leaving examination differ across the 16 federal states in Germany, school grades are standardised within federal states. Concerning the differences in occupation specific skills that are relevant for holding graduate jobs in a given field, especially university grades may be a sound proxy variable. University grades are standardised within fields of study

[10] Only small fractions of 3%, 2%, and 1% of the graduates in the estimation sample have been unemployed at the time of wave 1, 2, and 3, respectively. Respondents currently unemployed at the time of the survey were asked to refer to their last job after graduation when they answer questions regarding their "current" job (including the question on overqualification). As a robustness check, all estimations provided in this chapter have been re-run excluding all currently unemployed respondents but the results remain qualitatively unchanged.

and university types in order to account for substantial differences in the distribution of grades along these dimensions.

Study characteristics, such as field of study or university type, are relevant determinants of overqualification among graduates in several countries (Berlingieri and Erdsiek, 2012; Dolton and Vignoles, 2000; Green and McIntosh, 2007). In Germany, individuals can choose between two tracks of tertiary education. They can either enrol at traditional universities or at universities of applied sciences. In general, traditional universities are academically more demanding than the practically oriented study programmes at universities of applied sciences. A dummy variable is generated taking the value 1 for graduates from universities of applied sciences and 0, otherwise. The respondents' fields of study are divided into four subject groups. The first subject group consists of the three subjects Medicine, Law, and Teaching which require a state examination as finals and can solely be studied at traditional universities. The remaining subjects can be studied at both university types and are divided into three groups, namely Science, Technology, Engineering, and Mathematics (STEM subjects), Business & Economics, and Social & Cultural Sciences. The individuals' study duration is another potentially important study characteristic that future employers may use as productivity-related signal. Since average durations of programmes vary across subjects and university types, the individuals' time needed for course completion measured in semesters is standardised within subject groups and university types.

The family background of graduates may also affect the probability to find an adequate job at the outset of the career cycle (Erdsiek, forthcoming). As a proxy for various forms of capital transmitted within families, I include a dummy variable into the analysis indicating whether at least one of the graduate's parents obtained a tertiary degree. Social background may be related to the individuals' motivation or aspiration, may provide advantageous social networks for finding promising jobs, or may ease the pressure to take a job offer due to financial constraints.

Concerning the role of gender for the occurrence of overqualification, previous results are mixed (Leuven and Oosterbeek, 2011). Most studies for Germany find a higher prevalence of overqualification among women than men (Büchel, 2001). According to the theory of differential overqualification (Frank, 1978), married women in smaller labour markets may have a higher risk of overqualification because of the optimisation of dual job search for couples. Married female workers may be tied movers or tied stayers since their job search is undertaken under the condition that the job search of their husbands is optimised because they are often the primary earners. For Germany, Büchel and Battu (2003) find that married women have a higher risk of being overqualified, especially when they live in rural areas. In order to analyse whether female graduates obtain a higher risk of overqualification over the early career cycle holding the characteristics constant, a gender dummy is included in the estimation models. Furthermore, in order to analyse whether the role of potential determinants as well as overqualification dynamics differ according to gender, the estimations are performed for splitted samples.

So far, all presented explanatory variables are time-constant. In the main part of the analysis, three time-variant explanatory variables are accounted for. Changes in job preferences and family responsibilities over the observed time span may occur because of parenthood and marital status, partly discussed in the context of the theory of differential overqualification above. On the one hand, parenthood as well as getting married may increase the individuals' reservation wage which is a relevant factor for the decision to accept a job offer below the own qualification level. On the other hand, increased family responsibilities may change the preferences for specific job characteristics, such as working hours and overall workload, in a way that less demanding jobs become a more favourable option.[11] Changes in parenthood and marital status are observed in each wave of the survey, i.e. 1, 5, and 10 years after graduation.

In addition, unemployment experience is included as a time-variant explanatory variable. Based on calender information provided by the respondents, the duration of previous unemployment experience (in number of months) is calculated for each of the three waves. The related literature on unemployment scarring commonly finds that past unemployment causally increases the probability of future unemployment and also the probability to be low paid (Cappellari and Jenkins, 2008a; Stewart, 2007). Therefore, individuals exiting unemployment are more likely to only find jobs with low skill requirements. In a similar vein, previously unemployed university graduates may have problems to find an adequate job because of the negative productivity-related signal for potential future employers. A further potential mechanism could be that prolonged unemployment decreases the reservation wage and graduates are more likely to accept low-requirement job offers below their educational level (Stewart and Swaffield, 1999). For Germany, Boll et al. (forthcoming) find that previous unemployment increases the risk of overqualification.

3.3.3 Descriptive Statistics

Table 3.1 provides summary statistics for the relevant variables. One year after graduation (t=1), a substantial share of 17% of the graduates is working in jobs that do not require a tertiary degree. After four more years (t=5), the average share of overqualified graduates has slightly decreased to 16%. Finally, ten years after graduation (t=10), the rate of graduate overqualification has fallen to a share of 14%. At the aggregate level, job mismatch thus seems to occur throughout the early career of graduates in Germany with a tendency to decrease with potential labour market experience.

Turning to persistence at the individual level, Table 3.2 depicts the frequency of observed patterns of overqualification dynamics over the three time periods. The majority of graduates (72%) was holding appropriate jobs at each t. In contrast, 6% of the graduates have been permanently overqualified in every t. The columns 5 and 6 provide the distribution of dynamic patterns conditional on the initial state of overqualification. 86% of initially well-matched graduates remained in adequate employment 5 and 10 years after graduation. However, among

[11]For instance, studies on the effects of maternity leave on subsequent labour market participation emphasise that mothers may reassess their work preferences after first birth (e.g. Fitzenberger et al., 2016).

Table 3.1: Summary Statistics

	Mean	SD	Min	Max
Dependent Variable				
Overqualification ($t = 1$)	0.17	0.37	0	1
Overqualification ($t = 5$)	0.16	0.37	0	1
Overqualification ($t = 10$)	0.14	0.35	0	1
Time-invariant controls				
Female	0.50	0.50	0	1
University grade[a]	3.03	0.62	1.0	4.0
School grade[a]	2.83	0.63	1.0	4.0
Study duration[b]	11.17	2.56	6	20
University of applied sciences	0.28	0.45	0	1
Business Administration & Economics	0.16	0.36	0	1
Medicine, Law, & Teaching	0.23	0.42	0	1
STEM subjects	0.44	0.50	0	1
Social & Cultural science	0.18	0.38	0	1
Age at graduation	26.92	2.35	22	35
Parents high-skilled	0.51	0.50	0	1
Cohort: 1997	0.49	0.50	0	1
Time-variant controls[c]				
Married	0.41	0.50	0	1
Children	0.34	0.48	0	1
Months unemployed	1.73	3.77	0	53
Observations	5987			

Note: t depicts the time of observation 1, 5, and 10 years after graduation; [a] The German grading system is reversed, so that 1 is the lowest grade and 4 is the highest, i.e. the best, grade; [b] Measured in semesters; [c] Overall statistics are presented. *Source:* HIS-Graduate Panel 1997, 2001

initially overqualified graduates only 41% were matched in both later periods and approximately one third remained overqualified over the observed time span.

The transition matrices in Table 3.3 provide the probabilities for entering and exiting overqualification. Among graduates who were overqualified in t=1, a share of 50% has managed to find a matching job five years after graduation, while the other half of this group remained stuck in a mismatch (top panel). The probability to be overqualified in t=5 is considerably lower for previously well-matched graduates. The majority of the graduates who found a matching job at the outset of their professional career still hold an adequate job after five years of potential labour market experience. Only 10% of the previously well-matched graduates hold a formally inadequate job in t=5. Taken together, the probability to be overqualified in t=5 is 40 percentage points higher for graduates already overqualified in the previous period relative to previously well-matched graduates. Therefore, overqualification exhibits a substantial rate of raw state dependence during the first five years of graduates' careers. The raw state dependence between t=5 and t=10 is even higher because the probability to enter overqualification decreases while the risk of remaining mismatched increases. The panels at the bottom show the probabilities and numbers of observation if the transitions are pooled. Raw state dependence then amounts to 45 percentage points.

Table 3.2: Patterns of Overqualification

Patterns of Overqualification 0: Matched; 1: Overqualified			All graduates	Matched in $t = 1$	Overqualified in $t = 1$
$t = 1$	$t = 5$	$t = 10$	Percent	Percent	Percent
0	0	0	71.5	86.0	
0	1	0	4.5	5.5	
0	0	1	3.7	4.4	
0	1	1	3.5	4.2	
1	0	0	6.9		41.0
1	1	0	2.8		16.9
1	0	1	1.5		8.9
1	1	1	5.6		33.2
			100	100	100

Source: HIS-Graduate Panel 1997, 2001

Table 3.3: Transition Matrices

From $t = 1$ to $t = 5$:		Status in $t = 5$		
		Matched	Overqualified	Total
	Status in $t = 1$			
	Matched	90.4	9.7	100
	Overqualified	49.9	50.1	100
	Total	83.6	16.4	100
From $t = 5$ to $t = 10$:		Status in $t = 10$		
		Matched	Overqualified	Total
	Status in $t = 5$			
	Matched	93.8	6.2	100
	Overqualified	44.9	55.1	100
	Total	85.8	14.2	100
Pooled:		Status in t		
		Matched	Overqualified	Total
	Status in $t-5$			
	Matched	92.1	7.9	100
	Overqualified	47.4	52.6	100
	Total	84.7	15.3	100
Pooled: No. of Observations		Status in t		
		Matched	Overqualified	Total
	Status in $t-5$			
	Matched	9,197	789	9,986
	Overqualified	943	1,045	1,988
	Total	10,140	1,834	11,974

Note: When observations are pooled, the previous period is indicated by $t-5$; *Source:* HIS-Graduate Panel 1997, 2001

3.4 Descriptive Analysis: Observed Heterogeneity

The descriptive evidence presented in the previous section has shown that overqualification is highly persistent at the individual level, however no conclusion on the underlying mechanisms can be drawn from these results. In the econometric analysis, I therefore focus on the role of observed and unobserved individual characteristics as well as the true state dependence effect for explaining the observed degree of overqualification persistence. In a first step, this section focuses on the role of observed heterogeneity for the dynamic features of overqualification.

3.4.1 Determinants of Overqualification

As a starting point, the incidence of overqualification over the early career of graduates is provided for relevant subgroups of the sample. In particular, the sample is stratified according to gender, field of study, and quartiles of the university grade. As shown in Table 3.4, the rate of overqualification is higher among female graduates than among male graduates in each time period. For both groups, the incidence of overqualification has reduced after 10 years of labour market experience. Considerable differences according to the field of study show a clear pattern which endures over the observed time span. The lowest rate of overqualification is observed for the fields Medicine, Law, and Teaching (approx. 4%). The incidence of overqualification is considerably higher among graduates of the STEM subjects (13%). However, overqualification is remarkably more likely in the fields Business Administration & Economics (28%) and Social & Cultural Science (27%). A clear pattern also evolves regarding the distribution of overqualified graduates across the quartiles of university grades.[12] The incidence of overqualification gradually decreases from the lowest to the top quartile. Graduates in the lowest quartile are more than twice as likely to become overqualified than graduates in the top quartile. Again, while the rate of overqualification decreases for each quartile over time, the pattern across quartiles remains unchanged.

In order to gauge the importance of all observed characteristics as potential determinants of overqualification in a multivariate analysis, a static random-effects probit model is estimated. The random-effects model is based on the assumption that the observed explanatory variables, comprised in row vector x_{it}, are uncorrelated to the individual-specific time-invariant unobserved heterogeneity, μ_i. As dependent variable, overqualification for each individual i at all 3 points in time t is used, y_{it}. The model is supposed to follow the standard assumptions for random-effects models (see pp. 509–511 in Wooldridge, 2013). In latent variable form, the model is given by

$$y^*_{it} = x_{it}\,\beta + \mu_i + \varepsilon_{it} \qquad i = 1, ..., N \qquad t = 1, ..., T \tag{3.1}$$

$$y_{it} = I\left[\, y^*_{it} > 0 \,\right] \tag{3.2}$$

[12]Note that university grades are standardised within fields of study and university types in order to account for substantial differences in the distribution of grades along these dimensions.

Table 3.4: Incidence of Overqualification by Subgroups

	$t = 1$	$t = 5$	$t = 10$	Total
Gender:				
Females	18.6	17.5	15.5	17.2
Males	14.9	15.4	12.9	14.4
Field of study:				
BusAdmin/Econ	28.7	28.4	25.6	27.5
Med/Law/Teach	4.8	3.5	4.0	4.1
STEM subjects	13.1	14.5	12.2	13.3
Soc/cult sciences	30.7	27.4	22.1	26.7
University grade:				
1. Quartile (Lowest Grades)	23.2	23.0	19.1	21.7
2. Quartile	18.9	19.1	16.2	18.1
3. Quartile	15.1	13.5	12.7	13.8
4. Quartile (Highest Grades)	9.8	10.1	8.7	9.5

Source: HIS-Graduate Panel 1997, 2001

The average partial effects for the observed explanatory variables are presented in Table 3.5. As shown by specification 1 including all respondents, female graduates significantly obtain a 4 percentage points higher probability to be overqualified than their male peers. Graduates with higher ability are less likely to be overqualified. This holds for school grades that may proxy primarily for differences in general skills and ability as well as for university grades that may proxy for occupation specific skills that are relevant for holding graduate jobs in a given field. Graduates who needed a relatively long time to complete their study programme, as measured by the standardised study duration in months, are significantly more likely to be overqualified. Workers who graduated from a university of applied sciences are more likely to be mismatched than graduates from traditional universities, even when differences in the fields of study are accounted for. In comparison to graduates in Business Administration & Economics, graduates in Medicine, Law, & Teaching as well as in STEM subjects are more likely to be adequately matched. Family background of graduates is significantly related to the risk of overqualification. The offspring of highly educated parents are less likely to be mismatched than their peers with a less advantageous social origin. The duration of previous unemployment experience is positively associated with the probability to be overqualified. This result remains robust if the determinants of overqualification are estimated for each wave separately.[13] Especially for overqualification one year after graduation it might have been hypothesised that a longer job search, i.e. experiencing unemployment, could increase the probability to find a matching job. However, unemployment after graduation seems to indicate difficulties to find an adequate job and exiting involuntary unemployment may increase the risk of overqualification.

The findings discussed so far hold for female as well as male graduates and even the effect sizes are similar (specifications 2 and 3). However, a distinct difference is found concerning

[13]Results from wave-specific estimations are available upon request. The results of the static random-effects model do not qualitatively differ from the results based on separate wave-specific probit estimations.

Table 3.5: Results, Static RE Probit

	Dependent Variable: Overqualification					
	All (1)		Female (2)		Male (3)	
Female	0.038***	(0.007)				
University grade	-0.029***	(0.003)	-0.030***	(0.005)	-0.027***	(0.004)
School grade	-0.014***	(0.003)	-0.020***	(0.005)	-0.010**	(0.004)
Study duration	0.016***	(0.003)	0.021***	(0.005)	0.0012***	(0.004)
U. applied sciences	0.035***	(0.008)	0.031**	(0.012)	0.036***	(0.010)
BusAdmin/Econ	ref.		ref.		ref.	
Med/Law/Teach	-0.115***	(0.006)	-0.154***	(0.011)	-0.081***	(0.007)
STEM subjects	-0.097***	(0.009)	-0.106***	(0.013)	-0.090***	(0.013)
Soc/Cult science	-0.006	(0.009)	-0.017	(0.014)	0.002	(0.013)
Age at grad. < 27	-0.013*	(0.007)	-0.007	(0.011)	-0.018**	(0.008)
Parents high-skilled	-0.018***	(0.006)	-0.018*	(0.010)	-0.016**	(0.008)
Married	0.003	(0.006)	0.002	(0.009)	0.004	(0.008)
Children	0.014**	(0.007)	0.034***	(0.010)	-0.002	(0.008)
Months unemployed	0.004***	(0.001)	0.005***	(0.001)	0.003***	(0.001)
σ	1.235	(0.039)	1.245	(0.054)	1.222	(0.056)
ρ	0.604	(0.015)	0.608	(0.021)	0.599	(0.022)
Log. Lik.	-6255.0		-3220.8		-3026.0	
Obs. Indiv.	5987		3009		2978	
Obs. Total	17961		9027		8934	

Note: Random-effects probit estimation; Average partial effects; Standard errors in parentheses; ρ: estimate of the cross-period correlation of the composite error term $\mu_i + \varepsilon_{it}$; Significant at 1% ***, significant at 5% **, significant at 10% *.

the role of parenthood. While the coefficient of the dummy variable for having at least one child is significant and positive for female graduates, parenthood has no effect for the male workers. Therefore, constraints related to family responsibilities seem to prevent only female graduates from holding well-matching jobs. A further difference is that male workers who were younger than 27 at the time of graduation are less likely to be overqualified, whereas there is no significant difference for female workers.[14]

Since the random-effects model is based on the assumption that explanatory variables are uncorrelated with the unobserved individual-specific effect, it remains unclear whether the findings represent causal effects. For instance, one explanation for a causal effect of grades and study duration may be that they provide productivity-related signals that future employers incorporate in their hiring decisions. On the contrary, the variables may merely pick up effects of correlated unobserved attributes, e.g. individuals with worse grades and longer study duration may also have lower preferences for demanding graduate jobs. Indeed, the results of the static random-effects model indicate that unobserved heterogeneity is a key factor for the persistence of overqualification. The importance of the unobserved heterogeneity for explaining the total variance in overqualification can be gauged from the estimated equi-correlation of the composite

[14]The gender-specific effect of age at graduation remains unchanged if parenthood and marital status are ignored.

error term, i.e. $\rho = \sigma_\mu^2 \,/\, (\sigma_\varepsilon^2 + \sigma_\mu^2)$.[15] A significant share of 60% of the variation in the dependent variable is explained by unobserved heterogeneity in both samples of female and male graduates.

3.4.2 Overqualification Persistence

Turning to the dynamic features of overqualification, this section starts with a simple dynamic pooled probit model. In addition to the aforementioned explanatory variables, the lagged overqualification status is included as a determinant for future overqualification experience. The simple model is based on the assumption that previous overqualification is exogenously given. This critical assumption will be relaxed later on in this chapter. The econometrical model outlined in Section 3.5 will take potential selection into previous overqualification into account in order to estimate the extent of true state dependence. As for now, a stepwise inclusion of individual characteristics into a simple dynamic model allows us to gauge the relevance of observed factors for overqualification persistence from changes in the coefficient of the lagged dependent variable.

As shown in the first specification in Table 3.6, previous overqualification is strongly related to future overqualification.[16] Controlling only for cohort membership and gender, previously overqualified graduates obtain a 44 percentage points higher probability to be overqualified in the next period. This resembles the raw state dependence shown and discussed in the data section. The average partial effect of the lagged dependent variable is moderately reduced by 2 percentage points after including sociodemographic characteristics as well as previous unemployment spells into the model. Parental background, age at graduation, and unemployment experience are significantly related to overqualification. In contrast to most studies concerned with state dependence of labour market outcomes, I am able to include further explanatory variables concerning the study programme and individual ability. Accounting for differences across university types and fields of study in specification 3, the effect of previous overqualification is substantially reduced to 36 percentage points. Specification 4 additionally includes the proxy variables for ability resulting in a further reduction of the dynamic effect. Taken together, approximately one fifth of the average partial effect of previous overqualification can be explained by observed heterogeneity because the state dependence effect is reduced by 10 percentage points in specification 4 as compared to specification 1. Heterogeneity concerning study characteristics and individual ability seems to be particularly relevant.[17] The question to what extent the remaining dynamic effect of 34 percentage points can be attributed to unobserved heterogeneity or to true state dependence will be the focus of the main analysis in this chapter.

[15] Note that $\varepsilon_{it} \,|\, X_i, \mu_i \sim N(0,1)$ and $\mu_i \,|\, X_i \sim N(0, \sigma_\mu^2)$.

[16] Since the lagged dependent variable is included, the estimates are based on overqualification status five years as well as ten years after graduation as dependent variables. The standard errors are clustered at the individual level.

[17] The results remain unchanged if random-effects models are estimated instead of pooled probit models or if the sample is splitted for female and male graduates.

Table 3.6: Results, Dynamic Pooled Probit

	Dependent Variable: Overqualification							
	(1)		(2)		(3)		(4)	
Overqualification ($t-5$)	0.442***	(0.013)	0.423***	(0.013)	0.360***	(0.013)	0.342***	(0.013)
Female	0.014**	(0.006)	0.018***	(0.006)	0.024***	(0.006)	0.022***	(0.006)
University grade							-0.019***	(0.003)
School grade							-0.008**	(0.003)
Study duration							0.007**	(0.003)
U. applied sciences					0.022***	(0.007)	0.020***	(0.007)
BusAdmin/Econ					ref.		ref.	
Med/Law/Teach					-0.123***	(0.007)	-0.125***	(0.007)
STEM subjects					-0.057***	(0.008)	-0.058***	(0.008)
Soc/Cult science					-0.022***	(0.008)	-0.020**	(0.008)
Age at grad. < 27			-0.030***	(0.006)	-0.025***	(0.006)	-0.012*	(0.007)
Parents high-skilled			-0.018***	(0.006)	-0.008	(0.006)	-0.005	(0.006)
Married			-0.005	(0.007)	-0.005	(0.007)	-0.004	(0.007)
Children			0.011	(0.007)	0.013*	(0.007)	0.012*	(0.007)
Months unemployed			0.004***	(0.001)	0.004***	(0.001)	0.004***	(0.001)
Log. Lik.	-4116.3		-4068.7		-3933.4		-3897.2	
Obs. Indiv.	5987		5987		5987		5987	
Obs. Total	11974		11974		11974		11974	

Note: Pooled Probit estimation; Average partial effects; Standard errors clustered at the individual level; Previous period indicated by $t-5$; Significant at 1% ***, significant at 5% **, significant at 10% *.

3.4.3 Determinants of Overqualification Transitions

Analysing the role of observed characteristics for overqualification dynamics more directly, this subsection provides results on the determinants of transition probabilities, i.e. exits from and entries into overqualification. For this purpose, all observations in the data are characterised as first-order markov chains indicating the overqualification status in period $t-5$ and t.[18] Two split samples are constructed that comprise a) all observations for which the status in period $t-5$ has been well-matched and b) all observations for which the status in period $t-5$ has been overqualified. As depicted in the bottom panel in Table 3.3, the first sample of previously well-matched graduates comprises 9,986 observations and the second sample of previously overqualified graduates comprises 1,988 observations. Based on separate probit estimations on both samples, the probability of entering and remaining in overqualification can be analysed, respectively. In both equations, the binary dependent variable is overqualification status in period t, y_{it}, taking value 1 for overqualified graduates and 0, otherwise. It is important to note that sample selection into the state of overqualification in $t-5$ is not controlled for. Thus, in contrast to the econometric model that will be employed for the analysis of true state dependence in the next section, the initial condition is assumed to be exogenous in the analysis of the transition probabilities presented here.

[18]The first and second interview were conducted approximately 4 years apart and the second and third interview approximately 5 years apart. In order to increase readability, the previous period is indicated by $t-5$.

Table 3.7 presents the average partial effects of observed characteristics on the probability to enter overqualification from a previous adequate match (specification 1-3) and to remain in overqualification (specification 4-6). Holding the other characteristics fixed, a higher probability for both entering and remaining overqualified is found for female graduates. Transition probabilities are also related to the individuals' ability. Better university grades are significantly associated with a lower probability to enter overqualification as well as to remain overqualified, though the latter effect is only significant for female graduates. In addition, better school grades lower the risk of entering overqualification for female graduates. Concerning the role of study characteristics, differences in transition probabilities with respect to fields of study exhibit the most robust pattern. Relative to the reference group of Business Administration & Economics, graduates of the subjects Medicine, Law, Teaching as well as STEM graduates are significantly less likely to enter overqualification or to remain overqualified. Moreover, graduates from universities of applied sciences seem to be at higher risk to enter or stay in overqualification and a longer study duration is associated with a higher risk to enter overqualification for male graduates.

One finding for the determinants of overqualification presented in subsection 3.4.1 was that parenthood is associated with a higher probability of overqualification for female graduates only. This relation seems to stem from the fact that parenthood increases the risk of remaining overqualified rather than an effect of parenthood on entering overqualification. The probability to remain overqualified is 13% higher for mothers than for childless previously overqualified female graduates. For males, the effect of parenthood is much lower and insignificant. Unemployment seems to frequently precede the entry into overqualification. For both female and male graduates, experiencing longer periods of unemployment is significantly and positively correlated with the probability to enter overqualification. Unemployment experience also is positively correlated to the probability to remain overqualified, but the effect is only marginally significant for the pooled sample of female and male graduates.

Table 3.8 presents results for three further potential factors that may determine the probability to switch the matching status: occupational mobility, horizontal mismatch, and preferences for future job match. Many studies have shown that mobility across occupations is a widespread phenomenon.[19] Accounting for ability and further potential determinants, Longhi and Brynin (2010) find that overqualification experience is associated with a higher probability of a subsequent occupational move in Germany. However, they do not provide results on the matching quality in the new occupation. The related economic literature on occupational mobility primarily focuses on its effects on wages and the extent of transferability of specific human capital across occupations or firms (Gathmann and Schönberg, 2010; Groes et al., 2015). Contributing to this literature, I analyse whether occupational change is associated with the probability of a career progression as measured by the vertical job match for previously mismatched graduates. Occupational mobility is measured in terms of a dummy variable taking the value 1 if the worker

[19]See the extensive list of references provided by Fitzenberger et al. (2015) for the US and Western European labour markets.

Table 3.7: Results, Overqualification Transitions

	Dependent Variable: Overqualification in t					
	Matched in $t-5$			Overqualified in $t-5$		
	All (1)	Female (2)	Male (3)	All (4)	Female (5)	Male (6)
Female	0.016***			0.058**		
	(0.006)			(0.027)		
University grade	-0.015***	-0.015***	-0.014***	-0.043***	-0.051***	-0.028
	(0.003)	(0.004)	(0.004)	(0.012)	(0.016)	(0.018)
School grade	-0.007**	-0.013***	-0.001	-0.010	-0.006	-0.021
	(0.003)	(0.004)	(0.004)	(0.013)	(0.017)	(0.019)
Study duration	0.006**	0.005	0.009**	0.008	0.020	-0.005
	(0.003)	(0.004)	(0.004)	(0.011)	(0.016)	(0.017)
U. applied sciences	0.014**	0.014	0.015	0.053**	0.056	0.053
	(0.007)	(0.010)	(0.009)	(0.026)	(0.036)	(0.038)
BusAdmin/Econ	ref.	ref.	ref.	ref.	ref.	ref.
Med/Law/Teach	-0.090***	-0.107***	-0.076***	-0.216***	-0.242***	-0.129
	(0.006)	(0.010)	(0.007)	(0.053)	(0.064)	(0.107)
STEM subjects	-0.041***	-0.050***	-0.035***	-0.151***	-0.064	-0.207***
	(0.008)	(0.011)	(0.011)	(0.030)	(0.046)	(0.040)
Soc/Cult science	-0.014*	-0.022**	-0.011	-0.050	-0.050	-0.016
	(0.008)	(0.011)	(0.013)	(0.032)	(0.041)	(0.052)
Age at grad. < 27	-0.006	0.003	-0.016*	-0.052*	-0.067**	-0.033
	(0.006)	(0.009)	(0.008)	(0.027)	(0.034)	(0.045)
Parents high-skilled	-0.009*	-0.007	-0.011	0.026	0.011	0.039
	(0.005)	(0.008)	(0.008)	(0.024)	(0.031)	(0.037)
Married	-0.002	-0.007	0.003	-0.016	0.015	-0.055
	(0.006)	(0.009)	(0.010)	(0.027)	(0.035)	(0.044)
Children	-0.007	-0.003	-0.011	0.079***	0.126***	0.039
	(0.006)	(0.009)	(0.010)	(0.027)	(0.036)	(0.043)
Months unemployed	0.004***	0.0.004***	0.003***	0.004*	0.003	0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Pseudo-R^2	0.072	0.096	0.052	0.035	0.049	0.038
Observations	9986	4934	5052	1988	1084	904

Note: Pooled probit estimation; Standard errors clustered at the individual level; Significant at 1% ***, significant at 5% **, significant at 10% *.

has changed occupations between two periods and 0, otherwise.[20] The graduates' occupation in each wave is measured in terms of occupational fields defined by Tiemann et al. (2008). The authors employ German data on tasks that are performed in 369 different occupations defined at the 3-digit level of the German Classification of Occupations 1992 (KldB 1992) and identify 54 occupational fields that are highly homogenous in terms of tasks predominantly performed by job holders.

The results presented in Panel A of Table 3.8 show that the effect of an occupational move on future matching quality depends on the initial overqualification status. Among previously well-matched graduates, occupational mobility is significantly associated with an increase in the

[20]Note that I cannot observe within-firm mobility or firm changes that do not come along with occupational changes with the data at hand.

Table 3.8: Results, Overqualification Transitions, Additional Determinants

	Dependent Variable: Overqualification in t					
	Matched in $t-5$			Overqualified in $t-5$		
	All (1)	Female (2)	Male (3)	All (4)	Female (5)	Male (6)
Panel A:						
Occupational mobility	0.052***	0.083***	0.025***	-0.070***	-0.076**	-0.072**
	(0.007)	(0.011)	(0.009)	(0.023)	(0.053)	(0.033)
Occupation: Base year	No	No	No	No	No	No
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.084	0.126	0.055	0.038	0.053	0.042
Observations	9986	4934	5052	1988	1084	904
Panel B:						
Occupational mobility	0.028***	0.042***	0.013	-0.068***	-0.074**	-0.057*
	(0.007)	(0.010)	(0.009)	(0.022)	(0.029)	(0.033)
Occupation: Base year	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.144	0.197	0.097	0.110	0.153	0.088
Observations	9968	4926	4732	1953	1061	883
Panel C:						
Horizontal mismatch ($t-5$)	0.052***	0.056***	0.048***	0.062***	0.101***	0.005
	(0.010)	(0.015)	(0.014)	(0.023)	(0.031)	(0.035)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.078	0.103	0.058	0.039	0.060	0.038
Observations	9693	4762	4931	1961	1066	895
Panel D:						
Preference: Low	ref.	ref.	ref.	ref.	ref.	ref.
Preference: Medium	-0.024*	-0.027	-0.021	-0.085**	-0.136***	-0.016
	(0.014)	(0.018)	(0.020)	(0.041)	(0.053)	(0.064)
Preference: High	-0.047***	-0.050***	-0.043**	-0.173***	-0.198***	-0.127***
	(0.012)	(0.016)	(0.018)	(0.037)	(0.049)	(0.055)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.069	0.107	0.049	0.049	0.057	0.066
Observations	5003	2484	2519	984	525	459

Note: Pooled probit estimation; Standard errors clustered at the individual level; Significant at 1% ***, significant at 5% **, significant at 10% *.

probability to be overqualified of about 5 percentage points. In contrast, occupational changes seem to be utilised as a route out of overqualification. Previously overqualified graduates who change their occupation obtain a 7 percentage points lower probability to remain overqualified than previously overqualified stayers. In order to compare movers and stayers within occupations, Panel B introduces fixed effects for the initial occupation. Once previously well-matched movers are compared to their co-workers in the same occupation, the estimated positive effect on the risk to become overqualified decreases by approximately 50% and becomes insignificant for male graduates. In contrast, for previously overqualified workers the effects hardly change and they are still significantly more likely to achieve a career progression in terms of an adequate job match in comparison to their previous co-workers.

Following the article by Robst (2007), a growing number of studies recently has started to focus on horizontal mismatch as a further dimension of educational mismatch besides overqualification. These studies concentrate on the potential mismatch between an individual's *field* of education and the skill requirements of his/her occupation. As opposed to more general skills, it is hypothesised that the field-specific skills acquired during education have to meet the occupational skills required to work in a specific occupation in order to fully utilise the human capital of the workforce. Nevertheless, horizontal mismatch may occur voluntarily for supply-related reasons, e.g. if individuals change into a higher-paying and more career-oriented occupation. In this case, the loss of the potential pay-off to the individuals' occupation-specific skills will be compensated in the new occupation. Based on cross-sectional data, however, several studies have shown that horizontal mismatch is significantly associated with wage penalties for graduates even if possible selection with respect to cognitive ability is controlled for (Nordin et al., 2010; Robst, 2007). Studies focusing on the interplay of horizontal and vertical mismatch have found that these wage effects are most severe for graduates who are mismatched in terms of field and level of education at the same time (Montt, 2015; Robst, 2008).

As these studies document, a substantial share of the individuals who are mismatched in terms of one dimension are also mismatched in terms of the other at a given point in time.[21] A reason might be that if there are no open positions in their particular field, job seekers may have to downgrade to find a job. Furthermore, employers may hire job applicants from inadequate fields of study only below their educational level because of the lack of occupation-specific skills. However, the dynamic dependence between both measures of educational mismatch has not been analysed so far. A simple test for the role of horizontal mismatch for the probability to subsequently experience overqualification is provided in the following and presented in Panel C of Table 3.8. Similarly to the measure used by Robst (2007), I identify horizontal mismatch based on workers' self-assessment. In each wave, graduates had to indicate on a 5-point Likert-scale to what extent their current job matches their education in terms of field of study. I construct a binary indicator for horizontal mismatch taking the value 1 for all respondents opting for the Likert-values 2 and 1 (1 being titled "not at all").[22] The results indicate that the two dimensions of educational mismatch are not only related at a given point in time but exhibit also a dynamic dependence. Even among graduates previously matched in the vertical dimension, the probability to be overqualified is significantly higher if they have experienced a mismatch in the horizontal dimension in the last period. The difference amounts to roughly 5 percentage points and is significant for female and male graduates (specification 1-3). Therefore, it might be harder for graduates working outside the own field of study to maintain a position meeting their educational level. The amount of occupational skills acquired through on-the-job learning

[21] In Robst (2008), roughly half of the overqualified graduates are also mismatched in terms of field of study.

[22] In total, a share of roughly 16% of the graduates have been horizontally mismatched according to this definition (Table 3.A.4). In each of the three waves, approximately 40% (10%) of the overqualified (not overqualified) graduates are mismatched in the horizontal dimension.

might be surpassed by new applicants from fields providing the occupation-specific skills needed. In addition, the risk of remaining overqualified is higher if the previous mismatch occurred in the vertical and horizontal dimension simultaneously, though the effect is much higher and only significant for female graduates. The entrapment effect from field of study mismatches might thus be higher for female graduates than for male graduates who may more often choose occupations outside the own field voluntarily. However, also men do not seem to profit from horizontal mismatches in terms of a route out of a vertical mismatch.[23]

Individual preferences for being adequately employed are very likely to be an important determinant for the occurrence of overqualification. However, due to data constraints there are, to the best of my knowledge, no studies that incorporate direct information about individual-specific preferences concerning matching quality. The data set employed includes such information. Five years after graduation (t=5), the graduates were asked whether they would like to be adequately matched in five years from now (t=10). The respondents had to indicate the degree of their preference for the future job match on a Likert-scale taking values from 1 ("not at all") to 5 ("absolutely"). I use this information as an indicator for the commonly unobserved preference for holding an adequate job. Three dummy variables are generated: *Preference: Low* taking the value 1 for Likert-values 1, 2, and 3; *Preference: Medium* taking the value 1 for the Likert-value 4; *Preference: High* taking the value 1 for the Likert-value 5. Roughly one third of those graduates who have been overqualified at the time the question was asked indicated low preferences for a future job match. Among well-matched graduates, only a share of 12% indicated low preferences for a future job match. High preferences have been indicated by 41% (65%) of the overqualified (well-matched) graduates. Therefore, preferences for future job match significantly differ suggesting that also the selection into the state of overqualification at the time the question was asked may be substantial. Panel D in Table 3.8 depicts the role of individual preferences measured in t=5 for the probability to be overqualified in t=10, conditional on all baseline controls. Among previously matched workers, the probability to enter overqualification is significantly lower for those with a high preference than for those with a low preference for future job match. The probability to remain stuck in a mismatch is also significantly related to individual preferences. Previously overqualified graduates with a high (medium) preference obtain a 18 percentage points (9 pp) lower probability to remain overqualified than individuals with a low preference for future job match. However, also among those who strongly preferred a future job match, a share of 46% (5%) of previously overqualified (well-matched) graduates is overqualified 10 years after graduation despite their plan to hold an adequate job at that time. This might point to potential labour market frictions that cause graduates to involuntarily remain or become overqualified.

[23]Current horizontal mismatch is significantly and positively related to overqualification for both previously well-matched and previously overqualified graduates, irrespective of gender. Results are available upon request.

3.5 Methodology

After analysing the role of observed heterogeneity for explaining the high persistence of overqualification, the remainder of the study follows the main aim to estimate the size of its true state dependence. This section describes the econometric model and discusses related issues concerning implementation and data structure.

3.5.1 Econometric Model

Using dynamic random-effects probit models, the importance of a behavioural effect from past overqualification experience on future overqualification can be evaluated by controlling for individual heterogeneity (observed and unobserved). The treatment of unobserved heterogeneity and initial conditions is an important issue for the estimation of such models including the lagged dependent variable. Ignoring unobserved heterogeneity that exhibits persistence over time will lead to an overstatement of the true state dependence of overqualification.

The econometric model can be summarised as follows. Let y^*_{it} be the latent propensity for individual i to be overqualified at time t. The latent propensity depends on the previous (realised) overqualification experience $y_{i,t-1}$, on observable explanatory variables summarised in the row vector x_{it} and on individual-specific attributes μ_i that are unobservable and time-invariant. An individual is observed to be overqualified, i.e. $y_{it} = 1$, if y^*_{it} exceeds a constant threshold which is assumed to be zero. The model is given by:[24]

$$y^*_{it} = \gamma\, y_{i,t-1} + x_{it}\,\beta + \mu_i + \varepsilon_{it} \qquad i = 1, ..., N, \qquad t = 2, ..., T \tag{3.3}$$

$$y_{it} = I\,[\, y^*_{it} > 0\,] \tag{3.4}$$

where ε_{it} represents an idiosyncratic error term. It is assumed that $\varepsilon_{it}|y_{i1}, ..., y_{i,t-1}, x_i$ is $i.i.d.$ as $N(0, 1)$ and that $\varepsilon_{it} \perp (y_{i1}, x_i, \mu_i)$ with $x_i = (x_{i2}, ..., x_{iT})$. In such a model, the coefficient of the lagged dependent variable, γ, is interpreted as measuring the "structural" or true state dependence (Heckman, 1981a). "Spurious" state dependence due to permanent unobserved heterogeneity is accounted for by the term for constant individual-specific attributes μ_i. In the present study, this term may be interpreted to capture differences in the individuals' unobserved ability or preferences for specific job characteristics.

The estimation of this model requires to account for the initial conditions problem. It is caused by the presence and correlation between the past value of the dependent variable and the unobserved heterogeneity term in the equation. Treating the initial conditions as exogenous would lead to an overstatement of the true state dependence effect if the initial conditions are correlated with μ_i (Chay and Hyslop, 2014). In order to integrate out the individual-specific effect, its relationship with the outcome in the initial period y_{i1} has to be specified. As suggested

[24] Note that the model is presented in its standard notation indicating the lagged dependent variable as $y_{i,t-1}$. Due to the time structure of the data and following the notation used so far, the lagged dependent variable will be indicated by $y_{i,t-5}$ in the results section.

by Wooldridge (2005), one possibility is to assume that y_{i1} is random and to specify the distribution of μ_i conditional on y_{i1} and x_i which leads to the joint density of $(y_{i2}, ..., y_{iT})|y_{i1}, x_i$. Following this estimation strategy, it is assumed that the individual-specific effect depends on the initial condition and the strictly exogenous variables as follows:

$$\mu_i = \alpha_0 + \alpha_1 y_{i1} + \bar{x}_i\alpha_2 + a_i \tag{3.5}$$

The inclusion of the time-averages of the observed explanatory variables $\bar{x}_i = \frac{1}{T-1}\sum_{t=2}^{T} x_{it}$ accounts for potential correlation between the unobserved heterogeneity and the time-variant explanatory variables as suggested by correlated random-effects models (Chamberlain, 1984; Mundlak, 1978).[25] In this type of random-effects models, it is possible to estimate the effect of a change in x_{it} by holding the time-averages fixed. It is assumed that the error term a_i is *i.i.d.* as $N(0, \sigma_a^2)$ and that $a_i \perp (y_{i1}, \bar{x}_i)$. Thus, the distribution of the individual heterogeneity is specified as follows:

$$\mu_i|(y_{i1}, \bar{x}_i) \sim N(\alpha_0 + \alpha_1 y_{i1} + \bar{x}_i\alpha_2, \sigma_a^2) \tag{3.6}$$

Under these conditions, the probability to be overqualified is given by:

$$P(y_{it} = 1|y_{i1}, ..., y_{i,t-1}, x_i, a_i) = \Phi(\gamma y_{i,t-1} + x_{it}\beta + \alpha_0 + \alpha_1 y_{i1} + \bar{x}_i\alpha_2 + a_i) \tag{3.7}$$

As shown by Wooldridge (2005), integrating out a_i yields a likelihood function with the same structure as in the standard random-effects model including the initial condition y_{i1} and the time-averaged $\bar{x}_i$ as additional explanatory variables in each time period t. Incorporating the augmented set of explanatory variables, standard random-effects probit estimation methods can be employed to estimate $\gamma, \beta, \alpha_0, \alpha_1, \alpha_2$ and σ_a^2.[26]

If γ is estimated to be significantly greater than zero, true state dependence is present such that a previous experience of overqualification causally increases the probability to be overqualified in the next period. Due to the non-linearity of the model, however, the size of the state dependence effect cannot be gauged directly from the estimated coefficients. Therefore, the average partial effect (APE) for the lagged dependent variable is calculated in order to evaluate the extent of true state dependence. The fact that individual heterogeneity is unobserved is problematic for the estimation of partial effects. One way to overcome this problem is to estimate the APE under the assumption that the individual heterogeneity μ_i takes its average value. $E(\mu_i) = \alpha_0 + \alpha_1 E(y_{i1}) + E(\bar{x}_i)\alpha_2$ and can be consistently estimated by $\widehat{E(\mu_i)} = \widehat{\alpha}_0 + \widehat{\alpha}_1\bar{y}_1 + \bar{x}\widehat{\alpha}_2$ where $\bar{y}_1 = \Sigma_{i=1}^{N} y_{i1}$ and $\bar{x} = \Sigma_{i=1}^{N}\bar{x}_i$. The APE for the binary lagged dependent variable (previous

[25]The original Wooldridge model includes all values of the time-varying explanatory variables at each period (except the initial period). Most studies rely on the within-means of the time-varying explanatory variables instead. As shown by Rabe-Hesketh and Skrondal (2013), this specification does not lead to biases. They find that biases of the Wooldridge model in short panels documented by Akay (2012) are caused by including values of the initial period into the computation of time-averages. In line with Rabe-Hesketh and Skrondal (2013), I therefore use time-averages excluding the initial period. As a robustness check, the original Wooldridge model including leads and lags is also estimated and presented.

[26]For instance, the xtprobit command in Stata.

overqualification) can be calculated as the discrete change in the probability to be overqualified as the dummy variable changes from 0 to 1:

$$\widehat{APE} = \Phi[\widehat{\gamma} + x_i\widehat{\beta} + \widehat{\alpha}_0 + \widehat{\alpha}_1\bar{y}_1 + \bar{x}\widehat{\alpha}_2] - \Phi[x_i\widehat{\beta} + \widehat{\alpha}_0 + \widehat{\alpha}_1\bar{y}_1 + \bar{x}\widehat{\alpha}_2] \tag{3.8}$$

3.5.2 Implementation and Data Structure

While only scarcely employed in the overqualification literature, dynamic random-effects probit models accounting for unobserved heterogeneity have been widely used in related studies concerned with state dependence of low wage or unemployment (Arulampalam and Stewart, 2009). As compared to most of these studies, the structure of the data used in the present analysis differs with respect to several aspects. Most studies on state dependence use more than 3 waves of annual data for a sample of the entire working population at various stages of individual career cycles. In contrast, my data set comprises 3 waves conducted approximately 5 years apart. Therefore, I observe changes in the individuals' labour market status over the medium-run rather than annual short-run transitions. Due to the longer duration between the interviews, the advantage of covering the first ten years of individual career cycles comes at the cost of observing the individuals at only three points in time. As opposed to this drawback, the increased time lag between interviews eases a problem studies employing annual data will often face. Spurious state dependence may occur if a single spell of the labour market outcome investigated, e.g. unemployment, may span two consecutive years for a substantial share of individuals. For instance, Arulampalam et al. (2000) take this problem into account and report that over one third of the unemployment spells in their annual data set lasted longer than one year. As a further difference to most studies on state dependence, my data set solely comprises university graduates such that differences in the level of educational attainment do not occur in contrast to samples drawn from the entire working population. Therefore, I concentrate the analysis on the policy-relevant group of tertiary graduates and only compare individuals that are equally educated. Finally, the individuals are observed over the first ten years of their career cycles after entering the labour market as university graduates. Therefore, the initial condition is observed much more closely to the real start of the labour market experience than in most previous studies. Nevertheless, accounting for the initial conditions problem remains important. Even if the entire history of the process of overqualification experience is observed it would be a strong assumption that unobserved ability or preferences are independent from the initial state of overqualification (Wooldridge, 2005).

As already presented in the previous sections, the data set includes a rich set of explanatory variables that may affect the risk of being overqualified. Some of these explanatory variables do not vary over time at the individual level, such as the proxies for ability, the characteristics of the study programme, or the family background. As suggested by Wooldridge (2005), time-constant explanatory variables can be included in the dynamic random-effects model in order to increase explanatory power. However, the model is not able to separately identify the partial effects of the time-constant variables from their partial correlation with the unobserved individual heterogeneity.

The time-variant regressors included in the model are assumed to be strictly exogenous, conditional on the individual-specific unobserved effect μ_i. This generally rules out potential feedback effects from changes in the outcome variable on future values of explanatory variables (Wooldridge, 2000). Despite the fact that explanatory variables are often choice variables, studies allowing for feedback effects by relaxing the strict exogeneity assumption are scarce. Focusing on state dependence in poverty, Biewen (2009) allows for potential feedback effects from poverty to future employment status and from poverty to future household composition. The author concludes that in the context of poverty the assumption of strict exogeneity is violated for these explanatory variables and that ignoring feedback effects may lead to biased estimates of the state dependence effect. However, most studies concerned with state dependence in various labour market outcomes assume strict exogeneity for all explanatory variables. For instance, Arulampalam et al. (2000) and other studies focusing on state dependence of unemployment do not account for the possibility that the time-variant regressors marital status and number of children may depend in part on past unemployment experience. In comparison to the context of the present study, feedback effects from unemployment on future explanatory variables may be more likely and more severe than potential feedback effects from overqualification spells in which individuals still are active in the labour market. Therefore, I assume that marital status and parenthood are not affected by earlier overqualification experience. Furthermore, it is assumed that overqualification does not affect future unemployment experience. This assumption may be violated if, conditional on the individual-specific unobserved effect, overqualification experience reduces the individual's chances to find any job, for instance due to negative signals for employers. In a robustness check unemployment will be excluded from the model, but the main results do not change.

3.6 Main Results

Employing the presented dynamic random-effects probit model, selection into initial overqualification as well as individual heterogeneity is taken into account in this section. The results on the extent of true state dependence of overqualification are presented in Table 3.9. For the complete sample (specification 1), the average partial effect of the lagged overqualification experience is significant and amounts to 3 percentage points. This implies that even after controlling for observed and unobserved characteristics, graduates are on average 3 percentage points more likely to be overqualified at time t if they have already experienced overqualification in $t-5$.[27] Therefore, I find evidence for a true state dependence effect of graduate overqualification. However, the size of the causal effect of previous overqualification experience is substantially smaller than the observed raw state dependence of 45 percentage points. It is also much smaller

[27]Note again that $t-5$ indicates the lagged dependent variable even though the actual time lag between the first and second interview amounts to approximately 4 years.

Table 3.9: Results, Wooldridge Dynamic RE Probit

	Dependent Variable: Overqualification					
	All (1)		Female (2)		Male (3)	
Overqualification ($t-5$)	0.029**	(0.014)	0.031	(0.019)	0.028	(0.022)
Overqualification ($t=1$)	0.234***	(0.024)	0.220***	(0.031)	0.254***	(0.038)
Female	0.019***	(0.006)				
University grade	-0.019***	(0.003)	-0.023***	(0.005)	-0.015***	(0.004)
School grade	-0.008**	(0.003)	-0.014***	(0.005)	-0.003	(0.004)
Study duration	0.006**	(0.003)	0.009**	(0.005)	0.004	(0.004)
U. applied sciences	0.019***	(0.007)	0.023**	(0.011)	0.017*	(0.009)
BusAdmin/Econ	ref.		ref.		ref.	
Med/Law/Teach	-0.099***	(0.006)	-0.117***	(0.010)	-0.082***	(0.008)
STEM subjects	-0.055***	(0.008)	-0.057***	(0.013)	-0.053***	(0.011)
Soc/Cult science	-0.019**	(0.008)	-0.028**	(0.012)	-0.008	(0.013)
Age at grad. < 27	-0.010	(0.007)	-0.005	(0.010)	-0.016*	(0.009)
Parents high-skilled	-0.006	(0.006)	-0.006	(0.009)	-0.005	(0.008)
Married	-0.003	(0.010)	-0.006	(0.014)	0.000	(0.014)
Children	0.007	(0.010)	0.018	(0.014)	-0.003	(0.014)
Months unemployed	0.001	(0.001)	0.001	(0.002)	0.001	(0.003)
Mean: Married	-0.002	(0.013)	-0.003	(0.018)	-0.003	(0.018)
Mean: Children	0.009	(0.013)	0.013	(0.019)	0.008	(0.018)
Mean: Months unemployed	0.003**	(0.002)	0.004**	(0.002)	0.002	(0.003)
σ	1.201	(0.101)	1.366	(0.150)	1.023	(0.138)
ρ	0.591	(0.041)	0.651	(0.050)	0.512	(0.067)
Log. Lik.	-3827.1		-1920.5		-1894.3	
Obs. Indiv.	5987		3009		2978	
Obs. Total	11974		6018		5956	

Note: Random-effects probit estimation; Average partial effects; Standard errors in parentheses; ρ: estimate of the cross-period correlation of the composite error term $a_i + \varepsilon_{it}$; Significant at 1% ***, significant at 5% **, significant at 10% *.

than the average partial effect of lagged overqualification if only the observed heterogeneity is accounted for (34 percentage points).[28] The results thus suggest that most of the raw state dependence is due to unobserved heterogeneity across graduates rather than due to a causal dynamic impact. Therefore, unobserved factors seem to be the main driver of overqualification persistence over the early career for graduates in Germany. The size of the true state dependence effect is nearly the same for both female and male graduates, however, the effect loses its significance in the gender-specific models presented in specification 2 and 3.

The effect of the initial condition, i.e. overqualification experience 1 year after graduation, is highly significant and much larger than the effect for the lagged dependent variable in all three specifications. This implies a substantial correlation between the graduates' initial overqualification status and the unobserved heterogeneity. In contrast to comparable studies on state dependence effects, initial conditions are actually observed at the beginning of individual labour market careers in the current study. The results suggest that most of the observed

[28]See Table 3.3 for the raw state dependence and Table 3.6 for the estimated state dependence effect if only observed heterogeneity is accounted for.

persistence of overqualification is attributable to the initial selection into inadequate job matches based on unobserved factors.

In addition to their time-specific values, the model includes the averages for the time-variant explanatory variables. Only the time-averaged duration of unemployment experience is significant indicating a correlation to the unobserved heterogeneity for female graduates. In contrast to the static random-effects model, parenthood is not significantly related to overqualification of female graduates in the dynamic model. Therefore, parenthood may pick up the effect from the previous overqualification status in the static model. This also corresponds to the earlier finding that for female graduates parenthood is only positively associated with a higher probability to remain overqualified but not to enter overqualification from a previous match. In order to explicitly control for observed heterogeneity, the aforementioned time-constant explanatory variables are included although their causal effect cannot be estimated due to potential correlation with unobserved heterogeneity. The estimated effects are similar to the static model without modelling the unobserved heterogeneity with respect to sign and significance but are somewhat smaller.

To check the robustness of the estimated size of the true state dependence effect, Table 3.A.1 provides further specifications of the dynamic model for the complete sample. First, specification 1 includes the lags and leads of the time-variant explanatory variables as proposed in the original form of the Wooldridge estimator. The average partial effect of the lagged dependent variable, however, remains unchanged. Second, unemployment experience is excluded from the model since previous overqualification may exhibit potential feedback effects on future unemployment spells leading to biased estimates (Biewen, 2009). Again the main results remain unchanged. Third, the estimated effect of the lagged dependent variable only slightly increases if study characteristics and ability are excluded and only basic sociodemographic controls are included in the model. However, the significant negative effect of the initial overqualification experience increases considerably illustrating the high relevance of study characteristics and ability for the selection into early overqualification. Furthermore, the effect of parental education increases and becomes significant signalling that these individual characteristics are relevant pathways for family background effects on overqualification (Erdsiek, forthcoming).

3.7 Sensitivity Analyses

This section provides further robustness checks for the main results. First, the analysis is replicated using an alternative econometrical model that differs in the way of modelling unobserved heterogeneity and solving the initial conditions problem (Heckman, 1981b). Second, the analysis is replicated employing another measure for job mismatch as dependent variable, i.e. horizontal mismatch. Third, since the selection into initial overqualification seems to be of high relevance for its persistence, it is analysed whether this selection occurs because of favourable job characteristics in terms of a higher wage growth as suggested by the career mobility theory (Sicherman, 1991).

3.7.1 Heckman Model

For dynamic non-linear models with unobserved individual-specific effects, another approach for handling the initial conditions problem has been proposed by Heckman (1981b).[29] He suggested to model the initial outcome of the dependent variable, y_{i1}, jointly with the subsequent outcomes of the dependent variable, $y_{i2}, ..., y_{iT}$. In order to integrate out the unobserved effect μ_i, he suggested to approximate the unknown distribution of $y_{i1}|\mu_i, x_i$. In the latent variable form, the Heckman model can briefly be summarized as follows:

$$y^*_{i1} = z_i\,\lambda + \theta\mu_i + \varepsilon_{i1} \qquad i = 1, ..., N, \qquad t = 1 \tag{3.9}$$

$$y^*_{it} = \gamma\, y_{i,t-1} + x_{it}\,\beta + \mu_i + \varepsilon_{it} \qquad i = 1, ..., N, \qquad t = 2, ..., T \tag{3.10}$$

where z_i is a row vector of covariates including x_{i1} and additional exogenous instruments for the initial condition. By construction, μ_i and ε_{i1} are orthogonal to one another. It is assumed that the initial observation y_{i1} is uncorrelated with ε_{it} and also that ε_{i1} is uncorrelated with the x_{it} for all i and t. Moreover, it is assumed that both ε_{i1} and μ_i are normally distributed, the former with variance 1 and the latter with variance σ^2_μ. A test of exogeneity of the initial condition in this model is provided by the test of $\theta = 0$.

Equations (3.9) and (3.10) together specify a complete model for $(y_1, y_2, ..., y_T)$. The contribution to the likelihood function for individual i is given by

$$L_i = \int \left\{ \Phi[(z_i\lambda + \theta\mu)(2y_{i1} - 1)] \prod_{t=2}^{T} \Phi[(\gamma y_{i,t-1} + x_{it}\beta + \mu)(2y_{it} - 1)] \right\} g(\mu)\mathrm{d}\mu \tag{3.11}$$

where $g(\mu)$ is the probability density function of the unobserved individual-specific heterogeneity and Φ denotes the standard normal cumulative distribution function. With μ taken to be normally distributed, the integral in equation (3.11) can be evaluated using Gaussian–Hermite quadrature (Butler and Moffitt, 1982).

In contrast to the Wooldridge model, the Heckman estimator requires additional instruments, i.e. variables affecting the initial state but, conditional on this state, without an effect on transition probabilities. Heckman (1981b) suggested that when modelling labour market outcomes, initial conditions may be instrumented by using information prior to labour market entry. Most commonly, information on the respondents' family background have been used as instruments in previous applications of the Heckman model for various labour market outcomes such as unemployment (Arulampalam et al., 2000), low wage (Stewart, 2007), or

[29] Several studies have compared the performance of the Wooldridge estimator and the Heckman estimator. Based on monte-carlo simulations and an application for unemployment persistence, Arulampalam and Stewart (2009) conclude that the results of both estimators are very similar and that neither of them outperforms the other. In contrast, Akay (2012) concludes that in short panels (below 5 waves) the Heckman estimator should be preferred because the Wooldridge estimator overestimates the true state dependence and underestimates the persistence due to unobserved time-invariant individual characteristics. Rabe-Hesketh and Skrondal (2013) attribute this conclusion to a misspecification of the Wooldridge estimator as it is used in the study by Akay. They show that biases vanish if time-averages of the explanatory variables do not include the initial period.

social assistance receipt (Cappellari and Jenkins, 2008b). In particular, information on parental occupation, employment, or education has been used. Focusing on overqualification in Germany, Blázquez and Budría (2012) use information on the quality of the relationship with the parents as instruments.[30] Mavromaras and McGuinness (2012) also rely on parental employment as instruments in their study on the state dependence of skill mismatch. Although employed by numerous studies, one could argue that family background is not an ideal instrument. In the context of overqualification, it could be assumed that the offspring from wealthy and highly educated parents obtain a higher aspiration and motivation to escape from an initial mismatch than workers with an adverse family background.[31]

In contrast to the previous studies, I aim to use a measure for the labour market condition at the time of the first interview as an instrument for the initial overqualification status. Recently, a line of literature has provided evidence for persistent wage penalties for workers who graduated from university during a recession (Kahn, 2010; Oreopoulos et al., 2012). For Norway, Liu et al. (2016) show that graduates are more likely to be affected by skill mismatch if they entered the labour market in a bad economy. Furthermore, they find that initially mismatched workers experience persistent negative effects on earnings and unemployment from graduating in recessions. In contrast, workers who are adequately matched in bad times do not experience significant wage penalties or higher unemployment than workers who are well-matched in the same industry in good times. From that, Liu et al. (2016) conclude that cyclical mismatch might be an important mechanism for the persistent negative effects associated with unfavourable initial labour market conditions.

The authors employ the unemployment rate at the time of graduation as a measure for initial labour market condition and argue that it captures exogenous labor demand shocks. Since the present study relies on data from only two different graduate cohorts, variation in the unemployment rate over time cannot be used as an instrument for initial conditions.[32] As an alternative approach, I construct field-specific unemployment rates at the time of the first interview based on fine-grained information on the respondents' field of study. This might measure initial economic conditions affecting the probability to be overqualified, e.g. because a higher field-specific unemployment rate might force more graduates in that particular field to accept lower level jobs in order to avoid unemployment. Field-specific unemployment rates are not readily available and have been constructed as follows: Based on administrative data for Germany, the unemployment rates for tertiary graduates in 120 distinct occupations have been computed.[33] Merging this information to the original data set, the occupation-specific

[30]In particular, Blázquez and Budría (2012) use information such as the frequency of arguments with the parents when the individual was 14 years old. The authors employ a trivariate probit model in order to take the initial condition problem into account, nevertheless the requirements concerning the instruments are the same as in the Heckman model.

[31]For other analysed labour market outcomes, such as low wage or unemployment, one could assume the same.

[32]The aggregate unemployment rate for tertiary graduates was also very similar at the time of the first interview for both cohorts, 3,1% in 1998 and 3,3% in 2002 (IAB, 2015).

[33]Data source: Sample of Integrated Labour Market Biographies (SIAB), SUF (Regional File 1975-2010). Employer information coded at the 3-digit level of the German occupational classification KldB-1988 have been aggregated to 120 occupational groups. See vom Berge et al. (2013) for further information about the data set.

unemployment rate at the time of the first interview is given for all respondents. In the next step, the relevant labour market for each field of study is approximated by the pool of occupations held by graduates from a given field. Finally, field-specific unemployment rates are constructed by computing the unemployment rate among the entire pool of graduates in each field of the available classification differentiating 51 fields of study.

Using the field-specific unemployment rate as an instrument for the initial overqualification status in the Heckman model, the estimated coefficient was highly significant for the complete sample and the female sample but turned out to be slightly insignificant for male graduates. As an alternative, the occupation-specific unemployment rate has been used as an instrument directly. The main results concerning overqualification state dependence did not differ between both instruments. Therefore, Table 3.10 presents the results of the Heckman model including the occupation-specific unemployment rate as an instrument for the initial condition.[34]

Since estimation coefficients instead of partial effects are presented, the size of the parameters cannot be interpreted.[35] The top panel of the table depicts the main panel estimation results for time periods t=5,10, while the bottom panel depicts the results for the initial condition equation (t=1). The occupation-specific unemployment rate at the time of the first interview significantly increases the probability to be initially overqualified for both female and male graduates. Therefore, on average the risk of overqualification is higher in occupations with a lesser demand for graduates or excess supply of graduates even if some graduates select another occupation than preferred because of a currently high unemployment rate in the favourite occupation. The hypothesis of exogenous initial conditions is strongly rejected because the respective test statistic θ is significantly greater than zero. Similarly to the Wooldridge estimator, the coefficient on the lagged overqualification experience signals a significant true state dependence effect if the initial condition is jointly modelled with the subsequent periods. Furthermore, and in contrast to the Wooldridge estimator, the state dependence effect remains significant for both samples of female and male graduates.

In order to assess the robustness of the estimated size of the true state dependence, Table 3.11 presents the average partial effect of the lagged dependent variable from the Heckman model and the Wooldridge model as well as the raw state dependence observed in the data. The average partial effects are obtained by subtracting the predicted probabilities of being overqualified conditional on the previous overqualification status under the assumption that the individual-specific heterogeneity takes its average value. The Heckman model estimate of the true state dependence effect amounts to 4 percentage points which is only slightly higher than

[34] From a theoretical view, it might have been preferred to use field-specific rather than occupation-specific unemployment rates as an instrument since the latter is prone to selection into occupations. However, the direction of selection is not clear a priori since graduates might try to bypass overqualification by avoiding occupations with a high unemployment rate. Furthermore, if similar to previous studies parental education is used as an instrument, results do not qualitatively differ from the results presented here.

[35] In contrast to the Wooldridge estimator, the Heckman model cannot be estimated using standard random-effects models and need special software. For estimating the Heckman model, the *redprob* command for Stata is used which was also used by Stewart (2007) and can be downloaded under http://www2.warwick.ac.uk/fac/soc/economics/staff/mstewart/stata/. Since the command does not allow to estimate partial effects for the initial condition equation, only coefficients are presented in Table 3.10.

Table 3.10: Results, Heckman Dynamic RE Probit

	Dependent Variable: Overqualification					
	All (1)		Female (2)		Male (3)	
Main Panel Estimation						
Overqualification ($t-5$)	0.333***	(0.092)	0.386***	(0.127)	0.303**	(0.134)
Female	0.272***	(0.065)				
University grade	-0.241***	(0.034)	-0.267***	(0.051)	-0.210***	(0.045)
School grade	-0.106***	(0.033)	-0.163***	(0.051)	-0.064	(0.042)
Study duration	0.101***	(0.030)	0.133***	(0.047)	0.078*	(0.040)
U. applied sciences	0.256***	(0.068)	0.257**	(0.104)	0.253***	(0.090)
BusAdmin/Econ	ref.		ref.		ref.	
Med/Law/Teaching	-1.806***	(0.151)	-2.054***	(0.228)	-1.516***	(0.208)
STEM subjects	-0.739***	(0.088)	-0.817***	(0.147)	-0.670***	(0.111)
Soc/Cult science	-0.149*	(0.087)	-0.246*	(0.128)	-0.051	(0.128)
Age at grad. < 27	-0.140**	(0.066)	-0.090	(0.098)	-0.191**	(0.089)
Parents high-skilled	-0.109*	(0.060)	-0.103	(0.088)	-0.100	(0.079)
Married	-0.034	(0.059)	-0.050	(0.086)	-0.016	(0.081)
Children	0.131**	(0.061)	0.265***	(0.089)	0.013	(0.083)
Months unemployed	0.037***	(0.006)	0.041***	(0.008)	0.031***	(0.008)
Constant	-1.720***	(0.115)	-1.600***	(0.172)	-1.561***	(0.144)
Initial Conditions Estimation						
Female	0.240***	(0.057)				
University grade	-0.180***	(0.028)	-0.137***	(0.037)	-0.237***	(0.044)
School grade	-0.089***	(0.029)	-0.082**	(0.039)	-0.098**	(0.045)
Study duration	0.126***	(0.027)	0.123***	(0.036)	0.129***	(0.042)
U. applied sciences	0.182***	(0.061)	0.030	(0.083)	0.314***	0.094
BusAdmin/Econ	ref.		ref.		ref.	
Med/Law/Teaching	-1.296***	(0.102)	-1.327***	(0.127)	-1.366***	(0.189)
STEM subjects	-0.717***	(0.072)	-0.801***	(0.107)	-0.700***	(0.105)
Soc/Cult science	-0.079	(0.082)	-0.177*	(0.105)	-0.033	(0.140)
Age at grad. < 27	-0.067	(0.059)	-0.023	(0.078)	-0.113	(0.095)
Parents high-skilled	-0.156***	(0.054)	-0.116*	(0.070)	-0.203**	(0.085)
Married	0.105	(0.073)	0.094	(0.099)	0.136	(0.110)
Children	0.082	(0.093)	0.306**	(0.128)	-0.168	(0.143)
Months unemployed	0.039***	(0.011)	0.043***	(0.014)	0.035*	(0.019)
Unemployment rate	0.110***	(0.016)	0.133***	(0.023)	0.094***	(0.025)
Constant	-1.387***	(0.102)	-1.130***	(0.137)	-1.441***	(0.152)
θ	0.583	(0.055)	0.459	(0.057)	0.787	(0.121)
ρ	0.622	(0.039)	0.668	(0.050)	0.562	(0.064)
Log. Lik.	-6176.5		-3151.1		-3004.1	
Obs. Indiv.	5987		3009		2978	
Obs. Total	17961		9027		8934	

Note: Random-effects probit estimation; Estimation coefficients are displayed; Standard errors in parentheses; Stata command: *redprob*; ρ: estimate of the cross-period correlation of the composite error term $\mu_i + \varepsilon_{it}$; θ: statistic used to test whether the initial conditions are exogenous. The estimate of θ is significantly greater than zero, i.e. the hypothesis that the initial conditions are exogenous is rejected. Significant at 1% ***, significant at 5% **, significant at 10% *.

Table 3.11: Results, Predicted Probabilities of Overqualification

	All	Female	Male
Raw Data Probabilities			
$P(y_t = 1 \mid y_{t-5} = 0)$	7.9	8.0	7.8
$P(y_t = 1 \mid y_{t-5} = 1)$	52.6	55.2	49.5
Difference	44.7	47.2	41.7
Wooldridge Estimator Predicted Probabilities			
$P(y_t = 1 \mid y_{t-5} = 0)$	8.4	9.0	8.0
$P(y_t = 1 \mid y_{t-5} = 1)$	11.3	12.1	10.8
Difference	2.9	3.1	2.8
Heckman Estimator Predicted Probabilities			
$P(y_t = 1 \mid y_{t-5} = 0)$	6.1	6.5	5.8
$P(y_t = 1 \mid y_{t-5} = 1)$	10.0	11.1	9.5
Difference	3.9	4.6	3.7

Note: y_t depicts the overqualification status in time period t; Probabilities are predicted under the assumption that the individual heterogeneity takes its average value.

the Wooldridge model estimate of 3 percentage points. In contrast to the Wooldridge estimator, gender differences in the rate of true state dependence are more nuanced in the Heckman model. Female graduates experience a slightly higher behavioural effect of past overqualification than male graduates but the difference amounts to less than a percentage point. Overall, the result that the true state dependence effect is much smaller than the raw state dependence of 45 percentage points is robust to the choice of econometrical models that differ in the treatment of individual-specific heterogeneity and the initial conditions problem.

3.7.2 Horizontal Mismatch

As a robustness check on the finding that unobserved factors are the main driver of observed persistence of job mismatch, this section replicates the estimation of the Wooldridge model using another measure for educational mismatch as a dependent variable (Table 3.12). Instead of the vertical dimension indicating whether the educational *level* exceeds the job requirements, this section focuses on mismatches in the educational *field*. Educational mismatches in the horizontal dimension may occur if graduates acquired field-specific skills and knowledge that do not match the occupational skills required for their jobs. Therefore, their stock of human capital may not be fully utilised and investments into field-specific skills do not pay off. Educational mismatches do frequently occur in both dimensions simultaneously, e.g. because few vacancies are available within a field and graduates have to downgrade to find a job. However, they represent distinct forms of educational mismatch. Individual motives and preferences may be

Table 3.12: Results, Wooldridge Dynamic RE Probit, Horizontal Mismatch

	Dependent Variable: Horizontal Mismatch					
	All (1)		Female (2)		Male (3)	
Horizontal mismatch $(t-5)$	0.039**	(0.017)	0.044*	(0.025)	0.033	(0.023)
Horizontal mismatch $(t=1)$	0.193***	(0.023)	0.159***	(0.029)	0.236***	(0.038)
Female	0.011*	(0.006)				
University grade	-0.010***	(0.003)	-0.012***	(0.005)	-0.009**	(0.004)
School grade	-0.010***	(0.003)	-0.015***	(0.005)	-0.006	(0.004)
Study duration	0.010***	(0.003)	0.010**	(0.005)	0.011**	(0.004)
U. applied sciences	-0.007	(0.007)	-0.007	(0.011)	-0.008	(0.009)
BusAdmin/Econ	ref.		ref.		ref.	
Med/Law/Teach	-0.030***	(0.009)	-0.037***	(0.013)	-0.030**	(0.012)
STEM subjects	0.027***	(0.009)	0.018	(0.014)	0.031***	(0.011)
Soc/Cult science	0.035***	(0.012)	0.019	(0.015)	0.058***	(0.022)
Age at grad. < 27	-0.009	(0.007)	-0.012	(0.010)	-0.006	(0.009)
Parents high-skilled	-0.009	(0.006)	-0.003	(0.009)	-0.015*	(0.008)
Married	0.003	(0.010)	-0.000	(0.016)	0.006	(0.013)
Children	0.013	(0.011)	0.010	(0.016)	0.014	(0.014)
Months unemployed	0.000	(0.002)	-0.000	(0.002)	-0.001	(0.002)
Mean: Married	-0.008	(0.013)	-0.010	(0.019)	-0.006	(0.018)
Mean: Children	-0.010	(0.013)	0.002	(0.020)	-0.021	(0.018)
Mean: Months unemployed	0.004**	(0.002)	0.004*	(0.002)	0.004	(0.003)
σ	1.029	(0.093)	0.924	(0.122)	1.161	(0.146)
ρ	0.514	(0.045)	0.461	(0.065)	0.574	(0.062)
Log Lik.	-4064.0		-2067.4		-1979.3	
Obs. Indiv.	5827		2914		2913	
Obs. Total	11654		5828		5826	

Note: Random-effects probit estimation; Average partial effects; Standard errors in parentheses; ρ: estimate of the cross-period correlation of the composite error term $a_i + \varepsilon_{it}$; Significant at 1% ***, significant at 5% **, significant at 10% *.

very different for field of study mismatches than for overqualification. For instance, individuals may choose higher-paying or more career-oriented occupations outside the own field voluntarily.

Similarly to Robst (2007), I employ a subjective measure for horizontal mismatch. A dummy variable is constructed taking the value 1 if graduates indicated that their current job matches their field of study only to a low extent.[36] In each of the three waves, roughly 16% of the graduates are horizontally mismatched. Conditional on the previous matching status, the probability to hold a job that is barely related to the own field amounts to 45% (9%) for graduates who haven been previously mismatched (well-matched) in the horizontal dimension. Therefore, the raw state dependence of 36 percentage points is high but somewhat lower than the raw state dependence of overqualification. Table 3.12 provides the results of the Wooldridge estimator concerning the true state dependence of horizontal mismatch. For all graduates, the average partial effect of lagged horizontal mismatch is positive and significant indicating a true state dependence effect amounting to 4 percentage points. This result is very similar

[36]See Section 3.4.3 for more information on this measure and Table 3.A.4 for descriptives.

to the estimated true state dependence for overqualification. Gender differences concerning true state dependence are likewise small (specification 2 and 3). In line with the results for overqualification, the effect of the mismatch status in the initial period is much larger than the effect of the previous period indicating that selection into an early mismatch based on unobserved factors is highly important for the persistence.

Concerning observed heterogeneity, the results show that graduates with better grades and lower study duration are more likely to hold a job that is related to the own field of study. Signalling a high level of occupational skills by better university grades may help graduates to find suitable jobs within their field of study. This result is also in line with the previous finding that more able graduates are less likely to be overqualified.

3.7.3 Wage Growth

So far, the empirical results suggest that overqualification in Germany represents rather a persistent phenomenon than a transitory state at the beginning of graduates' careers in Germany. This contrasts the career mobility theory by Sicherman and Galor (1990) hypothesising that overqualification may represent a deliberate choice as part of individual career plans. According to the theory, individuals accept low-level positions at the offset of their career to obtain training and experience supporting subsequent upward mobility. Early overqualification is thus interpreted as part of a human capital investment strategy and supposed to be only short-lived at the individual level. In its original form, the career mobility theory is based on wage growth as an indicator for upward mobility (Sicherman and Galor, 1990). Providing a more direct test of the career mobility theory, this section analyses the effects of early overqualification on the wage growth over the first ten years of individual careers. Moreover, this analysis may shed light on the driving factors of the selection into the initial state of overqualification which has been shown to be highly relevant for overqualification persistence.

Previous tests of the career mobility theory have been carried out by Büchel and Mertens (2004) for Germany and Korpi and Tåhlin (2009) for Sweden. Employing panel data, they find no support for the hypothesis that overqualified workers may realise a higher wage growth. Both studies rely on data comprising a representative sample of the entire working population interviewed at different stages of individual career cycles. I contribute to their findings by focusing the analysis on highly educated individuals jointly observed at early stages of the career cycle. Therefore, I test the theoretical prediction of the career mobility model at the beginning of the individual careers when its hypothesis should matter most.

The graduates' wages are measured in terms of hourly wages and are observed at all three time periods.[37] Therefore, individual wage growth can be measured over different lengths of time. First, medium-term wage growth between the interviews 1 and 5 years after graduation and similarly between the interviews 5 and 10 years after graduation. Second, I can measure long-

[37]Gross monthly earnings indicated by the respondents in each wave have been divided by the number of their working hours and adjusted for inflation (base year 2005).

term wage growth between the first interview and the last interview 10 years after graduation. The following econometric model is employed for the wage growth regressions:

$$ln\,W_{i,t+k} - ln\,W_{i,t} \;=\; \tau_0 + \tau_1\,OV_{i,t} + \tau_2\,ln\,W_{i,t} + x_{it}\,\beta + \zeta_{it} \qquad (3.12)$$

where it is assumed that ζ_{it} represents a white noise error term normally distributed with variance 1. The row vector x_{it} includes the same explanatory variables as in the previous sections. Note that the values for the base year t are used for the time-variant explanatory variables. Overqualification in the base year is represented by $OV_{i,t}$ and is assumed to affect the future wage growth in the medium-run (k=5) and in the long-run (k=10). The starting wage level $W_{i,t}$ is also included as explanatory variable because wage careers involve substantial state dependence. Due to downward stickiness and differential growth rates across starting wage levels, previous wage rates will causally affect future wage rates (Korpi and Tåhlin, 2009).

Table 3.13 presents the results for the role of overqualification for subsequent medium-run and long-run wage growth. As a starting point, specification 1 shows that current overqualification is significantly and negatively related with the initial wage level one year after graduation. Specifications 2 and 3 provide the results on the medium-run wage growth between consecutive interviews approximately 5 years apart. Effects on the long-term growth rate over the first ten years of labour market experience are presented in specification 4. The medium-run as well as the long-run wage growth rate is significantly lower for overqualified graduates in relation to their adequately matched former classmates.[38] Between the first and tenth year after graduation, the wage growth rate is approximately 7 percentage points lower for graduates who have held an inadequate job in the base year than for initially well-matched graduates. A further interesting result is that graduates with better university grades achieve significantly higher starting wages and higher wage growth. In the long-run, a higher wage growth is also found for graduates with better school grades. In contrast, the starting wage level and subsequent wage growth is lower for female graduates and for previously unemployed workers. As expected, the base year's wage level is significantly and negatively related to subsequent wage growth signalling a ceiling effect.

Robustness checks for the significantly negative association between overqualification and wage growth are presented in Table 3.A.2. Panel A includes occupation fixed effects for the base year in terms of 54 occupational code dummies defined by Tiemann et al. (2008). Significance and effect sizes are highly robust if differences in the characteristics of the graduates' base year occupation are controlled for. In order to check whether the detrimental effect of educational mismatch on wage growth can be attributed to horizontal mismatches rather than vertical mismatches, Panel B and C include a dummy variable indicating field of study mismatches. The estimated effects for overqualification hardly change and remain significant. Horizontal mismatch is not significantly associated with the wage level or wage growth if occupation fixed effects are excluded from the model. However, when initial occupation is controlled for, a negative

[38]If study characteristics and ability measures are not included in the model, the negative effects of overqualification increase substantially.

Table 3.13: Results, Overqualification and Wage Growth

	Dependent variables: Starting wage and wage growth			
	lnW_1	$lnW_5 - lnW_1$	$lnW_{10} - lnW_5$	$lnW_{10} - lnW_1$
	(1)	(2)	(3)	(4)
Overqualification: Base year	-0.025*	-0.029**	-0.057***	-0.069***
	(0.014)	(0.013)	(0.011)	(0.013)
Female	-0.076***	-0.057***	-0.098***	-0.118***
	(0.011)	(0.010)	(0.009)	(0.010)
University grade	0.036***	0.016***	0.015***	0.018***
	(0.005)	(0.005)	(0.004)	(0.005)
School grade	0.003	-0.001	0.019***	0.018***
	(0.006)	(0.005)	(0.004)	(0.005)
Months unemployed	-0.007**	-0.011***	-0.005***	-0.012***
	(0.003)	(0.003)	(0.001)	(0.002)
Log Wage: Base year		-0.768***	-0.490***	-0.0752***
		(0.016)	(0.018)	(0.015)
Constant	2.962***	2.370***	1.740***	2.560***
	(0.017)	(0.051)	(0.057)	(0.047)
Occupation: Base Year	No	No	No	No
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.456	0.575	0.278	0.597
Observations	4357	4357	4357	4357

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; lnW_t is the logarithm of hourly wage in time period t; Base year is t=1 in specifications 1, 2, and 4; Base year is t=5 in specification 3; Significant at 1% ***, significant at 5% **, significant at 10% *.

association between horizontal mismatch with starting wage as well as with long-term wage growth is found. Therefore, horizontally mismatched graduates only suffer from wage penalties when compared to well-matched co-workers in the same base year occupation. These results suggest that horizontally mismatched graduates may often choose better paying occupations outside their own field but suffer wage losses if compared to their co-workers who obtained appropriate occupational skills from a matching field of study. As shown in Table 3.A.3, the significant link between overqualification and wage growth is similarly strong for female and male graduates.

Overall, the finding of a negative association between overqualification on subsequent wage growth contrasts the predictions of the career mobility theory. The assumption that graduates may deliberately self-select into initial overqualification in order to promote subsequent upward mobility is not supported. It therefore seems unlikely that low-level jobs can provide graduates with advantageous skills or experience fostering wage growth because they have already learned the most relevant occupational skills during tertiary education. As a result, career mobility theory might not provide a sound explanation for overqualification of graduates in Germany.[39]

[39]Büchel and Mertens (2004) draw a similar conclusion for overqualification of workers with vocational education in Germany.

3.8 Conclusion

In this study, I have analysed the dynamic features of overqualification over the early career cycle of tertiary graduates in Germany. The empirical analysis is based on panel data for two cohorts of graduates who participated in interviews conducted 1, 5, and 10 years after graduation. Overqualification is found to be highly persistent and to represent a permanent phenomenon for a substantial share of graduates. The probability to be overqualified is found to be 45 percentage points higher for those graduates who have already been overqualified approximately 5 years before. Accounting for a rich set of explanatory variables reduces the dynamic effect of previous overqualification experience to 34 percentage points. Therefore, raw state dependence partly arises due to observed heterogeneity affecting the probability to be overqualified at each point in time. Heterogeneity concerning study characteristics and individual ability, as measured by university and school grades, seems to be particularly relevant. Graduates with better university grades are less likely to enter or to be trapped in overqualification.

In order to analyse to what extent state dependence arises due to a behavioural effect or due to spurious correlation induced by unobserved factors, I employ the dynamic random-effects estimator proposed by Wooldridge (2005). Accounting for unobserved heterogeneity and the initial conditions problem, the results suggest that a moderate share of the overqualification persistence can be attributed to true state dependence. Previous overqualification experience is found to have a significant behavioural effect on future overqualification amounting to 3 percentage points. In conjunction with the finding that observed heterogeneity explains only a fraction of the persistence, these results suggest that unobserved factors are the main driver of the high persistence of overqualification. In particular, unobserved characteristics driving the selection into the initial state of overqualification are strongly related to the probability to remain overqualified later on. Such forms of unobserved heterogeneity might include preferences for particular job characteristics that can be found in low-requirement jobs, e.g. lower workload. Moreover, differences in ability that are not captured by grades may induce persistence because graduates with low ability lack the skills required to switch to an adequate job. The results are shown to be robust to the choice of the econometric model and the measure for educational mismatch. Overall, I find little evidence for gender-specific differences in the dynamics of overqualification. However, family responsibilities seem to have varying consequences because parenthood is only found to be positively associated with the probability of overqualification for female graduates.

Limitations of the current study may arise from the fact that only three observations per respondent are available in the data. In addition, the study does not account for a potential systematic attrition of respondents which may induce a selection of more able graduates into the estimation sample. Furthermore, the measurement of overqualification is subjective and relies on the respondents' valuation of skill requirements which is assumed to be constant over time.

The following policy implications can be drawn from this analysis. Since overqualification arises partly due to true state dependence, policy measures supporting tertiary graduates to avoid or to exit early overqualification could lead to a lasting reduction in the rate of overqualification. How these measures should be designed in detail, however, depends on which underlying mechanisms are most important for the true state dependence effect. Further research is needed in order to disentangle the relevance of potential mechanisms. The analysis reveals that heterogeneity in observed characteristics is a further source for persistence of overqualification. The results indicate that female graduates with children are more likely to get trapped in overqualification than male graduates with children. Though this may partly arise due to different preferences for working conditions, measures facilitating the exit from overqualification could be targeted to this at-risk group.[40] In contrast, no effect of motherhood on future overqualification is found for previously well-matched female graduates. One possible explanation could be that the better pre-birth job match increases the probability to return to the previous employer.[41]

A further implication is that the need for policy measures to reduce allocation constraints might differ across fields of study. By far the lowest incidence of overqualification is found for graduates in Medicine, Law, and Teaching who have to take a state examination which is a prerequisite for holding a civil service job or a job regulated by the state. These graduates will act on a highly specialised labour market narrowly focused on their own profession. The demand for graduates seems to be sufficiently high in these fields so that constrained options do not result in a high risk of overqualification. In contrast, allocation processes might be more difficult in the other fields leading to a higher share of mismatched graduates. A comparably low rate of overqualification among STEM graduates could be explained by the high demand for their field-specific skills. These skills are deemed to be highly important for innovation and technical developments as drivers of economic growth. In the light of the public debate about a potential shortage of STEM graduates, targeted measures could help to reconcile the actual available supply and the high demand for STEM graduates. The higher incidence of overqualification in Business Administration, Economics, Social and Cultural Sciences raises the question whether the demand for tertiary graduates in these fields is sufficiently high in order to absorb the increasing supply. Even after 10 years of labour market experience, more than one fifth of the graduates in these fields have not found a formally adequate job. Whether policies should focus on supporting a better match after course completion or should try to attract more applicants to other fields of study with lower rates of overqualification requires further research. In particular, policies aiming to attract more applicants for, e.g., STEM subjects have to be based on studies which account for potential self-selection into fields of study.

[40] As emphasised by studies on the effects of maternity leave on subsequent labour market participation, mothers may reassess their work preferences after first birth due to work-life conflict (e.g. Fitzenberger et al., 2016). Concerning the direct question on preferences for future job match available in the data, however, I find no significant differences between the answers of female graduates with and without children.

[41] Corresponding evidence is provided by, e.g., Arntz et al. (2014) and Fitzenberger et al. (2016). These studies measure job match quality by pre-birth job tenure, career progression, or relative wage position.

Two results of the analysis point to potential labour market frictions that cause graduates to involuntarily become or remain overqualified. This finding provides a more general argument for policy measures aiming to improve the allocation process. First, employing direct information on individual preferences for a future job match, I find that even graduates with high preferences face a substantial risk of being overqualified. Second, I find no support for the hypothesis of the career mobility theory assuming that workers voluntarily choose overqualification in order to facilitate a faster wage growth. In fact, I find that medium-run and long-run wage growth is lower for overqualified graduates. Though proxies for ability are included in the analysis, these results pointing to involuntary overqualification may partly arise due to differences in ability not captured by grades. In this case, public educational investments rather than the allocation of skills after graduation should be the focus of policy-makers.

Appendix

Table 3.A.1: Results, Wooldridge Dynamic RE Probit, Robustness

	Dependent Variable: Overqualification					
	(1)		(2)		(3)	
Overqualification $(t-5)$	0.029**	(0.014)	0.028**	(0.014)	0.032**	(0.015)
Overqualification $(t=1)$	0.234***	(0.024)	0.237***	(0.024)	0.317***	(0.030)
Female	0.019***	(0.006)	0.023***	(0.007)	0.013**	(0.006)
University grade	-0.019***	(0.003)	-0.019***	(0.003)		
School grade	-0.008**	(0.003)	-0.009*	(0.003)		
Age at grad. < 27	-0.011	(0.007)	-0.012*	(0.007)	-0.025***	(0.006)
Parents high-skilled	-0.006	(0.006)	-0.006	(0.006)	-0.016***	(0.006)
Married	-0.003	(0.010)	-0.003	(0.010)	-0.003	(0.009)
Children	0.007	(0.010)	0.007	(0.010)	0.006	(0.009)
Months unemployed	0.001	(0.001)			0.001	(0.001)
Married $(t=5)$	0.003	(0.010)				
Children $(t=5)$	0.006	(0.009)				
Months unemp $(t=5)$	-0.003	(0.010)				
Married $(t=10)$	0.000	(0.009)				
Children $(t=10)$	0.002	(0.002)				
Months unemp $(t=10)$	0.001	(0.001)				
Mean: Married			0.006	(0.013)	-0.004	(0.012)
Mean: Children			0.009	(0.013)	0.008	(0.012)
Mean: Months unemp					0.004**	(0.002)
Study charact.	Yes		Yes		No	
σ	1.201	(0.101)	1.217	(0.101)	1.252	(0.104)
ρ	0.590	(0.041)	0.597	(0.040)	0.610	(0.040)
Log. Lik.	-3827.0		-3849.4		-3983.6	
Obs. Indiv.	5987		5987		5987	
Obs. Total	11974		11974		11974	

Note: Random-effects probit estimation; Average partial effects; Standard errors in parentheses; ρ: estimate of the cross-period correlation of the composite error term $a_i + \varepsilon_{it}$; Significant at 1% ***, significant at 5% **, significant at 10% *.

Table 3.A.2: Results, Overqualification and Wage Growth, Robustness Checks

	Dependent variables: Starting wage and wage growth			
	lnW_1	$lnW_5 - lnW_1$	$lnW_{10} - lnW_5$	$lnW_{10} - lnW_1$
	(1)	(2)	(3)	(4)
Panel A:				
Overqualification: Base year	-0.034**	-0.036***	-0.061***	-0.069***
	(0.014)	(0.013)	(0.012)	(0.014)
Log Wage: Base year		-0.810***	-0.523***	-0.793***
		(0.017)	(0.018)	(0.015)
Occupation: Base year	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.511	0.586	0.311	0.612
Observations	4357	4357	4357	4357
Panel B:				
Overqualification: Base year	-0.023*	-0.027**	-0.059***	-0.061***
	(0.014)	(0.013)	(0.012)	(0.013)
Horizontal mismatch: Base year	-0.007	-0.003	-0.007	-0.018
	(0.015)	(0.013)	(0.011)	(0.013)
Log Wage: Base year		-0.768***	-0.487***	-0.751***
		(0.016)	(0.018)	(0.015)
Occupation: Base Year	No	No	No	No
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.448	0.574	0.275	0.592
Observations	4283	4283	4283	4283
Panel C:				
Overqualification: Base year	-0.027**	-0.031**	-0.064***	-0.062***
	(0.014)	(0.013)	(0.012)	(0.014)
Horizontal mismatch: Base year	-0.030**	-0.021	-0.008	-0.029**
	(0.014)	(0.013)	(0.011)	(0.013)
Log Wage: Base year		-0.810***	-0.522***	-0.792***
		(0.017)	(0.019)	(0.016)
Occupation: Base Year	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.504	0.586	0.308	0.608
Observations	4283	4283	4283	4283

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; lnW_t is the logarithm of hourly wage in time period t; Base year is t=1 in specifications 1, 2, and 4; Base year is t=5 in specification 3; Significant at 1% ***, significant at 5% **, significant at 10% *.

Table 3.A.3: Results, Overqualification and Wage Growth, by Gender

	Dependent variables: Starting wage and wage growth			
	lnW_1	$lnW_5 - lnW_1$	$lnW_{10} - lnW_5$	$lnW_{10} - lnW_1$
	(1)	(2)	(3)	(4)
Female:				
Overqualification: Base year	-0.036*	-0.039***	-0.070***	-0.070***
	(0.021)	(0.018)	(0.019)	(0.021)
Log Wage: Base year		-0.884***	-0.529***	-0.841***
		(0.023)	(0.028)	(0.022)
Occupation: Base year	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.500	0.646	0.276	0.643
Observations	2057	2057	2057	2057
Male:				
Overqualification: Base year	-0.036**	-0.038***	-0.058***	-0.068***
	(0.018)	(0.018)	(0.016)	(0.019)
Log Wage: Base year		-0.733***	-0.519***	-0.738***
		(0.026)	(0.024)	(0.022)
Occupation: Base year	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.461	0.517	0.352	0.579
Observations	2300	2300	2300	2300

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; lnW_t is the logarithm of hourly wage in time period t; Base year is t=1 in specifications 1, 2, and 4; Base year is t=5 in specification 3; Significant at 1% ***, significant at 5% **, significant at 10% *.

Table 3.A.4: Summary Statistics, Additional Variables

	Mean	SD	Min	Max	N
Horizontal mismatch ($t = 1$)	0.16	0.37	0	1	5827
Horizontal mismatch ($t = 5$)	0.16	0.37	0	1	5827
Horizontal mismatch ($t = 10$)	0.14	0.34	0	1	5827
Occupational mobility ($t = 5$)	0.34	0.47	0	1	5897
Occupational mobility ($t = 10$)	0.24	0.43	0	1	5897
Preference future match: Low ($t = 5$)	0.16	0.36	0	1	5987
Preference future match: Med. ($t = 5$)	0.23	0.42	0	1	5987
Preference future match: High ($t = 5$)	0.61	0.49	0	1	5987
Unemployment rate ($t = 1$)	3.74	1.64	1.05	16.48	5987
Log hourly wage ($t = 1$)	2.63	0.44	1.4	3.3	4357
Log hourly wage ($t = 5$)	2.91	0.33	1.6	3.6	4357
Log hourly wage ($t = 10$)	3.08	0.33	1.9	3.9	4357

Source: HIS-Graduate Panel 1997, 2001

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Chapter 4

Mobile Information and Communication Technologies, Flexible Work Organisation, and Labour Productivity: Firm-Level Evidence

Joint with

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Abstract

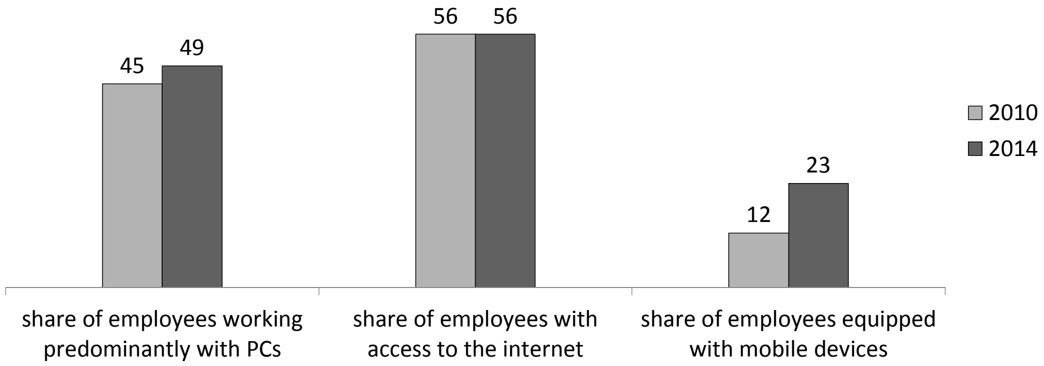
Mobile information and communication technologies (ICT) have started to diffuse rapidly in the business sector. This study tests for the complementarity between the use of mobile ICT and organizational practices providing workplace flexibility. We hypothesize that mobile ICT can create value if organizational practices grant employees appropriate autonomy over *when*, *where* and *how* to perform work-related tasks. Our data set comprises 1132 German service firms and provides information on the share of employees that have been equipped with mobile devices which allow for wireless internet access, such as notebooks, tablets and smartphones. Workplace flexibility is measured in terms of firms' use of working from home arrangements, working time accounts, and trust-based working time. Within a production function framework, we find that the use of mobile ICT is associated with a productivity premium only in firms granting workplace flexibility by means of trust-based working time. Robustness checks suggest that our results are not driven by increased workload, ICT-skill complementarity or by complementarity of mobile ICT with multiple alternative modern management practices.

4.1 Introduction

Mobile information and communication technologies (ICT) connecting to the internet, such as notebooks, tablets and smartphones, have been diffusing into the workplace during recent years. The expansion of mobile ICT marks the next step in the decentralisation of computing technologies after the development of the personal computer has relocated computing power from mainframe computers to the workers' desktops in the 1980s (Hitt and Brynjolfsson, 1997) and the diffusion of the internet has granted connectivity in the 1990s. In Germany, the diffusion of these two classical forms of ICT used at the workplace has nearly stagnated by now, as measured by the share of employees working predominantly at a personal computer or having access to the internet (Figure 4.1). In contrast, the share of employees who have been equipped with mobile ICT devices by their employer has nearly doubled from 12% to 23% between 2010 and 2014. The firms' adoption of mobile ICT is driven by dramatically declining prices for mobile ICT and improvements in the wireless infrastructure granting mobile connectivity. In the period from 2010 till 2014, for instance, hedonic prices for notebooks in Germany declined by about 40% (Destatis, 2015). Moreover, wireless digital connectivity is continuously improved allowing employees to access internal documents and information, or communicate with customers and business partners from virtually everywhere at any time. As digital communication and information processing is becoming ubiquitous, mobile ICT are widely expected to change how work will be organised in the future, dissolving its temporal and spatial boundaries.

In this study, we investigate the role of mobile ICT for firm performance with a special focus on organisational complements. As previous studies have shown, the returns to ICT investments depend heavily on organisational complements, such as decentralised work organisation

Figure 4.1: Recent Decentralisation of Computing Technologies in Germany



Source: Centre for European Economic Research (ZEW) (2015)

(Bresnahan et al., 2002). A complementary relationship between generic ICT and decentralised work organisation is founded in the difficulties to convey specific knowledge and the constraints to information processing abilities of 'bounded rational' individuals within the firm. As ICT have the capacity to mitigate both by reducing informational frictions and communication costs, these properties are deemed valuable especially when accompanied with respective changes in organisational practices and decision authority (Bloom et al., 2014; Hitt and Brynjolfsson, 1997).

Ubiquitous digital information processing and wireless connectivity are novel features of mobile ICT bearing the potential for enhanced labour productivity. Building on the ICT productivity literature, we hypothesise that mobile ICT can create value if organisational practices grant employees with appropriate decision rights and autonomy over *when*, *where* and *how* to perform work-related tasks. These organisational practices are frequently subsumed under the term *workplace flexibility*. This notion of complementarity also implies that firms which do not pursue workplace flexibility in their organisational design will experience lower returns to investments in mobile ICT. In order to test whether workplace flexibility is relevant for the efficient use of mobile ICT, we account for complementarities in a production function framework.

To explore our proposition, we gathered detailed survey data on the use of ICT and organisational practices in German service firms. We narrowed down the concept of workplace flexibility to formal organisational practices which grant employees control of their work schedule and hours, as well as flexibility with respect to the place of work.[1] In particular, we observe whether firms make use of working from home arrangements, working time accounts or trust-based working time. These measures broadly cover the most relevant organisational practices providing

[1] In this way, we delineate our analysis from aspects of flexibility that help employers to adapt to changes in supply and demand more quickly, such as part-time employment or reduced working hours, frequently discussed under the concept of external or numerical flexibility. Moreover, the focus of our analysis does not lie on management practices which formally provide for functional flexibility of employees, such as job-rotation (Hempell and Zwick, 2008; Origo and Pagani, 2008).

for workplace flexibility. They span the temporal and spatial dimension of flexibility and differ by the degree of autonomy granted to the employee.

We find support for complementarity between the use of mobile ICT and workplace flexibility. In particular, our results show that the use of mobile ICT is associated with a productivity premium in firms using trust-based working time. We do not find significant relations between mobile ICT and labour productivity in the absence of trust-based working time. As trust-based working time implies a step towards greater self-management and autonomy, our findings suggest that a high degree of workplace flexibility is crucial for the effective use of mobile ICT. Robustness checks suggest that our results are not driven by ICT-skill complementarity or by complementarity of mobile ICT with a wide variety of alternative modern management practices.

The remainder of the chapter is organised as follows. Section 2 provides a literature review on relevant previous results. Section 3 introduces the data and provides descriptive statistics. Section 4 describes the empirical methodology. Results are described in Section 5 and Section 6 concludes.

4.2 Background Discussion

This study is related to the vast literature on the effects of ICT and modern management practices on firm performance and, more specifically, to the literature on complementarities between ICT and organisational design. Moreover, our analysis is related to studies evaluating work-life balance practices and workplace flexibility.

Positive productivity effects of ICT as general purpose technology, often measured by IT investment, are well-documented at the firm level and the individual level (e.g. Bertschek, 2012; Draca et al., 2007; Kretschmer, 2012). Empirical evidence for more specific technologies, such as broadband technologies, are less conclusive (Bertschek et al., 2013; De Stefano et al., 2014). As mobile ICT have started to diffuse only quite recently, large-scale empirical evidence on their effects on firm performance is scarce. To the best of our knowledge, the only study focussing on productivity effects of mobile ICT is provided by Bertschek and Niebel (forthcoming). They find a positive association between mobile ICT and labour productivity for a sample of German manufacturing and service firms. Their analysis, however, abstracts from potential organisational complements to mobile ICT.

Complementarities between ICT and organisational practices have been found to be a main explanation for heterogenous returns on IT investments. The diffusion of ICT has coincided with radical changes in work organisation away form traditional tayloristic organisations to modern management practices emphasising decentralisation of decision authority and supporting incentives. Bresnahan et al. (2002) provide one of the first studies to show that firms can leverage their ICT investment by complementary organisational design. They find that productivity effects of ICT are higher among firms which pursue decentralised decision making and work in teams.[2] Bloom et al. (2012) show that the higher returns to ICT use of US-based firms compared to firms in Europe can be related to differences in the use of innovative people management practices that emphasise target setting, monitoring, promotion, rewards, hiring, and firing.

Going beyond the treatment of ICT as an homogeneous capital good, some authors highlight that different types of ICT can have distinct implications for performance and organisation (Aral and Weill, 2007; Bloom et al., 2014). Only quite recently studies started to explore complementarities between more particular technologies and specific organisational practices they were designed to support. Aral et al. (2012) document productivity effects of human capital management software when used in conjunction with performance pay and human resource analytics practices. Similar three-way complementarities are found between IT use, group-based decentralised decision-making and external focus of the firm (Tambe et al., 2012).

The effective use of mobile ICT supports an increasing decentralisation of work with respect to time and place. As summarised by Bloom et al. (2010), decentralisation in general involves a tradeoff between principal-agent problems (Prendergast, 2002) and the efficient use of private information favouring delegation and worker autonomy (Radner, 1993). Therefore, workplace flexibility might empower employees to work when and where they are most productive and creative, but could also lead to an increase in shirking. In fact, with regard to the existing literature the overall effects of working environments made up of mobile ICT and flexible working practices are unclear a priory.

Based on case studies and firm surveys, the literature on flexible working practices identifies several potential benefits.[3] While causal effects of organisational practices are inherently hard to pin down, this literature finds positive associations of flexible working practices with employees' work-life balance, absenteeism, employee turnover and, ultimately, productivity (e.g. Bloom and Van Reenen, 2006; Dalton and Mesch, 1990; Dionne and Dostie, 2007; Hill et al., 2008; Stavrou and Kilaniotis, 2010). Recent experimental evidence is provided by Bloom et al. (2015) who randomly assigned callcenter agents into working from home arrangements. They find considerable performance increases as well as improved work satisfaction induced by working from home. Furthermore, the allocation of authority can have strong motivational effects (Roberts, 2007) and increase commitment. Exploiting German firm level data, Beckmann and Hegedues (2011) and Godart et al. (forthcoming) provide evidence for positive effects of trust-based working time on productivity and innovation.

On the contrary, flexible working practices could also exhibit detrimental effects on productivity related factors. The technology driven availability for work-related purposes outside regular working hours and the interruption of leisure time can evoke work-family conflicts (Boswell and Olson-Buchanan, 2007), reduce job satisfaction or even cause mental strain and other health-related problems (Askenazy and Caroli, 2010). Allowing employees to work at disparate locations and times can furthermore be associated with higher coordination and monitoring

[2] Further studies confirm these complementarity effects in different contexts (e.g. Bartel et al., 2007; Bertschek and Kaiser, 2004; Garicano and Heaton, 2010).

[3] See Council of Economic Advisors (2010) or De Menezes and Kelliher (2011) for reviews.

costs within the firm (Alonso et al., 2008) and impede the exploitation of potential returns to scale (Thesmar and Thoenig, 2007). Finally, firms using mobile ICT may face costs related to IT-security.

In spite of a growing literature dealing with workplace flexibility in economics, this aspect has yet to be integrated into the IT productivity literature. As performance effects of mobile ICT are not clear to date, our study contributes to a more precise understanding about how these new technologies affect work outcomes and interact with firms' internal organisation.

4.3 Data

4.3.1 Data Set

We gathered fine-grained survey data on firms' use of ICT and flexible working practices within the scope of the ICT-Survey by the Centre for European Economic Research (ZEW).[4] The survey was conducted by computer assisted telephone interviews in 2014/2015 and covers manufacturing and service firms located in Germany. It was stratified according to 17 industries, three size classes and two regions (East/West Germany).

We confine our analysis to firms in the service sector, where knowledge work is a considerable input share and where we expect mobile ICT and the technological opportunities they create to be most relevant. By focusing on a more homogenous population of firms, we attempt to mitigate the problem of unobserved heterogeneity and avoid estimating production processes which are potentially quite heterogenous. After data cleaning and due to item-nonresponse we arrive at a final estimation sample of 1132 observations.

4.3.2 Measuring ICT

In this study, we focus on potential productivity effects brought about by the novel features of mobile ICT, i.e. wireless connectivity and ubiquitous digital information processing. Since firms that use mobile ICT might also exhibit a high general ICT intensity, we have to differentiate mobile ICT use from other forms of ICT used at the workplace.

In order to measure the firms' use of mobile ICT, we asked for the share of employees which firms equipped with mobile devices which provide wireless internet access, such as notebooks, smartphones or tablets (*% emp. using mobile ICT*). In addition, we measure the firms' general ICT intensity in terms of the share of employees who work predominantly with a computer (*% emp. working with PC*). This measure is a common proxy for general purpose ICT and has been widely used in the ICT productivity literature (e.g. Bloom et al., 2012; Bresnahan et al., 2002). Finally, the firms' general (mainly fixed-line) internet connectivity is measured by the share of employees who have access to the internet at the workplace (*% emp. internet access*). Table 4.A.5 provides an overview and descriptions of the main variables in our analysis.

[4] See the ZEW Research Data Centre for more information: `http://kooperationen.zew.de/en/zew-fdz/provided-data/zew-ict-survey.html`.

4.3.3 Measuring Workplace Flexibility

Extending the common organisational practices considered in the ICT productivity literature, we focus on flexible working practices which provide employees discretion over when, where and how to perform work-related tasks. In particular, we consider three generic measures of respective human resource management practices in our analysis.

First, with respect to spatial flexibility, we consider the use of *working from home arrangements* by the firm. Such arrangements, also discussed under the terms telecommuting or telework, first appeared in the academic discourse in the the 1970s (Nilles, 1975), and have become increasingly common ever since. To date, working from home arrangements are the dominating organisational practice which employers adopt to promote flexibility with regard to the place of work. Based on the question whether employees have the opportunity to work from home regularly, we generate a dummy variable taking the value one if working from home arrangements are used by the firm and zero, otherwise. We employ this variable in order to measure if the firm delegates decision authority to employees over where to perform work-related tasks.

Second, with respect to temporal flexibility, we consider the use of *working time accounts*. Working time accounts cover a variety of more specific arrangements which involve the accumulation of time credits/debits and differ by the period of time after which employees must balance their accounts. One of the most common forms are flextime arrangements, under which accounts must be balanced on a daily basis and which allow employees to exercise some choice over beginning and end of their workday around some mandatory core hours (Godart et al., forthcoming). Working time accounts in the form of flextime arrangements started diffusing during the 1960s and marked the onset of working time flexibility in Germany (Beermann and Brenscheidt, 2013). We measure the firms' use of working time accounts by a dummy variable taking the value one if working time accounts are used and zero, otherwise.

Third, we analyse the use of *trust-based working time*. In contrast to working time accounts, under trust-based working time employers typically completely renounce controlling working hours and grant employees complete discretion over how to manage their workday. They differ from other flexible working arrangements as they involve a transition from working time registration to a management by objectives strategy, i.e. a shift from input control to output control (Beckmann and Hegedues, 2011; Singe and Croucher, 2003). As employees are merely evaluated by their work output, trust-based working time imply flexibility along multiple dimensions. They refer to a form of self-managed work involving a high degree of autonomy but are also demanding in terms of self-reliance. Therefore, they arguably constitute the most radical form of workplace flexibility that we consider and that is empirically relevant among German firms today.

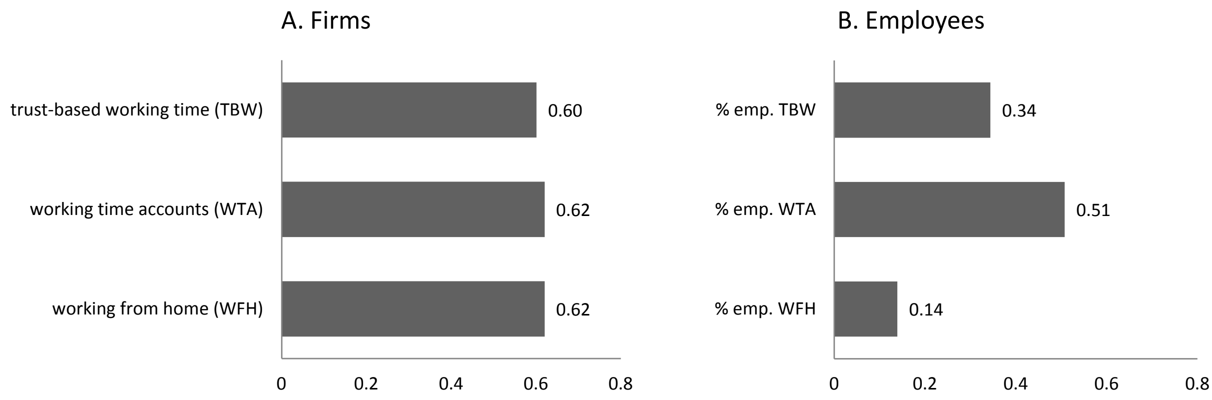
By focusing on working from home arrangements, working time accounts and trust-based working time, we consider the most obvious organisational complements to the technological novelty in mobile ICT over more traditional types of ICT. Our measures cover the most relevant organisational practices providing for workplace flexibility and enable us to aptly measure firms' organisational flexibility at large (BMFSFJ, 2013). At the same time, we are able to differentiate between spatial and temporal flexibility, as well as the degree of authority delegation. Thus, we can provide more nuanced insights into how mobile ICT are effectively used and which types of working environments they will likely promote as they continue to diffuse.

4.3.4 Descriptive Statistics

Figure 4.2 depicts the incidence of workplace flexibility practices among the firms in our sample. Interestingly, all three practices are equally common, as shown in panel A. Each practice is used by about 60% of the firms. Disparities in the prevalence of the different forms of workplace flexibility are revealed when looking at the share of employees actually working under the respective arrangement in the average firm in our sample, as shown in panel B. Whereas around 51% of the employees have working time accounts, only 34% of the employees work under trust-based working time. About 14% are working under official working from home arrangements on average.

Table 4.1 provides summary statistics for all main variables of our analysis. On average, the firms have 138 employees and achieved a volume of sales of 0.17 million Euros per employee. The median size of the firms amounts to 25 employees and reflects that our sample largely consists of small and medium sized establishments. The firms' average investment expenditures amount to 1 million Euro and 27% of the employees obtained a university degree. On average, the employers have equipped a share of 34% of their employees with mobile ICT devices. 86% of the firms in our sample use mobile ICT at all. Focusing on the firms' general ICT intensity, 62% of the employees work predominantly with a PC and 74% have access to the internet at the workplace on average. Table 4.A.1 displays the industry distribution among the firms in our sample.

Figure 4.2: Workplace Flexibility Practices



Notes: Panel A shows the averages of the binary variables indicating whether the firm generally offers working from home arrangements, working time accounts and trust-based working time. Panel B provides the averages of the respective shares of employees actually working under the arrangement in the 1132 firms in our estimation sample. *Source:* ZEW ICT-Survey 2014/2015

Table 4.1: Summary Statistics

	Mean	SD	Min	Max
Labor productivity				
sales (in mio. Euro) / employees	0.17	0.32	0.006	6.000
Workplace flexibility				
trust-based worktime	0.60	0.49	0	1
working time accounts	0.62	0.49	0	1
working from home	0.62	0.49	0	1
ICT use				
% emp. mobile ICT	0.34	0.33	0	1
% emp. working with PC	0.62	0.37	0	1
% emp. internet access	0.74	0.35	0	1
Qualification and age structure				
% high-skilled emp.	0.27	0.30	0	1
% medium-skilled emp.	0.58	0.29	0	1
% emp. below 30	0.24	0.18	0	1
Controls				
employees	138.45	697.42	1	15518
investments (in mio. Euro)	1.04	4.56	0	90
location in Eastern Germany	0.29	0.45	0	1
Observations	1132			

Source: ZEW ICT-Survey 2014/2015

4.4 Methodology

We investigate the hypothesis that the impact of mobile ICT use on firm performance hinges on the firms' organisational complements that are appropriate to take advantage of the novel features of mobile ICT. The seminal article by Milgrom and Roberts (1990) formalises this notion of complementarity. It requires that the contribution of (weakly) complementary input factors to a payoff function $\Pi(\cdot)$, such as productivity, is jointly higher (at least equal) than the sum of their individual contributions when implemented in isolation.[5]

$$\Pi(1,1) - \Pi(0,0) \geq \Pi(1,0) - \Pi(0,0) + \Pi(0,1) - \Pi(0,0) \tag{4.1}$$

In principle, the literature has put forward two types of statistical tests for the existence of complementarities between input factors as formalised by the inequality restriction in equation (4.1). Most commonly, studies test for complementarities indirectly, by looking at correlations between input factors (factor demand equations). If two activities are complements and this is well understood by the firm, one should observe a clustering of adoption decisions. A more direct test for complementarities focuses on analysing performance differences. This involves testing whether the hypothesised complements are more productive when adopted jointly rather than individually by estimating productivity equations.

[5] See also the discussion by Brynjolfsson and Milgrom (2013).

Each test tends to have the highest statistical power when the other is weakest. Given mobile ICT and workplace flexibility were actually complements, firms would seek to adopt them jointly. If managers are fully aware of a set of complements and have complete control over the individual factors, we would expect all firms to adopt the system of complements and correlation will be strong. A productivity test, on the contrary, would have little power to identify benefits form adopting the system of complements in this hypothetical situation, as firms would not adopt one complement in isolation. However, in a situation where firms are still experimenting with various practices or do not have full control over any of the complementary factors, correlation of complementary practices would not be perfect but there should be detectable differences in productivity (Aral et al., 2012; Brynjolfsson and Milgrom, 2013).

The latter case is likely more relevant to our application, especially due to the novelty of mobile ICT. As mobile ICT started diffusing to the business sector only recently and wireless internet infrastructure in Germany has matured only over recent years, firms' knowledge of the effective use of these young technologies is likely still limited. Jovanovic and Stolyarov (2000) and Bresnahan et al. (2002) show that complements might be upgraded at different times if their identification and implementation involves uncertainty and learning. In addition, we draw from the vast literature on organisational practices and complements, which assumes that organisational practices tend to persist over time and are hard to change for incumbent firms, as justified by high adjustment costs of organisational change (Autor et al., 2002; Milgrom and Roberts, 1990; Tambe et al., 2012). Consequently, when organisational practices are quasi-fix over the short run, managers were not able to act efficiently on them over the diffusion period of mobile ICT. While mobile ICT and relevant organisational complements might not be clustered under these circumstances, their joint impact on productivity will still be measurable. We therefore focus on analysing complementarities within a classical production function framework.

In testing directly for complementarities in production, the literature has primarily built on the Cobb-Douglas production function framework. In line with this literature, our primary regression model is an augmented Cobb-Douglas production function with complementary technology and organisational inputs entered independently and in pairs. It can be written as:

$$\begin{aligned} ln\left(\frac{Y_i}{L_i}\right) &= ln(A_i) + (\alpha_L - 1)ln(L_i) + \alpha_K ln(K_i) + \beta_{PC}PC_i + \beta_{IA}IA_i \\ &+ \beta_{mobICT}mobICT_i + \gamma_{TBW}TBW_i + \gamma_{WTA}WTA_i + \gamma_{WFH}WFH_i \qquad (4.2) \\ &+ [\delta_1 TBW_i + \delta_2 WTA_i + \delta_3 WFH_i] * mobICT_i + \lambda'\mathbf{x}_i + u_i \end{aligned}$$

Y_i denotes output of firm i measured in sales, which the production function relates to labour L_i, capital K_i and a Hicks-neutral productivity term A_i. As we do not observe capital inputs, we use investment expenditures to approximate capital, assuming that investments are proportional to the firms' capital stock. Labour is measured by the number of employees. In addition to capital and labour inputs, we augment the production function by our ICT inputs and organisational measures, which account for firms' use of workplace flexibility. As a measure of general ICT intensity, we include the share of employees working predominantly with computers (PC_i) as well as the share of employees with internet access (IA_i). Our key variable of interest is the share of employees equipped with mobile devices ($mobICT_i$). We account for workplace flexibility by three dummy variables indicating whether the firm uses trust-based working time (TBW_i), working time accounts (WTA_i), or working form home arrangements (WFH_i). $\mathbf{x}_i$ represents a vector of control variables and u_i is an idiosyncratic error term. As control variables, we include the share of employees with university degree, the share of employees with vocational education, and the share of employees below the age of 30 to account for the skill and age profile of the workforce. Moreover, we include nine industry dummies constructed from two digit standard industry codes (NACE) and a dummy indicating whether the firm is located in Eastern Germany.

The β and γ coefficients capture the main effects of ICT and workplace flexibility. Our primary interest lies in the model parameters $\delta_1 - \delta_3$. If mobile ICT and any type of workplace flexibility form a system of complements reinforcing each other, we would expect $\delta > 0$ after controlling for other factors affecting production. We estimate our model by ordinary least squares (OLS) with heteroskedasticity-robust standard errors.

4.5 Results

4.5.1 Correlation of Workplace Flexibility and ICT

Table 4.2 shows the correlation matrix between key variables in our analysis, i.e. the binary variables indicating whether a firm uses each of the three workplace flexibility practices and our three measures for ICT use at the workplace. We gain two main insights from these correlations.

First, the correlations between the workplace flexibility measures are only moderate and do not provide strong evidence for clusters of practices which firms implement jointly (Ichniowski et al., 1997). Instead, the correlations reflect that the concept of workplace flexibility is multidimensional. Firms implementing one of the observed practices do not necessarily adopt the other practices as well. No correlation is found between the adoption of working time accounts and trust-based working time. This finding is not counterintuitive since the former practice is based on keeping record of working hours whereas the latter disregards the employees' working hours by definition. The use of working from home arrangements is positively correlated with the use of trust-based working time ($r = 0.25$) and working time accounts ($r = 0.09$), however a relevant proportion of firms use just one of these organisational practices, if any. Consequently, we consider them separately in our analysis in order to get a more nuanced picture of which practices are relevant in leveraging investments in mobile ICT.

Second, the correlations between organisational measures and ICT variables provide first evidence that firms pursuing workplace flexibility in their organisational design differ from the remaining firms in terms of their ICT use. In line with our hypothesis, general ICT intensity and

Table 4.2: Correlation of Workplace Flexibility and ICT

	TBW	WTA	WFH	mobile ICT	PC
trust-based worktime (TBW)	1				
working time accounts (WTA)	-0.001	1			
working from home (WFH)	0.247***	0.087***	1		
% emp. mobile ICT	0.146***	-0.063**	0.224***	1	
% emp. working with PC	0.193***	-0.008	0.288***	0.296***	1
% emp. internet access	0.181***	-0.008	0.251***	0.360***	0.740***

Note: Significant at 1% ***, significant at 5% **, significant at 10% *.

the share of employees equipped with mobile devices is higher in firms that have implemented workplace flexibility practices. In particular, the use of working from home arrangements and trust-based working time is positively correlated to all three measures of the firms' ICT use. In contrast, the firms' use of working time accounts is not significantly correlated to general ICT intensity. The correlation with mobile ICT is even significantly negative, but comparably small. Overall, the mainly positive pairwise correlations reflect some joint adoption of mobile ICT and individual practices. While this might be taken as first evidence for complementarities between mobile ICT and workplace flexibility, we focus in the following on the more direct test for complementarities employing a productivity analysis.

4.5.2 Main Results

Table 4.3 provides the estimation results of the production function model in equation (4.2). In specification (1), mobile ICT use and the workplace flexibility practices are included separately in the production function. The share of employees equipped with mobile devices by the employer (*% emp. using mobile ICT*) is not significantly associated with labour productivity. The respective coefficient is positive, but marginally insignificant at conventional levels. Concerning the measures for workplace flexibility, we find a positive and significant association between the use of trust-based working time and labour productivity. Among firms using trust-based working time the labour productivity is on average 8 percent higher than among firms that have not adopted this flexible work practice. In contrast, for working time accounts and working from home arrangements the estimated coefficients are considerably smaller and statistically insignificant.

In line with the literature, we find a positive association between general ICT intensity, as measured by the share of employees working with a PC, and labour productivity. The share of employees with internet access at the workplace is not significantly related to productivity if the firms' general ICT intensity is taken into account. As a measure for the firms' human capital, the shares of high-skilled and medium-skilled employees are included. The coefficients for both shares are positive and highly significant, with the coefficient for high-skilled employees exceeding the one for medium-skilled employees.

Table 4.3: Baseline Regression Results

	Dependent Variable: ln(sales/employees)				
	(1)	(2)	(3)	(4)	(5)
% emp. mobile ICT	0.114	-0.089	0.020	0.007	-0.223
	(0.072)	(0.109)	(0.107)	(0.104)	(0.139)
trust-based worktime (TBW)	0.080*	-0.021	0.081*	0.078*	-0.017
	(0.044)	(0.058)	(0.044)	(0.044)	(0.059)
working time accounts (WTA)	0.009	0.012	-0.046	0.009	-0.045
	(0.046)	(0.046)	(0.062)	(0.046)	(0.063)
working from home (WFH)	0.044	0.041	0.044	-0.003	0.021
	(0.047)	(0.047)	(0.047)	(0.059)	(0.060)
% emp. mobile ICT * TBW		0.315**			0.305**
		(0.131)			(0.138)
% emp. mobile ICT * WTA			0.158		0.163
			(0.129)		(0.130)
% emp. mobile ICT * WFH				0.167	0.069
				(0.131)	(0.138)
% emp. working with PC	0.300***	0.299***	0.299***	0.298***	0.297***
	(0.098)	(0.098)	(0.098)	(0.098)	(0.097)
% emp. internet access	-0.001	0.015	0.000	0.012	0.021
	(0.091)	(0.091)	(0.091)	(0.092)	(0.091)
ln(employees)	-0.092***	-0.088***	-0.092***	-0.092***	-0.088***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
ln(investment)	0.118***	0.116***	0.119***	0.118***	0.117***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
% high-skilled emp.	0.453***	0.449***	0.450***	0.432***	0.437***
	(0.148)	(0.149)	(0.149)	(0.150)	(0.150)
% medium-skilled emp.	0.270**	0.266**	0.257**	0.260**	0.248*
	(0.127)	(0.128)	(0.126)	(0.128)	(0.128)
% emp. below 30	-0.181	-0.191	-0.183	-0.180	-0.193
	(0.126)	(0.125)	(0.126)	(0.126)	(0.126)
Constant	-1.632***	-1.616***	-1.582***	-1.609***	-1.556***
	(0.164)	(0.164)	(0.168)	(0.165)	(0.169)
Industry & Regional Dummies	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.35	0.35	0.35	0.35	0.35
Observations	1132	1132	1132	1132	1132

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; Significant at 1% ***, significant at 5% **, significant at 10% *.

In specifications (2)-(4), we subsequently include an interaction term between mobile ICT and one of the three workplace flexibility measures into the production function. We find a positive and highly significant coefficient for the interaction term between mobile ICT and the indicator variable for trust-based working time in specification (2). The main effects of mobile ICT and trust-based working time reduce substantially and become insignificant once the interaction term is included in the model. This result suggests that the joint adoption of mobile ICT and workplace flexibility in terms of trust-based working time exhibits positive productivity effects, while a separate adoption does not significantly affect the firm performance. In contrast, the interaction terms with working time accounts (specification 3) and working from home arrangements (specification 4) are positive but statistically insignificant. We thus do not find support for complementarities between mobile ICT and these individual practices providing for spatial and temporal flexibility.

Specification (5) provides the estimation results for the full model formulated in equation (4.2), with all interaction terms between mobile ICT and the workplace flexibility measures entering jointly. The positive coefficient for the interaction term between mobile ICT and trust-based working time remains nearly unchanged and, thus, is robust to the inclusion of the further interaction terms which are again much lower and insignificant.[6] We do not find any significant main effects for mobile ICT or workplace flexibility measures in this specification.

To illustrate the economic significance of our findings, Figure 4.A.1 provides predictive margins of labour productivity based on the estimation results of specification (5) in Table 4.3. The margins are predicted by assigning fix values of mobile ICT use and workplace flexibility to all firms in our sample, while retaining observed values for all other covariates. Panel A presents predictive margins for fixed shares of employees using mobile ICT differentiated by the use of trust-based working time. For instance, assuming that firms use trust-based working time and fixing the share of mobile ICT at a value of 20%, we predict a log labour productivity of -2.22 (depicted by the dashed red line).

4.5.3 Limitations and Robustness Checks

So far, our results provide first indicative conditional correlations in support of the hypothesis of complementarity between mobile ICT and workplace flexibility. However, we must be cautious in interpreting our results due to common challenges in testing for complementarities (Athey and Stern, 1998).

First, instead of the joint adoption of mobile ICT and trust-based working time affecting productivity, causality could potentially run in the opposite direction. For instance, firms with a positive productivity shock and improved cash flows might be more likely to invest in new technologies. Likewise, well performing firms might be in a better position to offer their employees the amenity of workplace flexibility.

Second, our results could be driven by unobserved factors causing mobile ICT, flexible working practices and productivity to move together. A widely expressed concern in the literature is that unobserved *good (human resource) management* is causing the joint adoption of new technologies and specific advanced management practices as well as their joint covariance with performance (Bloom and Van Reenen, 2011; Brynjolfsson and Hitt, 2000; Tambe et al., 2012).

Concerning the endogeneity of organisational practices in our model, we follow most of the literature and assume that organisational practices are quasi-fix over the short run.[7] In this vein, we assume that firms' organisational design only changed marginally during the short

[6] An F-test on the joint significance of all three interaction terms in specification (5) supports joint significance at the five percent level.

[7] See the discussion in section 4.4.

diffusion period of mobile ICT and does not constitute a choice variables in our model.[8] In this sense, one can interpret our regressions as assessing whether firm differences in organisational design, which existed prior to the diffusion of mobile ICT, affect the returns from using these technologies (Aral et al., 2012). Still, one might be particularly concerned about endogeneity of mobile ICT in our production function.

As a robustness check of our results, we address the problem of omitted variable bias. In particular, we focus on the issue that the positive coefficient on the interaction term (δ) might pick up unobserved management and organisational practices other than workplace flexibility. Our data include information on additional 'modern' managerial practices, which have been used to assess management quality of the firm (Bloom and Reenen, 2007) and have frequently been analysed in the ICT productivity literature and the personnel economics literature (Bartel et al., 2007; Black and Lynch, 2001; Cappelli and Neumark, 2001; Ichniowski and Shaw, 2003; Ichniowski et al., 1997). These management practices contrast with traditional hierarchical organisation and emphasise decentralisation of decision authority, incentives and target setting, monitoring and multitasking. Besides workplace flexibility, they have been characteristic for organisational change taking place since the 1990s. We augment our model in equation (4.2) by interactions of mobile ICT with these management practices in order to contrast workplace flexibility from possibly confounding managerial and organisational practices that could have biased our previous results.

Table 4.A.2 provides summary statistics on the indicator variables for additional management and organisational practices we are able to take into account. We observe whether the firm rewards employees based on effort by the use of incentive pay. We moreover take into account the existence of business units with own profit and loss responsibility, such as profit centers, which has been used to proxy general decentralisation of decision authority below central management (Acemoglu et al., 2007). We account for target setting and monitoring by the firms' use of regular objective agreements and written performance appraisals. Finally, we observe whether the firm makes use of job rotation models to develop the employees' functional flexibility.

In the columns (1)-(5) in Table 4.4 we augment our baseline specifications (provided in Table 4.3) by the interactions between mobile ICT and the measures on managerial and organisational practices we can account for. We find that, conditional on the additional management interactions our previous results remain unaffected. While the use of mobile ICT is positively and significantly associated with labour productivity when firms use trust-based working time, it is not when firms have adopted any other advanced management practice we consider. Moreover, the coefficient for the *mob ICT * TBW* interaction term remains similar in magnitude to our baseline results. Hence, this robustness check imposes further restrictions on any unobserved third factor that could bias our findings in support of complementarity between mobile ICT and trust-based working time. Such factor would have to drive the use of mobile ICT, trust-based working time,

[8] This assumption is supported by several studies showing that the use of many flexible working arrangements, such as working from home or trust-based working time remained largely constant in Germany over recent years (BMFSFJ, 2013; Brenke, 2014).

Table 4.4: Robustness Tests: Management Practices and Skill-Complementarity

	Dependent Variable: ln(sales/employees)					
	(1)	(2)	(3)	(4)	(5)	(6)
% emp. mobile ICT	0.084	-0.101	0.011	-0.000	-0.220	-0.213
	(0.108)	(0.139)	(0.122)	(0.124)	(0.151)	(0.145)
trust-based worktime (TBW)	0.072	-0.031	0.073*	0.070	-0.029	-0.018
	(0.044)	(0.058)	(0.044)	(0.044)	(0.059)	(0.059)
working time accounts (WTA)	-0.002	0.001	-0.059	-0.002	-0.063	-0.045
	(0.047)	(0.047)	(0.065)	(0.047)	(0.065)	(0.063)
working from home (WFH)	0.034	0.032	0.034	-0.015	0.006	0.019
	(0.048)	(0.048)	(0.048)	(0.061)	(0.062)	(0.062)
% emp. mobile ICT * TBW		0.324**			0.316**	0.305**
		(0.134)			(0.142)	(0.138)
% emp. mobile ICT * WTA			0.164		0.182	0.162
			(0.141)		(0.141)	(0.129)
% emp. mobile ICT * WFH				0.174	0.090	0.079
				(0.135)	(0.142)	(0.147)
incentive pay (IP)	0.094	0.098	0.096	0.098	0.102*	
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	
job rotation (JR)	-0.089	-0.089	-0.083	-0.086	-0.081	
	(0.075)	(0.075)	(0.076)	(0.075)	(0.076)	
profit center (PR)	0.096	0.100	0.101	0.103	0.109	
	(0.071)	(0.071)	(0.071)	(0.072)	(0.071)	
objective agreements (OA)	0.073	0.083	0.079	0.079	0.092	
	(0.078)	(0.077)	(0.078)	(0.078)	(0.078)	
performance appraisals (PA)	0.008	0.006	0.013	0.012	0.014	
	(0.076)	(0.076)	(0.077)	(0.077)	(0.077)	
% emp. mobile ICT * IP	0.009	-0.018	0.006	-0.009	-0.029	
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	
% emp. mobile ICT * JR	-0.069	-0.080	-0.083	-0.077	-0.100	
	(0.192)	(0.192)	(0.195)	(0.190)	(0.194)	
% emp. mobile ICT * PR	0.032	0.011	0.015	0.015	-0.017	
	(0.149)	(0.146)	(0.148)	(0.148)	(0.145)	
% emp. mobile ICT * OA	-0.079	-0.105	-0.097	-0.102	-0.137	
	(0.161)	(0.158)	(0.164)	(0.163)	(0.163)	
% emp. mobile ICT * PA	0.045	0.069	0.025	0.039	0.044	
	(0.161)	(0.161)	(0.165)	(0.160)	(0.164)	
% high-skilled emp. (HSE)	0.462***	0.461***	0.463***	0.444***	0.453***	0.458***
	(0.151)	(0.151)	(0.151)	(0.152)	(0.151)	(0.165)
% emp. mobile ICT * % HSE						-0.046
						(0.206)
% emp. working with PC	0.290***	0.290***	0.291***	0.290***	0.291***	0.297***
	(0.099)	(0.099)	(0.099)	(0.099)	(0.098)	(0.097)
% emp. internet access	-0.031	-0.017	-0.033	-0.022	-0.016	0.018
	(0.092)	(0.093)	(0.092)	(0.093)	(0.093)	(0.092)
Constant	-1.611***	-1.599***	-1.566***	-1.593***	-1.540***	-1.556***
	(0.165)	(0.165)	(0.168)	(0.167)	(0.169)	(0.169)
ln(emp) & ln(inv)	Yes	Yes	Yes	Yes	Yes	Yes
% med.-skilled & % below 30	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.35	0.35	0.35	0.35	0.35	0.35
Observations	1132	1132	1132	1132	1132	1132

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; Significant at 1% ***, significant at 5% **, significant at 10% *.

and firms' productivity simultaneously, but at the same time would have to be unrelated to any other form of managerial practice we consider.

In specification (6) presented in Table 4.4, we perform a further check of our main findings. It refers to the vast literature showing that new technologies, and ICT in particular, are complementary with skills (Autor et al., 2003). While we accounted for the skill profile of the workforce throughout all our estimations, we now include an additional interaction term between mobile ICT use and the share of high-skilled employees. We thereby test whether it is actually the simultaneous presence of mobile ICT and a skilled workforce in firms using trust-based working time that drives our findings. The results show that the coefficient for the additional interaction term is insignificant, while our previous findings remain unaffected. We thus assume that our main findings do not reflect complementarity of mobile ICT with skills.

In a further robustness check, we focus on differences in the firm-specific functionality of mobile ICT for work-related tasks. In particular, the effectiveness of mobile ICT usage might be contingent on the possibility to remotely access relevant corporate information. In order to account for this interdependence, we use information on the firms' provision of remote access to different types of internal digital resources. Provision of external access to following internal resources is observed: the corporate email account, wiki/intranet, software, and networks (see Table 4.A.3 for descriptives). As a robustness test, we perform a split sample analysis and distinguish firms that provide for a more advanced external access, i.e. access to corporate wiki, software, or networks, from firms providing no external access or only allowing to log in to the corporate email account. The descriptives statistics presented in Table 4.A.4 show that firms of the former group make use of mobile ICT and workplace flexibility more intensively than firms without an advanced external access provision. Still, nearly half of these latter firms used trust-based working time and equipped an average share of 24% of their employees with mobile ICT. We expect that our main results are contingent on the type of external access that is provided by the firm. The more advanced resources the employees can access remotely, the more effective we expect the use of mobile devices to be. For instance, only employees provided with an external access to corporate networks are able to remotely access and change relevant documents saved on internal networks. The results in Table 4.5 show that our main results indeed only hold for the firms which provide for advanced external access beyond mere possibility to log in to the corporate email account. Firms that do not provide their employees with an advanced access to internal resources are unlikely to make efficient use of the novel features of mobile ICT.

Finally, we address differences in the employees' workload as a potential confounding factor. As we have shown, output per employee is higher in firms providing for trust-based working time and equipping a higher share of employees with mobile ICT. However, working arrangements involving high workplace flexibility and mobile ICT usage are often criticised to potentially increase the employees' workload and lead employees to work longer hours. Thus, we aim to test whether our main finding is attributable to an increase in employees' workload rather than to a productivity effect because employees are able to work when and where they are most

Table 4.5: Robustness Test: Effects by External Access Provision

	Dependent Variable: ln(sales/employees)			
	Advanced Ext. Access[a]		No Advanced Ext. Access[b]	
	(1)		(2)	
% emp. mobile ICT	-0.273	(0.198)	-0.084	(0.223)
trust-based worktime (TBW)	-0.109	(0.074)	0.111	(0.096)
working time accounts (WTA)	-0.008	(0.084)	-0.082	(0.099)
working from home (WFH)	0.007	(0.081)	0.042	(0.118)
% emp. mobile ICT * TBW	0.462***	(0.158)	-0.032	(0.292)
% emp. mobile ICT * WTA	0.142	(0.158)	0.075	(0.274)
% emp. mobile ICT * WFH	0.103	(0.167)	-0.086	(0.346)
% emp. working with PC	0.259**	(0.115)	0.352**	(0.172)
% emp. internet access	0.113	(0.117)	-0.150	(0.155)
Constant	-1.352***	(0.222)	-1.720***	(0.268)
ln(emp) & ln(inv)	Yes		Yes	
% med.-skilled & % below 30	Yes		Yes	
Industry & Regional Dummies	Yes		Yes	
Adjusted R^2	0.357		0.323	
Observations	787		345	

Note: OLS estimations; [a] Firm provides external access to corporate wiki/intranet, software, or networks from outside the firm; [b] Firm provides solely external access to the corporate email account or no external access to internal network resources at all; Heteroskedasticity-robust standard errors in parentheses; Significant at 1% ***, significant at 5% **, significant at 10% *.

productive and creative. We employ the share of employees working overtime as a measure for the workload of a firm's employees. The share was indicated by the interview respondent and overtime is defined as extra work performed exceeding the weekly working hours agreed upon.[9] As a robustness test, we estimate our baseline equations but model the share of employees working overtime instead of the firms' labour productivity. Table 4.6 shows that the share of employees working overtime is significantly higher in firms using working time accounts. The positive relationship is logical and signals a mechanical dependence because employees accumulate overtime and get time off later in order to balance their working time accounts. However, we find no significant association between overtime and the firms' usage of trust-based working time or mobile ICT. Moreover, the coefficient for the interaction effect of trust-based working time and mobile ICT is also insignificant.[10] We thus find no evidence that our main results are merely driven by a higher workload in the firms providing for trust-based working time and mobile ICT.

Overall, our findings in support of complementarity between mobile ICT and workplace flexibility remain robust in the sensitivity checks we have conducted.

[9] In the average firm in our sample, a share of 48% of the employees is working overtime.

[10] While under trust-based working time the employer renounces controlling working hours, overtime hours must still be documented in order to comply with German labour law. Under trust-based working time, the task of recording hours is typically transferred to the employee. Still the employer is held responsible to assure that valid records are kept (Godart et al., forthcoming).

Table 4.6: Robustness Test: Effects on Overtime

	Dependent Variable: share of employees working overtime				
	(1)	(2)	(3)	(4)	(5)
% emp. mobile ICT	0.035	-0.019	0.060	0.029	0.010
	(0.042)	(0.065)	(0.060)	(0.064)	(0.086)
trust-based worktime (TBW)	-0.022	-0.049	-0.022	-0.022	-0.049
	(0.023)	(0.032)	(0.023)	(0.023)	(0.033)
working time accounts (WTA)	0.114***	0.115***	0.129***	0.114***	0.128***
	(0.023)	(0.023)	(0.034)	(0.023)	(0.034)
working from home (WFH)	0.015	0.014	0.015	0.012	0.017
	(0.025)	(0.025)	(0.025)	(0.032)	(0.032)
% emp. mobile ICT * TBW		0.084			0.085
		(0.075)			(0.079)
% emp. mobile ICT * WTA			-0.043		-0.039
			(0.072)		(0.072)
% emp. mobile ICT * WFH				0.009	-0.010
				(0.077)	(0.081)
% emp. working with PC	0.028	0.029	0.029	0.028	0.029
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
% emp. internet access	-0.042	-0.038	-0.042	-0.041	-0.038
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Constant	0.429***	0.433***	0.415***	0.430***	0.419***
	(0.086)	(0.086)	(0.090)	(0.087)	(0.090)
ln(emp) & ln(inv)	Yes	Yes	Yes	Yes	Yes
% med.-skilled & % below 30	Yes	Yes	Yes	Yes	Yes
Industry & Regional Dummies	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.052	0.053	0.052	0.051	0.051
Observations	1085	1085	1085	1085	1085

Note: OLS estimations; Heteroskedasticity-robust standard errors in parentheses; Significant at 1% ***, significant at 5% **, significant at 10% *.

4.6 Conclusion

In this study, we test for the complementarity between the use of mobile ICT and organisational practices providing workplace flexibility. We hypothesise that mobile ICT can create value if organisational practices grant employees more autonomy over *when*, *where* and *how* to perform work-related tasks. In line with our hypothesis, we find a positive association between mobile ICT and labour productivity in firms which delegate decision authority over the execution of work-related tasks in the form of trust-based working time. We find no significant association with labour productivity when the two are adopted separately. As trust-based working time implies a step towards greater self-management and autonomy, our findings suggest that a high degree of workplace flexibility is crucial for the effective use of mobile ICT. Robustness checks suggest that our results are not driven by increased workload, ICT-skill complementarity or by complementarity of mobile ICT with multiple alternative modern management practices. Furthermore, supporting our hypothesis, we only find evidence for complementarity if employees are provided with external access to relevant corporate information required for exploiting the potentials of higher worker autonomy and the novel features of mobile ICT.

Our analysis suffers from several limitations, which we have to leave to future research. Most importantly, while our study constitutes a first descriptive approach to the use of mobile ICT in the context of work organisation, we cannot fully account for unobserved heterogeneity or reverse causation which might bias our findings. Despite the extensive list of background characteristics we are able to take into account, the investment into mobile ICT in particular is possibly endogenous in our productivity equations.

In ongoing research, we attempt to allow for endogeneity of mobile ICT by exploiting exogenous variation. Future panel analysis might be another step to approaching a more causal interpretation of our results. Still, our research provides important insights into the diffusion process of mobile ICT and their relation to firm performance and work organisation. Our analysis poses a first step in attaining a better understanding of the effective use of these rapidly diffusing technologies and how they might shape our working environment in the future.

Appendix

Table 4.A.1: Industry Distribution

	NACE Rev. 2	N	Percentage
Retail Trade	45, 47	137	12.10
Wholesale Trade	46	111	9.81
Transport Services	49-53, 79	133	11.75
Media Services	18, 58-60	98	8.66
ICT Services	61-63	127	11.22
Financial Services	64-66	122	10.78
Consulting, Advertising	69, 702, 73	143	12.63
Technical Services	71-72	119	10.51
Business Services	74, 78, 80-82	142	12.54
Total		1132	100

Source: ZEW ICT-Survey 2014/2015

Table 4.A.2: Management Practices

	Mean	SD	Min	Max
incentive pay	0.51	0.50	0	1
job rotation	0.19	0.39	0	1
profit center	0.31	0.46	0	1
objective agreements	0.45	0.50	0	1
performance appraisals	0.38	0.49	0	1
Observations	1132			

Source: ZEW ICT Survey 2014/2015

Table 4.A.3: Provision of External Access

	Mean	SD	Min	Max
external access to corporate email-account	0.74	0.44	0	1
external access to wiki/intranet	0.50	0.50	0	1
external access to corporate software	0.54	0.50	0	1
external access to corporate networks	0.57	0.49	0	1
Observations	1132			

Source: ZEW ICT-Survey 2014/2015

Table 4.A.4: Mobile ICT and Workplace Flexibility by External Access Provision

	Advanced Ext. Access[a]		No Advanced Ext. Access[b]		
	Mean	SD	Mean	SD	Diff.
% emp. mobile ICT	0.378	0.331	0.238	0.303	0.139***
trust-based worktime	0.652	0.477	0.467	0.500	0.185***
working time accounts	0.648	0.478	0.562	0.497	0.086***
working from home	0.773	0.419	0.264	0.441	0.509***
Observations	787		345		

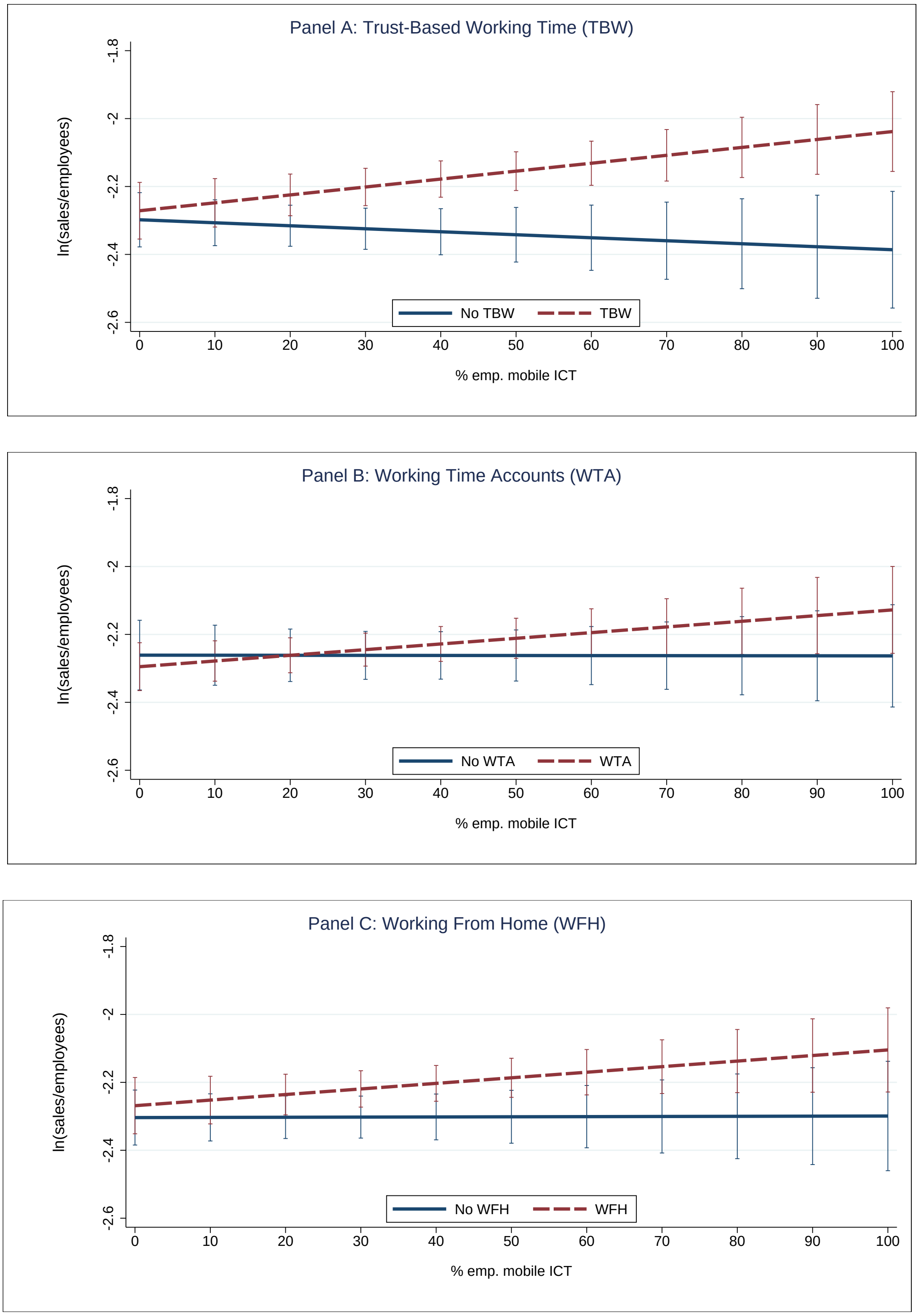
Note: [a] Firm provides external access to corporate wiki/intranet, software, or networks from outside the firm; [b] Firm provides solely external access to the corporate email account or no external access to internal network resources at all. *Source:* ZEW ICT-Survey 2014/2015

Table 4.A.5: Variable Descriptions

Variable	Description/Question
Dependent variable	
ln(sales/employees)	logarithm of labor productivity [sales (in mio. Euro) / no. of employees]
Workplace flexibility	
trust-based worktime	Does your company use trust-based working time, i.e. self-reliant organization of working time without recording of working time by the company?
working time accounts	Are there any regulations in your company related to working time accounts, i.e. everything in between flex time and annual working hours agreements?
working from home	Do you offer your employees the opportunity to work from home regularly, so called working from home arrangements?
ICT use	
% emp. mobile ICT	What share of your employees has been equipped with mobile devices which allow for wireless internet access, such as notebooks, tablets and smartphones?
% emp. working with PC	What share of your employees works predominantly with a computer at the workplace?
% emp. internet access	What share of your employees has access to the internet at the workplace?
Qualification and age	
% high-skilled emp.	Share of employees holding university, college or polytechnical degree
% medium-skilled emp.	Share of employees having completed apprenticeship or holding technical degrees
% emp. below 30	Share of employees under the age of 30
Management practices	
Does your company employ any of the following human resource management practices?	
incentive pay	Performance-related pay
job rotation	Job rotation
profit center	Cost/profit autonomy, profit centers
objective agreements	Regular written objective agreements
performance appraisals	Regular written performance appraisals
External Access	
Does your company provide your employees with off-site access to the following internal network resources?	
corporate email-account	External access to corporate email-account
wiki/intranet	External access to wiki/intranet
corporate software	External access to corporate software
corporate networks	External access to corporate networks, i.e. possibility to access and change documents and data
Overtime	
% of employees working overtime	What share of your employees has been working overtime in the previous year? Overtime is defined as extra work performed exceeding the weekly working hours agreed upon.

Source: ZEW ICT-Survey 2014/2015

Figure 4.A.1: Predictive Margins based on Specification (5) in Table 4.3



Note: Predictive margins are computed using the *margins* command in Stata and are based on the estimation results of specification (5) in Table 4.3. The margins are predicted by assigning fix values of mobile ICT use and workplace flexibility to all firms in our sample, while retaining observed values for all other covariates. In Panel A, the solid blue line depicts the predictive margins if all firms are treated as they would not use trust-based working time. The dashed red line shows margins predicted under the assumption that all firms use trust-based working time. Panel B focuses on the firms' use of working time accounts and Panel C focuses on the firms' use of working from home arrangements in combination to the use of mobile ICT. The vertical lines indicate the 95% Confidence Intervals for the point estimates.

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