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Occupational Skills and the Evolution of Wages

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Skill Prices, Skill Composition, and the Structure of Wages

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Abstract

In the discussion on the impact of technology on wages, the impact of changes in skills remains under-investigated. Using RIF regression-based decompositions, we find that changes in the skill composition decrease wage inequality, whereas changing skill prices largely increase wage inequality. Both changes account for about one third of the changes of the wage distribution.

JEL Classification: J00, J31, J40

Keywords: return to skills, skill-biased technical change, wage inequality, decomposition analysis, RIF regression

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1. Introduction

The United States and many European countries are witnessing substantial changes in their wage structure, attracting sustained attention of policy makers and the general public (Acemoglu and Autor 2011; Dustmann, Ludsteck, and Schönberg 2009; Card, Heining, and Kline 2013). Wage dispersion has been rising both within and across educational groups (Ingram and Neumann 2006; Altonji, Kahn, and Speer 2014). Most research has focused on changing returns to education and experience (Katz and Murphy 1992), changes in the workforce composition (Lemieux 2006b), or the decline in unionization (DiNardo, Fortin, and Lemieux 1996) as possible explanations for the observed changes.

Until recently, little attention has been paid to the role of occupational skills. With the pioneering work by Autor, Levy, and Murnane (2003), researchers started linking changes in the wage structure to the occupational structure of the economy, and particularly to the skill requirements of different occupations (Autor, Katz, and Kearney 2006; Goos, Manning, and Salomons 2009; Goos and Manning 2007). The main idea is that changes in the wage structure within- and between occupations are systematically related to the types of skills required in these occupations. Therefore, occupations are a key empirical channel through which we can assess the impact of technological change on wages.

To date, however, empirical research has been limited in its ability to systematically investigate the relationship between changes in skill requirements and changes in the wage distribution. In particular, researchers face difficulties in exactly quantifying the contribution of changes in skill requirements to changes in the wage structure. These difficulties arise due to methodological issues and the limited availability of suitable data. In terms of methodology, a simple mean decomposition of wages does not reach far enough, because changes in skill requirements might affect wages differently in different parts of the wage distribution. Only very recent methodological advances allow a decomposition method that goes beyond the mean (Firpo, Fortin, and Lemieux 2011; Fortin, Firpo, and Lemieux 2011; Machado and Mata 2005). Second, most available data contains only cross-sectional information on the skills required in occupations. Therefore, most studies make the implicit assumption that the skill requirements within an occupation remain constant over time and only the returns to skills change. To date, most studies can attribute changes in wages only to changes in skill prices, but not to changes in skill composition.

In this paper, we address both research gaps and quantify the contribution of changing skill prices and changing skill composition to changes in the wage structure. We use the

recently developed RIF regression-based decomposition approach by Firpo, Fortin, and Lemieux (2007), which enables the decomposition of any distributional statistic. This method is flexible enough to allow for different changes in different parts of the wage distribution. Drawing on Firpo, Fortin, and Lemieux (2011), we introduce a wage setting model where, conditional on skills, changes in occupational wages depend on within-occupation changes in skill requirements and skill prices. We use information on skills from the BIBB/IAB and BIBB/BAuA Employment Survey, a representative cross-section survey of roughly 20,000 to 30,000 fully employed workers. Each survey wave contains questions on the types of skills needed on the job. For each occupation, we distinguish between cognitive, interactive, and manual skills. Within occupations, we are able to identify how the share of these skills changes over time.

For the empirical analysis we match our skills information to the Sample of Integrated Labour Market Biographies (SIAB), a panel on complete job histories and wages. The SIAB is a two percent random sample of all social security records in Germany, covering the employment histories of about 1.5 million individuals from 1975 through 2008. Germany is a particularly important test case for analyzing changes in the wage structure. In response to a weak economic growth, the country implemented a series of labor market reforms in the early 2000s and has recently emerged as one of the most successful economies in the OECD (Eichhorst 2015). Understanding the source of this recent success may yield valuable lessons for other countries.

In the first step of the analysis, we provide descriptive evidence that the wage level and the wage dispersion have changed substantially over the observed period. In particular, we show that from the late 1970s through the late 1980s, changes in real wages were mostly concentrated at the upper part. From the early 1990s through the mid 2000s, wages at the lower parts of the wage distribution decreased, while wages at the upper part continued increasing. We also show that skill requirements varied substantially within- and between occupations. In particular, we see an overall increase in the importance of cognitive skills, while the importance of manual skills is decreasing.

In the second step, we perform RIF regression-based decompositions to investigate whether the observed changes in wages and skills are related. The decomposition allows taking into account employment composition effects, i.e., changes in worker and job characteristics, and wage structure effects, i.e., changes in the returns to these characteristics as drivers for changes in wages. Our decomposition results suggest that changes in the composition of skills are mostly decreasing wage inequality. This finding might imply that

over time workers are becoming more similar in terms of their skill sets. However, over the whole observation period, composition effects are relatively small and thus only play a minor role in the changes in wages. In contrast, wage structure effects drive most of the changes in wages. In particular, we find that from the early 1990s until the mid 2000s, changes in the returns to cognitive skills largely contributed to an increase in the dispersion of wages, both at the upper part and at the bottom part of the distribution.

We provide evidence that skills are a key empirical channel through which one can assess how technological change affects the wage structure. Quantifying the contribution of skills to changes in the wage structure allows a better understanding of why some occupations have experienced sharp decreases in wages, while others have experienced sharp increases. This paper therefore adds a new theoretical dimension to the recent discussions on technology-induced changes in the wage structure.

2 Theoretical Background

In this section, we first give a short overview of recent literature that has investigated changes in the wage structure in terms of changing returns to skill. We then introduce the wage setting model of Firpo, Fortin, and Lemieux (2011), which provides a rationale for how skills and wages are related.

2.1 Related Literature

In the early 1990s, a series of studies argued that technological change alters the demand for skilled work (Berman, Bound, and Griliches 1994; Bound and Johnson 1992; Juhn, Murphy, and Pierce 1993; Katz and Murphy 1992, Levy and Murnane 1992). These studies introduced the concept of a skill-biased technological change (SBTC), defined as a shift in the production technology that favors skilled over unskilled workers by increasing their relative productivity. The working hypothesis was that a burst of new technology caused a rise in the demand for highly skilled workers, which in turn led to a rise in earnings inequality.

However, the actual US wage development is not easily reconciled with the SBTC idea. Since the late 1980s, wages in the middle of the distribution stagnated, while wages of the lowest and highest percentiles of the wage distribution increased. More recently, a new literature has introduced a more “nuanced” view of the SBTC (Autor, Levy, and Murnane

2003). Instead of years of education, this new literature uses an alternative measure for skills, based on detailed descriptions of job content and skills requirements. In the spirit of Lazear (2009), the nuanced view of the SBTC posits that occupations are characterized by a bundle of single skills.¹ The main idea is that the introduction of information technologies has not simply depressed the relative demand for less educated workers, but instead changed the demand for certain types of skills required on the job.

Autor, Katz and Kearny (2006), Goos and Manning (2007), and Autor and Dorn (2013) argue that the nuanced view of technological change can account for the polarization of wages that has been observed since the late 1980s. In particular, they argue that the adoption of computers substitutes skills required in middle-wage jobs, while increasing the demand for skills required in low-wage and high-wage jobs. Goos and Manning (2007) show that the composition effect linked to changes in the distribution of occupations accounts for a substantial part of the increase in inequality in the United Kingdom. Autor, Katz, and Kearney (2008) provide evidence that the share of employment in occupations in the middle of the wage distribution has declined over time. Using a spatial equilibrium approach, Autor and Dorn (2013) show that local labor markets that are more specialized in routine jobs experienced more job polarization.

For the case of Germany, it was long believed that the country was characterized by a stable wage distribution (Steiner and Wagner 1998). Recent work has shown, however, that wage inequality started increasing already in the 1980s and accelerated in the 1990s and 2000s (Card, Heining, and Kline 2013; Dustmann, Ludsteck, and Schönberg 2009; Fuchs-Schündeln, Krueger, and Sommer 2009; Gernandt and Pfeifer 2007). Whether the nuanced view of the SBTC serves as an explanation for the rise in the German wage dispersion remains a contested issue.

In particular, in line with the SBTC view, Spitz-Öner (2006) shows that, between 1979 and 1999, changes in skill requirements have been strongest in occupations in which computerization was most pronounced. Similarly, Dustmann, Ludsteck, and Schönberg (2009) argue that the SBTC is the main driver of wage inequality in the 1980-2000 period in West Germany. Antonczyk, Fitzenberger, and Sommerfeld (2009), however, find that changing returns to skills only play a minor role in explaining the recent rise in the wage dispersion. Finally, Boockmann and Steiner (2006) actually find a decline in the returns to

¹ In this literature, skills are commonly measured through tasks that workers perform on the job. It is assumed that tasks are units of work activity that produce output, while skills are workers' endowments of capabilities for performing various tasks (Acemoglu and Autor 2011). In our analysis, we assume a one-to-one mapping between skills and tasks.

education. However, they do not use occupational skills as a skill measure, but instead use years of schooling.

In our analysis, we try to solve these conflicting results by taking into account different explanations for why the German wage dispersion has increased. We do not introduce the SBTC as an alternative, but rather as a complimentary explanation. Our unique data and the novel methodological approach allow us to consider several explanatory factors simultaneously. Before explaining our econometric strategy, we will briefly introduce the wage-setting model to clarify the connection between skills and wages.

2.2 Wage Setting in Occupations

In recent years, two major contributions have challenged the so-called “canonical model,” which follows a traditional Mincerian approach where wages are solely determined by observed and unobserved skills. In this model, technology is assumed to take a factor-augmenting form, which, by complementing either high- or low-skilled workers can generate skill-biased demand shifts. However, the canonical model does not provide satisfactory explanations for a number of empirical developments of recent years. For example, it cannot explain differential changes in inequality in different parts of the wage distribution. Acemoglu and Autor (2011) and Firpo, Fortin, and Lemieux (2011) address these shortcomings by proposing new wage-setting models. Acemoglu and Autor (2011) propose a general equilibrium model of skills, tasks, and wages that imposes very restrictive assumptions. In contrast, Firpo, Fortin, and Lemieux (2011) propose a partial equilibrium model with less restrictive assumptions. Although Firpo, Fortin, and Lemieux (2011)’s model cannot be solved in general equilibrium, it can be tested with available data and we therefore use it in this paper.

Formally, we assume that each worker i is characterized by a k -dimension set of skills $S_i = [S_{i1}, S_{i2}, \dots, S_{iK}]$, which include our three skill categories, cognitive, interactive, and manual skills. The amount of occupation-specific output Y_{ijt} produced by worker i in occupation j is assumed to depend linearly on skills:

$$Y_{ijt} = \sum_{k=1}^K \alpha_{jkt} S_{ik} \quad (2.2.1)$$

where the productivity α_{jkt} is occupation- and time-specific. In this model, each occupation requires different shares of different types of skills. Researchers, for example, require a large share of cognitive skills and a rather small share of manual skills. In contrast, machinists require the opposite configuration of skills.

In this framework, factors such as technological change have a different impact on wages in different occupations. If the introduction of computer technologies increases the marginal product of cognitive skills for researchers, both the level and the dispersion of their wages should increase. If computers depress the returns to skills, a symmetric pattern emerges. For example, if automated machines decrease the marginal product of manual skills of machinists, then the level and the dispersion of wages should decrease. Importantly, if manual skills are not a highly valued skill for researchers, then the change in the skill price for manual skills does not affect their wages.

In contrast to Firpo, Fortin and Lemieux (2011), we assume productivity to vary over time. This implies that workers cannot always perfectly match the skill requirements within an occupation because they are changing over time. Assuming that wages are set competitively, workers are paid for the output they produce. This yields the wage equation:

$$w_{ijt} = \theta_{jt} + \sum_{k=1}^K r_{jkt} Y_{ijt} + u_{ijt}, \quad (2.2.2)$$

where w_{ijt} is the wage of worker i in occupation j at time t , r_{jkt} are the returns to the skills component k specific to occupation j at time t , Y_{ijt} is the output produced in occupation j at time t , and θ_{jt} is a base payment that a worker receives in occupation j regardless of his skills.

This simple model predicts that wages might change due to changes in skill prices r_{jkt} or due to changes in productivity α_{jkt} , which would affect the output Y_{ijt} . In principle, we could treat the wage-setting equation like a structural model and estimate its parameters. However, we use a simpler and less parametric approach by carrying out decompositions at each point of the wage distribution. We introduce and explain this approach in the next section.

3. Econometric Model: RIF Regression-Based Decomposition

In our empirical analysis, we decompose changes in the wage structure into their contributing factors. The Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973) is the most commonly used decomposition method in the labor and discrimination literature (for an overview of the literature see e.g., Weichselbaumer and Winter-Ebmer (2005) and for a comprehensive overview of the application see Jann (2008)). This method divides the wage differential between two groups into a part that is explained by observable group differences such as education or experience and a residual part that cannot be accounted for by these differences. The residual part is often used as a measure for discrimination as it measures differences in the returns to observable characteristics. The Oaxaca-Blinder method, however, focuses on the difference in the mean of an outcome variable and does not allow decompositions along the wage distribution.

Until recently, no comprehensive approach was available for computing a detailed decomposition of the effect of single covariates for a distributional statistic other than the mean. Firpo, Fortin, and Lemieux (2007) introduce an approach that allows taking into account the whole unconditional wage distribution. It is very similar in spirit to the Oaxaca-Blinder decomposition and uses the recentered influence function (RIF) regressions. The idea is to use the RIF for the distribution statistic of interest as the left hand side variable in a regression.² Firpo, Fortin, and Lemieux (2007) apply a two-step procedure. In the first step, they use a reweighting method to divide the distributional changes into a wage structure effect and a composition effect. In the second step, they further decompose the wage structure effect and the composition effect into the contribution of each explanatory variable. Firpo, Fortin, and Lemieux (2007) and Fortin, Firpo, and Lemieux (2011) explain in great detail how to perform these decompositions. Here, we will present a short summary of their methodology.

In general, any distributional parameter can be expressed as a functional $v(F_Y)$ of the cumulative distribution of wages, $F_Y(Y)$. To formally discuss the RIF based decomposition method, we look at the difference in the wage distributions during two periods, 1 and 0. For individual i , let Y_{1i} be the wage that would be paid in period 1 and Y_{0i} the wage received in period 0. For each i , we can define the observed wage, Y_i , as $Y_i = Y_{1i} * T_i + Y_{0i} * (1 - T_i)$, where $T_i = 1$ if the individual is observed in period 1 and $T_i = 0$ if the individual is observed in period 0. The notation $F_{Y_{t|T=s}}$ denotes the distribution of wages that would prevail among

² In a recent paper, Riphahn and Schnitzlein (2011) use the SIAB data to apply RIF regression-based decompositions when studying wage mobility in East and West Germany.

workers observed in period s if they were paid under the wage structure of period t . Therefore, $F_{Y_0|T=0}$ indicates the actual distribution in period 0, and $F_{Y_1|T=1}$ denotes the actual distribution in period 1. In contrast, $F_{Y_0|T=1}$ denotes the counterfactual distribution that would have prevailed if workers in period 1 had been paid under the wage structure of period 0.

Consider Δ_0^v , the overall change over time in the distributional statistic v . We have:

$$\begin{aligned}\Delta_0^v &= v(F_{Y_1|T=1}) - v(F_{Y_0|T=0}) \\ &= v(F_{Y_1|T=1}) - v(F_{Y_0|T=1}) + v(F_{Y_0|T=1}) - v(F_{Y_0|T=0}),\end{aligned}\tag{3.1}$$

where the first difference is the unexplained part of the decomposition, which is called the wage structure effect, Δ_S^v . The second difference is the explained part of the decomposition, which is called the composition effect, Δ_X^v . The wage structure effect reflects that part of the wage differential that cannot be explained by differences in the distribution of observable characteristics, but is attributable to changes in the returns to these characteristics. The composition effect reflects that part of the wage differential that can be explained by differences in the distribution of covariates. Put differently, while the wage structure effect reflects the difference in the β 's, the decomposition effect reflects the differences in the distribution of the X 's and ε 's between the two groups. In our analysis, the X 's comprise the three skill categories: cognitive, interactive, and manual skills. In addition, we include a vector of control variables (age and experience, industry and region dummies) observed in both periods.

Combing back to the equation, $v(F_{Y_0|T=1})$ is the counterfactual distributional statistic that would have prevailed if workers observed in period 1 had been paid under the wage structure of period 0. As noted previously, to estimate this type of counterfactual distribution, Firpo, Fortin and Lemieux (2007) suggest using the approach by DiNardo, Fortin and Lemieux (1996), which is based on estimating a probit model on the probability of being observed in period 1. In essence, it consists of reweighting the period 0 data to have the same distribution of X 's as in period 1.³ The reweighted data allows performing an Oaxaca-Blinder type decomposition and obtaining the wage structure and the composition effects for any distributional statistic.

³ Firpo, Fortin, and Lemieux (2007) show that this reweighting provides a consistent nonparametric estimate of the counterfactual distribution.

However, we are interested in separating the contribution of single explanatory variables. To further decompose the wage structure and the composition effect into the contribution of single covariates, we perform RIF regressions on the reweighted data. The central idea of the RIF is to replace the dependent variable y by the corresponding recentered influence function. Recentering essentially means adding back the distributional statistic v to the influence function. Let $IF(y; v)$ denote the influence function corresponding to an observed wage y for the distributional statistic of interest v . The recentered influence function (RIF) is defined as:

$$RIF(y; q_\tau) = q_\tau + IF(y; q_\tau). \quad (3.2)$$

We can compute this influence function for a large number of different distributional statistics. For our case, we use quantiles. The recentered influence function of τ -th quantile is

$$RIF(y; q_\tau) = q_\tau + IF(y; q_\tau). \quad (3.3)$$

The τ -th quantile RIF regression aggregates to the unconditional quantile of interest and captures both the within and between effects of the explanatory variables. We then perform the decomposition by running two standard OB decompositions on the estimated recentered influence functions. The first decomposition compares period 0 with the reweighted period 0 (that mimics period 1) and allows us to obtain the pure composition effect. The second decomposition compares period 1 with the reweighted period 0, allowing us to obtain the pure wage structure effects.

Firpo, Fortin, and Lemieux (2007) show that we can write the estimate of the composition effect $\hat{\Delta}_{X,R}^v$ as:

$$\hat{\Delta}_{X,R}^v = (\bar{X}_{01} - \bar{X}_0) \hat{\gamma}_0^v + \bar{X}_{01}(\hat{\gamma}_{01}^v - \hat{\gamma}_0^v) = \hat{\Delta}_{X,p}^v + \hat{\Delta}_{X,e}^v. \quad (3.4)$$

i.e., divide the composition effect $\hat{\Delta}_{X,R}^v$ into a pure composition effect $\hat{\Delta}_{X,p}^v$ using the wage structure of period 0 and into a component measuring the specification error $\hat{\Delta}_{X,e}^v$.

Similarly, we can write the wage structure effect as:

$$\hat{\Delta}_{X,S}^v = \bar{X}_1(\hat{\gamma}_1^v - \hat{\gamma}_{01}^v) + (\bar{X}_1 - \bar{X}_{01})\hat{\gamma}_{01}^v = \hat{\Delta}_{S,p}^v + \hat{\Delta}_{S,e}^v. \quad (3.5)$$

which reduces to the first term, because the reweighting error $\hat{\Delta}_{S,e}^v$ goes to zero as $\bar{X}_{01} \rightarrow \bar{X}_1$.

4. Data

We are using two data sets for our empirical analysis, the Sample of Integrated Labor Market Biographies (SIAB) and the BIBB/IAB Employment Surveys. The SIAB provides us with the wage data, while the Employment Surveys provide us with the skill information. In this section, we introduce both data sources and provide descriptive analyses on how wages and skill requirements changed over the last three decades.

4.1 The Sample of Integrated Labour Market Biographies (SIAB)

Our main data set is a two percent random sample of administrative social security records in Germany from 1975 through 2008, covering the employment history of more than 1.5 million individuals. The SIAB is representative of all individuals covered by the social security system, roughly 80 percent of the German workforce. The data includes total earnings, days worked at each job in a year, as well as information on education, occupation, industry, and part-time or full-time status. Importantly, the occupational titles are constant over the observation period. To obtain a sufficiently large number of observations for each occupation, we use occupational titles at the two-digit level.

As in many administrative data sets, our data is right-censored at the highest level of earnings that are subject to social security contributions. Overall, each year between 9.4 percent and 14.2 percent of the male wage distribution is censored. To solve this censoring problem, we follow a method proposed by Gartner (2005) and use a series of Tobit models—fit by education level, industry, and region—to stochastically impute the upper tail of the wage distribution.

Our main empirical analysis focuses on workers with a vocational education and training (VET) degree for two main reasons: First, holding the educational degree constant allows us to avoid any bias arising from increased college wage premia and we can instead estimate the true economic effect of changes in the skill requirements. Second, wages in VET occupations are much less affected by censoring. In line with Dustmann, Ludsteck, and Schönberg (2009), our analysis of real wages focuses on the uncensored part of the wage distributions.

However, the underlying VET population might have been changing over time so that our effects might be biased due to a different cohort mix in different years. Therefore, we conduct a separate analysis, where we include all educational degrees in our sample. Results for this full sample analysis are reported in the Appendix in Tables A.2 through A.6.

While our econometric analysis focuses on men only, the descriptive analysis investigates the wage structure for both men and women. The labor force participation of women has increased considerably over the observed period. This increase is likely to have changed the selection of women into work. This problem is well-known in the gender wage gap literature.

Table 1 presents some basic characteristics of our wage data across four periods.⁴ The reported wages are log gross daily wages weighted by the number of days worked in a respective year. The wages are reported in Euros and deflated to 1978 wages, the first year of the analysis. The table shows that the average real daily wages of full-time men rose by about five percent between 1978 and 1986, again rose by about another five percent between 1986 and 1992, slowed down by rising one percent over the next eight years and remained relatively stable in the 2000s. The average real daily wages of full-time women rose by about four percent between 1978 and 1986, then increased more sharply and rose by nine percent between 1985 and 1992, rose another five percent between 1992 and 1999, but then stabilized at a level about 25 log points below the mean for men. The standard deviation of log wages for both genders rose slightly between 1978 and 1999, then surged over the next eight years, rising by seven log points for both men and women.

Table 1. Summary statistics for full-time VET workers

	Log real wages		
	Observations	Mean	St. Dev.
Panel A. Full-time men			
1978-79	261,163	3.7553	0.2408
1985-86	263,046	3.8023	0.2755
1991-92	291,677	3.8476	0.2785
1998-99	273,302	3.8608	0.3137
2005-06	246,509	3.8516	0.3544
Panel B. Full-time women			
1978-79	108,173	3.4227	0.3915
1985-86	126,281	3.4653	0.4064
1991-92	163,580	3.5512	0.4109
1998-99	154,920	3.6061	0.4310
2005-06	137,091	3.5904	0.4782

Notes: SIAB data 1978-2006, authors' calculations.

⁴ Table A.1 in the Appendix presents wage data for the full sample.

For our main analysis, we follow Dustmann, Ludsteck, and Schönberg (2009) and focus on full-time employed⁵ men between 21 and 65 years of age who are subject to social security contributions. Because both the level and the structure of wages differ substantially between East and West Germany, we use West German data only. Moreover, following Riphahn and Schnitzlein (2011), we drop all observations for which daily wages are less than 12 Euros.

At both the beginning and the end of the periods we analyze, we pool several years of data to improve the precision of the estimates. We use 1978/79 as the base year and 1985/86 as the end year for the first period we analyze; 1985/86 as the base and 1991/92 as the end year for the second period, 1991/92 and 1998/99 for the third, and 1998/99 and 2005/06 for the last. These periods are chosen to match the cross-sectional waves of the Employment Surveys that contain the skills data.

4.2 Wage Patterns

In the following section, we discuss wage patterns of our four periods for both male and female workers. Figures 1 and 2 show the distributional characteristics of the evolution of the wage structure for both male and female workers.⁶ We plot the fitted values of the difference in log wages between the two periods over the whole distribution. The vertical line shows the median wage change. The descriptive patterns give a first indication for why we need to perform distributional analyses to understand the wage dynamics. A simple analysis of the mean or median wage would miss the large changes that occurred at the top and the bottom end of the distribution.

The figures show that from 1978/79 to 1985/86 real daily wages increased overall. However, changes in real wages were mostly concentrated at the upper part of the distribution, with sharp increases beyond the eighth decile. At the 99th percentile, real daily wages increased by about 18 percent. From 1985/86 to 1991/92 real wages remained more or less stagnant, slightly increasing in the middle of the distribution, and slightly decreasing both at the very top end and the bottom end. Below the fifth percentile and above the 96th percentile, wages decreased between three and six percent.

⁵ Because the SIAB does not include hours of work, limiting our attention to full-time jobs reduces the impact of the hours dispersion that could confound trends in wage inequality. However, less than seven percent of male workers in the SIAB have no full-time job in a year, so the inclusion of wages for part-time men has only a small impact on the trends we study.

⁶ The wage patterns of the full sample are reported in the Appendix (Figures A.1 and A.2).

The 1990s paint a very different picture. While the median wage remained almost unchanged, wages below the median decreased, while wages above the median increased. Below the fifth percentile, real wages fell by about 10 percent. In contrast, above the 95th percentile, real wages increased by about five percent. Finally, from 1998/99 to 2005/06, real wages continued decreasing sharply below the median, while they continued increasing again above the median. While real wages decreased between 15 and 25 percent below the fifth percentile, real wages increased by about eight percent above the 95th percentile. The descriptive patterns largely hold for both male and female workers, although female wages changed more sharply. The patterns in our data are very similar to those of previous studies that have used earlier versions of the German administrative records, in particular, Fitzenberger (1999), Gernandt and Pfeiffer (2007) and Dustmann, Ludsteck, and Schönberg (2009). The wage patterns for the whole sample, reported in the Appendix, are largely similar to those of our VET sample.

Figure 1. Changes in real log wages of full-time VET men, 1978 to 2006



Notes: SIAB data 1978-2006, authors' calculations.

Figure 2. Changes in real log wages of full-time VET women, 1978 to 2006



Notes: SIAB data 1978-2006, authors' calculations.

4.3 BIBB/IAB and BIBB/BAuA Employment Surveys

The BIBB/IAB and BIBB/BAuA Employment Surveys on Qualification and Working Conditions (hereafter: Employment Surveys) are representative surveys among fully employed individuals in Germany. From 1979 to 1999, the survey was conducted by the Federal Institute for Vocational Education and Training (BIBB), together with the Institute for Employment Research (IAB), and thereafter in cooperation with the Federal Institute for Occupational Safety and Health (BAuA). For our analysis, we use four different waves: 1979, 1985/86, 1991/92, 1998/99, and 2006, each covering about 30,000 individuals.

The Employment Surveys report on the content of occupations and the education backgrounds of employees. They are particularly suitable for analyzing changes in skill requirements within occupations since these are categorized in all waves according to the classification of the German Federal Employment Bureau in 1988.⁷ This is a major improvement over, for example, the American Occupational Information Network (O*NET)

⁷ We use the two-digit level of classification, which includes about 65 different occupations. We provide a list of the used occupations in the Appendix, Table A.7.

and its predecessor, the Dictionary of Occupational Titles (DOT), the data most commonly used for studying skills and occupations. There, occupational titles do not remain consistent over time.

In addition, because in the O*NET occupational experts assign scores to different indicators characterizing the occupations, this data has been criticized for underestimating the true changes in job content. In contrast, in the Employment Surveys, respondents indicate what types of skills are required for their jobs. That this self-reporting causes an underestimation of true changes in job content is very unlikely.

The respondents are asked to report on a large set of skills that are required for performing their current job. Although most of the survey questions remain unchanged over time, some items are not included in all waves. To make skills comparable over time, we focus on those questions that remain unchanged. We distinguish among three skill categories: cognitive skills, interactive skills, and manual skills. Cognitive skills include reading and calculating, interactive skills include negotiating and supervising, and manual skills include equipping and using machinery, and repairing and renovating. Table 4.4.2 illustrates the assignment of skills requirements to the three categories.

Table 2. Classification of skills

Category	Skills
Cognitive Skills	researching and evaluating; calculating; writing; designing and planning; executing laws and interpreting rules
Interactive Skills	selling, buying and advertising; teaching and training; managing personnel; negotiating; organizing and coordinating
Manual Skills	equipping and operating machinery; repairing, renovating and reconstructing; manufacturing, installing or constructing; nursing; securing

Employment Surveys, 1979-2006, authors' calculations.

Because the unit of analysis is the occupation, we aggregate the individual data into occupational cells and use group means for our analysis in our decomposition analysis. Similarly to Spitz-Oener (2006), we first define skills at the individual level and then aggregate them to the occupational level. For individual i at time t , we define a skill category s as:

$$s_{ict} = \frac{\text{number of skills in category } c \text{ required by } i \text{ at time } t}{\text{total number of skills required by } i \text{ at time } t} \quad (4.3.1)$$

where $t = 1979, 1985/86, 1991/92, 1998/99$, and 2006 and category $c = 1$ (cognitive skills), $c = 2$ (interactive skills), and $c = 3$ (technical skills). To generate a skill category at the occupational level, we sum the individual skill categories s_{ict} in each occupation and divide them by the number of observations in that occupation.

Finally, the sampling population is not uniform across the four waves. Because of this changing sample design, the sample used have to be restricted to West German residents with German nationality, since these are the only groups of employees that were interviewed in each wave. Moreover, the sample does not include self-employed and unemployed persons, workers with agricultural occupations or working in the agricultural sector. In addition, we exclude persons younger than 18 and older than 65 from the sample.

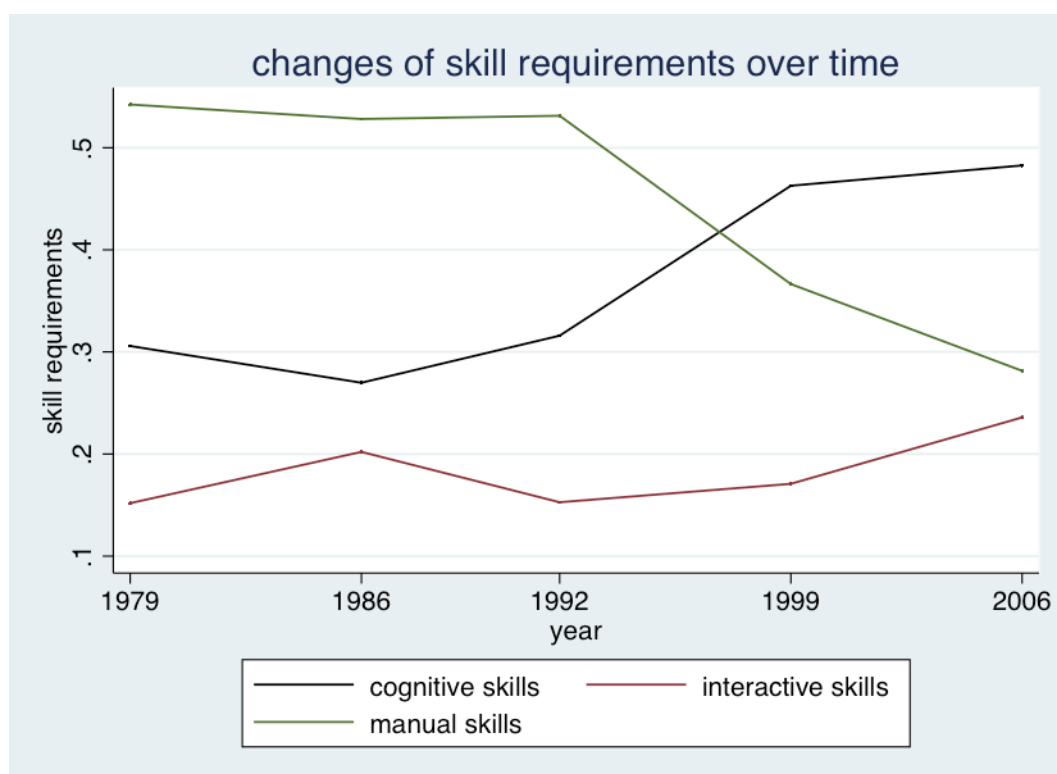
4.4 Skill Patterns

Figures 3 and 4 show the changes in skills requirements over time for men and women respectively. In the male sample, cognitive skills have been constantly rising since 1979, with the sharpest increases in the 1990s. In contrast, manual skills remained at a constantly high level of about 50 percent until the beginning of the 1990s and have then decreased sharply, falling to around 30 percent in 2006. Interactive skills have been steadily increasing since the beginning of the 1990s and make up about 30 percent of overall skill requirements in 2006.

For the female sample, the pattern is somewhat different. The share of cognitive skills has started increasing earlier than in the male sample, already rising since 1979. After 1992, however, the share remained constant at about slightly above 50 percent of all skill requirements. Similarly, the share of manual skills decreased very sharply and started doing so already in 1979. In 2006, the share of manual skills is slightly below 30 percent of all skill requirements. Finally, the share of interactive skills surged in the early 1980s, decreased again in the late 1980s and has been rising since 1992. In 2006, the share of interactive skills is slightly above 20 percent of all skill requirements.

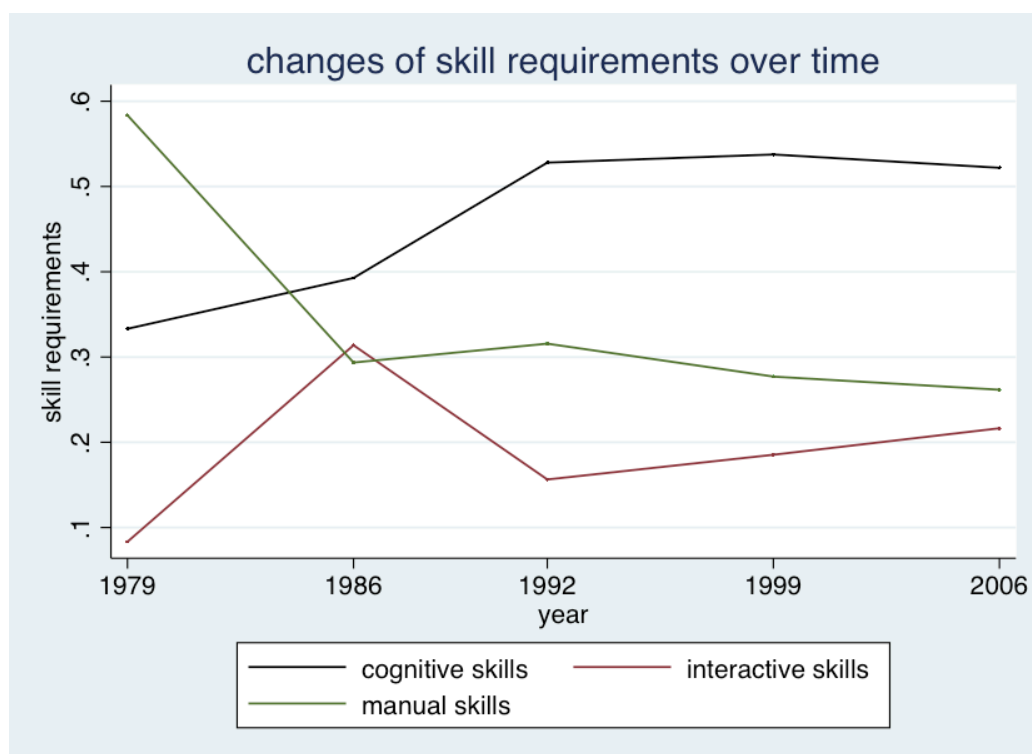
These patterns show that the skills requirements within occupations underwent substantial changes over period under consideration.

Figure 3. Changes in skill requirements over time, VET men



Notes: Employment Surveys, 1979-2006, authors' calculations.

Figure 4. Changes in skill requirements over time, VET women



Notes: Employment Surveys, 1979-2006, authors' calculations.

5. Decomposition Results

We use the decomposition approach of Firpo, Fortin and Lemieux (2007) to look at the contribution of several explanatory factors to changes in the wage distribution. These factors comprise our three measures of occupational skills as well as education (six categories), experience, marital status, firm size, industry. These factors are all included in the wage setting equation presented in Section 2.2. In line with previous research, we focus our discussion on men.

As we have pointed out previously, the decomposition method introduced by Firpo, Fortin and Lemieux (2007) consists of two steps. In the first step, we use a reweighting method to recover the counterfactual wage distribution. With the reweighted data we can already perform Oaxaca Blinder decompositions, but we are limited to aggregate results. In the first subsection we will present the aggregate results. The second step involves applying RIF regressions on the reweighted data and then performing decompositions on the RIF coefficients. This second step is a crucial methodological innovation, which allows us to obtain detailed decomposition results. In the second subsection, we present and discuss these detailed results.

5.1 Aggregate Decomposition Results

The decomposition analysis relates changes in the skills requirements to changes in the wage structure, according to the wage setting equation 4.2.2. To simplify the analysis, we focus on standard measures for upper-tail (90-50 gap), lower-tail (50-10 gap), and overall (90-10 gap) wage inequality. A widening of these gaps implies an increase in wage inequality. Because of our large sample size, almost all results are highly statistically significant, although not all of them are economically relevant.

Table 4.5.1 reports the aggregate decomposition results. In the first step, we focus on how wage inequality changed over the considered time period. In the second step, we look into which effects were driving the changes.⁸ Overall, the results are consistent with the descriptive analyses in Section 4.4.2 and with findings reported in Dustmann, Schönberg and Ludsteck (2009) and others. From 1978 to 1986, overall wage inequality increased by about six log points, whereby almost all changes in the wage structure were due to changes in the upper tail. Between 1986 and 1992, overall wage inequality hardly changed. However, lower-

⁸ The effect sizes and significance level are in line with Firpo, Fortin, and Lemieux (2011).

tail inequality increased by almost two log points, while upper-tail inequality decreased by two log-points.

From the beginning of the 1990s until the end of our observation period, wage inequality surged. During the 1990s, overall inequality increased by 10 log points. Both upper-tail inequality and lower-tail inequality increased evenly by about five log points. From 1999 to 2006, overall inequality increased further by another 16 log points. These increases are mostly attributable to increases in lower-tail inequality (11 log points increase in the 50-10 gap). The increasing wage inequality can be traced back to an increase in wages at the upper part of the distribution and a decrease in wages at the bottom part. Thus, in contrast to the U.S. and the UK, West German wages in the middle of the distribution remained largely stable.

The question now arises as to which factors have contributed to these developments. Table 3 divides the total wage change into the composition effect—due to group differences—and the wage structure effect—the residual part that cannot be accounted for by group differences. Both effects contribute significantly to the observed changes over all four periods. In contrast to what Lemieux (2006a) shows for the U.S., we find that composition effects have contributed to a decrease in wage inequality from the late 1970s to the mid 1980s. During this period, wage structure effects, i.e., differences in the β 's, were increasing upper-tail inequality, while composition effects slowed down this increase. These effects suggest that the underlying populations became more similar in terms of their X 's and ε 's.

From the mid-1980s to the beginning of the 1990s, again wage structure effects increased wage inequality, while composition effects decreased it. In the 1990s, wage structure effects continued driving lower-tail inequality, while composition effects started driving upper-tail inequality. Finally, from the late 1990s to the mid 2000s, wage structure effects again drove most of the increasing wage inequality, both at the upper tail and at the lower tail.

How can we interpret changing skill requirements in terms of the wage structure effect and the composition effect? The wage structure effect for each skill category can be interpreted as the change over time in the return to skills, whereas the composition effect is linked to changes in the skills composition of occupations over time. In other words, wage structure effects can be interpreted as increases in the demand for skills, and composition effects can be interpreted increases in the supply of skills. Two mechanisms can thus explain the relationship between changes in skills and changes in the wage structure: changing skills prices and changing skills requirements.

A first important result in Table 3 is therefore that, in terms of skills, increases in inequality are associated mostly with changes in skill prices, whereas changes in the skill composition of occupations actually narrowed the wage gap until the early 1990s. From the 1990s onwards, composition effects started driving inequality, too, but to a much smaller extent than changes in the wage structure.

Before discussing the detailed decomposition results, we should note one important feature of decomposition methods. While decompositions are useful for quantifying the contribution of different factors to a difference in outcomes such as the wage differential between two groups, they cannot provide information on the underlying mechanism between factors and outcomes. Just like program evaluation methods, decompositions provide valuable information about which factors are quantitatively important in a particular relationship, but they cannot provide information on the structural parameters of that relationship. They can thus be considered as a first important step in investigating a relationship. For example, if a decomposition shows that a large part of the gender wage gap can be accounted for by differences in the occupational affiliation, then, in the second step, this suggests exploring in detail how men and women choose their fields of study and occupations.

Finally, comparing the aggregate decomposition results for our sample of VET workers to the decomposition results for the full sample reported in the Appendix in Table A.2 shows that the changes in the wage structure are very similar. From the late 1970s until the mid 1980s, the wage dispersion was slightly larger in the full sample. This result can be expected given that the full sample also captures the between education dispersion. However, the size and the direction of contributing factors, i.e., wage structure and composition effects, are similar in the two samples.

From the 1990s until the mid 2000s, however, the wage dispersion was slightly larger in the VET sample, both at the upper tail and at the lower tail of the distribution. This finding underlines again the importance of changes in skills in explaining changes in wages. In this period, changes in skills were the main contributors to change in the wage structure.

Table 3. Aggregate decomposition results

Inequality Measure	90-10	50-10	90-50
A: 1978/79 to 1985/86			
Total Change	0.0588*** (0.000009)	0.0071*** (0.0003)	0.0517*** (0.0002)
Composition	-0.0440*** (0.000001)	-0.0074*** (0.0003)	-0.0367*** (0.0003)
Wage Structure	0.1029*** (0.00004)	0.0145*** (0.0004)	0.0884*** (0.0004)
B: 1985/86 to 1991/92			
Total Change	0.0041*** (0.0002)	0.0228*** (0.0004)	-0.0187*** (0.0002)
Composition	-0.0560*** (0.0002)	-0.0215*** (0.0002)	-0.0345*** (0.00001)
Wage Structure	0.0601*** (0.0002)	0.0443*** (0.0004)	0.0158*** (0.0002)
C: 1991/92 to 1998/99			
Total Change	0.1007*** (0.0004)	0.0485*** (0.0006)	0.0521*** (0.0002)
Composition	0.0011*** (0.0015)	0.0139*** (0.0024)	-0.0128*** (0.0010)
Wage Structure	0.0996** (0.0015)	0.0347* (0.0025)	0.0649** (0.0010)
D: 1998/99 to 2005/06			
Total Change	0.1640*** (0.0008)	0.1076*** (0.0011)	0.0565*** (0.0002)
Composition	0.0257*** (0.0005)	0.0244*** (0.0004)	0.0013*** (0.0000)
Wage Structure	0.1383*** (0.0008)	0.0832*** (0.0011)	0.0551*** (0.0003)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

5.2 Detailed Decomposition Results

Tables 4 to 7 show the detailed decomposition results for the four periods. While all decompositions include individual and firm specific controls, the tables report only the effects of our three skills categories to simplify the presentation of the results. We examine the explanatory power of our skill categories in the context of a formal decomposition of changes in the wage distribution. We recur to the aggregate decomposition results as guidance for the economic significance of the effects under investigation. While the aggregate decomposition results inform us about the size of the overall wage structure and composition effects, the detailed decomposition results inform us about the contribution of single explanatory variables in explaining wage structure and composition effects.

Table 4 presents the decomposition results for the period 1978/79 to 1985/86. The table shows that our skill categories have non-monotonic effects, a typical feature of the RIF regression. Changes in skills increase wage inequality at some parts of the distribution, while they decrease inequality at other parts. We have included the percentages to give an indication of the effect size. In Panel B, for example, the estimated effect of cognitive skills of 0.33 log points accounts for 32 percent of the increase in the 90-10 gap that is due to wage structure effects. The aggregate decompositions indicate how relevant wage structure effects are in this period. Panel A in Table 4 shows that the estimated effect (10.29 log points) accounts for a large part of the increase in the 90-10 gap. This result confirms that changes in the returns to skills played an important role in changes in the wage structure.

However, because of the non-monotonicity of the effects, the decomposition method does not allow a general statement of effect sizes. In our example in Panel B of Table 4, changes in the returns to cognitive skills contribute to a rise in wage inequality by 0.33 log points. Changes in the returns to manual skills contribute by 0.68 log points. In contrast, changes in the returns to interactive skills contribute to a decrease in overall wage inequality by 0.15 log points. Because changes in the returns of skills affect wages differently at different parts of the distribution, the effects of single skills might cancel each other out. Again, this underlines the need to consider single skills as well as the whole distribution rather than aggregate measures and the mean.

With regards to the composition effects in Panel A, the table shows that changes in cognitive and interactive skills are associated with an increase in inequality over the entire distribution. However, given that the overall composition effects decrease inequality, we can infer that these effects are counter balanced by other factors such as changes in the age or experience composition during this period. In contrast, changes in the composition of manual

skills decrease overall inequality and account for almost all of the decrease of the 90-50 gap. This observation goes hand in hand with the fact that changes in the returns to manual skills explain a large part of the increase of the 90-50 gap (panel B, column 3). It seems that during the early 1980s, most of the changes in wage inequality can be accounted for by changes in manual skills. Overall, the table shows that changes in skill prices have clearly been the driving force in the increased wage inequality from 1978 to 1986. Changes in the skill composition, on the other hand, have been closing the gap. A comparison to the full sample (table A.3 in the Appendix) shows that the size and the direction of the effects are very similar.

Table 4. Detailed decomposition results, 1978/79-1985/86

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	0.0229** (0.00005)	-0.52	0.0076*** (0.00004)	-1.03	0.0153*** (0.00009)	-0.42
Interactive Skills	0.0265*** (0.00000)	-0.60	0.0125*** (0.00008)	-1.69	0.0141*** (0.00008)	-0.38
Manual Skills	-0.0266 (0.00008)	0.60	0.0050** (0.00013)	-0.68	-0.0316*** (0.00022)	0.86
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	-0.0440*** (0.000001)		-0.0074*** (0.0003)		-0.0367*** (0.0003)	
Inequality Measure	90-10	%	50-10	%	90-50	%
B: Detailed Wage Structure Effects						
Cognitive Skills	0.0332*** (0.00001)	0.32	0.0094*** (0.00013)	0.65	0.0238*** (0.00012)	0.27
Interactive Skills	-0.0153** (0.00007)	-0.15	-0.0147*** (0.00031)	-1.02	-0.0006*** (0.00024)	-0.01
Manual Skills	0.0680*** (0.00006)	0.66	0.0024*** (0.00047)	0.16	0.0656*** (0.00041)	0.74
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.1029*** (0.00004)		0.0145*** (0.0004)		0.0884*** (0.0004)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table 5 shows the decomposition results for the period 1985/86 to 1991/92, when upper-tail inequality slightly decreased and lower-tail inequality slightly increased. With regards to the composition effect, our skill measures all contributed to a closing of the wage gaps. However, the size of the effects of changes in the composition of skills on changes in the wage structure is quite small. Similarly, wage structure effects are largely driven by other factors such as for example returns to experience. Overall, however, because wages stagnated during this period, a detailed discussion of the drivers of changes in wages is not necessary. The same conclusions hold when looking at the decomposition results of the full sample in Table A.4 in the Appendix.

Table 5. Detailed decomposition results, 1985/86-1991/92

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	-0.0075*** (0.0001)	0.13	-0.0020*** (0.0000)	0.09	-0.0055*** (0.0001)	0.16
Interactive Skills	-0.0327 (0.0000)		-0.0166 (0.0000)		0.0161*** (0.0001)	-0.47
Manual Skills	-0.0090*** (0.0001)	0.16	-0.0019*** (0.0000)	0.09	-0.0072 (0.0001)	
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	-0.0560*** (0.0002)		-0.0215*** (0.0002)		-0.0345*** (0.00001)	
Inequality Measure	90-10	%	50-10	%	90-50	%
B: Detailed Wage Structure Effects						
Cognitive Skills	-0.0339 (0.0001)		-0.0148 (0.0003)		-0.0191*** (0.0002)	-1.21
Interactive Skills	0.0413*** (0.0002)	0.68	0.0249*** (0.0003)	0.56	0.0164*** (0.0002)	1.03
Manual Skills	0.0075 (0.0001)		0.0107*** (0.0004)	0.24	-0.0032*** (0.0002)	-0.20
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.0601*** (0.0002)		0.0443*** (0.0004)		0.0158*** (0.0002)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table 6 shows the decomposition results for the period 1991/92 to 1998/99, when both upper-tail and lower-tail inequality started increasing. For the composition effect, changes in the composition of skills mostly decrease the wage gaps. This closing of the gap indicates that the 1998/99 population might have become more equal in terms of skill sets, at least with regards to interactive and manual skills. Changes in the composition of these skills do not provide a source for wage heterogeneity. However, changes in cognitive skills account for a large part for the increases the 50-10 gap. This finding relates a large part of the wage decreases at the bottom part to the fact that individuals at the bottom part of the wage distribution were not sufficiently equipped with cognitive skills. However, because the total composition effect at the 90-50 gap is so small (0.0011), these effects due to changes in the composition of skills only play a minor role in explaining increased upper-tail and lower-tail inequality.

The wage structure effects are much more interesting in terms of economic significance, because they account for almost all changes in wage inequality. In turn, our skills categories explain almost all of the wage structure effects at the different parts of the distribution. While changing returns to interactive and manual skills contribute rather modestly to an increase of the 90-50 gap, changing returns to cognitive skills explain almost the entire gap. Similarly, for the 50-10 gap, changing returns to cognitive skills explain all of the increase in the 50-10 gap. It seems that the 1990s were characterized by an overall increase in the demand for cognitive skills, which in turn, increased skill prices. This period coincides with the computerization of work, a change that has induced a substantial shift in the demand for skills (Spitz-Oener 2006).

Table A.5 in the Appendix shows the decomposition results for the full sample. Again, the results for the full sample are similar to those of the VET sample, both in direction and size of the effects. However, in the full sample, changes in the skill composition contribute to a decrease in wage inequality for the whole distribution, including the upper tail. But again, the size of the effects is very small. With regards to the wage structure effects, both in the VET sample and in the full sample, changes in the returns to cognitive skills increase the wage gap over the whole distribution, while changes in the returns to manual skills decrease the wage gap.

Table 6. Detailed decomposition results, 1991/92-1998/99

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	0.0079*** (0.0007)	7.22	0.0110*** (0.0011)	0.79	-0.0031*** (0.0004)	0.24
Interactive Skills	-0.0858*** (0.0013)	-78.06	-0.0655*** (0.0022)	-4.72	-0.0203*** (0.0009)	1.59
Manual Skills	-0.0336*** (0.0005)	-30.57	-0.0187*** (0.0009)	-1.35	-0.0149*** (0.0003)	1.17
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	0.0011*** (0.0001)		0.0139*** (0.0025)		-0.0128*** (0.0003)	
Inequality Measure	90-10	%	50-10	%	90-50	%
B: Detailed Wage Structure Effects						
Cognitive Skills	0.1189*** (0.0014)	1.19	0.0521*** (0.0024)	1.50	0.0668*** (0.0010)	1.03
Interactive Skills	0.0025*** (0.0001)	0.03	-0.0007* (0.0002)	-0.02	0.0032* (0.0001)	0.05
Manual Skills	-0.0137*** (0.0006)	-0.14	-0.0165*** (0.0009)	-0.39	0.0028*** (0.0004)	-0.21
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.0996*** (0.0001)		0.0347*** (0.0024)		0.0649*** (0.0004)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table 7 presents the decomposition results for our final period, 1998/99 to 2005/06, when both lower-tail and upper-tail inequality continued rising. Similar to the 1990s, overall composition effects are rather small. The composition effects of manual skills and interactive skills decrease inequality, indicating once again that the composition of these skills within the population becomes more equal over time. Overall, however, looking at the total composition effect at different parts of the distribution, the contribution of skills is counterbalanced by the contribution of other factors that increase overall wage inequality.

Turning to the wage structure effects, changes in the returns to cognitive skills and interactive skills contribute to a large part to the increases in wage inequality. This finding shows how the trend of the 1990s continued through the mid 2000s. At the upper part of the distribution, changes in the returns to interactive skills and to a much larger extent changes in the returns to cognitive skills account for almost all of the changes in wage inequality from the early 1990s to the mid 2000s. In contrast, changes in returns manual skills show a different pattern. They contribute to a large part to a decrease in overall wage inequality. This development could indicate that manual skills have decreased in importance for the production process and are thus equalizing wages across the distribution.

Finally, the results for the full sample (table A.6 in the Appendix) show similar patterns to those just described for the VET sample: Changes in the composition of skills hardly affect changes in the wage structure. With regards to the composition effects, factors other than skills are the main drivers of inequality. Changes in the returns to skills, on the other hand, are the main drivers for wage inequality over the whole distribution.

A number of valuable conclusions emerge from the detailed decompositions: First, we have empirically shown that changes in the composition of skills and changes in the returns to skill both account for changes in the wage structure. Second, the effects are highly non-monotonic, which emphasizes the necessity for a detailed decomposition a different parts of the distribution. Third, skills vary in their importance for changes in wages at different points in time. While from the late 1970s to the mid 1980s, changes in the composition of and the returns to manual skills are largely driving changes in the wage structure, from the 1990s onwards changes in the returns to cognitive skills were the main drivers for increasing wage inequality, both at the top and the bottom of the wage distribution.

Table 7. Detailed decomposition results, 1998/99-2005/06

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	-0.0003** (0.00004)	-0.01	0.0004*** (0.00001)	0.02	-0.0007** (0.00097)	-0.54
Interactive Skills	-0.0005*** (-0.00011)	-0.02	-0.0007* (0.00015)	-0.03	0.0002* (0.00207)	0.15
Manual Skills	0.0018* (0.00003)	0.07	-0.0002 (0.00015)	-0.01	0.0020 (0.00278)	1.53
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	0.0257*** (0.0005)		0.0244*** (0.0004)		0.0013*** (0.00005)	
Inequality Measure	90-10	%	50-10	%	90-50	%
B: Detailed Wage Structure Effects						
Cognitive Skills	0.0485*** (0.00262)	0.35	0.0032*** (0.00359)	0.04	0.0453** (0.00005)	0.82
Interactive Skills	0.0283*** (0.00558)	0.20	0.0131*** (0.00765)	0.16	0.0152*** (0.00003)	0.28
Manual Skills	-0.1475*** (0.00746)	-1.07	-0.1232*** (0.01024)	-1.48	-0.0242* (0.00012)	-0.44
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.1383*** (0.0008)		0.0832*** (0.0011)		0.0551*** (0.0003)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

6. Conclusion

West Germany has experienced substantial changes in the wage structure over the past 30 years. At the same time, the skill structure of occupations has drastically changed over the last three decades and substantially altered the demand for human capital (Autor and Dorn 2009). In this paper, we follow the nuanced view of the SBTC to relate changes in skills to changes in wages. This literature posits that the introduction of computer and information technology has changed the demand for occupational skills and thus changed the wage structure.

In an effort to better understand the contribution of changes in occupational to changes in the wage structure, we apply a decomposition procedure based on recentered influence functions. This procedure allows us to explicitly quantify the contribution of changes in skills to changes in wages. We use three skill measures: cognitive, interactive, and manual skills and hypothesize that both the returns to these skills and the within-occupation used share of these skills changes over time. Using long-running register data and combining them with unique longitudinal skill information, we first use quantile regressions to estimate wage equations at different percentiles and to construct the counterfactual wage distributions that would have been observed had individual and job characteristics remained constant over time. This step allows us to break down observed wage changes into changes due to varying worker and job characteristics and changes in the returns to those characteristics. Second, using RIF regression based decompositions, we further decompose these changes into single explanatory factors to single out the effects of changes in the composition of and returns to single skills.

The decomposition analyses show that changes in skill prices and skill composition have played an important role in generating changes in the wage distribution. We find that returns to skills not only are different in different parts of the wage distribution, but also have changed differently over time. Overall, changes in the composition of skills tend to decrease wage inequality, while changes in the returns to skills tend to increase it. However, wage structure effects are generally larger than composition effects so that the resulting net contribution is inequality enhancing.

To go into more detail, from the late 1970s to the mid 1980s, most of the changes in wage inequality can be accounted for by changes in returns to manual skills. The period from the early 1990s until the mid 2000s was characterized by large changes in the returns to cognitive skills (and to a smaller extent returns to interactive skills), which contributed to an increase of wage inequality, both at the top and at the bottom end of the wage distribution. This development is in line with the recent literature on the “nuanced” view of a skill-biased

technological change—that technology affects the bottom and the top end of the wage distribution (Spitz-Öner 2006).

Overall, our results closely relate to previous findings of the SBTC literature that posit that technological innovations decrease the demand for certain skills, while they increase the demand for other skills and thus drive wage inequality (Autor, Katz, and Kearney 2006; Autor and Dorn 2013; Goos and Manning 2007). While most of these studies explain the wage- and job polarization in the U.S. and the UK, our study shows that wages in West Germany have not become polarized. Rather, wages increased at the upper part of the distribution and decreased at the lower part of the distribution. This finding is in line with recent work on German wage inequality (Card, Heining, and Kline 2013; Dustmann, Ludsteck, and Schönberg 2009; Fuchs-Schündeln, Krueger, and Sommer 2009; Gernandt and Pfeifer 2007).

Moreover, while recent studies suggest that technological change played a major role in the 1990s and lost importance in the 2000s, this does not seem to be the case for Germany where the increase in the returns to cognitive skills (associated with the computerization of work) continued until the mid 2000s. This could be due to a delayed effect of structural changes on the West German wage structure. While the U.S. and the UK have experienced spikes in both upper-tail and lower-tail wage inequality as early as in the 1980s, this pattern appeared only in the 1990s in Germany. Therefore, it seems plausible that technological change continued resonating in Germany until the mid 2000s.

Our results show why models that do not account for occupations are likely to miss a significant part of the contribution of the skills content of jobs to changes in the wage distribution. Understanding which skills are most valued at which part of the wage distribution (and in which types of jobs) should ultimately provide helpful guidance both for policy makers in the design of training curricula and for individuals in the type of training that they should choose.

Our results have crucial implications for policy makers. The quantification of the effects of skills on wages provides valuable indication for both firms and individuals in terms of what types of skills they should invest in if they want to minimize risk. Finally, our study provides clear evidence that changes in the demand for skills have a direct impact on changes in wages. Therefore, a VET system that is market-driven and where firms contribute in designing education curricula seems to be an efficient and sustainable educational system. Since the VET curricula are aligned with the skill needs of firms, graduates of this system will not have difficulties in finding employment, while firms will not have difficulties in finding the rightfully skilled workers.

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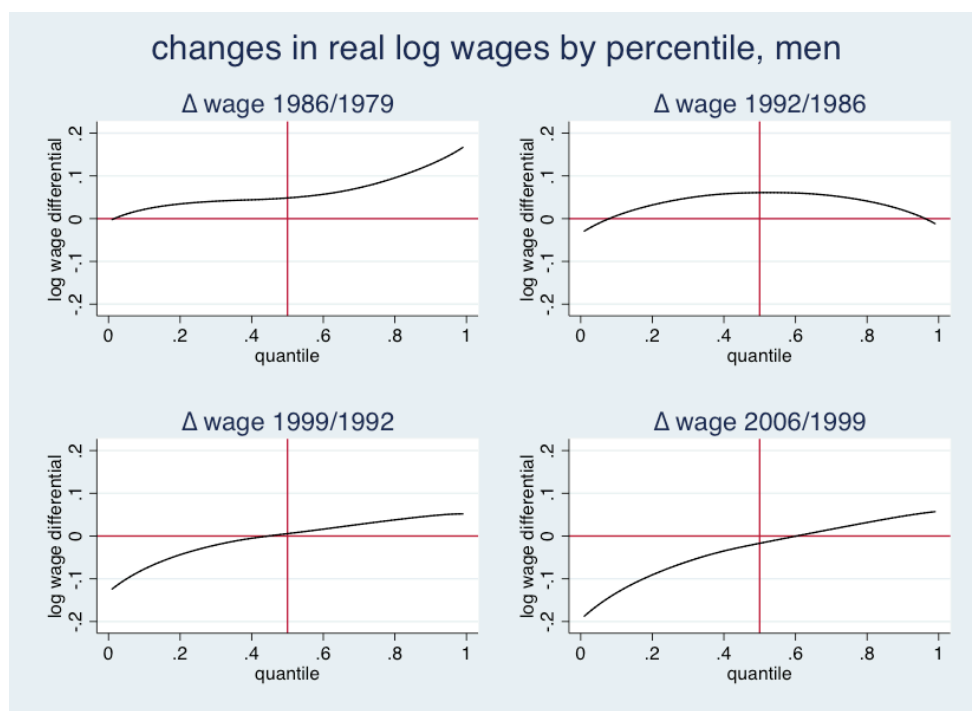
Appendix

Table A.1. Summary statistics for full-time workers

	Log real wages		
	Observations	Mean	St. Dev.
Panel A. Full-time men			
1978-79	389,411	3.7312	0.2630
1985-86	376,913	3.7897	0.3017
1991-92	416,150	3.8832	0.3095
1998-99	386,229	3.8286	0.3589
2005-06	362,896	3.8007	0.4196
Panel B. Full-time women			
1978-79	187,016	3.3722	0.3938
1985-86	193,996	3.4334	0.4110
1991-92	235,043	3.5215	0.4226
1998-99	216,100	3.5648	0.4574
2005-06	201,196	3.5295	0.5263

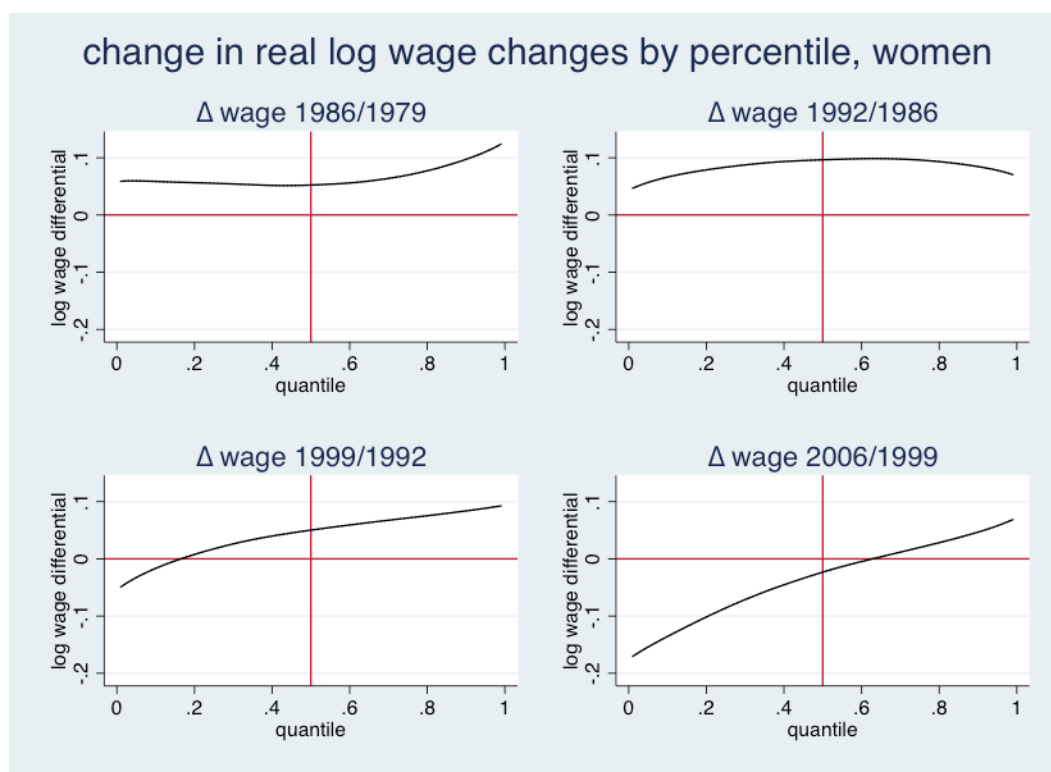
Notes: SIAB data 1978-2006, authors' calculations.

Figure A.1. Changes in real log wages of full-time men, 1978 to 2006



Notes: SIAB data 1978-2006, authors' calculations.

Figure A.2. Changes in real log wages of full-time women, 1978 to 2006



Notes: SIAB data 1978-2006, authors' calculations.

Table A.2. Aggregate decomposition results, full sample

Inequality Measure	90-10	50-10	90-50
A: 1978/79 to 1985/86			
Total Change	0.0739*** (0.00010)	0.0073*** (0.00026)	0.0666*** (0.00036)
Composition	-0.0274*** (0.00014)	-0.0122*** (0.00039)	-0.0151*** (0.00052)
Wage Structure	0.1013*** (0.00000)	0.0195*** (0.00050)	0.0818*** (0.00049)
B: 1985/86 to 1991/92			
Total Change	-0.0129*** (0.00005)	0.0153*** (0.00032)	-0.0282*** (0.00037)
Composition	-0.0361*** (0.00010)	-0.0165*** (0.00015)	-0.0195*** (0.00025)
Wage Structure	0.0231*** (0.00012)	0.0318*** (0.00039)	-0.0087*** (0.00027)
C: 1991/92 to 1998/99			
Total Change	0.0937*** (0.00021)	0.0487*** (0.00051)	0.0450*** (0.00029)
Composition	0.0004*** (0.00114)	-0.0258*** (0.00194)	0.0262*** (0.00079)
Wage Structure	0.0934*** (0.00121)	0.0745*** (0.00202)	0.0188*** (0.00081)
D: 1998/99 to 2005/06			
Total Change	0.1295*** (0.00056)	0.0801*** (0.00127)	0.0494*** (0.00071)
Composition	0.0301*** (0.00010)	0.0243*** (0.00019)	0.0436*** (0.00029)
Wage Structure	0.0994*** (0.00064)	0.0558*** (0.00124)	0.0058*** (0.00061)

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table A.3. Detailed decomposition results, 1978/79-1985/86, full sample

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	0.0178*** (0.00004)	-0.65	0.0083*** (0.00007)	-0.68	0.0095*** (0.00011)	-0.63
Interactive Skills	0.0223*** (0.00003)	-0.81	0.0122*** (0.00008)	-1.00	0.0101*** (0.00011)	-0.67
Manual Skills	-0.0282*** (0.00002)	1.03	-0.0006*** (0.00037)	0.05	-0.0276*** (0.00038)	1.82
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	-0.0274*** (0.00014)		-0.0122*** (0.00039)		-0.0151*** (0.00052)	
B: Detailed Wage Structure Effects						
Cognitive Skills	0.0231*** (0.00003)		0.0086*** (0.00024)		0.0145*** (0.00021)	0.18
Interactive Skills	0.0188 (0.00008)		0.0068*** (0.00042)	0.35	0.0119 (0.00034)	
Manual Skills	0.0988*** (0.00001)	0.98	0.0195*** (0.00079)	1.00	0.0793*** (0.00078)	0.97
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.1013*** (0.00000)		0.0195*** (0.00050)		0.0818*** (0.00049)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table A.4. Detailed decomposition results, 1985/86 – 1991/92, full sample

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	-0.0062*** (0.00004)	0.17	-0.0030*** (0.00002)	0.18	-0.0032*** (0.00006)	0.16
Interactive Skills	-0.0185*** (0.00000)	0.51	-0.0103*** (0.00008)	0.62	-0.0083*** (0.00009)	0.42
Manual Skills	-0.0101*** (0.00005)	0.28	-0.0011*** (0.00009)	0.07	-0.0090*** (0.00004)	0.46
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	-0.0361*** (0.00010)		-0.0165*** (0.00015)		-0.0195*** (0.00025)	
B: Detailed Wage Structure Effects						
Cognitive Skills	-0.0017*** (0.00013)	-0.07	0.0005*** (0.00046)	0.02	-0.0023*** (0.00033)	0.26
Interactive Skills	0.0153 (0.00019)		0.0092 (0.00063)		0.0061*** (0.00044)	-0.70
Manual Skills	0.0106*** (0.00009)	0.46	0.0036*** (0.00050)	0.11	0.0070*** (0.00041)	-0.81
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.0231*** (0.00012)		0.0318*** (0.00039)		-0.0087*** (0.00027)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.

Standard errors are in parentheses.

Table A.5. Detailed decomposition results, 1991/92 – 1998/99, full sample

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	0.0059*** (0.00109)	16.41	-0.0121*** (0.00180)	0.47	0.0180*** (0.00072)	0.69
Interactive Skills	0.0058*** (0.00007)	16.06	0.0026*** (0.00003)	-0.10	0.0032*** (0.00010)	0.12
Manual Skills	-0.0086*** (0.00045)	-23.87	-0.0175*** (0.00074)	0.68	0.0089*** (0.00029)	0.34
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	0.0004*** (0.00114)		-0.0258*** (0.00194)		0.0262*** (0.00079)	
B: Detailed Wage Structure Effects						
Cognitive Skills	0.0444*** (0.00095)	0.48	0.0289*** (0.00160)	0.39	0.0155*** (0.00065)	0.82
Interactive Skills	0.0120*** (0.00045)	0.13	-0.0039*** (0.00077)	-0.05	0.0159*** (0.00032)	0.84
Manual Skills	-0.0364*** (0.00065)	-0.39	-0.0203*** (0.00115)	-0.27	-0.0162*** (0.00050)	-0.86
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.0934*** (0.00121)		0.0745*** (0.00202)		0.0188*** (0.00081)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table A.6. Detailed decomposition results, 1998/99 – 2005/06, full sample

Inequality Measure	90-10	%	50-10	%	90-50	%
A: Detailed Composition Effects						
Cognitive Skills	0.0001*** (0.00005)	0.00	0.0019*** (0.00004)	0.08	0.0017*** (0.00009)	0.30
Interactive Skills	0.0033*** (0.00008)	0.11	0.0010*** (0.00013)	0.04	0.0023*** (0.00020)	0.40
Manual Skills	-0.0025*** (0.00012)	-0.08	-0.0031*** (0.00024)	-0.13	0.0006*** (0.00012)	0.10
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Composition Effect	0.0301*** (0.00010)		0.0243*** (0.00019)		0.0058*** (0.00029)	
B: Detailed Wage Structure Effects						
Cognitive Skills	0.0116*** (0.00369)	0.12	0.0329*** (0.00776)	0.59	0.0445*** (0.00407)	1.02
Interactive Skills	0.0049*** (0.00203)	0.05	0.0165*** (0.00266)	0.30	0.0116*** (0.00063)	0.27
Manual Skills	-0.1281 (0.00219)		-0.1302 (0.00122)		0.0021 (0.00097)	
Individual Controls	Yes		Yes		Yes	
Firm Controls	Yes		Yes		Yes	
Total Wage Structure Effect	0.0994*** (0.00064)		0.0558*** (0.00124)		0.0436*** (0.00061)	

Notes: SIAB data linked with BIBB/IAB Employment Surveys.
Standard errors are in parentheses.

Table A.7. Vocational occupations in Germany

Title of Occupation	
Miners, Stone-breaker, Mineral Processing	Beverage Production, Milk Production,
Concrete and Cement Finisher,	Bricklayer, Mason
Potter, Ceramicist, Gaffer	Carpenter
Chemical Processing	Road Builder
Plastics and Polymer Processing	Plasterer
Paper and Pulp Processing	Interior Decorator, Interior Designer
Printer, Typesetter, Typographer	Joiner, Cabinet Maker
Wood, Lumber, and Timber Processing	Painter
Metal and Iron Manufacturer	Product Tester
Molding, Shaping	Crane Driver, Crane Operator, Skinner,
Metal Presser and Molder	Technical Service Personnel
Metal Polisher, Sander, Buffer	Sales Personnel
Welder, Brazing, Soldering	Banker
Blacksmith, Farrier, Forger, Plumber	Traders, Trading Personnel
Locksmith	Truck Driver, Conductor
Mechanic, Machinist, Repairmen	Sailor, Seaman, Navigator, Mariner
Tool and Dye Maker, Instrument Mechanic	Mail Carrier and Handler, Postal Clerk
Metal Craftsman	Storekeeper, Warehouse Keeper
Electrician, Electrical Installation	Accountant, Bookkeeper
Assembler	Office Clerk
Weaver, Spinner, Knitter, Wool Trade	Guard, Watchman, Police, Security Personnel
Tailor, Textile Worker	Musician
Shoemaker	Nurse, Dietician, Physical Therapist Social Worker
Baker	Personal Hygiene Technician
Butcher	Cleaning Service Worker

Notes: list provided by the SIAB.

Translation taken from Gathmann and Schönberg (2010).