Job Tasks, Wage Formation and Occupational Mobility

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Abstract

This thesis consists of three essays that contribute to the empirical literature on wage formation regarding job contents. The first essay analyzes the formation and the closing of the gender pay gap with respect to gender-specific task inputs in 1986-2004 in Germany. Using a newly constructed data set that combines administrative panel data on wages with individual-level task information, I am able to estimate the association of individual task profiles with wages and their contribution to the formation of the pay gap. The results document that task contents and returns to them are gender-specific. In particular, relative prices for task-specific units are substantially related to the formation of the wage gap, though the evidence exhibits heterogeneity along the wage distribution. The second essay is devoted to the shifts in the demand for occupations based on the quasi-experimental case of occupational demand shifts in East Germany after reunification. Taking the parameters of the demand for particular occupations into account helps to identify the causal effect of imposed occupational change on wages. The magnitude of the estimated wage effect is huge and persistent, though it points towards a positive selection of the group of employees who experienced an occupational change due to reunification. The third essay focuses on the changes of job contents and their relation to individual wages. The estimation results show that the wage differential due to an occupational change correlates significantly with the degree of similarity between the source and the target occupation. Moreover, the essay provides novel evidence on the positive relation of changing occupational contents with wages for employees who stay in their occupation, which implies that a part of the effect of tenure on wages is due to the increasing proficiency in job tasks.

Keywords:

Labor economics, Tasks, Occupational mobility, Occupational change, Wage formation, Gender pay gap

Zusammenfassung

Die drei Aufsätze dieser Dissertation liefern einen Beitrag zur empirischen Literatur bezüglich der Lohnbildung mit besonderem Fokus auf die Rolle von Arbeitsinhalten. Der erste Aufsatz analysiert das Lohngefälle zwischen Männern und Frauen in Hinblick auf die geschlechtspezifischen Tätigkeitsinhalte. Mit Hilfe eines neu zusammengestellten Datensatzes, der deutsche administrative Paneldaten mit individuellen Tätigkeitsinhalten kombiniert, wird der Zusammenhang zwischen ausgeübten Tätigkeiten und Löhnen sowie die Entstehung von Lohnunterschieden zwischen den Geschlechtern in Deutschland zwischen 1986 und 2004 geschätzt. Die Ergebnisse zeigen, dass sowohl Arbeitsinhalte, als auch deren Erträge geschlechtspezifisch sind. Außerdem tragen relative Preise für Tätigkeitseinheiten wesentlich zur Entwicklung des Lohngefälles zwischen den Geschlechtern bei, wobei sich Heterogenitäten entlang der Lohnverteilung zeigen. Der zweite Aufsatz beschäftigt sich mit der strukturellen Veränderung in der Nachfrage nach unterschiedlichen Berufsgruppen und nutzt die deutsche Wiedervereiningung als Quasi-Experiment. Die Berücksichtigung der Charakteristiken der Nachfrage nach bestimmten Berufen ermöglicht die Schätzung des kausalen Effekts eines erzwungenen Berufswechsels auf Löhne. Der abschließende Aufsatz fokussiert sich auf die Veränderungen der Arbeitsinhalte und deren Relation zu Individuallöhnen. Die Ergebnisse zeigen, dass Lohndifferenziale bei einem Berufswechsel stark mit der Ähnlichkeit der Inhalte zwischen dem Ausgangs- und Zielberuf zusammenhängen. Außerdem liefert dieser Aufsatz neue Evidenz hinsichtlich der positiven Relation zwischen den sich verändernden Arbeitsinhalten und den Löhnen von Arbeitnehmern, die keinen Berufswechsel erleben. Dieses Ergebnis zeigt, dass wachsende Kompetenz in Tätigkeiten einen Teil des positiven Zusammenhanges zwischen Löhnen und der Dauer des Beschäftigungsverhältnisses erklärt.

Schlagwörter:
Arbeitsmarktökonomik, Tätigkeiten, Berufliche Mobilität, Berufswechsel, Lohnbildung, geschlechtsspezifisches Lohngefälle

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1 Introduction

1.1 Job Contents, Human Capital and Wage Formation

Changes in production processes caused by ongoing technological change have exerted a fundamental impact on the labor market by altering both the content of work and occupational structure. These changes are reflected in the altering of requirements on labor inputs, the composition of labor force and the formation of wages. Over the last decades, the main focus of the analysis of requirements on labor inputs was drawn to the studies of educational levels. However, a growing research body has recently been paying attention not merely to educational attainment, but also to the usability of education in the production process. This tendency can be observed both in policy-oriented and academic research. In 2012, the Organisation of Economic Cooperation and Development (OECD) launched their Skills Strategy that aims at developing policy advice in order to boost skills that are relevant in modern economies (OECD, 2013).

In academic research, the focus has also been shifting from the general concept of human capital proposed by Becker (1975) to the sources of human capital heterogeneity that lead to differentiated wage setting. The core of Becker's human capital theory is constituted by the model that explains how skills can be accumulated through education and on-the-job training, as well as how they can be transfered between jobs. As human capital theory generally summarizes attributes of employees, it describes the supply side of the labor market and is often combined with the matching theory in order to model the interplay of supply and demand in the labor market. Thus, the human capital and matching theories make up a framework that has been widely used in studies on monetary returns to education (e.g. Schultz, 1961; Weisbrod, 1962; Layard and Psacharopoulos, 1974) and job mobility (e.g. Flinn, 1986; Sicherman and Galor, 1990; Topel and Ward, 1992).

Recently, the issue of actual usage of skills has been receiving more attention in the literature on skill mismatch and over-education. This strand of research attempts to assess the adequacy of the skill supply related to the respective job requirements or to the average educational level in the occupation (Sicherman, 1991; Robst, 1995; McGoldrick and Robst, 1996; Bauer, 2002; Chevalier, 2003; Leuven and Oosterbeek, 2011).

An important strand of literature in studying accumulation of human capital and the extent to which it is used is represented by the literature that underlines the occupation-specific nature of human capital and the existence of occupation-specific job matches (Miller, 1984; McCall, 1990; Keane and Wolpin, 1997; Neal, 1999; Kambourov and Manovskii, 2009). These studies show that the occupational specificity of skills and the extent to which the contents of these jobs differ are crucial to human capital transformation between jobs. In particular, Neal (1999) documents the heterogeneities in human capital mobility depending on the "complexity" of the job switch with respect to job content alteration. Though the similarity of the contents of two jobs is an intuitively conceivable concept, further operationalization of it through the introduction of direct measures of job content within the task-based approach (especially brought forward by Autor et al., 2003) has opened a new perspective in studying heterogeneity of human capital.

The task-based approach relies on the notion of occupations being bundles of tasks and requires detailed data on job content description. The task literature mainly builds on the Dictionary of Occupational Titles (DOT) and its successor, O*NET, in the US, as well as the Qualification and Career Survey (QCS) in Germany. Using direct measures of job contents, several important findings related to human capital have been documented. First of all, quantification of job contents has advanced the differentiation between human capital stock as the supply-side attribute and its actual usage in the production process. For instance, Acemoglu and Autor (2011) develop an elaborate model of assigning skills to tasks that helps to explain task-related re-distribution of the labor force and earnings.

Moreover, it has been documented that tasks can be grouped into categories (following Autor et al. (2003): routine and non-routine, with further division into interactive/abstract and manual tasks) that are not only differentially rewarded by the labor market, but also exhibit differentiated dynamics due to their outsourcing potential or substitutability with computers (Card and DiNardo, 2002; Spitz-Oener, 2006; Goos et al., 2009). Technological progress, in particular, has brought about the increase in demand for non-routine cognitive tasks and their respective skills. This phenomenon has not only affected wage formation and distribution (Card and DiNardo, 2002; Autor et al., 2008; Autor and Handel, 2013; Black and Spitz-Oener, 2010; Lindley, 2012), but also labor market participation of women (Galor and Weil, 1996; Weinberg, 1998). Thus, adjustments of the skill supply to the demand for education-intensive tasks is documented to have evolved both at the extensive and intensive margins.

Furthermore, task-related studies have helped to shed additional light on the transferability of human capital between occupations. With descriptions of occupations at hand, it became possible to measure the similarity of job contents directly and to determine its positive relation to the transferability of human capital between occupations by defining task-related human capital (Gathmann and Schönberg, 2010). Moreover, Poletaev and Robinson (2008) have documented that task-related components of human capital have a bigger impact on the formation of wages than occupational or industry-specific components. Having a measure of similarity between occupations yields an additional advantage for modeling heterogeneity of human capital. Yamaguchi (2012) uses an occupational similarity measure to propose a model of human capital transferability and its occupation-specific remuneration without an excessive computational burden when comparing contents of multiple occupational categories. Thus, measures of job contents and the notion of task-related human capital have established a quantitative relation between distinct occupational categories.

1.2 Outline of this Thesis

This thesis includes three essays on various aspects of the relationship between wage formation and job contents. Chapter 2 "Closing the Gender Pay Gap and Individual Task Profiles: Women's Advantages from Technological Progress" deals with the gender-specific wage formation due to the differences in the job contents of men and women, as well as gender-specific returns to them. The existing literature has pointed towards the high relevance of job tasks for wage formation and has suggested that the observed closing of the gender pay gap is connected to the increasing share of women performing non-routine cognitive tasks. However, previous research on gender-specific tasks has been limited due a lack of data that would allow for the variation of tasks across and within occupations, as well as by gender, age and qualification. Using a newly constructed data set based on the IABS panel, augmented by individual-level information on tasks from the Qualification and Career Survey (QCS), I am able to contribute evidence on the role of gender-specific task input to the formation of the gender pay gap over time, within occupations, under the consideration of individual fixed effects, as well as by different quantiles of the wage distribution. Firstly, I find that the disproportional growth of non-routine cognitive tasks performed by women indeed plays a significant role in the formation of the gender pay gap, together with the increasing remuneration for these tasks. At the top of the wage distribution, where the gender pay gap has not declined, the contribution of non-routine cognitive tasks to the formation of the gender pay gap is growing. Secondly, I show that within occupations the overall advantages of women in non-routine cognitive tasks are almost non-existent. These findings suggest that the gender-specific selection process is highly heterogeneous between and within occupations, as well as along the quantiles of wage distribution.

The analysis in Chapter 3 "Changes in Occupational Demand Structure and their Impact on Individual Wages" investigates the empirical evidence on imposed occupational mobility due to structural changes in demand for occupations. The evidence of such a structural change comes from the German Reunification. In this study, I analyze wages of employees who experienced an occupational change after Reunification, using changes in the demand for occupations obtained in the former GDR to instrument the decision of an occupational change. The evidence is novel to the literature on occupational mobility due to its focus on structural changes using empirical data. The estimation shows that imposed occupational changes are associated with wage losses of about 10 percent that became non-observable 8 years after the structural shock. However, when accounting for occupational demand in an IV estimation, these changes become both tremendously large and remain very persistent over time. Additionally, this quasi-experimental framework confirms the predictions of the Roy model that shows that employees who choose to change occupations are positively selected with respect to their unobservable characteristics.

Chapter 4 "Occupational Changes, Changes in Occupational Contents and their Association with Individual Wages" analyzes the changes in job tasks for occupational movers and stayers. The motivation for this study arose from the fact that the evolution of job contents within occupations has been largely ignored in the task-based literature. In this study, I focus on the changes of job contents of employees who change their occupation and those who remain in the occupation of their apprenticeship. Using a direct measure of similarity between job tasks, I show that similarity plays a significant role for both occupational stayers and movers. For the movers, wages are positively correlated with the content similarity between previous and current employment, supporting the hypothesis of existing task-specific human capital that can be transferred between occupations. The novel evidence is obtained for the occupational stayers: a portion of the returns to tenure is found to be attributable to on-the-job changes of task contents. This new evidence on accumulation of task-specific human capital is shown to vary across age groups; this suggests the importance of further research of age-specific heterogeneity of task accumulation.

All three subsequent chapters are intended to be self-containing and can be read independently.

2 Closing the Gender Pay Gap and Individual Task Profiles: Women's Advantages from Technological Progress

2.1 Introduction

The narrowing gender pay gap has been documented in most industrialized countries since the 1950s and has attracted much attention in economic literature. Customarily, the decrease in gender-specific pay has been explained by the rising educational level of women, as well as by increases of respective returns to education (Blau and Kahn, 1996). In this paper, I provide analysis of the formation of wage differences between genders that stem from differences in their job contents and relates to the substitutability of genders in the production process. This approach has an advantage over the education-based perspective, since raised demand for qualified female labor is itself closely linked to technological progress and changes in demand for tasks (e.g. see Galor and Weil (1996) and studies for Germany by Fitzenberger and Wunderlich (2002); Spitz-Oener (2006)). Empirical studies also suggest a close link between changes in task contents and gender-specific pay. Black and Spitz-Oener (2010) document that contents of women's jobs in Germany have disproportionately shifted towards non-routine cognitive tasks, which are shown to be correlated with, on average, higher wages (Spitz-Oener, 2006). For the US, it is also documented that changes in prices for task units contribute to the closing of the gender pay gap: Yamaguchi (2013) shows that up to 40% of the closing of the gender pay gap is due to falling prices of motor skills.

In this study, I provide a detailed analysis of the formation of the gender pay gap over the quantiles of the wage distribution in Germany between 1986-2004. During this time period, narrowing of the gender pay gap was observed in the middle and at the low end of the wage distribution (Fitzenberger and Wunderlich, 2002) accompanied by the decrease in gender segregation of occupations. Taken at face value, this evidence suggests that men and women become better substitutes in production, which translates into more equal pay. However, the existing literature lacks evidence on gender-specific task contents conditional on age, education and occupational groups and little is known about the development of gender-specific wage structure with respect to tasks both in general and within occupations. This present paper aims to fill in some of the gaps in the existing literature.

So far, literature has focused on studying task variation at the occupational level or in cross-sections. To study the gender-specific wage formation with respect to tasks in detail, I employ a newly constructed data set that mainly features high-quality administrative panel data (IABS, launched by the German Institute for Employment Research) combined with survey-based information on task contents at the individual level (QCS, German Qualification and Career Survey).[1] The data allows an investigation of the interplay of wages and tasks in great detail, both with respect to gender-specific and occupation-specific variation of tasks. With these detailed data at hand, I am able to make several contributions to the existing empirical literature. Firstly, I employ individual-level task data to provide novel evidence on the differences in average task profiles of men and women, conditional on age, education and occupational group. Secondly, I investigate the evolution of gender-specific prices of task units, in particular, using regression based of the recentered influence function (RIF) and consistent estimation with individual and occupational fixed effects. Thirdly, I apply Firpo-Fortin-Lemieux (FFL) decomposition to analyze the contribution of tasks and prices for task units, along with educational controls, to the formation of the gender pay gap. Fourthly, I contribute evidence on the formation of the gender pay gap with respect to job tasks for both the median and low- and upper-tail of the wage distribution using the recentered influence function (Fortin et al., 2011).

The findings of the paper confirm the existing findings in the literature as well as contribute new evidence obtained from the previously unstudied data variation. Firstly, I find that the closing of the gender pay gap in the period from 1986 to 2004 was concentrated in the middle and at the lower tail of the wage distribution, which is in line with the findings of Fitzenberger and Wunderlich (2002). Then, I confirm the findings of Black and Spitz-Oener (2010) of observed disproportionate growth of non-routine cognitive tasks and disproportionate decline of routine tasks for women. However, using data variation within occupations reveals that female advantages in terms of task profiles are much less pronounced within occupations. In fact, within occupations one can observe convergence of the task profiles of men and women, something that suggests high substitutability of genders within occupations. Estimation of relative task prices reveals that relative prices for non-routine cognitive and non-routine manual tasks performed by women grow (though not within occupations). Since the mid-nineties, women have been paid more for non-routine manual tasks than men. Prices of non-routine cognitive tasks exhibit convergence over time, with some substantial differences over the wage distribution. At the low-end of the distribution, women's remuneration for non-routine cognitive tasks exceeds that of men. At the median and at the top, convergence of gender-specific returns to non-routine cognitive tasks can be observed. On the whole, prices of non-routine cognitive tasks are one of the main components in the formation of the gender pay gap, whose contribution falls with the decreasing pay gap.

The rest of the paper is organized as follows. In section 2.2, I review the theoretical models

[1] The upcoming study of Fedorets et al. (2013) features a version of individual-level imputation of task profiles to the administrative panel data, for male employees only. For the present study, I expand the imputation procedure to females.

that explain wage formation with respect to tasks, as well as the corresponding empirical literature. Section 2.3 introduces the data set and briefly describes the imputation procedure for the task information. Section 2.4 discusses the estimation methods (RIF-regression and FFL-decomposition), their limitations and assumptions necessary for consistent estimation of the coefficients of interest. In section 2.5, I provide detailed analysis of the evolution of the unconditional and conditional gender pay gap, as well as task profiles. Then, relative prices of the task units are estimated and their relation to the gender pay gap is described. I also briefly discuss the performed robustness checks in section 2.6. Section 2.7 concludes.

2.2 Conceptual Framework and Motivation

The existence of the gender pay gap stems from the fact that men and women constitute imperfect substitutes in the production process. The restricted substitutability can manifest itself in the difference of gender-specific production inputs. However, given equal productivity of genders, the law of one price (equal pay for equal production input) should hold. Otherwise, one could suggest presence of discriminating wage settings that can hardly be isolated from gender-specific productivity in an empirical study. In the following, my argumentation will mainly rely on the differences in production inputs and their respective prices, rather than discrimination that I cannot directly identify in the data.

Accompanied by the progress of technology over time, the difference in gender pay has been decreasing (see figure 2.1 for the years 1986-2004). In particular, these differences are shown to be linked to inequality in job content with respect to skill requirements and job complexity (Korkeamäki and Kyyrä, 2006). Indeed, parallel to the falling gender pay gap, a decrease in gender segregation by occupations can be observed (figure 2.2) and the growing share of women in traditionally male occupations is documented (Blau and Kahn, 2000). Thus, the evidence suggests that men and women have, over time, become better substitutes in the labor market (Weinberg, 1998).

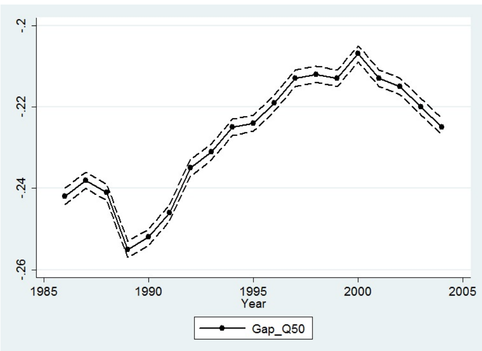


Figure 2.1: Gender pay gap at the median (with standard error bands). Own calculations based on the IABS data

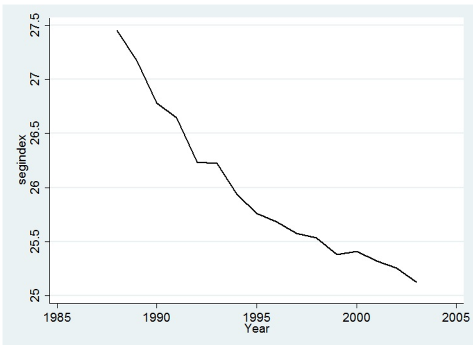


Figure 2.2: Gender segregation between occupations. Own calculations based on the IABS data. $I = \frac{1}{2}\sum_{i=1}^{n}|M_i - F_i|$

In order to study gender-based differences in production inputs, a task-based approach can be applied. The idea behind the task-based approach is based on the representation of job contents by bundles of tasks, which can be broadly classified into routine and non-routine (Autor et al., 2003). By definition, routine tasks are well-codifiable and, therefore, labor performing these tasks can be easily substituted by computers. In the model setup of Autor et al. (2003), exogenous changes in the price for computer capital triggers changes in demanded amounts of different tasks. In particular, a significant decrease in prices of computing power due to technological progress led to replacement of routine labor by capital as a production factor. Thus, labor input experiences a reallocation from routine towards non-routine tasks. The latter can be divided into non-routine cognitive tasks, with strong complementarity to computer input, and non-routine manual tasks, with limited opportunities for substitution by computers or complementarity. Therefore, we observe that demand for routine tasks decreases, whereas demand for non-routine manual and cognitive tasks increases. Given that routine-intensive jobs are placed in the middle of the wage distribution, employment polarization has been documented (Spitz-Oener, 2006; Goos and Manning, 2007; Cortes, 2012).

Changes in demand for tasks are found to have heterogeneous effects across genders. A stylized fact from the empirical literature postulates that women became disproportionately represented in non-routine cognitive jobs, whereas their relative share in routine jobs has disproportionately fallen over time (see figure 5.1 in appendix 5.1.3 that generally replicates findings of Black and Spitz-Oener (2010) for Germany). Additionally, empirical studies document rising demand for highly educated women (Spitz-Oener, 2006; Lindley, 2012) as well as a strong trend towards skill upgrading amongst women (Fitzenberger and Wunderlich, 2002). These findings show that the composition of the labor force has improved over time, especially concerning skills related to higher wages, which suggests that the supply of qualified labor has adjusted to the changes in demand for tasks.

Alongside the observed changes in demand for tasks and education, the task-based literature also provides explanations regarding changes in the wage structure. Firpo et al. (2011) empirically show that prices for task units constitute a substantial part of the wage structure and significantly contribute to changes in the wage distribution. Katz and Murphy (1992) also document that rising demand for skills is one of the major forces driving reallocation of labor between sectors and occupations, as well as relative labor prices. In the setup of Katz and Murphy (1992) prices are seen as an endogenous factor determined by changing demands in qualified labor. Endogenous prices are also typical to brain-and-brawn models that predict rising returns to non-routine tasks in response to rising input of computer technology, rising labor market participation of women and, hence, the narrowing of the gender pay gap (Galor and Weil, 1996; Weinberg, 1998; Rendall, 2010).

Generally, wage structure is found to be a major factor in explaining differences in wages between genders (Blau and Kahn, 1996). In particular, Yamaguchi (2013) estimates a structural model to show that falling prices for motor skills (non-routine manual tasks) explain more than 40% of the narrowing gender pay gap in the US. However, the latter study assumes that the law of one price holds for gender-specific task input, though men and women are likely to be imperfect substitutes in performing the same tasks and, hence, can be rewarded differently (e.g. as shown by Lindley, 2012).

An overview of the existing studies on the gender pay gap and tasks makes clear that technological progress has triggered fundamental adjustments in both the product and labor markets. Changes in demand and prices of tasks in the long run are certainly due to general equilibrium effects and must be studied in a dynamic setting (Galor and Weil, 1996; Rendall, 2010). At the same time, "deep" structural parameters that could describe the triggers of the technological progress and the related adjustment of demand and supply both at the product and the labor market remain undefined. Moreover, Autor et al. (2008) claim that the observed complex pattern of wage and employment adjustments due to technological change do not have a unicausal explanation.

An important issue that remains unstudied both in theoretical models and in empirical applications, is the heterogeneity of gender-specific inputs and pay within and across occupational groups. It is generally recognized that within-occupational differences play a substantial role in reducing the gender pay gap (Bayard et al., 2003; Olivetti and Petrongolo, 2011). In the task literature, substantial dynamics of tasks within occupations are also documented (Black and Spitz-Oener, 2010), though without establishing a direct link to the reduction of the gender pay gap. Moreover, evidence from the UK by Lindley (2012) shows that gender inequality with respect to tasks remains considerable within occupations.

2.3 Data

For the analysis I employ two data sets – the IAB Employment Sample (IABS) and the BiBB/IAB Qualification and Career Survey (QCS). I focus on the time span of 1986-2004, for which both data sets provide comparable data. During this time, both a closing of the gender pay gap and changes in task demands can be observed. The IABS is an administrative panel data set launched by the German Institute for Employment Research (IAB). The data set contains detailed daily information on the employment history of employees liable to social security. It includes main individual characteristics (gender, age, state of residence) as well as information on wages, educational level, occupational group and full- or part-time employment status. QCS is a cross-sectional employee survey that contains survey-based information on tasks that respondents perform in their jobs. QCS provides high-quality information on tasks at the individual level, which is one of its main advantages compared to the widely used DOT or O*NET data that contain occupational-level task data. Until now, QCS has been widely used in the task-based literature either for cross-sectional analysis (e.g. Spitz-Oener, 2006; Black and Spitz-Oener, 2010), or merged with panel data (IABS or SOEP) at the level of occupations (e.g. Gathmann and Schönberg, 2010). I employ a more embracive imputation method regarding tasks using a regression estimation that is based on occupational information alongside gender, age and education. More details on the imputation procedure can be found in appendix 5.1.1.

The task information from the QCS can be arranged into three broad task groups: routine (R), non-routine cognitive (NRC), and non-routine manual tasks (NRM); for details see table 5.4 of appendix 5.1.2. Note that the task categories sum up to one by construction and generally follow the categorization of the seminal paper of Autor et al. (2003). Using these three task categories, an individual task share for categories $j \in \{$non-routine cognitive, routine, non-routine manual$\}$ can be computed based on Antonczyk et al. (2009):

$$TS_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ at time } t}{\text{total number of activities performed by } i \text{ over all categories at time } t} \tag{2.1}$$

These task shares can be interpreted as an approximation of time share spent by each worker to perform tasks of the respective category.

For the imputation procedure, both IABS and QCS were restricted along the same lines. The initial data were restricted to the sample of full-time employed male and female German natives aged between 25 and 55. Moreover, in order to level out the differences in labor market behavior and incentives of men and women in IABS, I impose further restrictions on "stable" employment histories prior to the year of observation. The latter excludes employees with long spells of inactivity (more than 366 days in 2 years), more than one occupational change and long (more than 95 days) interruptions between spells of employment.[2] After all restrictions, I am left with a sample of approximately 2.1 million men and 930 thousand women. Additionally, I use employment intensity measured by the fraction of full-time employment in a calendar year as weights in the econometric estimation.

2.4 Empirical Implementation

Focusing on the exercise of decomposing wages at different quantiles of the wage distribution, I build on the empirical estimation based on the recentered influence function (RIF), introduced by Firpo et al. (2009). The main advantage of RIF when working with evidence on quantiles comprises computational efficiency and a possibility to perform both aggregate and detailed decomposition of the differences in the variable of interest between two groups. The decomposition method of Firpo et al. (2009) constitutes a generalization of the popular Oaxaca-Blinder decomposition for a broad range of distributional measures. In the subsequent analysis I will estimate the decomposition of log wages at the 25, 50 and 75th percentile (the choice of quantiles is imposed by data censoring).[3] Moreover, estimation of regression specifications with variables other than real log hourly wages on the left-hand side

[2] Though these restrictions were crucial for consistent estimation, the overall conclusions drawn from the estimation remain unaffected compared to the sample with "instable" employment history.

[3] In several regression specification, it was necessary to switch from the 75th to 72nd percentile due to the censoring of the wage distribution of women. All output based on the 72nd percentile is respectively marked.

is conducted using estimation on subsamples that belong to 5-percentage point bands at the 25, 50 and 75th percentiles of the initial wage distribution.

2.4.1 RIF-Regression

RIF-regressions differ from standard regression methods by featuring recentered influence functions in place of the dependent variable. RIF constitutes a linear approximation of any non-linear distributional statistics $\nu(F_Y)$. In my case, the dependent variables are quantiles of wage distribution $Q_\tau(F_Y)$. The recentered influence function (RIF) is defined by the sum of the statistics of interest and the corresponding influence function $\mathrm{IF}(y;\nu)$: $\mathrm{RIF}(y;\nu) = \nu(F_Y) + \mathrm{IF}(y;\nu)$. The influence function is an empirical distribution, $\mathrm{IF} = \lim_{\varepsilon\to 0}(\nu(F_\varepsilon) - \nu(F))/\varepsilon$ with, by definition, a mean of zero: $\int_{-\infty}^{\infty} \mathrm{IF}(y;\nu)dF(y) = 0$. Therefore, integrating the RIF along the distribution $F(y)$ yields the distributional statistics of interest: $\int \mathrm{RIF}(y;\nu)dF(y) = \nu(F_Y)$. Using the law of iterated expectations, the RIF can be re-written for the case of conditional distributions:

$$\nu(F) = \int \mathbb{E}\left[\mathrm{RIF}(y;\nu)|X = x\right] \cdot dF_X(x). \tag{2.2}$$

In the case of quantiles, the recentered influence function is given by:

$$\mathrm{RIF}(y, Q_\tau) = Q_\tau + \frac{\tau - \mathbb{1}\{y \le Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau} \cdot \mathbb{1}\{y > Q_\tau\} + c_{2,\tau}, \tag{2.3}$$

with $c_{1,\tau} = 1/f_Y(Q_\tau)$ and $c_{2,\tau} = Q_\tau - c_{1,\tau} \cdot (1-\tau)$. Thus, linearization is performed under the assumption that the relationship between counterfactual proportions and counterfactual quantiles is locally linear. RIF is estimated by computing the sample quantile $\widehat{Q}_\tau$, and estimating the density at that point using kernel methods. Then, the estimates for $\widehat{Q}_\tau$ and $\widehat{f}(\widehat{Q}_\tau)$ are plugged into the equation 2.2 to obtain estimates of the RIF for each observation. Afterwards, standard (linear) estimation can be performed using specifications with the initial variable of interest y replaced by the corresponding $\widehat{\mathrm{RIF}}$. Therefore, estimates of the coefficients of the unconditional quantile regression can be written as:

$$\widehat{\gamma}_\tau = \left(\sum_{i\in I} X_i \cdot X_i\right)^{-1} \cdot \sum_{i\in I} \widehat{\mathrm{RIF}}(Y_i; Q_\tau) \cdot X_i. \tag{2.4}$$

Due to local linearization, the time required for computation of $\widehat{\gamma}_\tau$ is considerably lower than in the case of standard estimation methods of quantile regression.

2.4.2 Firpo-Fortin-Lemieux (FFL) Decomposition

Local linearization also makes RIF-regressions suitable for decompositions of any (non-linear) distributional statistics, very similar to the decomposition procedure proposed by Oaxaca and Blinder for the mean. Analogous to the Oaxaca-Blinder procedure, the overall estimated difference between groups M and W ($\widehat{\Delta}_O^\tau$, in my case: unconditional wage quantile) can be rewritten as a sum of the estimates of wage structure and composition effects (respectively denoted by $\widehat{\Delta}_S^\tau$ and $\widehat{\Delta}_X^\tau$):

$$\widehat{\Delta}_O^\tau = \underbrace{\bar{X}_M\left(\widehat{\gamma}_{M,\tau} - \widehat{\gamma}_{W,\tau}\right)}_{\widehat{\Delta}_S^\tau} + \underbrace{\left(\bar{X}_M - \bar{X}_W\right)\widehat{\gamma}_{W,\tau}}_{\widehat{\Delta}_X^\tau}, \tag{2.5}$$

where the estimates of $\widehat{\gamma}_{M,\tau}$ and $\widehat{\gamma}_{W,\tau}$ are obtained in the separate estimation of equation (2.4) for the groups $g =$ M, W:

$$\widehat{\gamma}_{g,\tau} = \left(\sum_{i \in G} X_i \cdot X_i\right)^{-1} \cdot \sum_{i \in G} \widehat{\mathrm{RIF}}(Y_{gi}; Q_{q\tau}) \cdot X_i, \quad g = \mathrm{M, W}. \tag{2.6}$$

It should be mentioned that the FFL-decomposition delivers consistent estimates of the aggregate composition and wage structure effect under the common assumptions of ignorability and overlapping support.

Assumption 1: Ignorability. Let (G, X, ε) have a joint distribution. For all x in X: ε is independent of G given $X = x$. (Where G denotes groups, here: M, W.)

Assumption 2: Overlapping support. For all $x \in X$, $p(x) = \mathbb{P}[G = M | X = x] < 1$ and $\mathbb{P}[G = M] > 0$.

The latter assumption states that there are no x in X that are only observed among the individuals of one group. This assumption is met for my data (in particular, occupational groups were aggregated to contain both male and female workers). For consistent detailed decomposition of the gender pay gap into the contributions of single variables, stronger assumptions than ignorability (independence and strict monotonicity in the random scalar) should be met. Under these assumptions, both $\widehat{\Delta}_S^\tau$ and $\widehat{\Delta}_X^\tau$ can be re-written in terms of the sum of the contribution of each variable $k \in \{1, \ldots, K\}$ to obtain the detailed decomposition. As in the Oaxaca-Blinder decomposition, subcomponents of the detailed decomposition sum up to the aggregate effect: $\widehat{\Delta}_S^\tau = \sum_{k=1}^K \widehat{\Delta}_{S,k}^\tau$ and $\widehat{\Delta}_X^\tau = \sum_{k=1}^K \widehat{\Delta}_{X,k}^\tau$. Thus, the decomposition results are easy to interpret as contribution of each variable and price for its units to the composition and wage structure effects.

My first approach to the assumptions for the aggregate and detailed decomposition is to impose the additional sample restrictions on stable career profiles of men and women working in full-time positions (see section 2.3 for details). This restriction assures that labor market behavior of men and women is comparable in terms of incentives and other unobservable characteristics.

Moreover, Fortin et al. (2011) suggest a reweighted-regression decomposition that helps to obtain consistent estimates of the wage structure and decomposition effect in cases when the conditional mean is a non-linear function. For the present paper, an application of reweighting is necessary, since it can be shown that the relationship between tasks and wages is non-linear (based on my own calculations and evidence from Fedorets et al. (2013)).

Reweighted composition and wage structure effects are given by:

$$\widehat{\Delta}^{\tau}_{S,p} = \bar{X}_M \left(\widehat{\gamma}_{M,\tau} - \widehat{\gamma}^{C}_{W,\tau}\right) \quad \text{and} \quad \widehat{\Delta}^{\tau}_{X,p} = \left(\bar{X}^{C}_{W} - \bar{X}_W\right) \widehat{\gamma}_{W,\tau}, \tag{2.7}$$

where the subsample W is reweighted to mirror the composition of the subsample M, so that $plim(\bar{X}^{C}_{W}) = plim(\bar{X}_M)$.

Despite the convincing strengths of the FFL-decomposition, it is subject to several limitations. However, none of these limitations plays a significant role in the present study. Firstly, RIF-based decomposition requires the ignorability assumption (or in other words, invariance of the conditional distribution), which, in the case of applying the processes over several years, does not yield general equilibrium effects. My analysis, however, relies on the separate estimation of RIF regressions in consecutive cross-sections and two-year panels, which allows for changes in the conditional distribution over time. Secondly, RIF regressions are based on local linearization, which might constitute a problem when measurement errors common to reported wages are present. In the subsequent analysis I employ administrative data with high-quality wage information that are not prone to heaping. Thirdly, RIF-based detailed decomposition is susceptible to the problem of the base group choice, also common to other decomposition methods. As a robustness check, I performed respective Oaxaca-Blinder and FFL-decompositions of contributions of each covariate with different choices of the base and comparison groups. Though, as expected, the estimation results were numerically nonidentical, they indeed delivered very similar qualitative results. Moreover, as the focus of the present paper is on the components of the wage structure, the choice of women being the comparison group seems appropriate as it delivers lower estimates of the wage structure effect.

Though the subsequent analysis is not aimed at causal inference, problems of selection should be discussed. In the case of FFL-decomposition, these problems can cause violation of the independence assumption and, consequently, affect consistency of the estimation. The data set employed in the empirical analysis does not contain enough variables to address selection into labor force using the Heckman selection model. However, estimation with fixed effects helps to address selection on observables, time-invariant unobservables, whereas the restriction to locally stable employment histories also considerably reduces the influence on time-variant unobservables.

2.5 Gender Pay Gap, Task Profiles and Task Prices

In the following section, I first analyze the evolution of the unconditional and the conditional gender pay gap at different quantiles of the wage distribution between 1986-2004 before describing the dynamics of tasks for the same time span. Introducing tasks as control variables to the wage regression allows me to obtain estimates of the returns to task units. These returns can be interpreted as prices of tasks and are further analyzed on their contribution to the formation of the gender pay gap.

2.5.1 Descriptive Statistics for Men and Women and the Unconditional Pay Gap

Before providing estimations of the gender pay gap, the differences in observable characteristics of men and women should be considered. Descriptive statistics for the time span 1986-2004 (table 5.5 of appendix 5.1.4) show that subsamples of men and women are very similar in terms of age, tenure and educational levels (though, men are more likely to have a higher level of formal education). At the same time, women perform more non-routine cognitive, but less non-routine manual tasks than men; the over-time average share of routine tasks is almost equal between genders. As it is empirically shown that non-routine cognitive tasks are related to higher wages (Spitz-Oener, 2006), it becomes obvious that advantageous task profiles of women with prevailing non-routine cognitive tasks are not directly translated into higher wages, as the unconditional difference in wages between genders is about 0.3 log points at the median, at both the bottom and the top of the wage distribution.

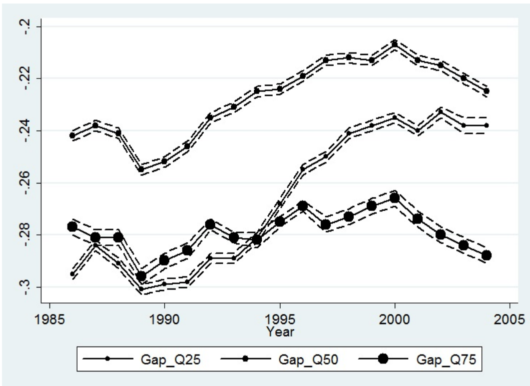


Figure 2.3: Unconditional gender pay gap at the 25th, 50th, 75th percentile (with standard error bands), 1986-2004

When considering the evolution of the unconditional gender pay gap over time, it becomes apparent that it has been closing at the middle and at the low end of wage distribution (figure 2.3). Moreover, the most dynamic closing of the pay gap at the median was observed in the 90s, after which we observe a stagnation and even a slight increase in the gap at the median. The gender pay gap at the 25th percentile exhibits a very similar, though more pronounced dynamic. At the 75th percentile, the unconditional gender pay gap is one of the highest and does not decrease with time. The trends in the evolution of the gender pay gap are generally in line with the literature for the German labor market (Fitzenberger and Wunderlich, 2002).

2.5.2 Conditional Gender Pay Gap

In order to control for differences in observable characteristics in the formation of the gender pay gap, I estimate the conditional wage gap using the following regression specification:

$$\mathrm{RIF}(\ln W_i; Q_\tau) = \beta_0 + \beta_1 \mathrm{Female}_i + \gamma X_i + \varepsilon_i, \quad \tau = \{25, 50, 75\}. \tag{2.8}$$

where Female is an indicator variable for women and X is a set of controls that varies between specifications:

(1) set of year dummies, age and age squared,

(2) additionally to (1): dummies for being high- or medium-skilled (low-skilled taken as base category), tenure with the current employer,

(3) additionally to (2): individual task profiles,

(4) additionally to (2): set of dummies for the current occupation,

(5) additionally to (2): set of dummies for the current occupation and individual task profiles.

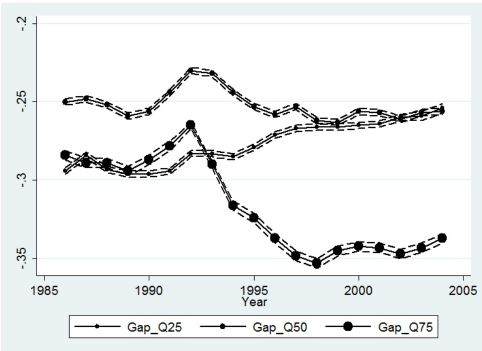
Table 2.1: Conditional gender pay gap 1986–2004, $N = 3058336$, RIF based on real log hourly wages

	(1)	(2)	(3)	(4)	(5)
Gap Women-to-Men, percentile 25	-0.257***	-0.245***	-0.281***	-0.245***	-0.242***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.113	0.155	0.174	0.263	0.263
Gap Women-to-Men, percentile 50	-0.210***	-0.189***	-0.254***	-0.221***	-0.220***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Adjusted R^2	0.098	0.182	0.245	0.320	0.321
Gap Women-to-Men, percentile 75	-0.258***	-0.216***	-0.325***	-0.276***	-0.273***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.079	0.228	0.313	0.385	0.386
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Age, Age^2	Yes	Yes	Yes	Yes	Yes
Educational level		Yes	Yes	Yes	Yes
Tenure with employer		Yes	Yes	Yes	Yes
TS_{NRC} & TS_{NRM}			Yes		Yes
Current occupation				Yes	Yes

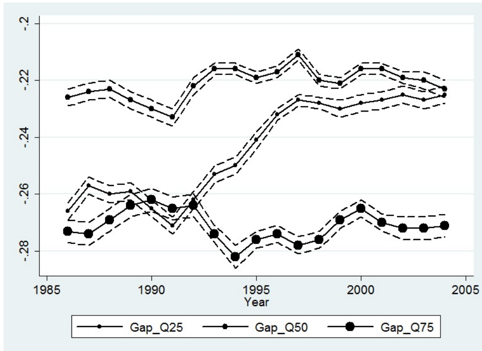
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.1 features the estimates of the conditional wage gap for the 25th, 50th and 75th percentile of wage distribution. Comparing specifications (1)-(5), it becomes apparent that controlling for task profiles yields lower estimates for the pay gap (specification 3 against 1-2). This increase generally confirms the finding of the literature that the structure of female task profiles is positively correlated with wages, that is, females are positively selected with respect to tasks they perform in their jobs. Such an advantage is negligible when controlling only for the occupation of employment (specification 4). Moreover, including controls both for task profiles and occupation already suggests that positive correlation of female wages and tasks is almost non-existent within occupations. However, comparison of specifications (2) and (4) point to a positive selection of women into occupations at the median and the top of the wage distribution, though conditioning on tasks (cp. specifications 3 and 5) implies the opposite. This pattern is observed in the estimates for all three distributional quantiles. Table 2.1 shows that tasks are strongly relevant to the formation of the gender pay gap, though their impact is heterogeneous between and within occupations.

In order to illustrate the evolution of the conditional gender pay gap, I chose specifications (3) and (5) to estimate the gender pay gap in consecutive cross sections (figure 2.4).



(a) Controls: age, education, tenure, task profiles



(b) Controls: age, education, tenure, task profiles, occupational group

Figure 2.4: Conditional gender pay gap at the 25th, 50th, 75th percentile (with standard error bands), 1986-2004

On the whole, the observed pattern of the conditional gender pay gap does not differ much from its unconditional counterpart. The main difference is that, after conditioning on individual and occupational covariates, closing of the gender pay gap is only observed at the 25th percentile of the conditional wage distribution. In contrast, conditional on individual covariates only, the gender pay gap exhibits growth at the 75th percentile.

2.5.3 Development of Relative Task Shares

Empirical evidence of the task-based literature has focused on explaining the closing of the gender pay gap with changes in the composition of performed tasks that favored women more than men. Using the QCS data, I am able to reproduce the finding of Black and Spitz-Oener (2010) that women have experienced a disproportional increase of non-routine cognitive tasks in their job contents, whereas their share of routine tasks has disproportionately fallen (see figure 5.1 in appendix 5.1.3). At first glance, these results seem to suggest a decrease in the gender pay gap. However, it is unclear how task shares would evolve when conditioning on education, age and tenure. Empirical evidence on differences in task profiles conditional on occupations is absent. Moreover, there is evidence from the UK that women are not paid wage premium related to non-cognitive tasks within broad sectors (Lindley, 2012).

In order to estimate differences in relative task shares, I perform separate OLS estimations of task shares $TS_j,\ j = \{NRC,\ R,\ NRM\}$ regressed on different sets of control variables:

$$\mathrm{TS}_j i = \beta_0 + \beta_1 \mathrm{Female}_i + \gamma X_i + \varepsilon_i, \tag{2.9}$$

where Female is an indicator variable for women and X is a set of controls that varies between specifications:

(1) set of year dummies, age and age squared,

(2) additionally to (1): dummies for being high- or medium-skilled (low-skilled taken as base category) and tenure with the current employer,

(3) additionally to (2): set of dummies for the current occupation.

Table 2.2: Conditional task profiles 1986–2004, $N = 3058336$, OLS

	(1)	(2)	(3)
Dependent var: Non-routine cognitive task share TS_{NRC}:			
Female	0.102***	0.121***	-0.026***
	(0.000)	(0.000)	(0.000)
Adjusted R-squared	0.100	0.304	0.824
Dependent var: Routine task share TS_R:			
Female	-0.028***	-0.038***	0.042***
	(0.000)	(0.000)	(0.000)
Adjusted R-squared	0.125	0.222	0.611
Dependent var: Non-routine manual task share TS_{NRM}:			
Female	-0.074***	-0.083***	-0.016***
	(0.000)	(0.000)	(0.000)
Adjusted R-squared	0.046	0.136	0.763
Additional covariates:			
Year	Yes	Yes	Yes
Age, Age^2	Yes	Yes	Yes
Educational level, Tenure		Yes	Yes
Current occupation			Yes

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Separately estimated conditional mean differences in task profiles are featured in table 2.2. Specifications (1) and (2) show that in the period of 1986 to 2004 women were employed in jobs with, on average, higher shares of non-routine cognitive tasks and lower shares of routine and non-routine manual tasks. Interestingly, this finding holds between occupational groups, but not within them (specification 3). Within occupations women exhibit even lower shares of non-routine cognitive tasks and higher shares of routine tasks than men. Though the coefficient for female indicator is negative in all specifications for non-routine manual tasks, its magnitude is much lower within occupations. The estimation makes clear that female advantages in task profiles that have been found in the literature until now are not observed within occupational groups. Including interactions of the independent variables with the indicator (tables 5.6, 5.7 and 5.8 in appendix 5.1.4) for women provides a similar conclusion about females' advantageous task profiles on the whole, but not within occupations.

In order to shed light on the dynamics of conditional task profiles, I analyze specifications 2 and 3 at the quantiles of the wage distribution by year. For this exercise, I define 5-percentage points bands at the wage quantiles of interest (25th, 50th and 75th percentile) and use OLS to estimate mean task shares for men and women separately by year and quantile of the wage distribution. Mean differences in task shares at quantiles are displayed in figures 5.2 and 5.3 of appendix 5.1.3. The results clearly state that the dynamics of conditional task profiles generally follows the trends of the unconditional profiles. However, task profiles within occupations exhibit these changes at a much lower magnitude. Indeed, one observes relative growth in both non-routine tasks and a decrease in the routine tasks, but these changes cannot be qualified as disproportionate growth. Rather, one could speak of leveling out the initial disproportions in task shares that are present in the beginning of the analyzed time span. Interestingly, this finding is robust across quantiles of wage distribution and might be related to the growing substitutability of men and women within occupations.

A comparison of unconditional and conditional task shares points towards the fact that the closing of the gender pay gap is mainly carried out by the differences between occupations that have favored women.

2.5.4 Gender-Specific Returns to Tasks and Their Contribution to the Pay Gap

Alongside gender differences in endowments, gender-specific wage determination and wage inequality can be explained through wage structure, defined as "prices set for various labor market skills and the rents received for employment in particular sectors of the economy" (Blau and Kahn, 1996). In order to approach the question of possible gender-specific differences in returns to task units, I estimate separate wage regressions for men and women:

$$\mathrm{RIF}(\ln \mathrm{W}_i; Q_\tau) = \beta_0 + \beta_1 \mathrm{TS}_{NRC,i} + \beta_2 \mathrm{TS}_{NRM,i} + \gamma X_i + \varepsilon_i, \quad \tau = \{25, 50, 75\}. \qquad (2.10)$$

where X is a set of controls varying across specifications. I report estimates for the following sets of variables in X: (1) age, age squared, education, tenure, (2) age, age squared, education, tenure and occupational groups.

A remark should be made about the exclusion of one task category (as NRC, R and NRM share sum up to one by construction). Performing robustness checks with different combinations of tasks showed a qualitatively stable picture of the evolution of task prices and their contributions to the gender pay gap. However, choosing routine tasks as the excluded category in the regression analysis yields several advantages. Firstly, the estimates are easily interpretable using the brain-and-brawn framework that focuses only on non-routine cognitive and manual tasks and disregards the routine tasks (for instance, the study of Yamaguchi (2013) also focuses on these task categories). Secondly, exclusion of a task category which exhibits a declining share over time has the advantage that the estimated relative prices for the other two categories can be seen as lower bound of estimates for relative task prices. This is due to both the general equilibrium effect that leads to relative price decrease for the included task categories and the fact that the quantity of the routine tasks diminishes.

Cross-sectional estimates of the relative task prices together with corresponding standard errors are depicted in figures 5.5 and 5.9 of appendix 5.1.3 (conditional on individual, and individual plus occupational covariates, respectively). Moreover, figures 5.4 and 5.8 report the contributions of the respective price estimates to the formation of the gender pay gap based on the Firpo-Fortin-Lemieux decomposition for unconditional quantiles of the wage distribution.

Relative task prices conditional on age, education and tenure:

Conditional on individual covariates only (figure 5.4), relative prices for non-routine cognitive tasks contribute substantially to the formation of the gender pay gap. The contribution of NRC-tasks also rises along the wage distribution, reflecting the growing importance on non-routine cognitive tasks in the formation of high earners' wages. For the sake of comparison, figure 5.4 contains the contribution of the returns to education that has been used in the existing literature to explain the formation of the gender wage differences. It is apparent that the role of tasks in the formation of the gender pay gap is more important than those of education, as the contribution of tasks is both higher in magnitude and exhibits more dynamics over time.

As figure 5.5 shows, the relative task prices have evolved over time in favor of women. In particular, prices for non-routine cognitive tasks performed by women increased over time. However, this result is observed in varying magnitude along the wage distribution. For instance, at the 25th percentile women receive a substantially higher remuneration for the same task units since the mid-nineties. At the median, convergence of gender-specific prices for NRC tasks is observed. For high earners, convergence in prices of non-routine cognitive tasks is not accomplished and plays a decisive role in the formation of the gender pay gap. The evolution of task prices for manual tasks is also advantageous for women. Since the mid-nineties they have been significantly higher remunerated for NRM tasks, though it does not make a sizable contribution to the formation of the gender pay gap.

Relative task prices conditional on age, education, tenure and occupation:

Within occupations, relative prices for non-routine cognitive tasks also play a remarkable role in the formation of the gender pay gap (figure 5.8). They contributed negatively to the gender pay gap until the late nineties, when the gender pay gap began to close. Then, their contribution rose until 2000 and has been falling since then. An explanation for this dynamics in the formation of the gender pay gap can be seen in the evolution of task-specific prices within occupations depicted in figure 5.9. Starting at a higher level relative to men, the prices of NRC-task performed by women exhibit falling dynamics until 2000 before recovering slightly. Prices of non-routine manual tasks display no convergence patterns, though their contribution to the formation of the pay gap is much less sizable.

2.5.5 Gender-Specific Returns to Tasks: Consistency Check Using Fixed Effects Estimation

The performed estimation of gender-specific task prices can be further checked for consistency using the panel structure of the data. In his book, Koenker (2005) refers to quantile regression estimation based on longitudinal data as the "twilight zone" of econometric analysis. One of the practical problems in application of fixed effects stems from changes in the underlying distribution of the analyzed variables when applying a within-transformation of variables. In the following, I apply two methods that address time-invariant individual productivity and provide heterogeneous inference for estimates of task prices along the wage distribution.

Long-term fixed effects:

The first approach to checking consistency of the cross-sectional estimates relies on the assumption of existing time-invariant fixed effects proposed by Koenker (2004). Based on the pooled cross-sections, individual fixed effects can be estimated, assuming that individual productivity is invariant in the long run.[4] In the following, the estimated *long-term fixed effects* are subtracted from the right-hand side variable, which is then used to estimate (annually) the task prices at unconditional quantiles of the wage distribution net of the respective fixed effects. The estimation results are displayed in appendix 5.1.3, figure 5.6 and 5.10.

Conditional on individual covariates only, the relative prices for tasks have evolved almost in parallel since 1995, to the disadvantage of women in the case of non-routine cognitive tasks and to their advantage in the case of non-routine manual tasks (figure 5.6). At the same time, returns to non-routine cognitive and non-routine manual tasks diverge over time. Within occupations (figure 5.10), this divergence is also present, though only slightly pronounced. This finding is especially prevalent at the top end of the wage distribution. Concurrently, the remuneration for tasks performed by men and women in occupations exhibits convergence over time, when accounted for fixed effects.

Short-term fixed effects:

The second approach to estimating task prices under consideration of fixed effects extends the idea used in Card and de la Rica (2005) for inference based on panel data under consideration of fixed effects. For this procedure, the data is grouped in consecutive two-year panels.

[4]Alternatively, I estimated the evolution of gender-specific prices for task units under the assumption of time-invariant individual productivity *in occupation*, which generally delivered similar results and is not included in the current version of the paper.

Then, for each first year of the two-year panels, the 25th, 50th and 75th percentiles of the initial unconditional gender-specific wage distributions are defined and the data is restricted to 5-percentage point bands around these quantiles ($\tilde{\tau}$). Then, within each quantile band a *two-year fixed effects* wage regression is estimated:

$$\ln \mathrm{W}_i | W \in \tilde{\tau} = \beta_0 + \beta_1 \mathrm{TS}_{NRC,i} + \beta_2 \mathrm{TS}_{NRM,i} + \gamma X_i + \varepsilon_i, \quad \tau = \{25, 50, 75\}. \tag{2.11}$$

where X is a set of controls containing age, age squared, education, tenure and (in an additional specification) occupation.

The point estimates and the respective standard errors are displayed in figures 5.7 and 5.11 in appendix 5.1.3. Both figures make apparent that short-term fixed effects take away most of the variation of the data that could have explained differences in gender-specific remuneration to tasks. Thus, the estimates exhibit almost no significant differences both between gender-specific prices for tasks, and between remuneration for different tasks.

2.6 Robustness Checks

In order to test the stability of the obtained results, various robustness checks were performed. First, the formation of the gender pay gap conditional on tasks and other covariates was estimated for the mean of the wage distribution using the Tobit analysis (due to the censoring of the wage variable) and the corresponding Oaxaca-Blinder decomposition. The quality of the results remained unchanged.

Second, the overall picture was checked on stability of samples with and without the restriction on the stable employment histories. Different ways of restricting careers to make labor market behavior of men and women more comparable, also did not provide qualitatively different results.

Third, the robustness checks were performed by taking different combinations of the included and base categories for the estimation of the relative task prices. In all cases, prevailing relevance of the non-routine cognitive tasks over years and quantiles remained a strongly pronounced result.

2.7 Conclusion

The goal of the present paper is to provide comprehensive evidence on the evolution of the gender pay gap in Germany with a focus on gender-specific task inputs. The main advantage of applying the task-based approach to the analysis of the gender pay gap is that it allows a direct comparison of the job contents between men and women to de drawn. Moreover, tasks and returns to them are directly involved in the formation of wages. In contrast, parameters of education that have been widely used in the existing literature mirror the supply of skills and have no straightforward relation to the parameter of the demand for skills. Though education is correlated with the evolution of tasks, it can be also seen as a response of the supply side to the shifts in the demand for tasks. Therefore, in the analysis I focus on the role of tasks in the formation of the gender pay gap, but also introduce educational levels as a control variable. The econometric analysis has shown that job tasks are closely related to the formation of the gender pay gap. Moreover, the contribution of the returns to tasks to the formation of the gender pay gap is substantially higher than the contribution of educational controls.

Like Black and Spitz-Oener (2010), I find sizable changes in the relative content of job tasks over time that favor women. However, this evidence is almost non-existent at the occupational level, exhibiting a mere convergence of gender-specific job tasks within occupations. This finding points at the growing substitutability of genders within occupations. The assumed comparative advantage of women in performing non-routine cognitive tasks seems to be able to be translated into females being employed in occupations that require higher inputs of these tasks. Yet, within occupations, the task profiles of women do not exhibit overproportionate shares of non-routine cognitive tasks. This evidence suggests the existence of different selection mechanisms with respect to job content on the whole and within occupations.

For the formation of the gender pay gap, the returns to task units play a substantially more important role than task inputs themselves. In particular, non-routine cognitive tasks sizably contribute to the formation of the gender pay gap, with the rising magnitude from the lower tail to the top of the wage distribution. Thus, this finding supports the evidence that non-routine cognitive tasks play a highly important role in the formation of high earners' wages. More specifically, prices for non-routine cognitive tasks performed by men and women exhibit convergence over time, though convergence of prices is diminishing from the low end to the top of the wage distribution. The finding of converging gender-specific task prices is generally supported by the estimation using long-term individual fixed effects.

Within occupations, the dynamics of prices for non-routine cognitive tasks performed by women is more volatile, though convergence towards men's remuneration for NRC-tasks over time is present (again, less pronounced at the top of the wage distribution). When accounting for individual fixed effects, the evidence of converging task prices is supported along the whole wage distribution.

Though the presented evidence stems from a reduced-form estimation, it points towards an increasing level of gender substitutability in production over time both in terms of task content and its remuneration, especially within occupations. However, gender differences in the remuneration of non-routine cognitive tasks seem to play a sizable role in the formation of the gender pay gap.

3 Changes in Occupational Demand Structure and their Impact on Individual Wages

3.1 Introduction

Occupational change is a common phenomenon in modern economies and is often used as a strategic tool in career planning (Miller, 1984; Witte and Kalleberg, 1995). Therefore, occupational change is often accompanied by wage growth, despite its association with high risks such as substantial loss of occupation-specific human capital (see e.g. Kambourov and Manovskii, 2009). These results, however, may not hold in cases of occupational changes that are superimposed by exogenous shifts in demand for occupations caused by quick structural economic transitions. In this paper, I provide novel empirical evidence on the negative wage effects of imposed occupational change due to demand shifts during the transition from a planned to a market economy. My empirical findings do not only contribute to transition economics, but also to the literature on involuntary job mobility by illustrating how big and persistent wage effects can be after a shock to the occupational structure.

In the existing literature, occupational change is seen as a job change of high complexity concerning content alteration (Neal, 1999). Thus, an occupational change is associated with a loss of occupation-specific human capital and a possible improvement of the match between worker and occupation. Under stable economic conditions, most occupational changes occur at the beginning of a career, as young workers face lower costs of un-, or non-employment when changing job or occupation, and cause the highest wage growth.[1] The decision to change occupation is, thus, largely endogenous with the associated wage differentials likely to be upward-biased given the positive selection of occupational movers following the predictions of the Roy model. Until now, the wage *effect* of occupational change has been estimated using instrumental variables such as military service, firm closures, employment in newly emerged occupations, and apprenticeship in industry vs. artisanry (see Acemoglu and Pischke, 1998; Fitzenberger and Spitz, 2004). Most of these instruments address endogeneity at the individual level, yet none address unanticipated exogenous shifts in the demand for occupations. In the current study I use parameters of post-transition demand for occupations that are acquired before the transition process has started. More

[1] See Johnson (1978), McCall (1990) for underlying theories and Topel and Ward (1992), Neal (1999) for supporting empirical arguments. The most similar study in terms of data and estimation design is Fedorets (2011); it also finds higher occupational mobility rates among the young.

precisely, I use the occupation-specific employment rate in East Germany and occupation size in West Germany in order to instrument the change out of an occupation acquired in the pre-transition period.

German reunification is not only an example of a transition from a planned to a market economy, it also constitutes a unique case of market integration. In the socialist system of the German Democratic Republic, decisions regarding the occupational structure were integrated into the overall state planning process, which resulted in the formation of individual preferences being state-assisted, or at least not completely voluntary as commonly assumed. The fall of the Berlin Wall triggered the process of multidimensional adjustments of employment, wage and occupational structure.[2] Despite its deep structural influence, anticipation of possible reunificaiton came shortly before actual reunification, which made it impossible for Eastern Germans to anticipate future demand for their occupations and to adjust accordingly. These unanticipated structural changes can thus be used in an experimental design to study labor market effects. Unfortunately, studies using German reunification as an experiment are rare due to a lack of reliable data on pre-transition East Germany. Most of the studies rely on data starting from 1990. One of the few studies of labor mobility using post-reunification changes in legislation is provided by Prantl and Spitz-Oener (2009). The authors look at the changes in entry regulations into self-employment to uncover the negative effect of regulations on occupational mobility. Hunt (2001) evaluates the evolution of post-unification wages in East Germany with respect to voluntary and involuntary *job* changes, as well as migration to the West. She documents an insignificant effect of an involuntary job change on the wages of East Germans, whereas both voluntary changes and moves to the West make employees better off.

However, the massive wave of occupational changes following reunification remains mostly uncovered in literature. Though it is documented that post-reunification adjustments were associated with human capital replacement, imposed occupational changes and high unemployment rates (e.g. Evans et al., 1999; Burda and Hunt, 2001; Burda, 2006), the empirical studies are lacking due to the scarcity of data.

For the analysis of post-reunification wage losses due to occupational changes I employ data from the German Qualification and Career Survey (QCS) that contains retrospective information on apprenticeships obtained in East Germany prior to reunification alongside information on current employment. The analysis is conducted for the two subsequent waves of the QCS – 1991/92 and 1998/99 – on condition that an apprenticeship was obtained in East Germany before 1990. I additionally restrict the sample so that it contains male employees with vocational training who currently live in East Germany.

The estimation results document high, and persistent, human-capital losses stemming from human capital relocation during the transition process. When running a wage regression using OLS, an occupational change at a 2-digit level is, on average, associated with 10%

[2]A detailed documentation of the transition process in East Germany can be found in Akerlof et al. (1991), Sinn and Sinn (1994) and Burda (2006). The evolution of wage and efficiency wages in particular was analyzed by Akerlof et al. (1991), Topel and Ward (1992), Burda and Hunt (2001), Riphahn et al. (2001).

lower wage in 1991/92, and less than 4% lower wage in 1998/99. However, IV estimation shows that an occupational change has a significantly greater effect on wages – about 40 log points in 1991/92. Surprisingly, this effect does not disappear over time even given the eventual upswing of the East-German economy. Even by 1998/99 the negative effect on wages amounts to more than 20 log points. The results document negative wage differentials of occupational movers, which is not in line with the main predictions of the Roy model, yet can be explained by the imposed nature of occupational change (as found in the literature on involuntary job mobility, see e.g. Addison and Portugal, 1989; Carrington, 1993; Burda and Mertens, 2001). Moreover, the results imply positive selection of movers, as one would expect to find according to the Roy model.

This paper begins with the description of the identification strategy in Section 2. A brief introduction of the data and sample restrictions follows in Section 3. Section 4 describes the main variables of the wage regression. Section 5 contains the results of the regression analysis and section 6 concludes.

3.2 Identification Strategy

Changes in the demand structure for occupations after German reunification and the specific conditions of pre-transition East Germany lie at the core of my identification strategy. The identification idea follows Angrist and Krueger (2001) and employs exogenous *demand* shifts as an instrument for occupational change which belongs to decisions that are met on the side of labor *supply*.

My identification strategy relies on the parameters that characterize shifts in demand for occupations after reunification started. In particular, the first instrumental variable is the size of the respective occupational group in West Germany in 1990; the second instrument is the occupation-specific unemployment rate in East Germany in 1993.[3] The initial distribution of occupations in pre-transition East Germany was unaffected by the occupational structure in West Germany. With reunification, East Germany was integrated into the institutional environment of West Germany and experienced a major shift in demand for occupational groups (Sinn and Sinn, 1994; Burda and Hunt, 2001). Therefore, at the beginning of reunification, one could anticipate that a low-demand occupation in West Germany would also experience low demand in East Germany, influencing the decision to change occupation. The high unemployment rates that can be observed in the initial occupation may have forced employees to change occupations in order to lower the individual risk of becoming unemployed. Figures 3.1 and 3.2 illustrate the differences in East and West German occupational structure and unemployment across 24 broad occupational categories. Thus, the introduced instrument picks up on the falling demand for particular occupational groups due to post-reunification economic adjustment. A possible concern with the described identification strategy would arise if the underdemanded occupations were already declining

[3] Due to the lack of statistical information for the years right after reunification, 1993 is the first year with reliable and comparable unemployment statistics in East Germany.

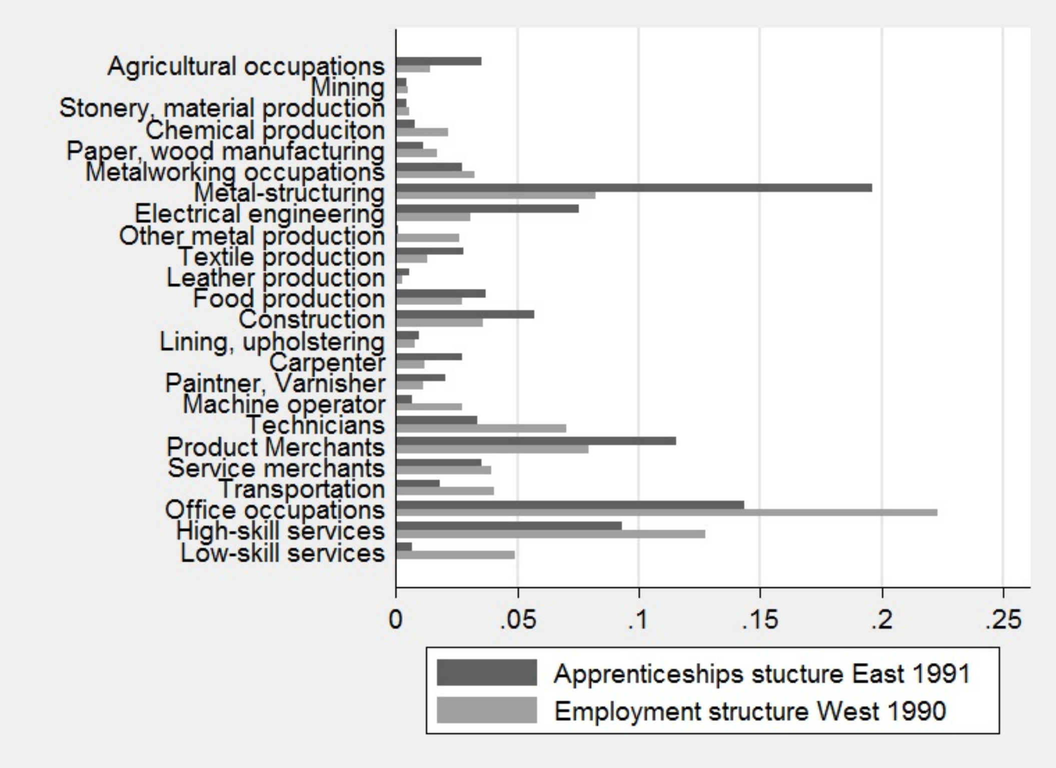


Figure 3.1: Structure of apprenticeships in the GDR and West-German occupational structure in 1990. Source: Federal Employment Office, QCS data, own calculations

in the pre-reunification period. However, statistical evidence points to a stable occupational structure in the GDR (see e.g. Ulrich et al., eds, 1991).

It is important to underline the fact that the reunification of East and West Germany was widely unanticipated by the population. The political turn that caused the opening of the border came suddenly in 1989 and formal reunification of the two states was carried out within several months. As a result, workers in the GDR could not foresee the possible reallocation of the labor force and take action in changing occupations to one that would offer more opportunities in a unified Germany. Moreover, due to the fact that apprenticeships last several years, the choice of apprenticeships in the GDR was certainly not affected by the oncoming post-reunificaton changes.

Before proceeding, some additional remarks should be made concerning the vocational training systems in East and West Germany and the recognition of apprenticeship qualifications achieved in the GDR.[4] The German tradition of apprenticeship training reaches back to the middle ages with the formation of the current system dating back to the 19th century and the formal institutions being established in the 1960s.[5] The system has become so highly institutionalized in the economy and society that experts agree that it would be impossible to

[4]For a detailed description of the dual apprenticeship system and its history see e.g. Timmermann (1993), Witte and Kalleberg (1995), Münch (1995) and Franz and Soskice (1995).

[5]See e.g. Mitter (1990), Bundesinstitut für Berufsbildung (2006).

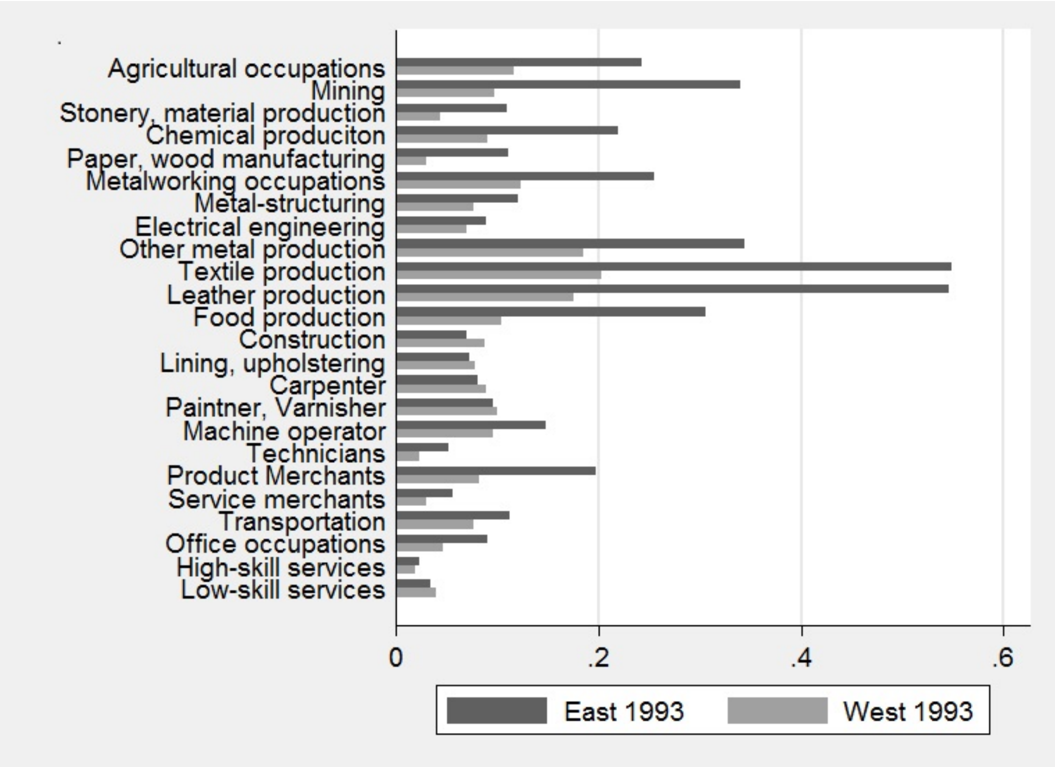


Figure 3.2: Occupation-specific unemployment rates, East and West Germany, 1993. Source: Federal Employment Office, own calculations

quickly transfer the West-German dual apprenticeship system to other countries.[6] Though skills acquired in the apprenticeship systems of pre-transition East and West Germany are not perfect substitutes, some essential facts besides the long pre-partition history speak for a high degree of their comparability.[7] The basic structure of the apprenticeship system in the GDR was overtaken after reunification without deep institutional transformations.[8] The apprenticeship graduation certificates obtained in the GDR were fully accepted in the FRG by the Unification Treaty, Article 37. Thus, observed occupational changes were driven by economic conditions and not by obstacles with the formal recognition of qualification.

By treating individual wages as a proxy for productivity in a market economy, it can be stated that the link between unobserved individual ability, productivity and occupational choice in the former GDR was very weak. The main reason for this weak relation is due to the economic and political system of the GDR (see e.g. Schmitt, 1975). Under socialism, the state directs the economy by setting up exact plans not only for the production and distribution of goods and services, but also for the allocation of available resources. Thus,

[6]See e.g. Timmermann (1993), den Broeder (1995), Harhoff and Kane (1997), Korpi and Mertens (2003), Sharpe and Gibson (2005).

[7]Some information on challenges to the educational system after reunification may be found in Mitter (1992). Moreover, Bonin and Zimmermann (2001) mention the high level of formal qualification of East-German workers.

[8]Consult Ertl (2000) for detailed information on the underlying legislation process, as well as the arguments for the similarity of the two systems. The transformation of qualifications after reunification is also discussed by Mayer et al. (1997).

the process of decision making is generally under the control of a central planner, rather than single individuals. In contrast to the market economy, the social planner is responsible for forecasting future needs in particular occupations with respect to production and in order to guarantee that the youngsters choose the occupations that will fulfill the production plans. Although the choice of occupation cannot be said to be completely involuntary, various mechanisms existed that made the initial occupational choice far from voluntary in comparison with Western economies (Uthmann, 1991; Ulrich et al., eds, 1991; Trappe and Rosenfeld, 1998; Solga and Konietzka, 1999). The state began guiding the preferences of future workers for particular occupations at an early stage. Already in primary school occupational orientation existed, which was designed to direct students' interests towards particular professions. The direct choice of the apprenticeship after school was restricted by existing quotas for the apprenticeship places in each occupation. Moreover, the likelihood of getting a place in a particular occupation of interest was dependent on family background, place of residence and even the gender of the applicant. The important underlying reason for the distribution of the quotas was the policy of creating equal opportunities for men and women, as well as for working-class children.[9] Moreover, the idea of full employment, and related "anti-parasite" laws, made it possible to coerce those secondary school graduates who had not entered an apprenticeship a year after graduation into an occupation chosen by state officials. Afterwards, occupational mobility was not desirable since a human capital reallocation would destroy at least some of the previous investments in training, something which results in losses for the society (Huinink et al., 1995). Accordingly, the occupational mobility I observe in the data can be assigned to the reunification-related adjustments.

It must be mentioned that reunification was also accompanied by a massive wave of geographic mobility from East to West Germany (Burda and Hunt, 2001). Though I will analyze only those workers who chose to remain in the former East Germany after having completed an apprenticeship there, some remarks must be made about the selection of the movers. Both the migration flow and occupational changes can be generally explained by the Roy model: occupational as well as geographic movers are likely to exhibit positive selection compared to the stayers. Also the results of Hunt (2001) suggest that geographical movers from East to West Germany are more positively selected than *job* changers who stayed in the East, whereas the latter are positively selected compared to those who did not exhibit any mobility.

3.3 Data and Sample Restrictions

The empirical analysis employs data from the German Qualification and Career Survey (QCS). The survey is carried out by the Federal Institute for Vocational Education and Training (BiBB) together with the Institute for Employment Research (IAB) and is available as a series of cross-sections for 1979, 1985/86, 1991/92, 1998/99 and 2006. Data on East

[9] For reference see, e.g. Trappe and Rosenfeld (1998) and Miethe (2007).

Germany has been included since 1991/92. The questionnaire contains a large block of questions on education with a particular focus on vocational training, making the survey especially suitable for studies of middle-skilled workers. QCS contains reliable retrospective information on the apprenticeships that were obtained in the former GDR (occupation and the year of graduation) alongside the current labor market outcomes, something which makes this survey a unique data source on the pre-transition period.

As this study focuses on the occupational mobility of East Germans after reunification, the sample contains only East Germans who completed their first apprenticeship completed in the GDR (before 1990) and who were employed in the respective survey year. The sample is further restricted to full-time workers of prime age (20-55) with vocational training as the highest level of completed education. Moreover, the analysis is restricted to employees with jobs in so-called "recognized occupations", consisting of the most traditional and well-established occupations. This ensures rather homogeneous preferences, career opportunities and, hence, labor market behavior of the respondents in the sample.

In order to examine wage differential due to post-reunificaiton occupational changes in East Germany, I employ cross-sections of 1991/92 and 1998/99. Unfortunately, the next available QCS wave of 2006 does not contain an adequate amount of respondents whose first apprenticeship was obtained in the GDR after necessary sample restrictions. Due to the high unlikelihood of occupational mobility before 1990, occupational changes observed in the labor market histories by 1991/92 are likely to have happened within a two-year window. Thus, the results from 1991/92 will reveal short-term effects of an occupational change. Occupational changes observed in labor market histories in 1998/99 have happened within a nine-year time window and can be seen as long-term effects.

Although it results in a loss of variation, in an effort to keep my sample as homogeneous as possible I exclude all the respondents who moved from East to West Germany after reunification: movers and stayers are likely to exhibit fundamental differences in preferences. By implementing this restriction I exclude other channels through which initial occupation of apprenticeship may have affected the decision to change occupations and the resulting effect on individual wages.[10] Furthermore, the decision to move to West Germany, as well as the decision to change occupations, is endogenous. This means that keeping both “migrants” and “non-migrants” would require an estimation strategy that can clearly disentangle the decisions to migrate and to change occupation, complicating matters given the available data. Thus, the suggested estimation strategy only takes account of occupational changes for those East-German employees with vocational training degrees who remained in East Germany.

Under the restrictions described above, 565 observations for 1991/92 and 625 observations for 1998/99 remain in the sample. Although the sample size is quite moderate, it is still possible to identify significant and robust tendencies concerning the average wage effect of an occupational change.

[10]Main descriptive statistics for the group of migrants from East to West can be found in appendix 5.2.1. They show that, on average, migrants have substantially higher wages than non-migrants.

3.4 Descriptive Statistics

Table 3.1 shows the means of the variables for the subsamples of occupational movers and stayers (at the level of 2-digit occupations) both in 1991/92 and 1998/99; t-tests show that the means of all variables for the two subsamples are statistically indifferent from one another. However, the real log hourly wages for occupational movers in 1991/92 is lower than those of the stayers; the difference in average log wages becomes even lower by 1998/99. The average tenure with current employers of occupational movers in 1991/92 is 0.7 months higher those of the stayers, whereas in 1998/99 it is nearly 5 months lower. Accordingly, the overall average number of employers is somewhat higher for the occupational movers than for the stayers.

Moreover, occupational movers in 1991/92 are slightly older than the stayers. This difference becomes negligible by 1998/99. Occupational movers tend to be higher qualified than the stayers, as they are more likely to have a foreman certificate in their occupations. Both variables indicate that movers have more labor market experience and are, on average, more qualified than stayers, implying positive selectivity of the movers. Consequently, I expect the OLS estimates of the association between individual wages and occupational change to be upwardly biased.

The distribution by firm size and the state of residence (Bundesland) of those who changed occupations does not significantly differ from those of the occupational stayers in the sample.

The last panel of table 3.1 presents the distributions of apprenticeships obtained in the GDR over occupational groups. Although the sample size only allows us to make rough observations on the outflows from particular occupations, it is apparent that machine operators and product merchants often experienced occupational changes, whereas for electricians, nutritional, construction, and painting & varnishing occupations, changes were less common.

Measured using the 2-digit occupational codes,[11] about 58% of employees in the sample had changed occupations by 1991/92. By 1998/99, the fraction of occupational movers had risen by only 2 additional percentage points. According to my own computations in Fedorets (2011), respective numbers for West Germany during the same period were nearly 15 percentage points lower in both 1991/92 and 1998/99. The mobility rates at the 3-digit level are respectively higher – 63% in 1991/92 and 65% in 1998/99 (see table 5.10 in appendix 5.2.2). These high levels of mobility are likely to be directly associated with reunification. The fact that most occupational changes took place a short time after reunification is in line with the findings of Hunt (2001) on *job* changes associated with German reunification.

The descriptive statistics show that the largest differences between the subsamples of occupational movers and stayers are associated with the occupational group of their apprenticeship.

[11] Based on the German KldB occupational classification in the version of 1988.

Table 3.1: Descriptive statistic for the samples of 1991/92 and 1998/99, occupational mobility at a 2-digit level

	1991/92		1998/99	
	Stayers	Movers	Stayers	Movers
	(1)	(2)	(3)	(4)
N	255	357	269	406
Fraction of stayers and movers (2-digit level)	41.6%	58.4%	39.9%	60.1%
Individual characteristics				
Log real hourly wages	1.707	1.604	1.923	1.890
	(0.390)	(0.367)	(0.296)	(0.351)
Age	33.290	35.992	39.706	39.793
	(8.287)	(9.057)	(7.181)	(7.604)
Tenure, curr. employer	2.067	2.151	6.394	5.946
	(1.068)	(1.124)	(3.027)	(3.001)
Number of employers	2.667	2.815	2.851	3.175
	(0.919)	(0.942)	(0.922)	(0.844)
Foreman certificate= 1	0.102	0.140	0.112	0.135
Distribution of workers across firms (column total=1)				
Less than 5 employees	0.071	0.082	0.055	0.086
5 to 9 employees	0.204	0.140	0.204	0.131
10 to 49 employees	0.357	0.325	0.476	0.438
50 to 99 employees	0.145	0.148	0.108	0.133
100 to 499 employees	0.161	0.174	0.123	0.150
500 to 1000 employees	0.035	0.039	0.019	0.020
More than 1000	0.027	0.092	0.015	0.042
Distribution of workers across federal states (Bundesland, column total=1)				
East Berlin	0.114	0.084	0.093	0.079
Brandenburg	0.071	0.115	0.156	0.177
Mecklenburg-Vorpommern	0.180	0.140	0.115	0.121
Saxony	0.239	0.168	0.357	0.281
Saxony-Anhalt	0.165	0.204	0.171	0.187
Thuringia	0.231	0.286	0.108	0.155
Distribution across the occupational groups of the apprenticeship (column total =1)				
Agricultural occupations	0.043	0.036	0.015	0.064
Mining, material production	0.012	0.003	0.000	0.000
Chemical industry	0.000	0.017	0.004	0.005
Wood and paper production	0.004	0.008	0.004	0.007
Metalworking occupations	0.012	0.020	0.030	0.000
Metal-structuring, engineering	0.173	0.118	0.216	0.126
Electrical engineering	0.173	0.017	0.219	0.010

Apparel industry, leather production	0.004	0.000	0.000	0.000
Food industry	0.082	0.008	0.037	0.007
Construction	0.302	0.115	0.301	0.118
Lining, upholstering	0.043	0.011	0.033	0.089
Carpenters	0.031	0.008	0.041	0.030
Painters, varnishers	0.063	0.025	0.063	0.025
Machine operators	0.004	0.062	0.011	0.069
Technicians	0.008	0.017	0.000	0.010
Product merchants	0.008	0.084	0.000	0.094
Service merchants	0.000	0.022	0.000	0.022
Transportation	0.020	0.269	0.019	0.217
Office occupations	0.008	0.090	0.000	0.071
High-skilled services	0.008	0.031	0.007	0.012
Low-skilled services	0.004	0.039	0.000	0.025

3.5 Econometric Model and Estimation Results

The estimation of the correlation between an occupational change and individual wages was performed separately for the two subsequent survey waves of 1991/92 and 1998/99:

$$\ln w_{it} = \alpha_t + \beta_t \cdot \text{Occ. change}_{it} + \gamma_t \cdot X_{it} + \varepsilon_{it}, \quad t = 1991/92,\ 1998/99. \tag{3.1}$$

The main variable of interest is occupational change. The vector X_i contains additional controls depending on the specification. The first stage for the 2SLS estimation takes up the demand characteristics of the initial occupation of the employee, where $\bar{L}^W_{1990,j}$ denotes the size (in thousands) of the respective 3-digit occupational group in West Germany in 1990 and $u^E_{1993,j}$ denotes the 2-digit occupation-specific unemployment rate in East Germany in 1993:[12]

$$\text{Occ. change}_{it} = \alpha'_t + \beta'_t \cdot \bar{L}^W_{1990,j} + \beta''_t \cdot u^E_{1993,j} + \gamma'_t \cdot X_{it} + \varepsilon'_{it}, \quad t = 1991/92,\ 1998/99. \tag{3.2}$$

Table 3.2 presents both OLS and IV estimation results for 1991/92 in three specifications. The first (see columns 1 and 4) is a “bare bones” specification that contains only age and age squared, whereas the specification in columns 2 and 5 is extended by such variables as tenure with the current employer, dummy for having a foreman certificate, a sets of dummies for the firm size and state of residence (Bundesland). In addition, the specifications in columns 3 and 6 contain broad 1-digit occupational groups of the current employment to capture

[12] Unfortunately, reliable data on occupation-specific unemployment rates in East Germany up until 1993 are not available. Consequently, I use the earliest existent post-reunification data on unemployment as a proxy.

group-specific wage developments. Table 5.11 in appendix 5.2.2 contains the first-stage estimation to the respective columns 4-6 both for 1991/92 and 1998/99.

OLS estimation reveals a negative correlation between occupational change and wages. The estimates in table 3.2 indicate about 10% lower wages for those who changed occupations at the 2-digit level up to 1991/92. This number falls to an insignificant 4% or less by 1998/99. The estimates for 1998/1999 are, expectedly, lower – about 7% at the 2-digit level and about 2% at the 3-digit level. The negative wage differential associated with occupational change can be explained by the imposed character of occupational mobility. In the 2SLS estimation, the negative effect of an occupational change at the 2-digit level amounts to more than 40 log points in all specifications in 1991/92 (at the 3-digit level – also 30 to 40 log points). Although the OLS estimates indicate no significant wage losses in 1998/99, the IV estimates still point to a significant negative effect of more than 20 log points. These numbers show that post-reunification fundamental changes of the occupational structure in East Germany can be evaluated as both tremendous and persistent. Generally, the estimated IV coefficients for occupational change are much lower than their OLS counterparts, which indicates dramatic wage losses after accounting for sample selectivity. The coefficients imply positive selectivity of the group of occupational movers, which is in line with the Roy model and empirical findings on the selectivity of job and occupational changers (see e.g. Hunt, 2001).

The first-stage estimations (table 5.11 in appendix 5.2.2) confirm that the occupation of apprenticeship plays a significant role in a worker's post-reunification decision to change occupations. The East-German occupation-specific unemployment rate is positively correlated with the decision to change occupation, which confirms that depressed economic conditions in an occupational group were likely to lead to an occupational change. The size of the respective West-German occupational group denotes the chances of one finding a new job in the same occupation as the position held previously, and is, as expected, negatively correlated with occupational change. These general results of the first stage hold both for 1991/92 and 1998/99.

Certain statistical properties of the IV estimation serve to further justify the empirical strategy. The F-statistics of the formal Angrist-Pischke test prove the validity of the applied instruments.[13] The null hypothesis of the Sargan test for the validity of overidentifying restrictions is not rejected, confirming the validity of the instruments. Similar coefficients for other controls in the OLS and IV regressions also show that the instrument has an effect through the channel associated with occupational change imposed by changes in the occupational structure.

[13] The instruments were also tested on their validity separately. In both estimations, first-stage and second-stage estimates were similar, which points to the robustness of the results. F-statistics for the separate estimations are over 20.

Table 3.2: Wage effect of an imposed occupational change

Dependent variable:	OLS			IV[14]		
ln wages	(1)	(2)	(3)	(4)	(5)	(6)
Wave 1991/92, $N = 612$						
Occ. change 2-dig	-0.115***	-0.109***	-0.065**	-0.468**	-0.415**	-0.419
	(0.034)	(0.027)	(0.027)	(0.229)	(0.206)	(0.267)
Adjusted R^2	0.037	0.163	0.194			
Angrist-Pischke (F-stat)				43.66	45.33	35.14
Sargan test (p-value)				0.259	0.559	0.587
Occ. change 3-dig	-0.078*	-0.074*	-0.025	-0.439*	-0.390**	-0.300
	(0.045)	(0.038)	(0.037)	(0.225)	(0.198)	(0.217)
Adjusted R^2	0.025	0.152	0.190			
Angrist-Pischke (F-stat)				43.46	49.67	51.68
Sargan test (p-value)				0.071	0.201	0.251
Wave 1998/99, $N = 675$						
Occ. change 2-dig	-0.032	-0.031	-0.010	-0.228**	-0.200*	-0.231
	(0.031)	(0.030)	(0.025)	(0.115)	(0.117)	(0.209)
Adjusted R^2	-0.002	0.129	0.163			
Angrist-Pischke (F-stat)				75.26	76.38	35.09
Sargan test (p-value)				0.396	0.548	0.140
Occ. change 3-dig	-0.026	-0.025	-0.000	-0.234*	-0.201*	-0.261
	(0.033)	(0.032)	(0.021)	(0.120)	(0.118)	(0.193)
Adjusted R^2	-0.003	0.128	0.163			
Angrist-Pischke (F-stat)				85.67	87.95	45.88
Sargan test (p-value)				0.619	0.764	0.305

Additional covariates

Specification (1) & (4): age, age^2

Specification (2) & (5): age, age^2, tenure, firm size, foreman certificate= 1, bundesland

Specification (3) & (6): age, age^2, tenure, firm size, foreman certificate= 1, bundesland, 1-digit occupations

Standard errors are clustered at the level of 2-digit occupations and are displayed in parentheses;

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interestingly, average wages in the source occupation did not prove to be a valid instrument, which suggests that occupational changes occurred not because of rent-seeking, but rather as a reaction to avoid unemployment. This finding further underlines the involuntary nature of the examined occupational mobility. Though in the estimation above I compare wages of occupational movers and stayers, the latter might be a poor reference group in terms of comparability with respect to labor market outcomes. Indeed, under economic transition

[14]The displayed estimation refers to the IV with linear probability model in the first stage. As a robustness check, the probit model in the first stage was estimated and delivered similar results.

and imposed occupational mobility, unemployment is a more likely alternative to being an occupational mover. Thus, the wage cut associated with the occupational change can be considered to be a more desirable alternative than unemployment, either in terms of pecuniary benefits, or because of a general preference of employment. Though the latter was very characteristic of the socialist working morale, it is hard to quantitatively estimate this observation in practice.

3.6 Conclusion

Though literature on occupational mobility sometimes exploits "demand shocks" when looking at labor market outcomes, empirical examples of such shocks are rather rare. In this current paper, I use adjustment of occupational structure in East Germany after reunification in 1990 as an exogenous event that has affected individual decisions to change occupation. Thus, I examine occupational changes that, though not identified as completely involuntary, can at least be classified as superimposed due to adjustment processes at the macroeconomic level. As expected by the literature on involuntary *job* mobility, I find a negative and persistent effect on wages caused by post-reunification adjustments. The IV estimation reports that an occupational change for middle-skilled employees caused a wage loss of more than 40 log points in the short-, and one of more than 20 log points in the long-run. The first stage estimation demonstrates that the decision to change occupations is positively correlated with the occupation-specific unemployment rate in East Germany, demonstrating the high uncertainty of demand for these occupational groups. At the same time, it is negatively correlated with the size of the respective occupational group in West Germany, that is, the chance of finding a job in the initial occupation under the new demand structure. Interestingly, mean wages within occupations failed as an instrument. My findings confirm that the post-reunification wave of occupational changes was mainly driven by the search for stable employment rather than by rent-seeking motives. Although the group of occupational movers is positively selected, the wage decrease disappears very slowly. This illustrates the rigidity of occupation-specific human capital to quick fundamental adjustments and the persistence of the negative wage effect.

Compared to a wage increase that accompanies an occupational change under stable economic conditions, my calculations show that structurally imposed *occupational* change leads to a substantial and persistent wage decrease. Moreover, the magnitude of the decrease is higher than what is documented by the existing literature on involuntary *job* changes.

4 Occupational Changes, Changes in Occupational Contents and Their Association with Individual Wages

4.1 Introduction

The heterogeneity of human capital with respect to tasks performed in a job has enjoyed much attention in literature in recent years. Following Autor et al. (2003), the view that occupations are bundles of tasks has been established and supported by international evidence.[1] The task-based approach implies that the remuneration of work is closely related both to the occupational affiliation of workers, and the tasks that they perform. Moreover, skill portfolios at the individual level have a stronger effect on wages than industry or occupational affiliation alone (Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009). This paper contributes to the existing literature by introducing a similarity measure of *time-variant* task contents in a Mincer-type wage regression. Though the association of changing task content when changing occupations was thoroughly studied by Gathmann and Schönberg (2010), their study only considers employees who changed occupation under the assumption of time-invariant occupational contents. In my study I relax the latter assumption and construct a *time-variant* task measure of occupational contents. The introduction of this measure, together with an indicator variable for occupational change, allows me to use the variation, both between occupations as well as over time, in order to estimate the association of wages with the following components: (1) changes in the value of occupation-employee match (measured by an indicator of having changed occupation), (2) transferability of human capital across occupational groups (quantified by a similarity measure between the source and the target occupation), and (3) value of changes in task portfolios over time for those who stay in an occupation (based on the similarity measure of contents of same occupation at different time points). Thus, the study provides additional task-based evidence on the mechanisms of human capital accumulation and transferability as well as match improvements which are due to an occupational change. My empirical results extend the findings of Gathmann and Schönberg (2010) for the case of time-variant occupational contents.

In the existing labor market literature, occupational and job changes, and their association with individual wages, are widely studied using the concepts of human capital, as well as

[1] See Card and DiNardo (2002), Autor and Handel (2013) for the US, Spitz-Oener (2006) and Black and Spitz-Oener (2010) for Germany, Goos et al. (2009) for Europe.

search and matching. Due to a lack of appropriate data, most studies of wage differentials associated with job changes[2] do not account for content similarities between jobs. Yet theoretical models point to the importance of similarity for human capital transferability between occupations (McCall, 1990; Neal, 1999). Empirically, the differentiation of occupational changes by their complexity can be easily quantified by using the task-based approach. Representing occupations by vectors in a multidimensional continuous task space (Yamaguchi, 2012; Gathmann and Schönberg, 2010) allows the differentiation of occupational contents requiring only a small set of control variables. In the subsequent analysis, I empirically demonstrate that human capital losses after an occupational change are greater, the lower the similarity of contents between the source and the target occupation is. Along with human capital losses, the correlation of wage with the occupational change indicator is positive, which points to the increase in employee-occupation match.

The accumulation of human capital within an occupation has also been well-documented. Becker (1975) postulates that there should be an "effect of the productive process itself on worker productivity". However, the literature on *job* tenure (Altonji and Shakotko, 1987; Altonji and Williams, 2005) is largely inconclusive regarding the channels through which job tenure affects wages. From a task-based approach, one of these channels is the increase in individual proficiency in tasks over time, therefore remuneration to the task proficiency is reflected in wages (Gathmann and Schönberg, 2010). In my analysis, I provide an additional explanation of the positive association of wages and tenure: in occupations with a higher degree of content changes, remuneration is higher. This finding implies that contacts with different kinds of related tasks help to build a more comprehensive stock of human capital to gain additional remuneration. Until now, gains from intertask learning remain insufficiently studied in the existing literature.[3]

Such a detailed analysis of task contents demands high-quality task data that exhibits variation over time. I use the German Qualification and Career Survey (QCS) that contains detailed self-reported information on the tasks performed by the respondents in their jobs. Aggregating the task content information at the occupational level, I will put to use the variation of tasks between occupations and over time.

In this paper, I analyze the association of individual wages with task contents of medium-skilled male workers in Germany. Restricting the data to this particular sample assures consistency of occupational classification and avoids the issue of tenure gaps, which women are more likely to experience. The results for West Germany provide evidence supporting to the standard theoretical models (e.g. as presented in Keane and Wolpin, 1997). The occupational change as such is associated with higher wages for West-German employees both in the short and in the long run. This indicates that, on average, an occupational change results in a better match between employees and occupations. Transferability of human

[2]See, e.g. Addison and Portugal (1989), Carrington (1993), Harhoff and Kane (1993), Werwatz (1997), Acemoglu and Pischke (1998), Franz and Zimmermann (1999), Burda and Mertens (2001), Couch (2001).

[3]To my knowledge, Snower and Görlich (2013) is the only study in the area. They find evidence on intertask learning among complementary tasks.

capital between occupations is positively associated with the similarity of the source and the target occupations. Thus, starting in a new occupation with new contents implies a higher wage penalty. Staying in occupations with dynamic task contents creates a positive payoff, which is also existent in the presence of tenure as a control variable. When restricting the sample to young employees, the estimated coefficients generally increase in magnitude, which is in line with the prediction that accumulation of human capital is expressed in more vivid wage dynamics at the beginning of a career (Johnson, 1978; Neal, 1999).

This paper proceeds along the following lines. The next section sketches the underlying economic mechanism, section 4.3 describes the data structure and the estimation design. Section 4.4 provides descriptive statistics of the data. Estimation results complemented by a subsection on heterogeneity of outcome for the group of younger employees are found in section 4.5. Section 4.6 concludes.

4.2 Conceptual Framework

4.2.1 Definition of Occupational Change

Assume an individual who graduated at time $t-1$ from an apprenticeship in occupation A_{t-1} and who at the current time point t is employed in occupation E_t. An occupational change is defined to have occurred if A_{t-1} and E_t do not coincide. Otherwise, no occupational change took place. This definition of occupational change is mainly predetermined by the structure of the QCS data that contain only the information on the current occupation and the occupation of apprenticeship. This definition has been used in similar studies on occupational mobility (Fitzenberger and Spitz, 2004).

4.2.2 Transfer of Human Capital and Employee-Occupation Match

The considered economic mechanism of an occupational change is mainly rooted in the human capital and search and matching theories.

Following Becker (1975), *human capital theory* postulates the dependence of individual productivity on two components – general and specific human capital. With regard to occupational mobility, general human capital can be defined as knowledge or skills that can be transferred between occupations without loss. In contrast, occupation-specific human capital is not fully transferable when an occupational change occurs. Introducing a measure of content similarity between two occupations, the main principle of human capital transferability can be reformulated: the more similar the contents of occupations are, the higher the amount of human capital that can be transferred when an occupational change occurs.[4] The fraction of human capital $H(\cdot)$ that can be transfered from A_{t-1} to E_t will be denoted by δ:

$$H(E_t) = \delta_t \cdot H(A_{t-1}). \tag{4.1}$$

[4]By now, the term "similarity" is used as an intuitively conceivable concept. A precise definition and discussion of similarity measures follows later in this section after the introduction of the general economic mechanism.

The parameter δ should be naturally restricted to the interval of $[0,1]$. This parameter increases with the similarity of occupations A_{t-1} and E_t.[5]

$$\delta = \delta(\text{similarity}(A_{t-1} \leftrightarrow E_t)), \quad \delta' > 0. \tag{4.2}$$

Search and matching theory (McCall, 1990; Neal, 1999) allots a special role to the value of the match between employee and job. For occupational changes, one can think of the match between employee and occupation. Thus, the value of the match with the occupation of apprenticeship at time point $t-1$ can be denoted by $M(A_{t-1})$, and the value of the match with the current occupation as $M(E_t)$.

Consequently, the individual's productivity (P) in the given occupation can be represented by a function of two (endogenous) components – human capital (H) and the value of the occupation-employee match (M):

$$P(A_{t-1}) = f(H(A_{t-1}), M(A_{t-1})) \quad \text{and} \quad P(E_t) = f(H(E_t), M(E_t)) \tag{4.3}$$

The first partial derivatives are assumed to be positive: $f_{H(.)} > 0$ and $f_{M(.)} > 0$.

As the exact expressions for the productivity components are not defined, the partial derivatives $f_{H(.)}$ and $f_{M(.)}$ can be normalized to one without loss of generality. Assuming $f(H(.), M(.))$ to be linearly homogeneous in its arguments, allows the application of the Euler theorem and yields the following simplified form of the productivity functions:

$$P(A_{t-1}) = H(A_{t-1}) + M(A_{t-1}) \quad \text{and} \quad P(E_t) = H(E_t) + M(E_t) \tag{4.4}$$

Ex post, the difference in productivities in the two occupations can be written as:

$$P(E_t) - P(A_{t-1}) = (H(E_t) - H(A_{t-1})) + (M(E_t) - M(A_{t-1})) \tag{4.5}$$

Plugging in the definition (4.1) into (4.5) yields:

$$P(E_t) - P(A_{t-1}) = (\delta - 1) \cdot H(A_{t-1}) + (M(E_t) - M(A_{t-1})) \tag{4.6}$$

Note that the factor $(\delta - 1)$ is negative. This indicates that the specific part of human capital accumulated during an apprenticeship will not be used in a different occupation, which gives rise to a wage penalty given the loss of human capital. More specifically, the terms in (4.6) can be intuitively described as follows:

- $P(E_t) - P(A_{t-1})$ denotes the change in individual productivity and can be approximated by individual wage in occupation of employment E_t.
- $(\delta - 1) \cdot H(A_{t-1})$ is associated with the fraction of human capital that is transferable between A_{t-1} and E_t. Its impact on the productivity differential is less negative, the

[5] Note that, for simplicity, symmetry of the concept is assumed, i.e. for the similarity measure it would not matter whether the change has occurred from occupation $A_{(\cdot)}$ to $E_{(\cdot)}$, or from the occupation $E_{(\cdot)}$ to $A_{(\cdot)}$.

more similar the source and target occupations are.

- $M(E_t) - M(A_{t-1})$ reflects the changes in the value of the occupation-employee match between $t-1$ and t when an occupational change occurs. Assuming occupational changes are largely voluntary, i.e. being a strategical tool in career planning, an occupational change should normally lead to a better occupation-employee match.

4.2.3 Special Case: No Occupational Change Occurs

So far, no restrictions have been placed on A_{t-1} and E_t. Now consider a special case when no occupational change occurs, that is, A_{t-1} and E_t represent the same occupation.

This restriction does not change the underlying economic mechanism. Task content of occupations may change over time, meaning the contents of any occupation at time point $t-1$ and t are different: $E_{t-1} \neq E_t$. The vectors of task compositions change over time, which predetermines non-zero distances between the same occupations in different time periods. With regard to the previous analysis, A_{t-1} and E_t may refer to the same occupation with changing task contents.

The largest adjustment of the model predictions for this special case concerns the transferability of the occupation-specific human capital. As the individual's occupation remains unchanged, changing job requirements would necessarily lead to a permanent skill adjustment. Experiencing task content changes should lead to a deeper and diversified understanding of the production process within the occupation, which in turn gives rise to a wage premium due to intertask learning. Thus, the term $(\delta - 1) \cdot H(A_{t-1})$ in (4.6) can be now associated with the skill adjustment within the occupation and is no longer assumed to have a negative impact on wages. This term can be interpreted as the influence of tenure in the occupation.

The term $M(E_t) - M(A_{t-1})$ vanishes under the assumption that an occupation-employee match is invariant over time. Moreover, in the empirical estimation, it would be impossible to disentangle the adjustment of the skills from the improvement of the match if the occupation remains unchanged.

4.2.4 Similarity Measure

So far, the similarity of the occupations has not been precisely defined. Intuitively, the definition of similarity should reflect the proximity of the contents of the two occupations. In the task-based approach provided in Gathmann and Schönberg (2010), the content of any occupation is defined by a task vector, which can be used in the construction of a similarity measure. In order to formalize the idea, each occupation is assumed to consist of J different tasks: $\tau_1, ..., \tau_J$, which are subject to the following assumptions:

- The tasks themselves are general in nature and are transferable between occupations.

- Different occupations combine tasks in different ways.

Formally, it implies that any occupation can be represented by a weighted sum of tasks $\tau_1...\tau_J$:

$$A_{t-1} \equiv \sum_{j=1}^{J} q_{A,j}\tau_j \quad \text{and} \quad E_t \equiv \sum_{j=1}^{J} q_{E,j}\tau_j \tag{4.7}$$

As this study employs dichotomic individual data on whether or not each task $\tau_1,...,\tau_J$ is performed, the weights are computed as the proportion of workers in each occupation who carry out a particular task. In this case, $q_{A,j}$ denotes the fraction of workers in occupation A_{t-1} performing task j. The resulting task composition constitutes a J-dimensional vector, specified for each occupation. This allows the use of distances between points associated with different occupations to construct a similarity measure.

In the subsequent analysis, similarity of occupations is measured using angular separation (or uncentered correlation) borrowed from Gathmann and Schönberg (2010), who in turn refer to this measure being most common in the literature on proximity of production technologies:

$$AngSep_{A\leftrightarrow E} = \frac{\sum_{j=1}^{J} q_{A,j} \cdot q_{E,j}}{\left[\left(\sum_{j=1}^{J} q_{A,j}^2\right)\left(\sum_{k=1}^{J} q_{E,k}^2\right)\right]^{1/2}}. \tag{4.8}$$

The distance measure is then defined by $Dis_{A\leftrightarrow E} = 1 - AngSep_{A\leftrightarrow E}$. The measure varies between zero and one, taking higher values for less similar occupations. In the following, I will include the distance measure in the analysis, bearing in mind that it is an additive inversion to the similarity measure.[6]

4.3 Data

The data stem from the German Qualification and Career Survey (QCS) carried out by the Federal Institute for Vocational Education and Training (BiBB) together with the Institute for Employment Research (IAB). The survey consists of several cross-sections that, amongst others, contain retrospective questions on the labor market history of the respondents. The unique advantage of the data set for this research is that it contains detailed information on tasks performed by the respondents. Due to the self-reported nature of the QCS data an underestimation of true changes in job content is unlikely (Black and Spitz-Oener, 2010). Moreover, the QCS is based on a consistent set of occupational classifications.

Following the approach of Gathmann and Schönberg (2010), I arrange the available information on tasks into 13 categories that can be interpreted as dimensions of a task space (the description of dimensions of the task space can be found in table 5.12 of Appendix 5.3.1). Using this information, I construct multidimensional task vectors representing the

[6] A possible alternative similarity measure can be constructed using Euclidean distances. In the following empirical analysis a measure based on Euclidean distances was employed as a robustness check and delivered similar results.

content of each occupation (defined by 3-digit groups of occupational classification KldB88) at different time points (1985, 1991, 1998).[7] The entries of the vector represent the fraction of respondents in a particular occupational group who report to perform a particular task. These vectors can be used to compare task contents between occupations, as well as changes in the contents of one occupation over time. In particular, in case of an occupational change, one can compare the contents of the source and target occupations.

The target occupation is defined as the occupation of current employment in 1991 or 1998. The source occupation is defined as the occupation of the first apprenticeship[8] obtained before 1990. The latter definition allows me to measure task content of the source occupation using the data from 1985. Related to task contents from 1985, the content similarity measure in 1991 denotes *short-term* developments in occupational contents, whereas the similarity measure in 1998 denotes *long-term* developments.

The analyzed sample is restricted to contain only male employees with an apprenticeship as their highest educational level in the so-called accredited occupations. The sample contains prime-age (20-55) full-time workers with German citizenship[9] and is restricted to West-Germans who have spent their lives in West Germany, ruling out migrants with apprenticeships obtained in East Germany prior to German reunification in 1990. The final sample contains approximately 4200 observations for 1991 and 3000 observations for 1998.

4.4 Descriptive Statistics

4.4.1 Task Contents of Occupations and Distances

The basic summary statistics on task intensities measured by the proportion of workers performing the particular task type are reported by survey waves in table 5.13 of Appendix 5.3.1.[10] On average, task intensities for all three broad task groups increase over time, although the trends for the 13 task dimensions are different and often non-monotonic. The increasing intensity of all tasks might reflect the increasing multi-task nature of occupations.

[7] The data for the survey was gathered in December and January. Henceforth, I will refer to the waves by the first year of the survey.

[8] An additional test of the employed definition of an occupational change was performed using the extension of the questionnaire in 1998 compared to 1991. In 1998 there are variables on several possible apprenticeships, both completed or not completed by the respondents. Thus, the information on the contents of the occupation of the apprenticeship was constructed using information on all apprenticeships in which the respondent was trained, even if these were not completed. This information was used to run various checks involving the minimum distance (maximum similarity) between the current occupation and the apprenticeship(s). However, this more precise measure did not deliver more significant results compared to the usage of only the first apprenticeship completed by the respondent. Thus, the application of variables involving only the first completed apprenticeship in both 1991 and 1998 is legitimate.

[9] Generally, such a design may be compared to a cohort study with broadly defined cohorts. As a robustness check, I have restricted the sample in 1991 to the ages between 20 and 48 and the sample in 1998 to the ages between 27 and 55. Thus, I could follow the same broad age group over time. However, the estimation results were very close to those with the common age restriction 20 to 55 that are presented here.

[10] Note that each of the 13 task dimensions (AT1-AT4, MT1-MT6, IT1-IT3) can be arranged in three broad groups — manual tasks, analytical tasks and interactive tasks; this classification is widely used in the literature on the task-based approach (Autor et al., 2003).

For a better understanding of content changes and the growing importance of multitasking, it might be informative to take a closer look at one particular occupation. Table 4.1 presents task intensities of clerks for 1985, 1991 and 1998. The occupation "clerk" was defined based on belonging to the occupational group 781 of KldB88. The fact that the proportion of workers performing AT1 "Research, evaluate and measure" has grown is illustrative of the change in job profile. Such manual tasks as MT1 "Equip and operate machines" and MT4 "Serve and accommodate" have gained in importance, while among interactive tasks, the increase in the share of clerks performing IT2 "Teach and train others" is remarkable.

The observed changes in task intensities over the time span included in the data occur largely due to the changes in the contents of particular occupations. In the case of clerks, one can think of permanent changes in the responsibilities of office workers, for instance increased multitasking and the use of various office appliances. Additionally, changes in task content may be affected by measurement errors, which arise from inconsistencies in the questionnaires through time as well as from employees' own perceptions of the relevance of their responsibilities at work. For instance, as the notion of multitasking became a widely cited phenomenon, the respondents in later waves may have been more likely to report all possible tasks they perform, whereas respondents of earlier waves may have focused more on the "main" tasks typical for their occupation. A robustness check, however, based on the sum of task intensities normalized to one (which takes into account more prevalent multitasking) does not substantially affect the regression estimation.

Table 4.1: Average task intensity of clerks

Tasks	1985	1991	1998
	Mean	Mean	Mean
AT1: Research, evaluate and measure	0.049	0.041	0.123
AT2: Design, plan and sketch	0.037	0.019	0.047
AT3: Program	0.119	0.179	0.014
AT4: Execute laws or interpret rules	0.230	0.162	0.079
MT1: Equip or operate machines	0.036	0.026	0.068
MT2: Repair, renovate or reconstruct	0.011	0.010	0.008
MT3: Manufacture, install or construct	0.007	0.006	0.007
MT4: Serve and accommodate	0.002	0.001	0.089
MT5: Pack, ship or transport	0.058	0.113	0.060
MT6: Secure	0.018	0.046	0.031
IT1: Sell, buy or advertise	0.238	0.191	0.138
IT2: Teach or train others	0.0448	0.0428	0.219
IT3: Employ, manage personnel, organize	0.152	0.166	0.118
Observations	781	584	469

The percentages of occupational movers and stayers for 1991 and 1998 are provided in table 4.2. The fraction of movers in 1991 is about 40%, growing by about 4 percentage points in 1998. The table also contains the mean distances of movers and stayers. Concerning the distances of the stayers, the short-term task distance measure in 1991 is lower than the long-term measure in 1998, denoting that a longer time span is associated with more dynamics in occupational contents. The mean distances of the movers are substantially higher than those of the stayers, but do not significantly change between 1991 and 1998. In an overall comparison, stayers show lower average distances with lower variances compared to occupational movers. This implies that the changes of task portfolios experienced "within" occupations are less pronounced and less dispersed than those arising from an occupational change.

Table 4.2: Fractions of occupational stayers and movers by year and distances of change

	1991		1998	
	Stayers	Movers	Stayers	Movers
Fraction of stayers/movers	0.608	0.392	0.564	0.436
Distance - mean	0.096	0.443	0.193	0.425
(st.d.)	(0.054)	(0.266)	(0.112)	(0.213)
Observations	4248		3041	

The importance of accounting for similarity is well illustrated by taking a look at the changes associated with the longest and the shortest task dissimilarities (table 4.3). Using only an indicator variable of occupational change would not allow differentiation between these changes. Therefore, it is appropriate to introduce the distance measure alongside the indicator variable of occupational change to the empirical estimation.

Table 4.3: Examples of occupational changes at short and long distances, 1991 and 1998

Shortest distances
1991:
Clerk to insurance specialist
Miller to lathe operator
Pressman to printer
1998:
Storage keeper to vehicle driver
Carpenter to lathe operator
Toolmaker to miller
Longest distances
1991:
Design draftsman to vehicle driver
House-painter to security, detective
Pipe man to Waiter, steward
1998:
Design draftsman to road builder
Waiter, steward to machinist
Chemistry lab assistant to vehicle driver

4.4.2 Sample Descriptive Statistics

The mean values of the observable characteristics for stayers and movers broken down by year are reported in table 4.4 below.

Log wages capture real hourly wages in the current job (calculated in prices in 1991). In 1991, the unconditional average log wages of occupational movers are not significantly higher than those of stayers, whereas in 1998 they are.[11]

Table 4.4: Descriptive statistics for the covariates for 1991 and 1998, separately by the subsamples of occupational stayers and movers

	1991		1998	
	Stayers	Movers	Stayers	Movers
Log real hourly wage	2.298	2.311	2.356	2.332
	(0.302)	(0.297)	(0.319)	(0.305)
Age	36.11	39.21	39.47	40.62
	(9.749)	(9.129)	(7.394)	(7.225)
Tenure w/current employer	12.96	12.44	15.95	13.38
	(8.998)	(8.950)	(9.420)	(9.043)
Number of employers	1.921	2.592	2.112	2.786
	(1.067)	(1.088)	(1.144)	(1.105)
Observations	2603	1681	1714	1327
	4284		3041	

Age is a broad approximation of potential labor market experience. In West Germany in 1991, the average age of the employees who had completed an apprenticeship before 1990 was approximately 36 years amongst stayers and 39 years among movers. In 1998, the average age of movers is also greater, although the difference between stayers and movers shrinks to 1 year. In both years, the differences in age are insignificant.

Tenure with the current employer measured by the number of years spent with current employer reflects the firm-specific human capital accumulated by the respondent. Tenure with current employer is longer for the stayers than for the movers, although the difference is insignificant. Tenure squared included in the regression did not improve the estimation and hence was excluded from the final specification.

Number of employers captures the number of job changes of the respondent and serves as a control for the overall mobility of respondents. Unsurprisingly, the average number of employers amongst movers is somewhat higher than for stayers both in 1991 and 1998.

In addition, sets of dummies for the occupational groups of firm size (7 categories), federal states (Bundesland, 11 categories) and the current employment (21 categories) are included. The latter helps to control for wage trends within broad occupational groups.

4.5 Estimation

Based on the economic framework described in section 4.2, I employ a standard Mincer-type wage regression (equation 4.9) to estimate the association of wages with different components

[11] In the study of Fitzenberger and Spitz (2004) that employs the same data source, and a very similar estimation design, the authors find a comparable in magnitude, though positive, wage differential, both conditionally and unconditionally. However, their sample contains employees with vocational training who proceeded their studies at a post-secondary institution.

of an occupational change separately for the cross-sections of 1991 and 1998.

$$\ln w_{it} = \alpha_t + \beta_1 \text{Occ. change}_i + \beta_2 \text{Distance}_i + \beta_3 \text{Occ.change * Distance}_i + \gamma_t X_{it} + \varepsilon_{it}, \quad (4.9)$$

for $t = 1991,\ 1998$. In the following, I compare specifications containing only the indicator for occupational change (*Occ. change*) with specifications that additionally include distances for stayers (*Distance*) and movers (*Occ. change * Distance*). The vector X_t contains individual and employment characteristics described above.

Table 4.5: OLS estimation of the wage equation

Dep. Variable:	Year=1991		Year=1998	
Log Real Hourly Wages	(1)	(2)	(3)	(4)
Occupational change (dummy)	-0.022*	0.038*	-0.026	0.089**
	(0.012)	(0.021)	(0.020)	(0.036)
Distance		0.273*		0.255
		(0.157)		(0.182)
Distance * Occ. change		-0.371**		-0.419**
		(0.152)		(0.167)
Tenure w/current employer	0.005***	0.005***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.046***	0.046***	0.029***	0.029***
	(0.004)	(0.004)	(0.008)	(0.007)
Age squared	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of employers	0.019***	0.020***	0.002	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
1-digit occ. groups (dummies)	Yes	Yes	Yes	Yes
Firm size (dummies)	Yes	Yes	Yes	Yes
Bundesland (dummies)	Yes	Yes	Yes	Yes
Constant	1.040***	1.024***	1.356***	1.306***
	(0.104)	(0.107)	(0.140)	(0.153)
Adjusted R^2	0.238	0.242	0.200	0.206
Observations	4284	4284	3041	3041

Standard errors in parentheses.

Standard errors are clustered at the level of 2-digit occupational groups.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The first row of table 4.5 describes the conditional wage gap between stayers and movers with and without accounting for the distance of change. When not accounting for distances (specifications 1 and 3), wages of movers are, on average, lower than those of stayers. However, when including *Distance* and its interaction with *Occ. change* (specifications 2 and 4), the estimation perfectly illustrates the mechanisms of human capital and search and matching theories. The indicator variable (*Occ. change*) points to a significantly positive association between the occupational change and individual wages. This can be interpreted as an improvement of employee-occupation match after an occupational change. The interaction of *Distance* and *Occ. change* shows that transferability of human capital from one occupation to another declines with the distance in task contents between these occupations. Note that in 1991, the mean distance for those who had changed occupation was 0.443, implying that an occupational change is associated with, on average, lower wages: $0.038 - 0.371 \cdot 0.443 = -0.126$. The same holds for 1998. The variable *Distance* reflects changes of content in an occupation. Thus, being employed in an occupation that has larger changes in task content is associated with higher wages. Over longer period of time this premium remains positive, although it loses significance. All other variables included in the regression specification are significant, lending support to the predictions of human capital and search and matching theories.

A comparison of specifications 1 and 3 to 2 and 4 shows that, using the distance measure, a negative wage gap between movers and stayers can be decomposed into the parts associated with match improvement and human capital transferability. Whereas the correlation of individual wages with match improvement is positive, the correlation with human capital transferability is negative.

4.5.1 Shapley-Owen Decomposition of R^2

The contribution of task-related variables alongside the standard variables on human capital accumulation and matching can be analyzed by a Shapley-Owen decomposition of R^2. Table 5.14 of appendix 5.3.2 provides an overview of contributions of single variables or sets of variables to the total explained variation of individual wages. Compared to the standard variables of human capital accumulation and matching (emphasized in the table), the task-related components make a comparably sizable contribution to R^2.

4.5.2 Estimation Bias

The interpretation of the coefficients regarding the association between individual wages, occupational change and its distance must take into account their potential biasedness. It should be noted that the estimation above does not solve the selection problem, which is inevitable when analyzing the association between individual career choices and wages (Sullivan, 2010). Generally, one would expect that both the decision to change an occupation and the distance of the change are endogenous with respect to unobservable characteristics of the respondents, such as motivation and talents in particular tasks or occupations. However, the sign of the correlation between the error term and the distance of change is not clear. The most motivated and talented employees might tend to change their task profile very radically, as they are flexible and ready to adjust their skills as soon as possible. Alternatively, they might be strategic in the usage of their accumulated human capital and tend to choose their new occupation such that it requires a similar skill profile to the one they acquired during their apprenticeship.

With respect to the endogeneity of the occupational change itself, the direction of the bias is unambiguous and theoretically substantiated. From the literature available on both job and occupational mobility, it is known that the group of movers is positively selected with respect to their average characteristics (Booth and Satchell, 1996; Fitzenberger and Spitz, 2004; Winkelmann, 1996). Especially in cases of voluntary mobility, it is argued that workers decide in favor of changes if they (at least in the long-run perspective) expect better pecuniary or non-pecuniary career perspectives even after accounting for possible wage losses. Involuntary mobility resulting from a layoff or firm closure normally concerns workers with weaker labor market characteristics, i.e. those with lower productivity, less tenure, young workers etc. (see e.g. Addison and Portugal, 1989; Neal, 1999; Burda and Mertens, 2001). Moreover, there is evidence that occupational mobility after an apprenticeship is affected by negative selectivity of movers (Von Wachter and Bender, 2006). Using the QCS data, it is impossible to identify whether an occupational change was made voluntarily or was imposed by external factors. However, based on the identification strategy of Von Wachter and Bender (2006), I could estimate a Heckman selection model with the occupation-specific average rate of occupational changes as exclusion restriction. As a robustness check, I calculate the averages for different levels of aggregation of the KldB88. The calculated IMRs support the hypothesis of positive selection bias of the subsample of movers on unobservables. The details of the calculations are available upon request.

4.5.3 Outcome Heterogeneity: Estimation Results for Younger Workers

In order to gain more insights into how potential tenure affects the wage outcome associated with an occupational change, I will now restrict the sample to "young" employees, i.e. those aged between 20 and 27 in 1991, and follow this cohort in 1998. The follow-up of the young employees is imposed by the restriction on graduation from an apprenticeship before 1990 due to the issues of content measurement based on 1985 task data.

For several reasons, young employees is one of the relevant groups to be analyzed on their wage correlation with the occupational change and the extent of content changes. This group can be characterized by its higher mobility, as the young workers face lower costs of an occupational change. Indeed, young workers spent less time accumulating human capital on the labor market, therefore they can afford to search for a better employee-career or an employee-employer match (Johnson, 1978; Neal, 1999; Werwatz, 1997; Franz and Zimmermann, 1999; Von Wachter and Bender, 2006).

Moreover, theoretical models (Johnson, 1978; Neal, 1999) predict that complex occupational changes are more likely to take place in the beginning of the career, at young ages. It implies that young employees tend to change occupation more often than older ones. Moreover, it might also be hypothesized that the observed distance of change for young employees is on average "longer", as they tend to change the task content more radically when changing occupation. First, consider the proportion of movers among young workers. The results in table 5.15 of appendix 5.3.3 reveal that for all subgroups the fraction of movers is lower compared to the full sample (see table 4.2). Generally, the naïve comparison indicates that occupational mobility takes place, for the most part, at a young ages.

A comparison of the average distances of occupational change for young employees with the full sample reveals that young employees have, on average, lower distances of change. Thus, the hypothesis that a more radical character of occupational mobility measured by "longer" distances of occupational changes among the young cannot be supported by a naïve comparison between the sample means.[12]

Table 5.15 of appendix 5.3.3 presents sample averages of the main variables for young employees. Compared to the full sample, young West-German employees have on average lower wages, especially in 1991 when the average age of young employees is substantially lower than in the full sample. Both in 1991 and 1998 the unconditional wages of stayers are higher, though the wage gap is insignificant. Movers are on average insignificantly older. Expectedly, young workers have, on average, lower tenure and overall number of employers.

The regression results on wage returns associated with different components of an occupational change are reported in table 5.16 of appendix 5.3.3. The regression explains a smaller part of the variance of wages of the young employees, compared to the full sample. However, the differences in the distinct coefficients are more striking. Without taking account of distances (specifications 1 and 3), the wage gap between movers and stayers is negative.

[12] An OLS estimation did not reveal any sizable and significant association between the distance of the change and age. The results of this estimation are not included in the current paper, but are available upon request.

Given lower mean wages of the young employees, the wage gap between movers and stayers is considerably higher than in case of the full sample. When including variables related to *Distance* (specifications 3 and 4), one observes a similar correlation pattern as in the full sample. The indicator of occupational change becomes positive, whereas its interaction with distance is estimated to be negative. Again, the signs of the coefficients point at an improvement of occupational match and a loss of human capital associated with occupational change. Especially in 1991, when the average age of young employees is considerably lower than in the full sample, the correlation of wages, with both distance within occupations and distance of an occupational change, are considerably higher than in the full-sample case. This evidence supports the theoretical finding that young employees have a steeper wage profile and have higher wage penalties due to human capital losses.

Biasedness of the estimates in the case of young workers is not straightforward. On the one hand, my sample restriction, together with the calculation of Inverse Mills Ratios (using the same model discussed in subsection 4.5.2), indicates positive selection on unobservables of occupational movers. On the other hand, there is evidence of negative selection into occupational mobility for young workers in West Germany (Von Wachter and Bender, 2006). The study employs data that allows exact identification of the time of occupational change, which explains the differences to my findings.

4.6 Conclusion

The main goal of this study was to apply the task-based approach to disentangle components of occupational change and provide additional evidence on the mechanisms of human capital accumulation and transition. The estimation results using the task-based approach confirm the main predictions of the human capital and search and matching theories. For instance, an occupational change is associated with a wage premium, which indicates that occupational changes are often used as a strategic career instrument to achieve higher pecuniary outcomes. At the same time, distant occupational change are negatively correlated with wages, which can be explained by higher human capital losses that emerge due to changes in the task content of work. In case no occupational change occurs, i.e. the respondent stays in the occupation, a wage increase due to gradual adjustment to changing occupational content is observed. This evidence suggests that contact to various occupation-specific tasks might trigger intertask learning and help to build a more comprehensive human capital stock that is associated with higher wages. The evidence is conclusive regarding the importance of accounting for content similarities between occupations when analyzing job or occupational mobility.

5 Appendix

5.1 Appendix to Chapter 2 “Closing the Gender Pay Gap and Individual Task Profiles: Women’s Advantages from Technological Progress”

5.1.1 Data and Imputation Procedure

This appendix features a summary of an appendix appearing in the current draft of Fedorets et al. (2013) that employs the same data sources and data imputation procedure for the subsample of men. For the purposes of the present study, I exclude individual wages from the imputation procedure and perform it separately for men and women.

Data

The main data source for the present study is the IAB Employment Sample (IABS) launched by the German Institute for Employment Research of the Federal Employment Service. The data contains a 2 percent representative sample of all individuals for which social insurance is compulsory. The employment histories are recorded on a daily basis and contain individual-level information on wages, educational level, occupational group and full- or part-time employment status along with selected individual characteristics (gender, age, state of residence). The panel structure of this data set allows detailed analysis of wage dynamics. As these data do not contain any information on tasks, I use regression analysis to impute the lacking task data from the QCS.

QCS is an employee survey launched by Federal Institute for Vocational Education and Training (BiBB) together with the Institute for Employment Research (IAB). This data set includes the four cross-sections of QCS launched by BiBB and IAB in 1979, 1985/86, 1991/92 and 1998/99, as well as the later wave of the "Working-Population Survey" launched by BiBB and the Federal Institute for Occupational Safety and Health (BAuA) in 2006. QCS is a rich data set that has been widely used in the task-based literature as it contains individual-level information of activities that respondents perform in their jobs alongside other characteristics such as occupation of employment, gender, age, qualification, wages. The individual-level task information contained in QCS is seen as its main advantage over the common US data sources on tasks.[1] The task data from the QCS is, until now, either used in their initial cross-sectional form, or as a basis for calculation of task intensities at occupational level and their further merger with other data sets (IABS or GSOEP). Yet the latter procedure allows for panel data analysis, it destroys variation of tasks within occupations. Fedorets et al. (2013) and the present paper employ imputation using regression analysis that helps to maintain initial task variation within occupational groups.

Based on the time span covered by IABS and QCS, I am able to perform the imputation procedure for the years from 1986 to 2004.

[1] The widely used Dictionary of Occupational Titles (DOT) and O*NET include task information at occupational level. Individual-level task data from the Princeton Data Improvement Initiative are now available as a single cross-section of 2008.

Calculation of Task Shares in QCS

The questionnaires of QCS for different years contain sets of questions on activities that respondents perform in their jobs in the form of either binary variables, or a Lickert scale (that is commonly re-scaled to a binary variable). Table 5.4 illustrates how the reported activities are assigned into three task categories: non-routine cognitive (NRC), routine (R) and non-routine manual (NRM).

Following Antonczyk et al. (2009) and after necessary sample restrictions, an individual-level share of each of the three categories is calculated for each cross-section:

$$TS_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ at time } t}{\text{total number of activities performed by } i \text{ over all categories at time } t}$$

Thus, TS_{ijt} approximates the share of working time that individual i spends on task j at time t. Table 5.1 documents evolution of task categories for men and women over time. As expected, the share of routine tasks falls for both men and women over time, though the trend is more pronounced for women.

Table 5.1: Average task intensities in QCS by year and gender, original and fitted values

	original				fitted			
	1986	1992	1999	2004	1986	1992	1999	2004
Men								
NRC tasks	39%	37%	43%	47%	39%	37%	43%	47%
R tasks	37%	35%	32%	26%	37%	35%	32%	27%
NRM tasks	24%	27%	24%	26%	24%	28%	25%	26%
Women								
NRC tasks	41%	40%	60%	60%	41%	41%	60%	60%
R tasks	47%	45%	19%	15%	47%	45%	19%	16%
NRM tasks	13%	15%	21%	24%	13%	15%	21%	24%

Imputation of Task Shares in IABS

These task indexes (individual task profiles) were then imputed from QCS to IABS data. Firstly, the calculated task shares were regressed on a set of variables regressed on employee's characteristics using separate OLS estimation for genders as well as different QCS waves (1986, 1991, 1998 and 2006). The set of the predictors (occupational groups, age, qualification as well as interaction terms) was chosen to be available both in QCS and IABS, and the data sets were restricted along the same lines. Moreover, the specifications were chosen to be invariant over time but varying by gender in order to achieve the best fit of the predicted task shares. In order to avoid task shares that are bigger than one or negative, a truncation of misfitting values is performed.

Secondly, the estimated single coefficient of the predicting variables were interpolated for the analyzed time span of 1986-2004 using linear weights according to the following rule:

$$\widehat{\beta}_{x(ijt)}(t) = \frac{t_1 - t}{t_1 - t_0}\widehat{\beta}_{x(ijt)}(t_1) + \frac{t - t_0}{t_1 - t_0}\widehat{\beta}_{x(ijt)}(t_0),$$

where t indicates a year of the time span 1986-2004 with t_0 and t_1 being the most close years out ot the available QCS waves (1986, 1991, 1998 and 2006).

Thirdly, the interpolated coefficients were used to predict the individual task profiles in IABS based on the same set of predictors.

Such an imputation procedure constitutes an approximation of task shares for further empirical analysis and captures natural correlation of individual task profiles with other individual characteristics. In order to control for quality of the imputing procedure, the following measures were taken (detailed tables can be found in Fedorets et al. (2013)):

- The distributions of the predicting variables in QCS and IABS were thoroughly investigated and found to be roughly equal.
- The distribution of the initial task shares in the QCS and the fitted values both in the QCS and IABS were compared. The imputation procedure in IABS delivered task values close to the original and fitted values in the QCS data for both genders (see table 5.2).

Table 5.2: Average predicted task intensities in IABS by year and gender

	1986	1992	1999	2004
Men				
NRC tasks	40%	38 %	47%	49%
R tasks	37%	36%	31%	27%
NRM tasks	23%	26%	23%	24%
Women				
NRC tasks	43%	40%	66%	65%
R tasks	45%	46%	15%	13%
NRM tasks	12%	14%	20%	22%

- In order to prove the importance of including variables other than occupation into the imputation procedure, an alternative imputation based only on occupations was performed. Comparing the variations of the initial task shares to their fitted values based on the two imputation procedures, one can conclude that, though most of the variation in tasks comes from occupations, additional covariates (such as age and gender) help to reach almost the total variation in the initial variable (see table 5.3).

Table 5.3: Standard deviation in the original task categories, as well as in task categories predicted by occupations with and without additional covariates

	NRC	R	NRM	NRC	R	NRM
1986		Men			Women	
SD: Orig. BiBB info	0.140	0.076	0.083	0.121	0.100	0.060
SD: Pred. by Occ & X	0.135	0.064	0.078	0.100	0.078	0.046
SD: Pred. by Occ	0.104	0.044	0.068	0.089	0.077	0.039
1992						
SD: Orig. BiBB info	0.170	0.096	0.101	0.152	0.142	0.069
SD: Pred. by Occ & X	0.168	0.092	0.097	0.142	0.135	0.059
SD: Pred. by Occ	0.140	0.078	0.087	0.131	0.132	0.056
1999						
SD: Orig. BiBB info	0.146	0.086	0.068	0.105	0.080	0.051
SD: Pred. by Occ & X	0.144	0.082	0.064	0.097	0.072	0.035
SD: Pred. by Occ	0.120	0.071	0.051	0.088	0.072	0.028
2006						
SD: Orig. BiBB info	0.140	0.076	0.083	0.104	0.049	0.072
SD: Pred. by Occ & X	0.135	0.064	0.078	0.094	0.040	0.063
SD: Pred. by Occ	0.104	0.044	0.068	0.076	0.039	0.044

5.1.2 Assignment of Tasks into Categories

This appendix features a table from Fedorets et al. (2013) that describes assignment of activities from the QCS questionnaire into task categories. A very similar classification with 5 task categories can be found in Spitz-Oener (2006).

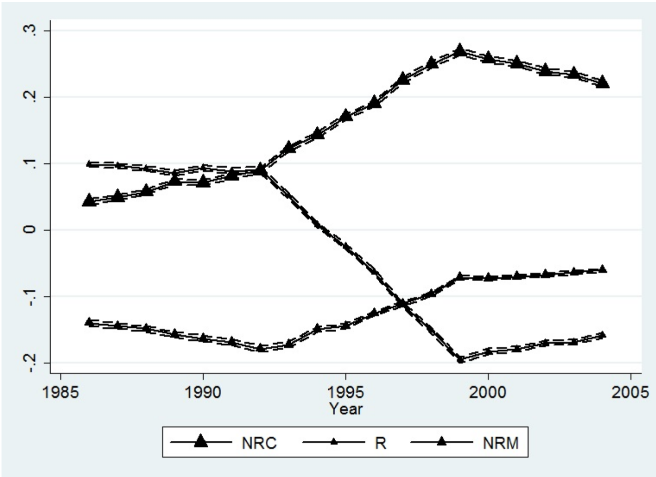
Table 5.4: Task classification

Task categories	Tasks
Non-routine cognitive (NRC)	**Human resources management**: recruiting, negotiating, prescribing rules, instructing. **Research and development**: researching, analyzing, evaluating, construction, designing, developing. **Public relations**: marketing, publishing, acquisition, presenting, consultation, lobbying. **Management and organization**: purchasing, sales, coordinating, planning, legal interpretation. **Education:** teaching, training.
Routine (R)	**Accounting and controlling**: calculating, bookkeeping, archiving, sorting, correction. **Quality management**: measuring, monitoring, quality checks. **Production**: producing, packaging, loading, transporting, sending, operate machines.
Non-routine manual (NRM)	**Maintenance**: repairing, renovation, servicing machines, restoring. **Construction**: building, installing. **Hotel and restaurant**: serve, accommodating, catering. **Other Services**: cleaning, security, care.

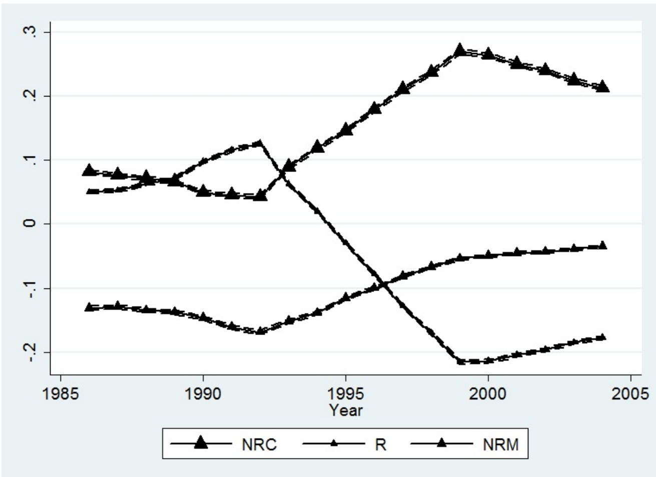
5.1.3 Figures

Figure 5.1: Unconditional mean relative task profiles (women-to-men) at different quantiles of the wage distribution (with standard error bands), 1986-2004

(a) at 25th percentile



(b) at 50th percentile



(c) at 75th percentile

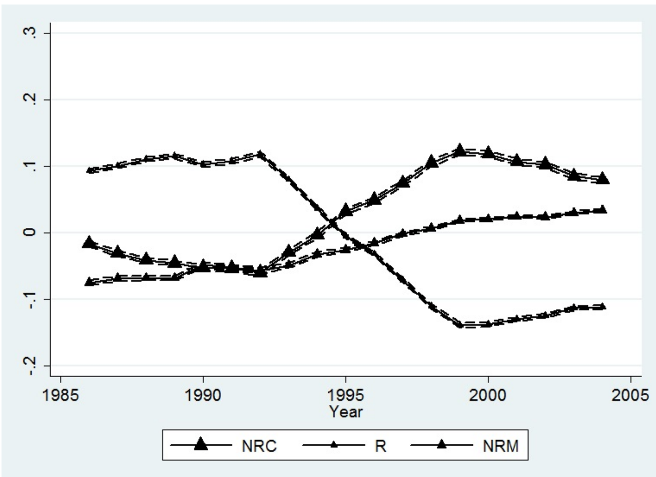
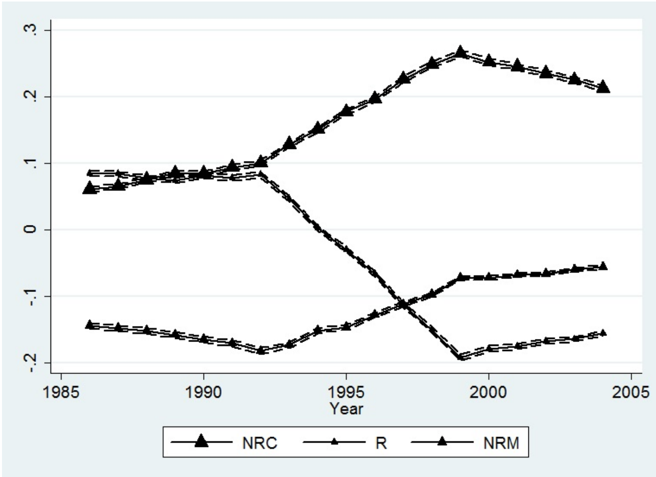
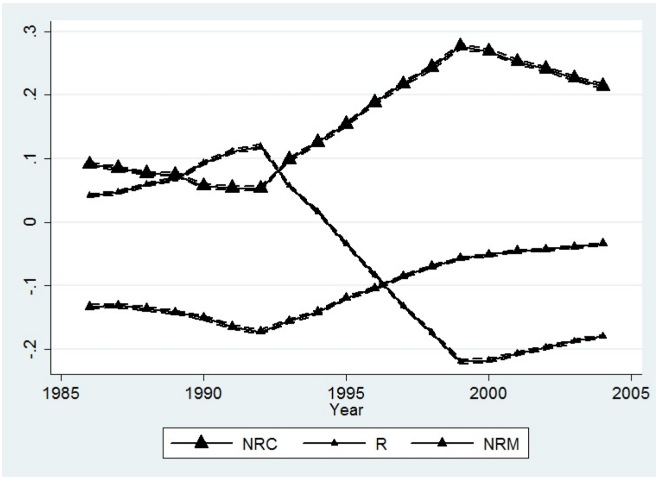


Figure 5.2: Mean relative task profiles (women-to-men) at different quantiles of the wage distribution, conditional on age, education, tenure (with standard error bands), 1986-2004

(a) at 25th percentile



(b) at 50th percentile



(c) at 75th percentile

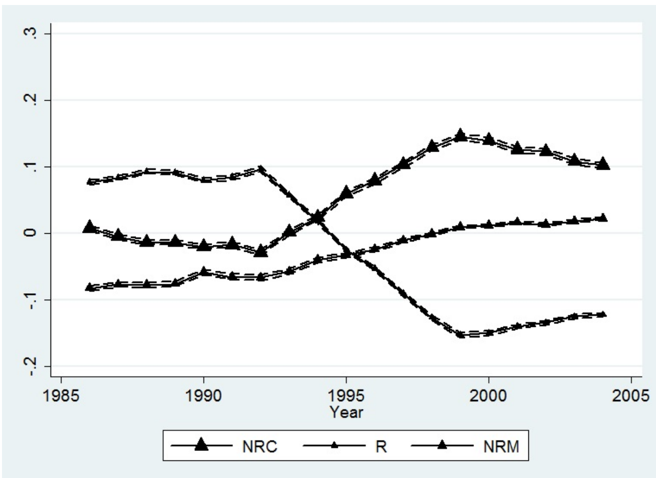
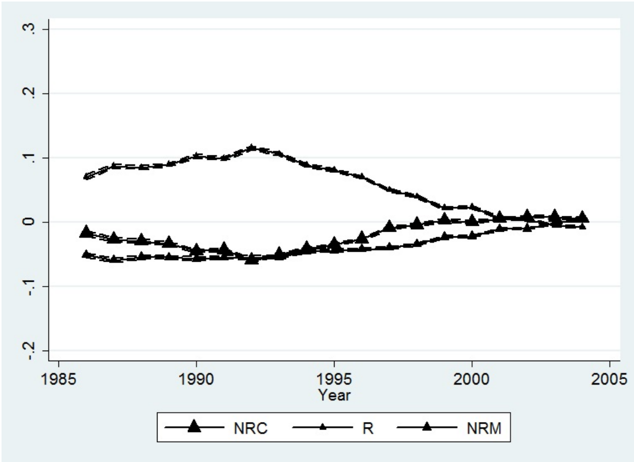
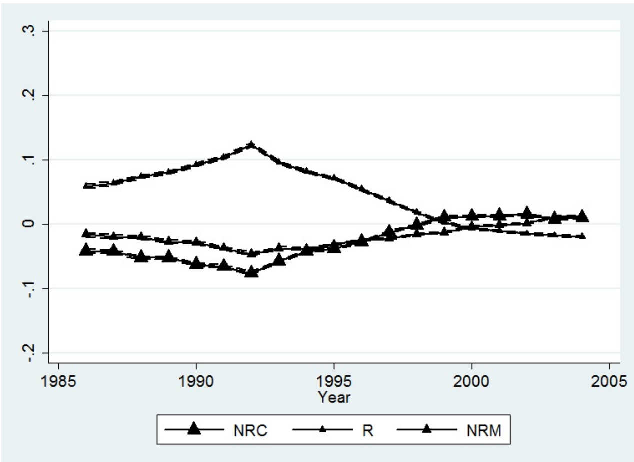


Figure 5.3: Mean relative task profiles (women-to-men) at different quantiles of the wage distribution, conditional on age, education, tenure and occupation (with standard error bands), 1986-2004

(a) at 25th percentile



(b) at 50th percentile



(c) at 75th percentile

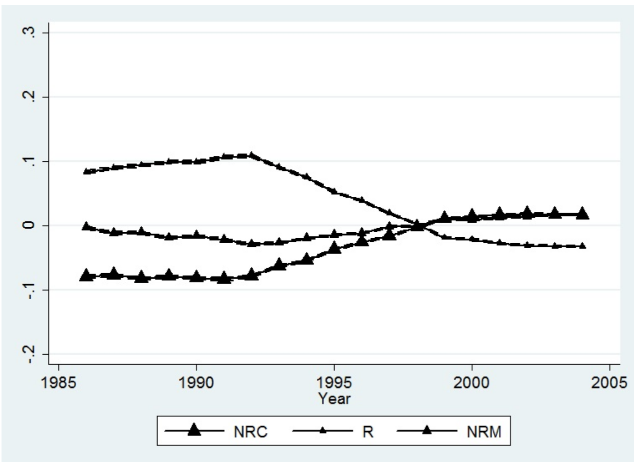
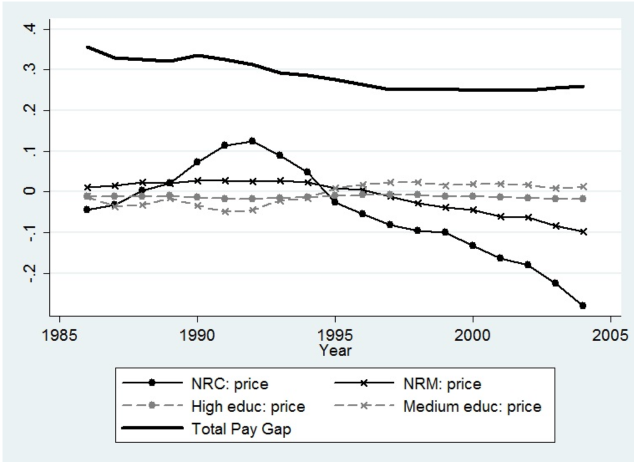
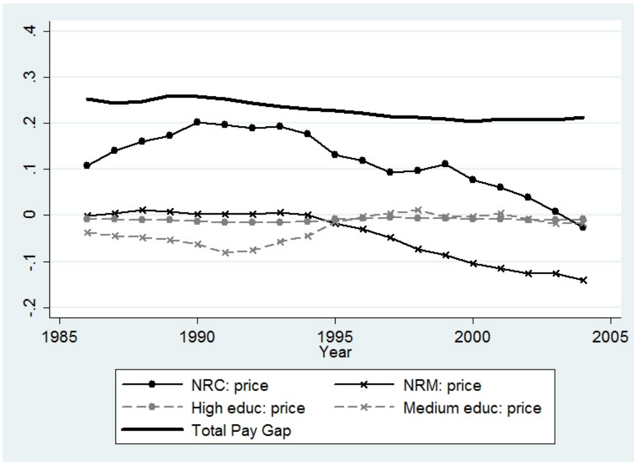


Figure 5.4: Total contribution of gender-specific task prices conditional on *age, education, tenure* to formation of the gender pay gap, 1986-2004

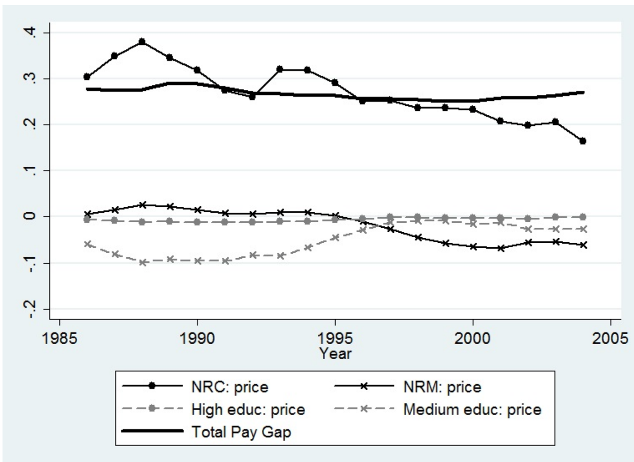
(a) at 25th percentile



(b) at 50th percentile



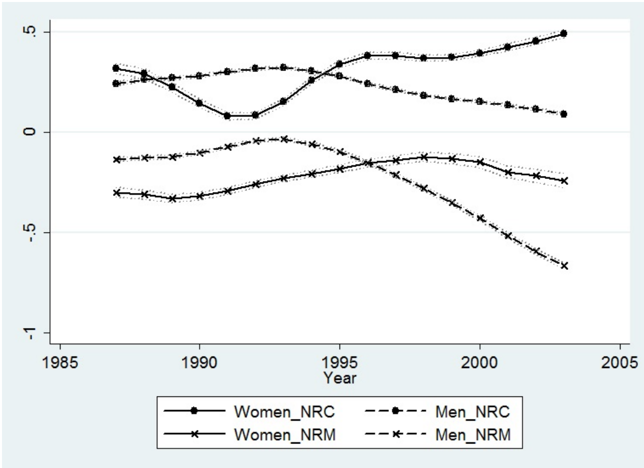
(c) at 72nd percentile



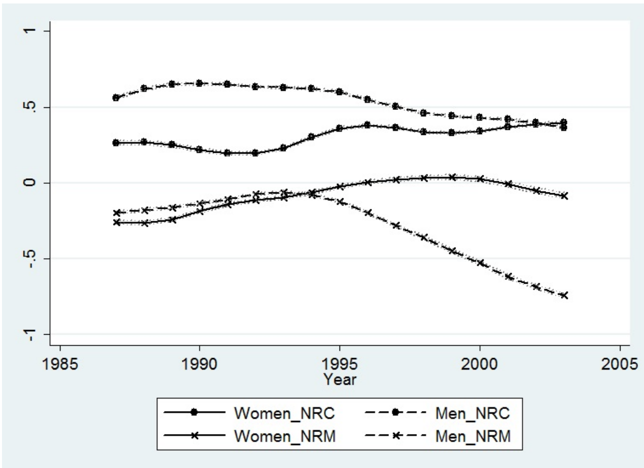
Note: Gray-colored lines refer to contributions of returns to education and are displayed for the sake of comparison

Figure 5.5: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure*, 1986-2004. Estimation in cross sections.

(a) at 25th percentile



(b) at 50th percentile



(c) at 72nd percentile

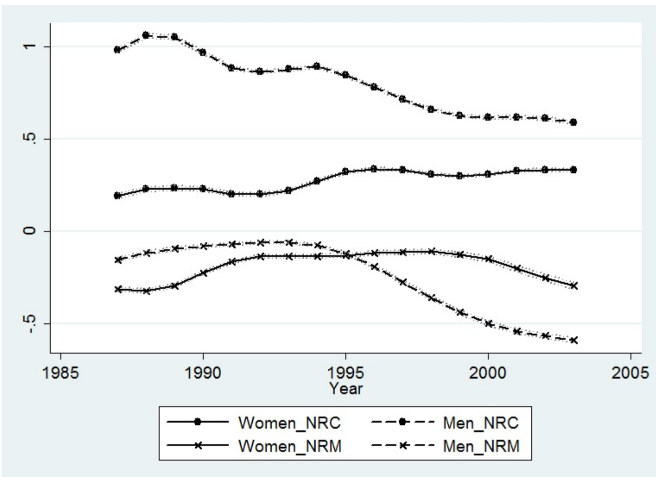
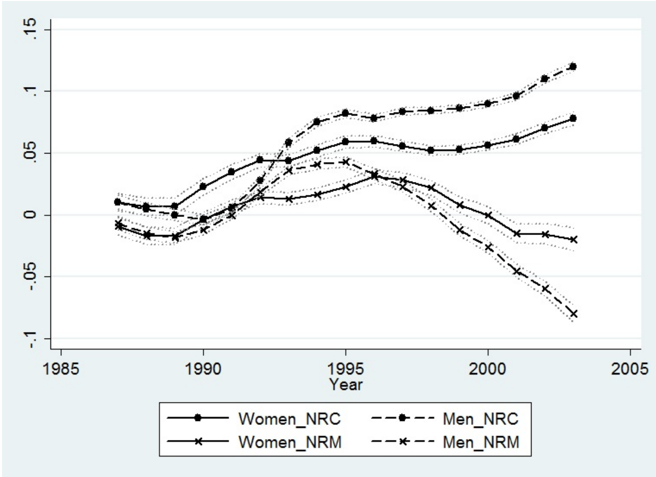


Figure 5.6: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure*, 1986-2004. Estimation with long-term individual fixed effects

(a) at 25th percentile



(b) at 50th percentile

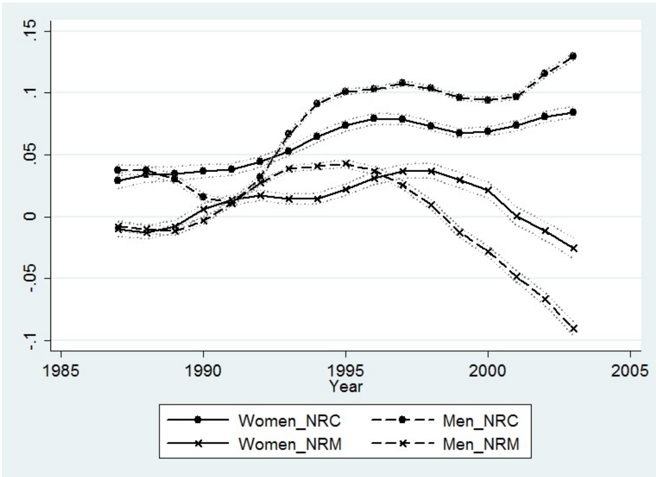


Figure14rifQ50_Prices_constFEpersnr_NRCNRM_S2d.jpg

(c) at 72nd percentile

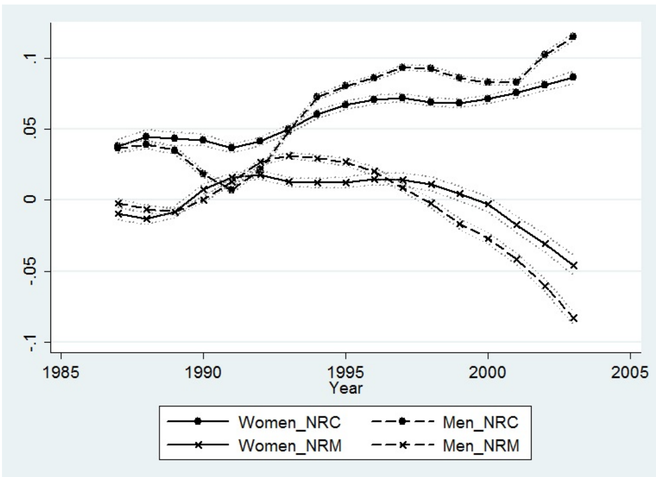
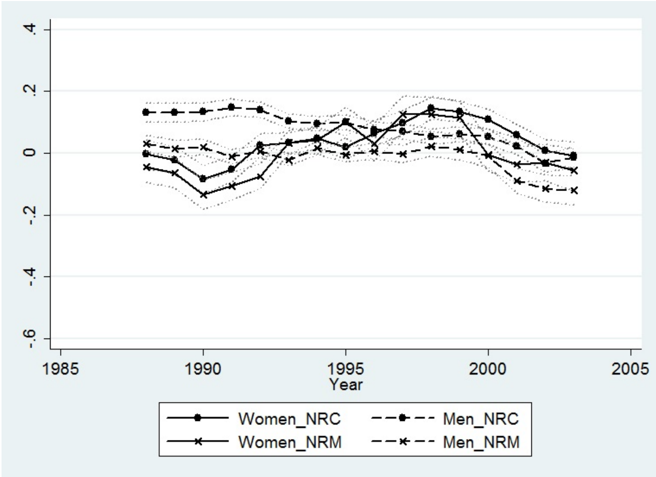


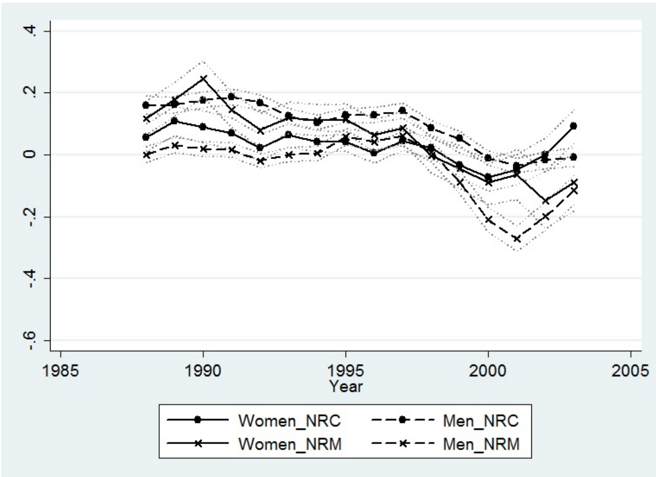
Figure14rifQ72_Prices_constFEpersnr_NRCNRM_S2d.jpg

Figure 5.7: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure*, 1986-2004. Estimation with two-year individual fixed effects

(a) at 25th percentile



(b) at 50th percentile



(c) at 72nd percentile

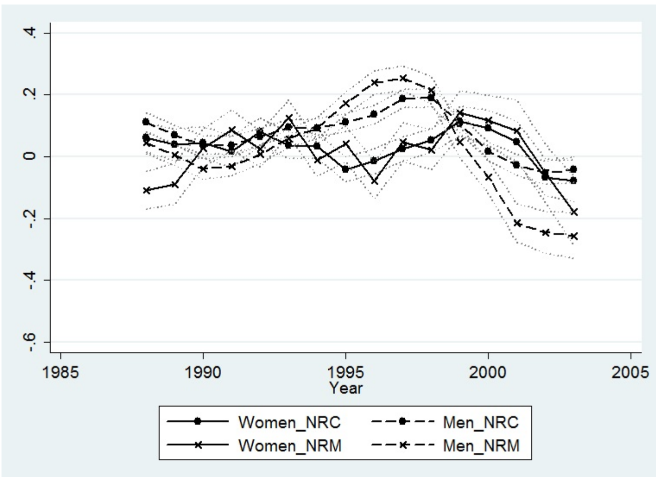
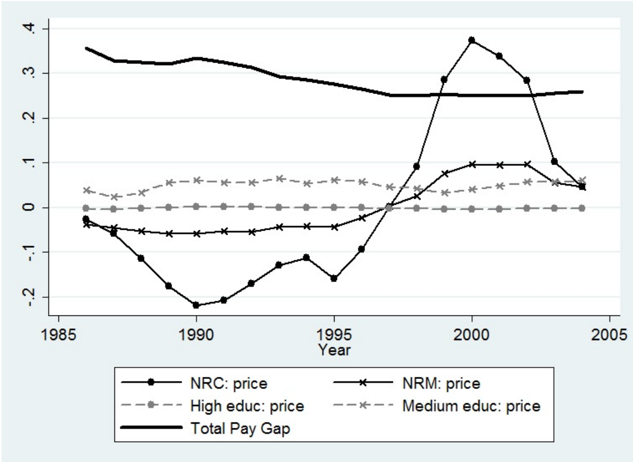
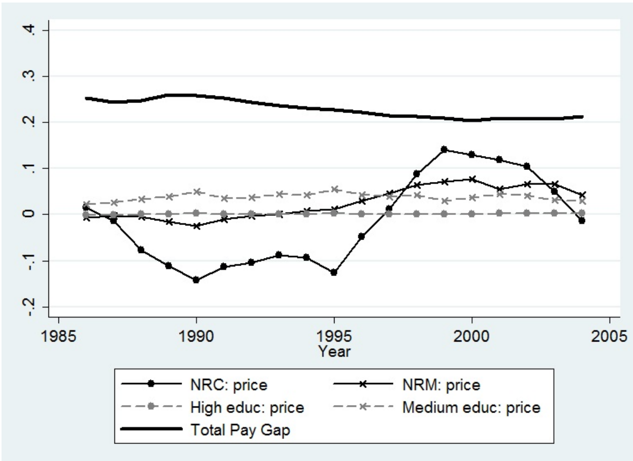


Figure 5.8: Total contribution of gender-specific task prices conditional on *age, education, tenure and occupation* to formation of the gender pay gap, 1986-2004

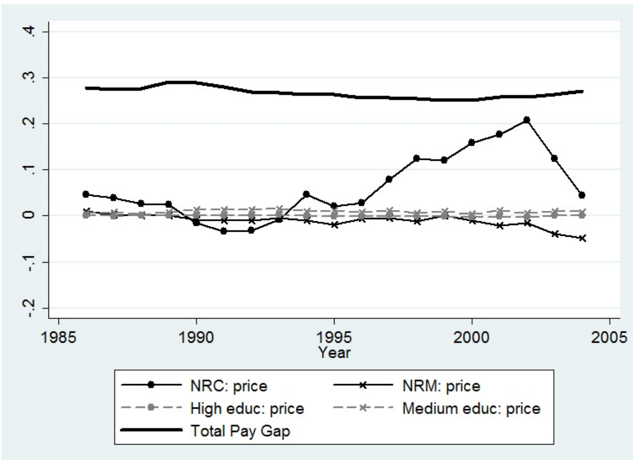
(a) at 25th percentile



(b) at 50th percentile



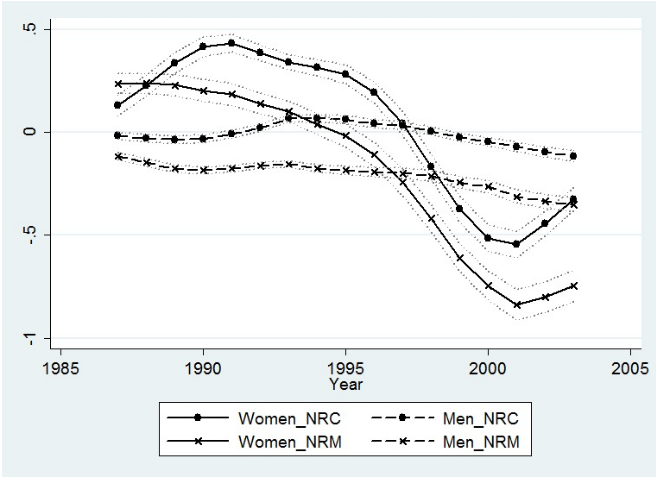
(c) at 72nd percentile



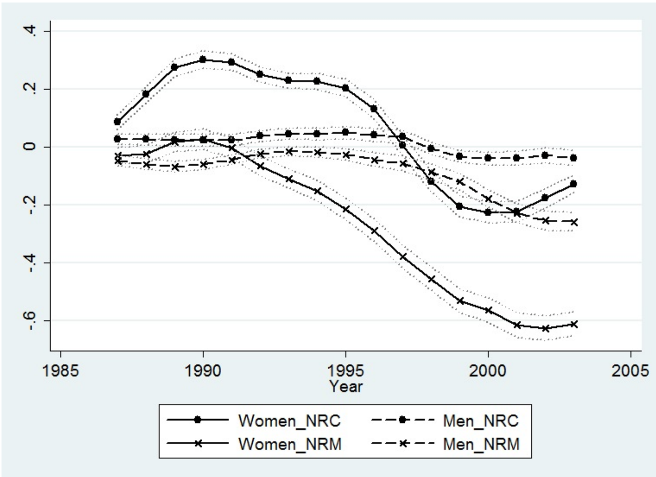
Note: Gray-colored lines refer to contributions of returns to education and are displayed for the sake of comparison.

Figure 5.9: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure and occupation*, 1986-2004. Estimation in cross sections

(a) at 25th percentile



(b) at 50th percentile



(c) at 72nd percentile

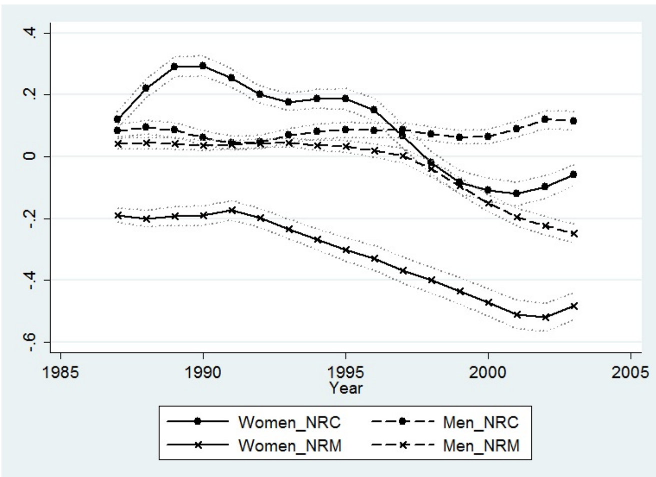
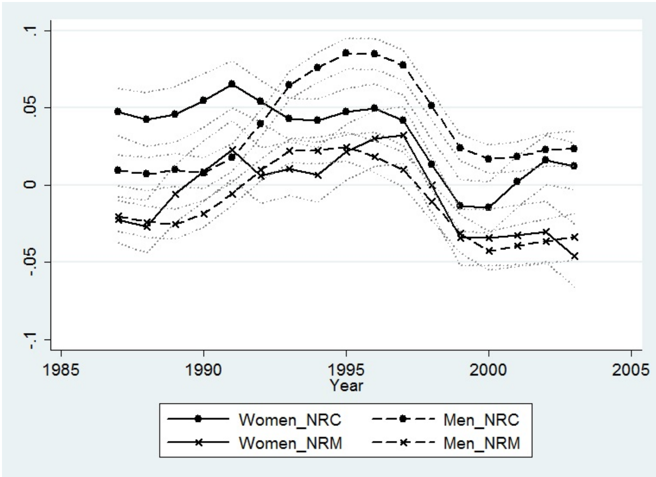


Figure 5.10: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure and occupation*, 1986-2004. Estimation with long-term individual fixed effects

(a) at 25th percentile



(b) at 50th percentile

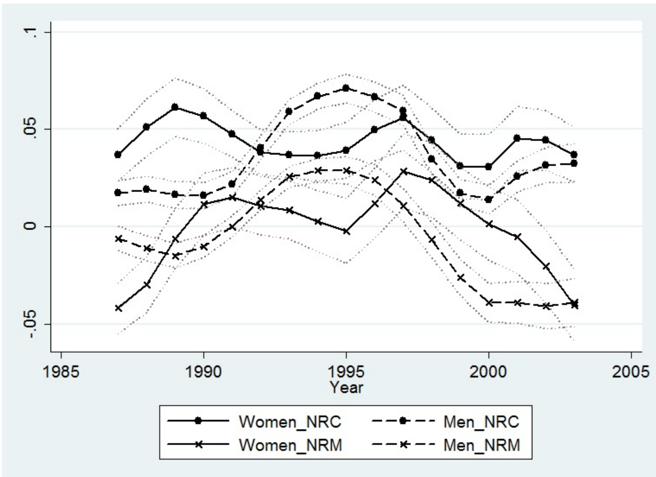


Figure14rifQ50_Prices_constFEpersnr_NRCNRM_S2e.jpg

(c) at 72nd percentile

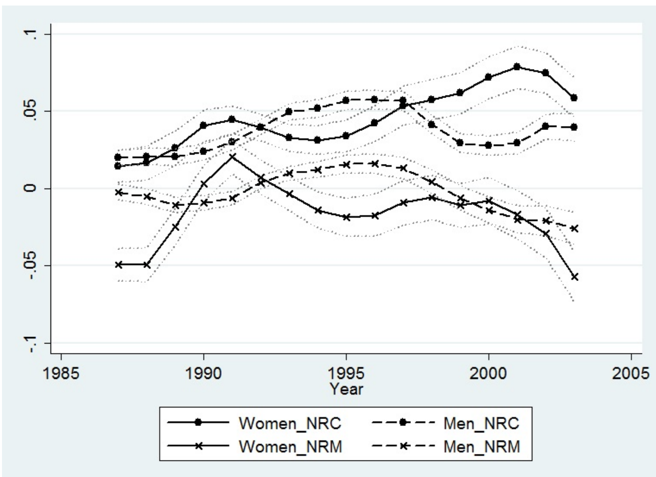
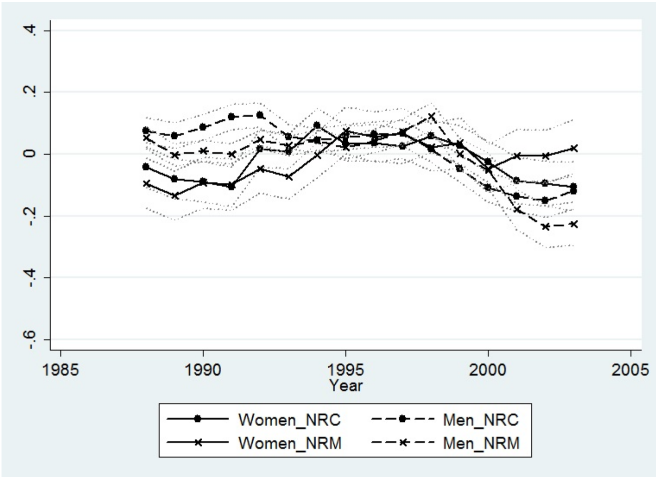


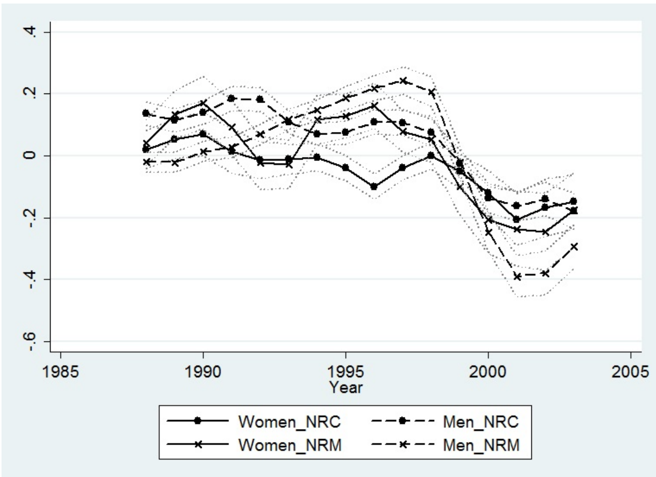
Figure14rifQ72_Prices_constFEpersnr_NRCNRM_S2e.jpg

Figure 5.11: Gender-specific prices for task units (with s.e. bands) conditional on *age, education, tenure and occupation*, 1986-2004. Estimation with two-year individual fixed effects

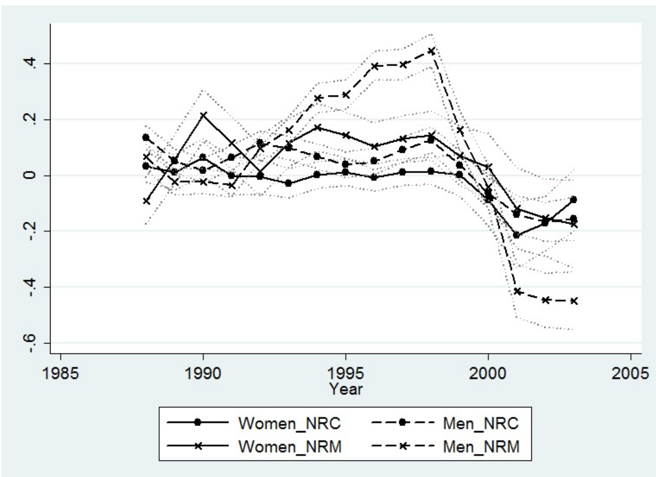
(a) at 25th percentile



(b) at 50th percentile



(c) at 72nd percentile



5.1.4 Tables

Table 5.5: Descriptive statistics for the subsamples of men and women, 1986–2004

	Men		Women	
Log hourly wage : 25th percentile	2.36		2.07	
Log hourly wage : 50th percentile	2.55		2.32	
Log hourly wage : 75th percentile	2.81		2.54	
Low-skilled : mean	0.062		0.068	
Medium-skilled : mean	0.812		0.863	
High-skilled : mean	0.126		0.069	
Non-routine cognitive tasks : mean (s.d.)	0.443	(0.243)	0.543	(0.221)
Routine tasks : mean (s.d.)	0.327	(0.168)	0.298	(0.237)
Non-routine manual tasks : mean (s.d.)	0.230	(0.170)	0.159	(0.152)
Tenure with current employer : mean (s.d.)	10.99	(6.593)	10.74	(6.260)
Age : mean (s.d.)	40.23	(7.93)	38.93	(8.40)
Observations	2131143		927193	

Table 5.6: Conditional profile of non-routine cognitive tasks 1986–2004, $N = 3058336$

Dependent Var: TS_{NRC}:	(1)	(2)	(3)	(4)	(5)
Female	0.097***	0.526***	0.389***	0.470***	0.093***
	(0.000)	(0.007)	(0.006)	(0.006)	(0.003)
Age		0.030***	0.020***	0.022***	0.013***
		(0.000)	(0.000)	(0.000)	(0.000)
Age · Female		-0.019***	-0.010***	-0.015***	-0.004***
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2		-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2 · Female		0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Medium-skilled			0.191***	0.196***	0.093***
			(0.001)	(0.001)	(0.000)
Medium-skilled · Female			-0.002*	-0.018***	-0.038***
			(0.001)	(0.001)	(0.000)
High-skilled			0.526***	0.525***	0.199***
			(0.001)	(0.001)	(0.000)
High-skilled · Female			-0.160***	-0.155***	-0.018***
			(0.001)	(0.001)	(0.001)
Tenure				-0.002***	-0.000***
				(0.000)	(0.000)
Tenure · Female				0.007***	0.003***
				(0.000)	(0.000)
Adjusted R-squared	0.091	0.103	0.312	0.318	0.826
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.7: Conditional profile of routine task 1986–2004, $N = 3058336$

Dependent Var: TS_R:	(1)	(2)	(3)	(4)	(5)
Female	-0.025***	-0.211***	-0.099***	-0.172***	0.050***
	(0.000)	(0.006)	(0.005)	(0.005)	(0.004)
Age		-0.013***	-0.008***	-0.010***	-0.004***
		(0.000)	(0.000)	(0.000)	(0.000)
Age · Female		0.008***	0.003***	0.008***	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2		0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2 · Female		-0.000***	-0.000***	-0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Medium-skilled			-0.118***	-0.122***	-0.071***
			(0.000)	(0.000)	(0.000)
Medium-skilled · Female			-0.040***	-0.026***	0.010***
			(0.001)	(0.001)	(0.001)
High-skilled			-0.283***	-0.282***	-0.125***
			(0.001)	(0.001)	(0.000)
High-skilled · Female			0.015***	0.010***	-0.012***
			(0.001)	(0.001)	(0.001)
Tenure				0.001***	0.001***
				(0.000)	(0.000)
Tenure · Female				-0.006***	-0.004***
				(0.000)	(0.000)
Adjusted R-squared	0.120	0.126	0.224	0.231	0.614
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.8: Conditional profile of non-routine manual task 1986–2004, $N = 3058336$

Dependent Var: TS_{NRM}:	(1)	(2)	(3)	(4)	(5)
Female	-0.071***	-0.316***	-0.291***	-0.299***	-0.143***
	(0.000)	(0.005)	(0.005)	(0.005)	(0.003)
Age		-0.017***	-0.012***	-0.012***	-0.009***
		(0.000)	(0.000)	(0.000)	(0.000)
Age · Female		0.011***	0.007***	0.007***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2		0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age^2 · Female		-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Medium-skilled			-0.073***	-0.075***	-0.023***
			(0.000)	(0.000)	(0.000)
Medium-skilled · Female			0.043***	0.044***	0.028***
			(0.001)	(0.001)	(0.000)
High-skilled			-0.243***	-0.243***	-0.073***
			(0.001)	(0.001)	(0.000)
High-skilled · Female			0.146***	0.146***	0.031***
			(0.001)	(0.001)	(0.000)
Tenure				0.001***	-0.001***
				(0.000)	(0.000)
Tenure · Female				-0.001***	0.001***
				(0.000)	(0.000)
Adjusted R-squared	0.042	0.047	0.144	0.145	0.765
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Appendix to Chapter 3 "Changes in Occupational Demand Structure and their Impact on Individual Wages"

5.2.1 Migrants from East to West in the QCS Data

Although the low number of observation does not allow to conduct a detailed analysis on the subsample of East Germans who has migrated to West Germany after reunification, it is informative to study the descriptive statistics of these subsamples (see table 5.9 below). On the whole, the observable characteristics of the migrants who changed or did not change occupation is similar with the respective groups of non-migrants. However, the important difference is observed for the mean unconditional wages. In 1991, mean wages of migrants who have changed occupation is higher. This evidence points at the fact that migration to West Germany has allowed for strategic use of occupational changes as a career-boosting tool.

Table 5.9: Descriptive statistic for the samples of migrants in 1991/92 and 1998/99

	1991/92 Migrants		1998/99 Migrants	
	Stayers	Movers	Stayers	Movers
	(1)	(2)	(3)	(4)
Log real hourly wages	2.081	2.187	2.161	2.156
	(0.318)	(0.293)	(0.308)	(0.348)
Age	32.24	33.59	38.51	38.86
	(8.833)	(8.926)	(7.613)	(7.909)
Tenure, curr. employer	2.514	2.283	7.585	6.419
	(0.932)	(0.958)	(3.082)	(3.188)
Number of employers	2.838	3.087	2.976	3.203
	(0.866)	(0.865)	(0.851)	(0.921)
Foreman certificate	0.027	0.109	0.073	0.135
Observations	37	46	41	74

5.2.2 Tables

Table 5.10: Descriptive statistic for the samples of 1991/92 and 1998/99, occupational mobility at a 3-digit level

	1991/92		1998/99	
	Stayers	Movers	Stayers	Movers
	(1)	(2)	(3)	(4)
N	227	385	237	438
Fraction of stayers and movers (3-digit level)	37.1%	62.9%	35.1%	64.9%
Individual characteristics				
Log real hourly wages	1.690	1.621	1.921	1.894
	(0.381)	(0.378)	(0.298)	(0.347)
Age	33.348	35.761	39.582	39.854
	(8.254)	(9.058)	(7.160)	(7.582)
Tenure, curr. employer	2.088	2.132	6.414	5.968
	(1.073)	(1.118)	(3.091)	(2.968)
Number of employers	2.696	2.787	2.869	3.142
	(0.936)	(0.933)	(0.927)	(0.855)
Foreman certificate	0.106	0.135	0.118	0.130
Distribution of workers across firms (column total=1)				
Less than 5 employees	0.062	0.086	0.063	0.080
5 to 9 employees	0.203	0.145	0.211	0.132
10 to 49 employees	0.366	0.322	0.464	0.447
50 to 99 employees	0.159	0.140	0.101	0.135
100 to 499 employees	0.154	0.177	0.127	0.146
500 to 1000 employees	0.035	0.039	0.017	0.021
More than 1000	0.022	0.091	0.017	0.039
Distribution of workers across federal states (Bundesland, column total=1)				
East Berlin	0.101	0.096	0.093	0.080
Brandenburg	0.070	0.112	0.156	0.176
Mecklenburg-Vorpommern	0.172	0.148	0.122	0.116
Saxony	0.242	0.171	0.359	0.285
Saxony-Anhalt	0.163	0.203	0.156	0.194
Thuringia	0.251	0.270	0.114	0.148
Distribution across the occupational groups of the apprenticeship (column total =1)				
Agricultural occupations	0.049	0.034	0.013	0.061
Mining, material production	0.013	0.003	0.000	0.000
Chemical industry	0.000	0.016	0.004	0.005
Wood and paper production	0.000	0.010	0.000	0.009
Metalworking occupations	0.009	0.021	0.017	0.009
Metal-structuring, engineering	0.163	0.127	0.194	0.144
Electrical engineering	0.145	0.044	0.219	0.025
Apparel industry, leather production	0.004	0.000	0.000	0.000
Food industry	0.093	0.008	0.042	0.007
Construction	0.326	0.114	0.325	0.119
Lining, upholstering	0.035	0.018	0.030	0.087
Carpenters	0.031	0.010	0.046	0.027
Painters, varnishers	0.070	0.023	0.072	0.023

Machine operators	0.004	0.057	0.008	0.066
Technicians	0.009	0.016	0.000	0.009
Product merchants	0.004	0.081	0.000	0.087
Service merchants	0.000	0.021	0.000	0.021
Transportation	0.022	0.249	0.021	0.201
Office occupations	0.009	0.083	0.000	0.066
High-skilled services	0.009	0.029	0.008	0.011
Low-skilled services	0.004	0.036	0.000	0.023

Table 5.11: First stage of the IV estimation, OLS

	(1)	(2)	(3)
Wave: 1991/92			
Dependent variable: Occ. change 2-dig			
Size of occupational group, West, in ten thousands	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Unemployment rate in occupation, East	0.891***	0.849***	0.354*
	(0.228)	(0.227)	(0.195)
Adjusted R^2	0.079	0.104	0.374
Dependent variable: Occ. change 3-dig			
Size of occupational group, West, in ten thousands	-0.005***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)
Unemployment rate in occupation, East	0.616***	0.573**	0.127
	(0.224)	(0.223)	(0.201)
Adjusted R^2	0.072	0.096	0.311
Wave: 1998/99			
Dependent variable: Occ. change 2-dig			
Size of occupational group, West, in ten thousands	-0.002***	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)
Unemployment rate in occupation, East	1.611***	1.540***	0.836***
	(0.222)	(0.222)	(0.197)
Adjusted R^2	0.090	0.105	0.355
Dependent variable: Occ. change 3-dig			
Size of occupational group, West, in ten thousands	-0.001	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)
Unemployment rate in occupation, East	1.489***	1.442***	0.780***
	(0.216)	(0.217)	(0.200)
Adjusted R^2	0.095	0.105	0.303

Additional covariates

Specification (1): age, age^2

Specification (2): age, age^2, tenure, firm size, foreman certificate= 1, bundesland

Specification (3): age, age^2, tenure, firm size, foreman certificate= 1, bundesland, 1-digit occupations

Standard errors are clustered at the level of 2-digit occupations and are displayed in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Appendix to Chapter 4 "Occupational Changes, Changes in Occupational Contents and Their Association with Individual Wages"

5.3.1 Task Space

Table 5.12: Description of the 13 dimensions of the task space

Task (space dimensions)	Description based on the QCS questionnaires
Analytical tasks	
Task 1: Research, evaluate, measure	Analyze, research, test, evaluate, measure, quality control, evaluate information, develop
Task 2: Design, plan, sketch	Plan, construct, project/design, draw, usage of graphical software
Task 3: Program	Computational tasks, programming, software development, system analysis
Task 4: Execute laws, interpret rules	Execute, interpret rules or laws, legal expertise, knowledge of employment law
Manual tasks	
Task 5: Equip and operate machines	Install, setup, retool, program, control machines, automates or other equipment, usage of manually driven, semiautomatic or computer-controlled machines
Task 6: Repair, renovate, reconstruct	Repair, service machines
Task 7: Manufacture, install, construct	Manufacture, extract, process, mold materials, cook, build
Task 8: Serve and accommodate	Serve, wait, accommodate, nurse
Task 9: Pack, ship, transport	Pack, load, transport, deliver, sort/deposit, ticketing, operate vehicles
Task 10: Secure	Secure, guard
Interactive tasks	
Task 11: Sell, buy, advertise	Sell, buy, encash, communicate, customer service, negotiate, advertise, marketing, acquisitions
Task 12: Teach, train others	Educate/teach/train, mentoring help, consult, inform
Task 13: Employ, organize	Guide/instruct employees, employ, administrate, organize, coordinate, manage personnel
Due to over-time inconsistency following categories excluded compared to Gathmann and Schönberg (2010)	(1) Correct tests or data, (2) Calculate, bookkeeping; (3) Cultivate; (4) Cleaning; (5) Publish, present, entertain.

Table 5.13: Average task intensity of occupations (proportion of workers performing the respective task)

Tasks	1985	1991	1998
	Mean	Mean	Mean
Analytical tasks (AT)	0.536	0.641	0.720
AT1: Research, evaluate and measure	0.105	0.101	0.124
AT2: Design, plan and sketch	0.040	0.026	0.029
AT3: Program	0.030	0.054	0.008
AT4: Execute laws or interpret rules	0.045	0.057	0.032
Manual tasks (MT)	0.765	0.816	0.909
MT1: Equip or operate machines	0.145	0.153	0.128
MT2: Repair, renovate or reconstruct	0.149	0.0938	0.0836
MT3: Manufacture, install or construct	0.107	0.0741	0.0797
MT4: Serve and accommodate	0.011	0.003	0.061
MT5: Pack, ship or transport	0.118	0.143	0.138
MT6: Secure	0.012	0.094	0.055
Interactive tasks (IT)	0.456	0.444	0.688
IT1: Sell, buy or advertise	0.133	0.102	0.0725
IT2: Teach or train others	0.024	0.023	0.125
IT3: Employ, manage personnel, organize	0.081	0.077	0.065
Observations	6426	4284	3041

5.3.2 Shapley-Owen Decomposition of R^2

Table 5.14: Shapley-Owen decomposition of R^2 into contributions of single variables or groups of variables, in percent

Dependent Variable: Log Real Hourly Wages	Year=1991	Year=1998
Distance (within-occupational change)	0.92	3.57
Occupational change	0.61	2.59
Distance * Occ. change	0.97	6.36
Tenure w/current employer	16.38	12.90
Age	30.16	8.56
Number of employers	2.03	2.64
1-digit occ. groups (dummies)	25.48	28.90
Firm size (dummies)	21.15	29.88
Bundesland (dummies)	2.01	4.58
Adjusted R^2	0.249	0.217
Observations	4284	3041

5.3.3 Estimation Results for Younger Workers

Table 5.15: Descriptive statistics for the covariates for 1991 and 1998 for younger employees

	1991		1998	
	Stayers	Movers	Stayers	Movers
Fraction of stayers/movers	0.776	0.224	0.639	0.361
Distance (within-occupational change)	0.0990	0.388	0.179	0.403
	(0.0556)	(0.267)	(0.102)	(0.218)
Log real hourly wage	2.108	2.086	2.287	2.238
	(0.305)	(0.310)	(0.303)	(0.281)
Age	23.81	24.32	30.90	31.22
	(1.716)	(1.675)	(1.569)	(1.541)
Tenure w/current employer	5.375	4.215	10.18	7.371
	(2.608)	(2.498)	(5.112)	(4.456)
Number of employers	1.423	1.861	1.975	2.714
Observations	499	144	439	248

Table 5.16: OLS estimation of the wage equation for younger employees

Dep. Variable:	1991		1998	
Log Real Hourly Wages	(1)	(2)	(3)	(4)
Occupational change (dummy)	-0.036	0.059	-0.044**	0.042
	(0.026)	(0.041)	(0.021)	(0.053)
Distance (within-occupational change)		0.578***		0.170
		(0.203)		(0.221)
Distance * Occ. change		-0.699***		-0.320
		(0.220)		(0.219)
Tenure w/current employer	0.017***	0.015***	0.002	0.001
	(0.005)	(0.005)	(0.003)	(0.003)
Age	0.446*	0.436*	-0.040	-0.016
	(0.254)	(0.252)	(0.319)	(0.314)
Age squared	-0.009*	-0.009*	0.001	0.000
	(0.005)	(0.005)	(0.005)	(0.005)
Number of employers	0.036**	0.034**	-0.009	-0.008
	(0.015)	(0.015)	(0.014)	(0.014)
1-digit occ. groups (dummies)	Yes	Yes	Yes	Yes
Firm size (dummies)	Yes	Yes	Yes	Yes
Bundesland (dummies)	Yes	Yes	Yes	Yes
Constant	-3.440	-3.383	2.491	2.092
	(2.989)	(2.969)	(4.923)	(4.857)
Adjusted R^2	0.165	0.172	0.143	0.145
Observations	643	643	687	687

Standard errors in parentheses. Standard errors are clustered at the level of 2-digit occupational groups.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Selbstständigkeitserklärung

Ich erkläre, dass ich die vorliegende Arbeit selbstständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 24. März 2014 Alexandra Fedorets,