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The Polarization of Employment in German Local Labor Markets*

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Abstract

This paper analyzes the polarization of employment and wages in Germany between 1979 and 2006, focusing on the role of technological progress. We exploit spatial variation in the exposure to technological progress which arises due to initial regional specialization in routine task-intensive activities. We show that the occupational structure of labor markets that were particularly susceptible to computerization has polarized, as employment shifted from middle-skilled, routine clerical and production occupations to less-skilled non-routine manual and service occupations. We find this shift to be the main driver of employment polarization at the lower tail of the wage distribution. Occupational shifts are gender-specific, with gains in service employment being exclusively realized by female employees. We further show that technological change contributes to a dispersion of the wage structure, as employment gains in services are accompanied by significant wage losses.

Key Words: Job Tasks, Polarization, Technological Change, Service Occupations, Regional Labor Markets.

JEL Classification: J24, J31, J62, O33, R23.

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1 Introduction

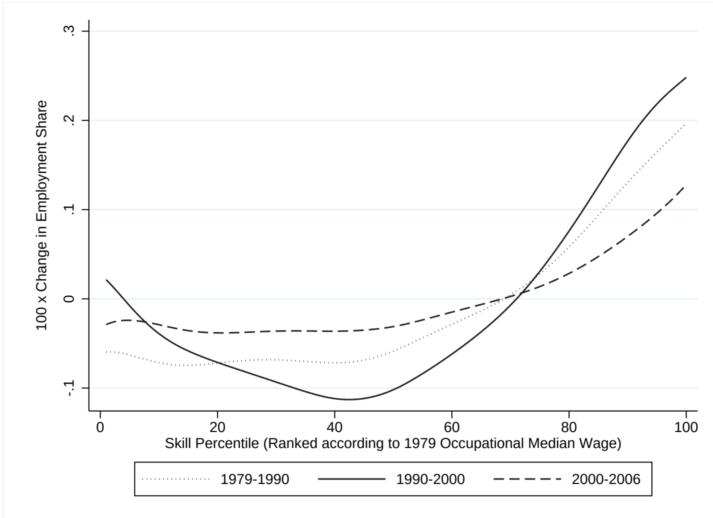
In many industrialized countries, employment growth has been concentrated among low- and high-skilled employees, while the employment outcomes of workers in the middle of the skill distribution have deteriorated.[1] As illustrated in Figure 1, this pattern is also evident for Germany. The Figure plots the change in occupational employment shares for different subperiods between 1979 and 2006 ranked by occupational skill level, which is approximated by the respective median wage in 1979. It reveals that employment in high-skill occupations grew at the expense of less-skill occupations in all periods. In addition, particularly between 1990 and 2000, employment also grew at lower percentiles, resulting in the typical u-shaped pattern of employment polarization.

This paper empirically analyzes the occupational shifts that drive the twisting of the employment distribution and their relation to technological progress. In order to directly link labor market outcomes to technological change, we use variation in technology exposure at the level of local labor markets. Our analysis builds on the seminal paper by Autor et al. (2003) that links job polarization to rapid productivity increases that came along with substantial declines in real prices of information and communication technologies. To understand the labor market impact of this development, work is conceptualized into a series of tasks, characterized as *routine* and *non-routine*, depending on their substitutability or complementarity with computer technology (see Acemoglu and Autor (2011) for a comprehensive overview of the task literature). Routine tasks are well-defined and follow explicit rules, which makes them particularly susceptible to substitution by computer technology. In contrast, computers complement *non-routine cognitive* tasks that involve high complexity and problem-solving, as they rely heavily on information as an input, resulting in productivity gains of employees performing these tasks. *Non-routine manual* tasks, which require environmental and interpersonal adaptability, are not directly influenced by computerization. Declining demand for routine tasks leads to employment polarization because tasks are not evenly distributed across the skill distribution. Figure 2 depicts the distribution of task usage in occupations across the skill distribution, which is approximated by the occupational median wage in 1979. It shows that non-routine cognitive tasks are prevalently performed in occupations located at the top of the skill distribution,

[1]For the US, Autor et al. (2006) show that medium-skilled employment has deteriorated relative to low- and high-skilled employment starting in the 1990's, corroborating the conjecture that technological change is rather task- than skill-biased. Goos and Manning (2007) find similar trends for Great Britain, showing that employment in occupations with the lowest and highest median wages in 1979 experienced growth in subsequent decades, while employment in the middle of the distribution declined. Using data from the European Union Labour Force Survey, Goos et al. (2009; **?**) present similar evidence for labor market polarization in 16 Western European countries.

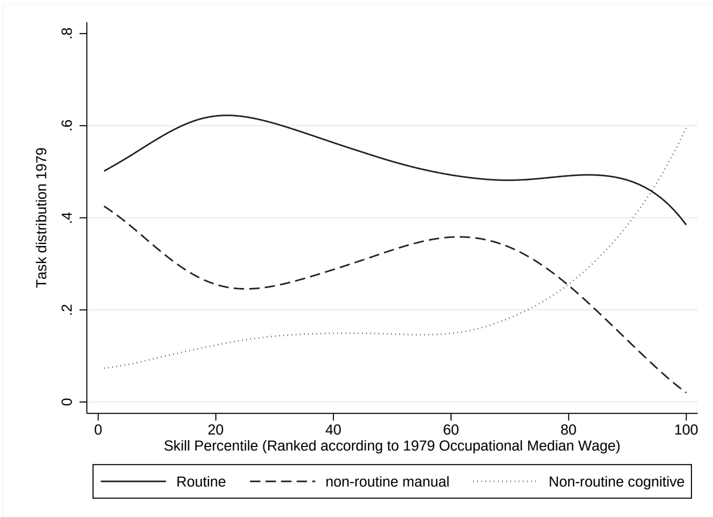
while routine and non-routine manual tasks are mainly performed by less-skilled workers.

Figure 1: Smoothed Changes in Employment by Skill Percentile



Notes: Smoothed changes in employment by skill percentile in indicated periods. Occupations are ranked according to their 1979 median wage using the SIAB-R. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.

Figure 2: Task Inputs by Skill Percentile



Notes: Shares of workers performing routine, non-routine manual and non-routine cognitive tasks. Occupations are ranked according to their 1979 median wage using the SIAB-R. Task intensity is derived from BIBB/IAB wave 1979 and defined as in equation 2.

In a recent study, Autor and Dorn (2013) extend this framework to a two sector spatial equilibrium setting. In their model, technological progress displaces less-skilled workers performing routine tasks in the production of goods, which induces them to supply non-routine manual tasks to produce services instead. The positive labor supply effect initially depresses wages in less-skilled services. Yet, the authors show that employment polarization is accompanied by wage polarization if the increase in the supply of workers performing non-routine manual tasks is offset by an increase in the demand for these tasks, which occurs if goods produced by routine labor and services produced by non-routine manual labor are at least weakly complementary to each other. If, however, goods and services are not complementary, the demand for services does not rise sufficiently to increase the price for non-routine manual relative to routine tasks and wages do not polarize. Autor and Dorn (2013) test the hypotheses derived from the theoretical model for the United States at the level of commuting zones and find robust support for technology driven employment and wage polarization. These findings confirm existing evidence at the aggregate level presented, amongst others, by Autor et al. (2008) and Acemoglu and Autor (2011). They further show that the twisting of the lower tail of the employment and wage distribution is almost exclusively attributable to the growth of service occupations, an employment category which requires disproportionally high inputs of non-routine manual tasks.

To our knowledge, we are the first to test the implications of the model proposed by Autor and Dorn (2013) for the German labor market. We show that local labor markets differ substantially in the degree to which they employ routine task performing labor. Given these initial task specializations, regions are differently exposed to technological change. Previewing our key results, we present evidence that this measure of technological progress is highly predictive of a reallocation from routine to non-routine intensive employment. We then show that initially routine-intensive labor markets also experienced a stronger growth in personal service occupations, although this development is restricted to female employees. Our analysis of wages suggests that female employment gains in service occupations were accompanied by significant wage losses. These countervailing developments provide no evidence for increasing demand for personal services in Germany. This stands in contrast to findings for the United States and highlights the importance of demand side factors in explaining differences in the evolution of employment and wages across industrialized countries. We complement our analysis by exploring alternative adjustment patterns in migration and unemployment, but find no robust evidence that labor markets have responded to technological shocks along these margins.

Our study advances the literature on employment polarization in Germany, which documents a polarizing pattern of employment (Spitz-Oener, 2006; Dustmann et al., 2009), but has so far focused on aggregate developments. By directly linking technological change to labor market outcomes at the regional level, we are able to explore the underlying mechanisms of polarization. Our results on regional wage patterns complement previous research for Germany that presents evicence for wage dispersion rather than compression at the lower tail of the wage distribution (Dustmann et al., 2009; Kohn, 2006; Antonczyk et al., 2010, 2009). Yet, as existing studies mainly focus on explanations such as deunionization and implicit minimum wages, we add to the understanding of recent wage developments by showing that technological change has reinforced the dispersion of the wage distribution.

The remainder of the paper proceeds as follows. In section 2, we describe the empirical approach, the data set and the variables used in our analysis. Section 3 presents summary evidence on trends in regional task intensities and information technology. We then investigate the relationship between the regional routine share and the growth of routine and non-routine employment, focusing on trends in personal service employment. Furthermore, we analyze whether employment developments are accompanied by wage trends in the same direction and consider alternative adjustment mechanisms such as unemployment and migration. Section 4 concludes.

2 Data and Methods

2.1 Empirical Approach and Estimation Strategy

Our empirical approach is closely linked to the strategy in Autor and Dorn (2013), which exploits the variation in industry specialization patterns across regions. The starting point of the analysis is the observation that at the onset of technological progress, regions employed different shares of routine, non-routine manual and non-routine cognitive task inputs depending on the task requirements for the production of particular goods and services. These differences in regional task structures create variation in the degree to which regions are exposed to technological change. Hence, we are able to directly link employment and wage outcomes to a measure of technology exposure and to test the predictions derived from the spatial model presented by Autor and Dorn (2013). In particular, we explore whether regions characterized by a strong initial exposure to technological change

1. adopt information technology to a larger extent and exhibit a differential decline in routine employment,
2. experience larger growth in non-routine employment, particular in personal service occupations, resulting in employment polarization,
3. experience wage polarization,
4. witness a differential increase in unemployment and outward migration.

In order to analyze the relationship between the regional task structure in 1979 and subsequent employment and wage changes, we set up an empirical model of the following form:

$$\Delta Y_{rs} = \alpha + \beta_1 RSH_r + \mathbf{X}_\mathbf{r}'\beta_2 + \gamma_s + e_{rs}. \tag{1}$$

Depending on which of the aforementioned hypotheses is tested, the dependent variable Y_{rs} represents the change in one of the following measures in region r located in state s between the years 1979 and 2006: (1) share of employees working with a computer, (2) share of employees performing routine, non-routine manual or non-routine cognitive tasks, (3) share of personal service employment in overall employment, (4) employment shares and wages in different major occupational groups, and (5) unemployment rate and net migration share.[2] The main parameter of interest, β_1, is the coefficient on the measure of regional technology exposure in 1979, RSH_r, as measured by the share of routine employment in a specific region *before* technological progress kicked in. As computerization only started to spur during the 1980's, the routine employment share in 1979 should be largely unaffected by computerization (Autor et al., 1998; Bresnahan, 1999).[3]

All regressions include state dummies, γ_s, that control for mean differences in employment and wages across states. The vector X_r includes additional covariates which control for the regional human capital and demographic composition as well as for local economic conditions in 1979.

[2]Autor and Dorn (2013) employ stacked first differences over three time periods to estimate the relationship between regional routine intensity and the growth of non-college service employment. If we follow this approach we obtain very similar results in terms of effect size and statistical significance as shown in section 3.2.3.

[3]Nordhaus (2007) estimates that after a period of very modest price decreases in the 1960's and 1970's, the cost of computation sharply declined thereafter.

2.2 Data and Construction of Variables

2.2.1 Data Sources: Labor Market Outcomes

All information concerning local employment and wages is obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies, provided by the Institute of Employment Research by the Federal Employment Agency. This highly reliable administrative data comprises marginal, part-time and regular employees as well as job searchers and benefit recipients (for details, see Dorner et al. (2011)). The dataset provides detailed information on daily wages for employees subject to social security contributions (wages of civil servants or self-employed workers are not included), as well as information on occupation, industry affiliation, workplace location and demographic information on age, gender, nationality and educational attainment.

We restrict the sample to prime-aged workers between 20 and 60 years of age working in West Germany and exclude public sector and agricultural workers. Employment is expressed in full-time equivalents, following the weighting procedure proposed by Dauth (2013). For the analysis of wages we use information on real gross daily wages of employees. As the data lacks information on hours worked, wages of part-time employees are measured less accurately and we are forced to restrict our analysis to full-time workers. Whenever we construct aggregate or average outcomes, we weight each employment spell by the number of days worked. The Data Appendix provides more details on the sample selection and the basic processing of the SIAB-R.

For the analysis it is crucial to consider functionally delineated labor market regions. Hence, the 326 administrative districts in West Germany are aggregated to 204 labor market regions (Koller and Schwengler, 2000), which take commuter flows into account and therefore reflect local labor markets more appropriately (Eckey et al., 2006; Eckey and Klemmer, 1991).

In order to construct regional control variables, we include information from the Establishment History Panel (BHP), a 50 percent sample of all establishments throughout Germany with at least one employee liable to social security, stratified by establishment size. The additional covariates are expressed as fractions of overall full-time employment and chosen to control for the qualification and demographic structure as well as for general economic conditions at the local level. Descriptive statistics for the regional covariates in 1979 and 2006 are summarized in Table 1.

2.2.2 Measuring Task Supplies

The information on task requirements of employees is derived from the BIBB/IAB Qualification and Career Survey (QCS) in 1979 which covers approximately 30,000 individuals. The dataset is particularly well suited for our research as it includes detailed information on the activities individuals perform at the workplace. For each individual i, these activities are pooled into three task categories: (1) non-routine cognitive, (2) routine and (3) non-routine manual tasks. In the assignment of tasks we follow Spitz-Oener (2006) and construct individual task measures TM_i^j for task j in the base year 1979 according to the definition of Antonczyk et al. (2009):

$$(2) \quad TM_i^j(1979) = \frac{\#\text{ of activities in category } j \text{ performed by } i \text{ in } 1979}{\text{total }\#\text{ of activities performed by } i \text{ over all categories in } 1979} \times 100,$$

where $j = C$ (non-routine cognitive), R (routine), M (non-routine manual). In order to match the task information to the SIAB-R, the individual task measures are aggregated at the occupational level, where the task input of individual i in occupation k in 1979 is weighted by its respective weekly working hours $L_{ik}(1979)$:

$$(3) \qquad TI_k^j(1979) = \left(\sum_i \left[L_{ik}(1979) \times TM_{ik}^j(1979)\right]\right)\left(\sum_i L_{ik}(1979)\right)^{-1}.$$

To obtain task measures at the regional level, the occupational task information from the QCS is matched to the SIAB-R, exploiting the fact that both datasets employ a time-consistent definition of occupational titles according to the three-digit 1988 occupational classification provided by the Federal Employment Agency. As the focus of our analysis lies on occupational shifts induced by technological change, we abstract from changes in the task structure within occupations over time and construct task supplies $T_r^j(t)$ for each region r and time t as:

$$(4) \qquad T_r^j(t) = \left(\sum_k \left[L_{kr}(t) \times TI_k^j(1979)\right]\right)\left(\sum_k L_{kr}(t)\right)^{-1},$$

where $L_{kr}(t)$ is employment in occupation k in labor market r in time t. Thus, changes in $T_r^j(t)$ represent only the between-occupational dimension of task shifts. Summary statistics of the three task measures in 1979 and 2006 are provided in the upper Panel of Table 1. The average share of routine and non-routine manual tasks declined slightly between 1979 and 2006 while non-routine cognitive tasks became more prevalent. The relatively modest changes in regional task structures confirm existing evidence showing that most of the task adjustments occur within occupations (Spitz-Oener, 2006).

Similar to the task shares, we construct a measure of regional computer usage with information derived from the QCS. Regional computer prevalence is measured as the share of employees using one of the following devices: (1) personal computers, (2) terminals or (3) electronic data-processing machines in region r in 1979 and 2006. Table 1 confirms that the prevalence of personal computers at the workplace has increased tremendously from 5% in 1979 to 75% in 2006.

2.2.3 Measuring Technology Exposure

Our main explanatory variable is a measure that reflects the regional exposure to technological progress. To generate this, we follow the approach of Autor and Dorn (2013): we use the occupational routine task index in 1979, $TI_k^R(1979)$ to identify the set of occupations that are in the upper third of the routine task distribution. Using these routine-intensive occupations, we calculate for each labor market r a routine employment share measure RSH_r for the year 1979, equal to:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI_k^R > TI_k^{R,P66} \right] \right) \left(\sum_k L_{kr} \right)^{-1}, \tag{5}$$

where L_{kr} is employment in occupation k in labor market r in 1979, and $\mathbb{I}[\cdot]$ is an indicator function, which takes the value of one if the occupation is routine-intensive. The average regional routine share in 1979 is .423. A region at the 85th percentile of the routine share distribution has a 7.4 percentage points higher routine intensity than a region at the 15th percentile ($RSH^{P15} = .387$, $RSH^{P85} = .461$). To get an impression of the spatial variation in technology exposure, Appendix Figure 1 maps the geographic distribution of the regional routine intensity in 1979 across Germany. Regions with a strong exposure to technological change constitute a mixture of industrial strongholds, such as Wuppertal and Wolfsburg, as well as human capital intensive regions, such as Düsseldorf and Cologne.[4] Hence, a high exposure to technological change is not only related to the existence of a large manufacturing sector in a region, but also stems from the prevalence of

[4]In 1979, the share of manufacturing employment in overall employment in Wuppertal and Wolfsburg amounts to 54% and 83%, respectively, which is far above the average. For both, Düsseldorf and Cologne, the share of high-skilled employees is more than two standard deviations larger than the average.

white-collar clerical and administrative support occupations. Regions with a low routine share tend to be specialized in the tourism and hospitality industry, for example Husum or Bad Reichenhall which are located near the Alps or the sea.

Table 1: Descriptive Statistics of German Local Labor Markets

Variable	1979	2006
Average task shares and PC use		
Non-routine cognitive (T^C)	.168	.193
	(.015)	(.017)
Routine (T^R)	.537	.534
	(.019)	(.020)
Non-routine manual (T^M)	.295	.273
	(.025)	(.027)
Personal Computer Use (PC)	.051	.753
	(.011)	(.034)
Main explanatory variable		
Routine share	.423	–
	(.038)	–
Covariates		
Fraction full-time employed/total pop.	.250	.217
	(.067)	(.059)
Fraction female employees/full-time empl.	.330	.323
	(.045)	(.038)
Fraction foreign employees/full-time empl.	.081	.108
	(.048)	(.052)
Fraction high to low- and medium-skilled full-time empl.	.030	.095
	(.016)	(.051)
Fraction manufacturing empl./full-time empl.	.439	.354
	(.125)	(.118)
Average region population	297,494	313,296
	(376,437)	(359,030)
Population density	301	317
(number of inhabitants per square kilometer)	(418)	(400)

Notes: $N = 204$ labor market regions. Standard deviations in parentheses. All employment variables are based upon employment subject to social security contributions for a given region. Fractions are computed with respect to total full-time employment.

3 Results

3.1 Task Specialization, Adoption of IT and the Displacement of Routine Tasks

The task-based framework predicts that information technology substitutes for routine tasks performing labor, thereby inducing a reallocation from routine to non-routine manual task supplies. Hence, we expect labor markets that were particularly exposed to technological progress to differentially adopt computer capital, alongside pronounced changes in the regional task structure. In the following, we will test these predictions, starting with computer adoption. To this end, we regress the change in regional computer penetration between 1979 and 2006 on the technology exposure measure, state dummies and a measure of population density to capture differences in urban concentration across regions, as captured in equation 6:

$$\Delta PC_r = \alpha + \beta_1 RSH_r + \gamma_s + e_r. \tag{6}$$

The results, displayed in the first column of Table 2, indicate that computer adoption is indeed positively correlated with a region's initial exposure to technological progress. To interpret the estimated coefficient quantitatively, we compare the predicted changes in computer adoption of a region at the 15th percentile of the technology exposure distribution with a region at the 85th percentile. The point estimate of .151 implies a differential increase of 1.1 percentage points. Relative to an average increase in computer adoption of almost 70 percentage points between 1979 and 2006, the economic significance of the coefficient is rather small.[5]

In a next step, we explore whether computer adaption was accompanied by displacement of routine employment. To do so, we estimate a variant of equation 6, where the dependent variable is the change in the regional routine employment share between 1979 and 2006. The negative coefficient in column 2 of Table 2 confirms this hypothesis, implying that a region at the 85th percentile of the technology exposure measure experienced a differential decrease in routine employment by 1.6 percentage points relative to a region at the 15th percentile. To put this number into perspective, it is compared to a relatively modest average decline in the (between-occupational) routine share of around .4 percentage points. Thus, the estimated coefficient is of substantial economic significance, reinforcing the general downward trend in routine-intensive employment.

Columns 3 and 4 present complementary estimates for the change in the non-routine manual and non-routine cognitive task shares. The results show that relative declines in routine-intensive employment are primarily offset by significant increases in the supply of non-routine manual tasks (column 3). In contrast, changes in non-routine cognitive task inputs are positive but remain insignificant.[6] This is not surprising given that the performance of non-routine cognitive tasks usually requires a relatively high skill level or some educational attainment that might not be met by work-

[5] As we only consider the use of personal computers, our measure of computer prevalence is limited in its ability to reflect technological progress.

[6] The sum of the three task shares adds up to one by construction. Therefore, as a region's routine employment share declines, the other shares automatically increase. However, it is noteworthy that losses in routine employment are not distributed uniformly to both the non-routine manual and the non-routine cognitive employment share.

ers who formerly engaged in routine tasks.

Table 2: Changes in the Shares of Regional Routine and Non-Routine Employment, 1979-2006

Dependent variable: Δ 1979-2006	ΔPC	ΔT^R	ΔT^M	ΔT^C
	(1)	(2)	(3)	(4)
Panel A: All				
Routine Share 1979	.151***	-.217***	.180***	.037
	(.042)	(.036)	(.034)	(.029)
R^2	.366	.234	.229	.102
Panel B: Men				
Routine Share 1979	.203***	-.202***	.154***	.048
	(.054)	(.045)	(.041)	(.037)
R^2	.333	.169	.165	.130
Panel C: Women				
Routine Share 1979	.064*	-.173***	.180***	-.006
	(.036)	(.051)	(.049)	(.027)
R^2	.295	.190	.167	.067

Notes: $N = 204$ labor market regions. All models include dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer) as well as a constant. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

To explore whether task adjustment patterns are uniform across genders, Panel B and C display the results separately for male and female workers. Technology exposure predicts a more pronounced increase in computer usage combined with a larger decline in the performance of routine tasks for male workers compared to female counterparts. Further, female employees have exclusively reallocated their task supply towards non-routine manual tasks, while males also experienced slight increases in non-routine cognitive tasks, although the coefficient on the routine share is imprecisely estimated.

As the emphasis of this paper lies on occupational shifts, the changes in the dependent variable solely reflect between-occupational changes and abstract from changes in the task structure within occupations. Yet, it bears notice that the same conclusions can be drawn when considering both within- and between-occupational task changes (Senftleben-König and Wielandt, 2014).

3.2 The Growth of Personal Service Sector Employment

3.2.1 Overall Trends in Major Occupational Groups

So far, we have shown preliminary evidence of a significant technology-related shift away from routine towards non-routine employment at the level of regional labor markets. Bearing in mind the polarizing pattern of employment depicted in Figure 1, the question arises whether this growth in non-routine manual tasks indeed drives the twisting of the lower tail of the wage distribution.

To investigate this question in greater detail, Table 3 displays task intensities in 1979 for five broad occupational groups, classified according to Blossfeld (1985). Notably, two employment categories are dominated by non-routine manual task inputs. Personal service occupations, which involve assisting and caring for others, such as hairdressers, cleaners, table waiters and security guards, as well as construction occupations, such as painters and carpenters.[7] Both occupations exhibit high shares of employees without formal education, but differ significantly from each other with respect to their location on the occupational wage distribution. That is, employees performing construction occupations earn on average 15% percent more than workers in service occupations, who have the lowest average wage across the occupational groups. More importantly, the share of workers employed in service occupations grew by roughly 18% between 1979 and 2006, while construction occupations witnessed a sharp decline by 4.7 percentage points over the same period. Table 3 additionally depicts aggregate employment patterns and the occupational task structure in 1979 separately by gender. Although the share of employees working in service occupations grew for men and women, the numbers reveal stronger increases for women by approximately 1.5 percentage points. Furthermore, the share of low-educated workers is larger for the female subsample which is also reflected in lower average wages across all occupations. While the occupational routine task intensities are similar for both genders, women's work has on average lower non-routine cognitive task contents and higher non-routine manual tasks contents. Interestingly, service occupations are distinct in their gender-specific task structure in the sense that women mainly perform non-routine manual tasks, while men equally provide routine and non-routine manual tasks.

As personal service occupations exhibit low wages, high levels of non-routine manual task inputs and have experienced high levels of employment growth, this particular occupational group

[7] It bears emphasis that in the context of our analysis, service *occupations* are to be distinguished from the service *sector*: While service occupations mainly comprise less-skilled personal services, the service sector represents a broad category of industries that can also be highly knowledge-intensive.

Table 3: Employment, Wages and the Task Structure by Broad Occupation Categories 1979

	Task structure			%low-	Empl.	Log	Δ 1979-2006	
	T^C	T^R	T^M	skilled	share	Wage	Empl.	Wages
All								
Professionals	.438	.389	.173	.024	.114	4.460	.020	.063
Clerical/Sale	.126	.844	.030	.089	.238	4.099	.050	.150
Production	.117	.554	.328	.190	.354	4.146	-.055	.032
Construction	.129	.391	.480	.183	.118	4.213	-.047	.016
Service	.138	.353	.513	.179	.177	4.062	.032	-.032
Males								
Professionals	.476	.406	.118	.038	.128	4.581	.004	.090
Clerical/Sale	.152	.823	.025	.074	.119	4.389	.042	.099
Production	.115	.541	.344	.269	.405	4.256	-.006	-.011
Construction	.131	.390	.479	.194	.178	4.219	-.066	.017
Service	.137	.426	.437	.297	.169	4.218	.026	-.087
Females								
Professionals	.349	.349	.303	.066	.088	4.131	.048	.112
Clerical/Sale	.115	.853	.032	.153	.460	3.940	.030	.150
Production	.124	.589	.287	.706	.256	3.819	-.118	.042
Construction	.080	.429	.491	.683	.004	3.827	-.001	.080
Service	.136	.246	.623	.462	.191	3.754	.041	.085

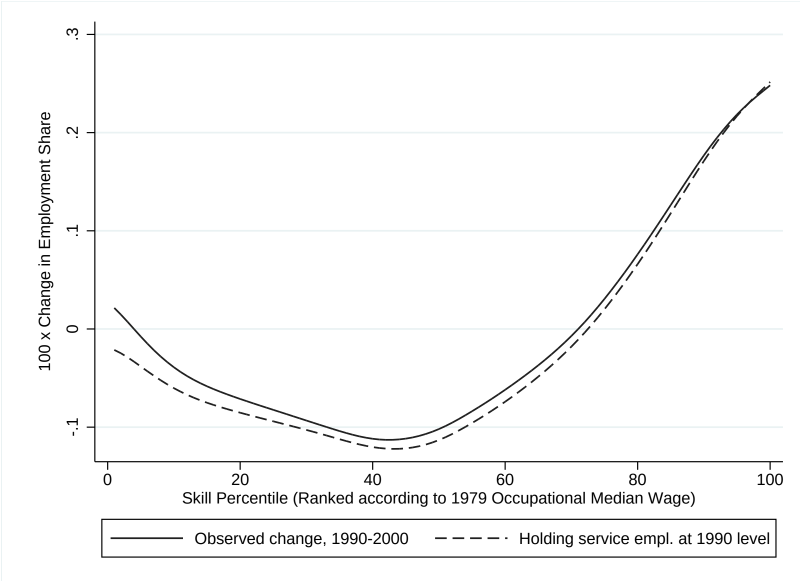
Notes: SIAB Regional File. Sample includes persons aged 20 to 60 living in West Germany. Military and agricultural employment is excluded. Labor supply is measured as the number of days worked in a given year. Part-time work is included and weighted by average working hours according to Dauth (2013).

deserves special attention when investigating the phenomenon of employment polarization. The relevance of employment developments in personal service occupations for employment polarization becomes evident in Figure 3. Here we illustrate a counterfactual situation of employment growth along the skill distribution between 1990 and 2000, with service employment held constant at its 1990 level. Apparently, employment polarization would have occurred in the counterfactual scenario as well, while the positive growth of employment at the lower tail of the wage distribution is exclusively attributable to the growth of personal service occupations. In contrast, developments at the upper tail of the distribution are not related to services.

3.2.2 Baseline Estimates

Having shown that the evolution of personal service employment plays a crucial role when investigating the phenomenon of polarization, we will now analyze whether this growth is related to technological change, as shown for the US by Autor and Dorn (2013). In order to directly link employment trends to technological change, we will conduct this investigation within the framework of a regression analysis at the level of local labor markets. As we are mainly interested in

Figure 3: Observed and Counterfactual Changes in Employment by Skill Percentile, 1990-2000



Notes: Smoothed changes in employment by skill percentile between 1990 and 2000. Occupations are ranked according to their 1979 median wage using the SIAB Regional File. To construct the counterfactual we keep service employment at its 1990 level. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.

employment dynamics at the lower tail of the wage distribution, we restrict the analysis to low- and medium-skilled employees.[8]

We begin by estimating a model described by equation 1, where the dependent variable is the change in the share of service employment in overall employment between 1979 and 2006. The positive and significant estimate, displayed in column 1 of Table 4, suggests that regions which were prone to computerization witnessed a differential growth in service employment. The estimated coefficient of .107 implies that a region at the 85th percentile of the routine share distribution is predicted to increase its share of personal service employment by .8 percentage points more than a region at the 15th percentile over the observed period. Given an average increase of 2.2 percentage points, the degree to which a region is exposed to technological change is of substantial economic significance for later employment developments.

As other local labor market conditions might affect the growth of local service sector employ-

[8]While the model proposed by Autor and Dorn (2013) focuses on employment changes of low-skilled labor exclusively, we consider developments among both low- and medium-skilled workers. This is due to the special nature of the German vocational system, in which there is a vocational degree for the vast majority of existing occupations. If we restricted our analysis to low-skilled workers only, we would concentrate on a rather small subset of employees working in service occupations, which is not the purpose of our investigation.

Table 4: Estimated Impact of Technology Exposure on Service Sector Employment

Dep. variable: Δ SVC employment 1979-2006	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Total employment				
Routine Share 1979	.107**	.104**	.097*	.084*	.100**	.092*	.120**	.104*
	(.049)	(.049)	(.050)	(.051)	(.050)	(.050)	(.052)	(.055)
Share employed/pop.			.037	.060	.017	.024		.060
			(.064)	(.059)	(.069)	(.066)		(.064)
Share female/empl.				.065				.034
				(.053)				(.059)
High/low skilled empl.					.120			.023
					(.115)			(.125)
Share foreign empl./empl						.038		.033
						(.043)		(.047)
Share manuf. empl./empl							-.027	-.022
							(.017)	(.019)
Population density	no	yes	yes	yes	yes	yes	yes	yes
R^2	.114	.116	.118	.127	.123	.121	.130	.135
				B. Male employment				
Routine Share 1979	.034	.024	.010	-.013	.016	.004	.057	.033
	(.060)	(.060)	(.061)	(.063)	(.061)	(.061)	(.065)	(.069)
R^2	.134	.150	.155	.170	.170	.156	.183	.191
				C. Female employment				
Routine Share 1979	.247***	.256***	.267***	.265***	.263***	.259***	.249***	.241***
	(.067)	(.065)	(.066)	(.070)	(.066)	(.069)	(.069)	(.075)
R^2	.124	.133	.135	.135	.138	.136	.137	.142

Notes: $N = 204$ labor market regions. All regressions include dummies for the federal state in which the region is located, regional covariates as indicated as well as a constant. Covariates in all Panels are identical and enter with the expected sign. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

ment, the model is augmented step-by-step by additional control variables as displayed in the remaining columns of Table 4. Column 2 includes a measure of population density to control for differences in the degree of urbanization across regions, with the estimate on the routine share being virtually unaltered. Columns 3 to 5 add variables that are expected to influence the demand for personal services. Column 3 includes the fraction of the regional population subject to social security contributions, which serves as a proxy for the regional employment rate. A higher share of working population should raise the demand for personal services such as restaurant meals or housekeeping as household production is substituted by market-based production of services. This substitution effect is supported by the positive albeit insignificant coefficient reported in column 3. Along the lines of this argument, the regression is further augmented with the share of female employees which we suspect to increase service sector employment (Manning, 2004; Mazzolari and

Ragusa, 2013). The positive coefficient on the fraction of female employment in column 4 verifies this conjecture. Column 5 adds the ratio of high- to low-skilled workers as a measure to reflect differences in the educational structure across regions. Its positive sign suggests that a higher relative supply of high-skilled workers is related to larger growth of service employment. The inclusion of each of the potential demand shifters decreases the size of the coefficient of interest, rendering it less statistically significant in some cases. Column 6 adds an indicator that potentially influences the supply of services by including the share of the working population that has foreign nationality (Cortes, 2008). Indeed, this variable is positively related to the growth of service employment, but the point estimate is not statistically different from zero. Again, the inclusion leads to a decline of the coefficient on the regional routine intensity. As local labor demand conditions might be relevant for regional employment patterns, column 7 includes the share of manufacturing employment, which dampens the growth in service occupations. Once we include the full set of covariates in the model (column 8), the estimate on the regional routine share is similar in size compared to the coefficient reported in the baseline specification in the first column but is less precisely estimated and significant only at the 10% level.

So far, we have implicitly assumed that the relation between technological change and the growth of service sector employment is uniform across individuals. Given the steeper increase in service employment for female than for male workers and higher levels of non-routine manual task inputs (see Table 3), this assumption might not be justified. Furthermore, Black and Spitz-Oener (2010) show that the polarization pressure has been more pronounced for female employees as women have been more exposed to technological change owing to a larger share of days worked in routine-intensive occupations. We therefore re-estimate the previous model separately for male and female employees and present the findings in Panel B and C of Table 4. Indeed, the results confirm the existence of gender-specific trends in the evolution of service employment. For male workers, there is effectively no correlation between the initial routine share of a region and subsequent growth in personal service employment. As opposed to this, the point estimate for females is economically large and statistically significant irrespective of the inclusion of additional covariates. The predicted increase in service employment for the female sample in the region at the 85th percentile of the technology exposure distribution is 1.8 percentage points larger than in the 15th percentile region, a change that is more than twice as large as in the pooled sample.

3.2.3 Robustness Checks

So far, we have found evidence that regions which were particularly exposed to technological change experienced differential increases in service sector employment, although this adjustment is limited to female workers. In this section, we investigate the robustness of this main result to several specification choices and depict results in Table 5. For ease of comparison, the baseline estimate for the effect of technological change on service employment is reproduced in Panel 1.

We start by analyzing whether the results of our analysis hinge on the particular construction of our main explanatory variable, the regional routine share. To this end, we re-construct the technology exposure measure using the top 25 or 50 percent most routine-intensive occupations instead of the top tercile. In line with the baseline results, the estimates on the alternative routine share measures in Panel 2 are similar in magnitude to the baseline, although they are more precisely estimated. Consistent with the baseline results, the gender-specific estimates indicate that this positive effect is mainly driven by female service employment growth.

One concern about the simple OLS results is that they neglect the spatial dependency across single labor markets. To address this potential source of bias in the estimates, we re-estimate spatial error models with continguity and inverse distance weighting. As the results in Panel 3 suggest, both weighting methods yield very similar point estimates compared to previous results. Moreover, there is only minor evidence of significant spatial autocorrelation as suggested by the Wald test statistic and the associated p-value.[9]

So far, the dependent variable in our analysis is the single difference in employment shares based on the year 1979. This approach focuses on the long-run component of differences in the regional task structures, thus circumventing the potential endogeneity problem related to the use of subsequent routine shares. Yet, as depicted in Panel 4, the results remain similar if we follow the empirical strategy by Autor and Dorn (2013) and employ stacked first differences over three time periods to estimate the relationship between technological change and subsequent growth in service employment.

While our study focuses on West German labor markets, the time period includes German re-

[9]While the contiguity matrix only consists of zeros and ones, the inverse-distance weighting matrix assigns weights that are inversely related to the distance between regions. Distance-based weight matrices are in general better suited to account for spatial dependency among regions than contiguity-based matrices as they describe the regional integration more accurately. As the coefficient estimates in our baseline analysis do not differ from the results obtained from the spatial weighting we are not concerned by the relatively low p-value when using the inverse distance weighting.

Table 5: Robustness Checks, 1979 - 2006

Coefficient on RSH	All (1)	Males (2)	Females (3)
Panel 1: Baseline	.104*	.026	.254***
	(.058)	(.072)	(.078)
Panel 2: Alternative RSH measure			
50% most routine	.126**	.031	.281***
	(.055)	(.066)	(.082)
25% most routine	.164***	.118*	.220***
	(.051)	(.063)	(.083)
Panel 3: Spatial error models			
Inverse distance weighting	.101*	.022	.253***
	(.054)	(.068)	(.075)
Contiguity weighting	.100*	.026	.247***
	(.053)	(.062)	(.075)
Panel 4: Stacked first differences	.052*	.000	.148***
	(.029)	(.034)	(.054)
Panel 5: Exclude border regions	.087	.024	.197**
($N = 171$)	(.062)	(.078)	(.087)
Panel 6: Contemporaneous changes	.094*	.041	.208***
	(.053)	(.067)	(.072)

Notes: $N = 204$ labor market regions. Each cell reports the coefficient on the routine share for one separate regression. All models include a constant, dummies for the federal state in which the region is located, a measure of population density as well as the covariates listed in Table 4. Regressions in Panel 4 additionally include time dummies. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

unification in 1990. For regions in close proximity to the former border, we may be concerned that our results are driven by exogenous increases in the labor supply due to migration following the fall of the wall. To rule out that this development drives our overall result, we exclude labor markets along the border. The results in Panel 5 are consistent with the results from the baseline specification. We further tested the generality of our results by experimenting with different subsamples depending on the size and the region type of the specific labor market. We obtain similar results considering urban or rural regions separately or estimating models for large (population>200 T in 1979) and small (population<=200 T in 1979) regions. Further, the conclusions of our analysis remain unaltered by the selection of different start and end dates.[10]

Finally, we repeat the OLS estimation using contemporaneous changes of the regional covariates instead of their 1979 levels. The resulting coefficients presented in Panel 6 are comparable in magnitude to the prior specifications. Nevertheless, it should be clear that some of these contem-

[10]Results are available from the authors upon request.

poraneous changes in the workforce composition are a result of technological change themselves (Autor and Dorn, 2013).

3.3 Employment and Wage Changes in Major Occupational Groups

The preceding analysis has shown that regional technology exposure is highly predictive of declining routine and rising non-routine employment, equally pronounced for men an women. It has also established a positive relationship between technological change and employment reallocation towards service occupations, although this development is restricted to female employees. To investigate further reallocation patterns, we now broaden the focus of our analysis beyond service employment and analyze employment changes in all other major occupational groups. The results are depicted in Table 6. In addition to service occupations, construction occupations and professional jobs are characterized by a high level of non-routine task contents. Theoretically, the share of these occupations in overall employment should increase - similar to what is observed in service occupations. In contrast, occupations with high routine task requirements, i.e. clerical and production occupations, should decline. In columns 1 to 3 of Panel A, we analyze the relationship between technological change and employment growth in non-routine intensive occupations. While employment gains in service occupations are realized by women only (column 1), column 2 highlights a differential reallocation of male employment into construction occupations. The coefficient of .197 is statistically highly significant and implies that a 7.4 percentage point higher routine share in 1979, equal to the gap between the 85th and the 15th percentile labor market, predicts a 1.5 percentage points higher increase in the employment share of construction occupations between 1979 and 2006. The estimates for professional occupations (e.g. scientist, professionals, teachers) are very small in magnitude and statistically insignificant for both males and females. This is not surprising, given that this group of occupations primarily employs workers with tertiary education which are excluded from our sample.

Columns 4 and 5 of Panel A present the results for two occupation groups with a high level of routine employment in 1979: clerical and sales occupations (e.g. bookkeeper, accountants, sales personnel) and blue-collar production occupations. The results verify that employment losses in routine-intensive occupations are more pronounced in routine-intensive regions, although the coefficients for clerical occupations are imprecisely estimated.

Table 6: Technology Exposure and Change in Occupational Employment, 1979 - 2006

		Service occ.	Construction occ.	Professionals/ Education	Clerical/ Sales	Production occ.
Panel A: Employment changes		(1)	(2)	(3)	(4)	(5)
I: All	Routine Share 1979	.104*	.197***	.012	-.059	-.254***
		(.055)	(.056)	(.048)	(.072)	(.096)
II: Males	Routine Share 1979	.033	.268***	-.033	-.059	-.208*
		(.069)	(.087)	(.063)	(.068)	(.109)
III: Females	Routine Share 1979	.241***	-.005	.085	-.022	-.298**
		(.075)	(.022)	(.057)	(.107)	(.121)
Panel B: Wage changes						
I: All	Routine Share 1979	-.010	.257***	.020	-.088*	.045
		(.039)	(.050)	(.045)	(.044)	(.042)
	N	140,485	80,907	80,106	160,944	253,620
II: Males	Routine Share 1979	.053	.247***	.076	.089	.048
		(.042)	(.050)	(.053)	(.057)	(.042)
	N	92,414	79,642	55,270	60,857	198,913
III: Females	Routine Share 1979	-.161**	.121	-.148*	-.184***	.063
		(.071)	(.888)	(.084)	(.057)	(.065)
	N	48,071	1,265	24,836	100,357	54,707

Notes: Panel A: $N = 204$ labor market regions. All models include a constant, dummies for the federal state in which the region is located, a measure of population density as well as the covariates listed in Table 4 Robust standard errors in parentheses.
Panel B: Regression models include an intercept, region-occupation group fixed effects, time trends for occupation groups and states, two dummies for education levels, a quartic in potential experience, dummies for foreign-born, and interactions of all individual level controls with the time dummy. Pooled sex models also include a female dummy and its interaction with the time dummy. Observations are weighted by each worker's number of days worked in the respective year. Robust standard errors are clustered on the level of regions. * Significant at 10%, ** at 5%, *** at 1%.

To allow for further heterogeneity of the employment effects, we additionally split the overall sample into subsamples bifurcated by age (age 20-39 vs. age 40-60), education (low- and medium-skilled) and working-time arrangement (full-time vs. part-time) and present the results in Appendix Table 1. Employment patterns are very similar across the subsamples with some notable exceptions. The decline in routine-intensive occupations alongside a more pronounced reallocation towards service and construction occupations is more pronounced for older workers. For younger workers, the patterns are similar yet the coefficients are substantially smaller in size, resulting in estimates that are statistically insignificant (columns 1 and 2).[11] We also observe that employment of low- and medium-skilled workers evolves similarly. Notably, declines in production occupations

[11] This is in line with evidence presented by Autor and Dorn (2009), showing that the decline in routine-intensive jobs for older workers is almost entirely absorbed by employment gains in non-routine manual occupations.

are mainly realized by low-skilled employees, while medium-skilled workers experience employment losses in clerical and sales occupations. This is in line with descriptive evidence in Table 3, which shows that clerical and sales occupations have on average higher education levels compared to production occupations. Finally, the results separated by working-type indicate that full-time employment declines in both routine-intensive occupation groups and is offset by employment growth in construction occupations and to a somewhat smaller extent in services. Part-time employment on the other hand decreases mainly in production occupations and relocates solely towards services. However, the coefficients for part-time workers are less precisely estimated due to smaller sample sizes.

The spatial model by Autor and Dorn (2013) predicts that together with employment polarization, routine-intensive labor markets should experience a more pronounced earnings growth at both tails of the wage distribution. To analyze the relation between technological progress and wage changes, we pool wage data for the years 1979 and 2006 to regress log daily wages of individual i, in region r, state s, occupation k and time t on the main predictive variable RSH_r, separately for each of the five occupational groups:

$$\ln w_{irkts} = \alpha + \beta_1 \left(RSH_r \times \mathbb{I}\left[t = 2006\right]\right) + \mathbf{X_i}'\beta_2 + \phi_{rk} + \gamma_{ts} + e_{irkt}. \tag{7}$$

In this setting, the technology exposure variable is interacted with a dummy for the year 2006, thus reflecting the relationship between regional routine intensity in 1979 and subsequent wage growth. The regression is augmented with individual-level covariates (gender, education, nationality, a quartic in potential experience), their interactions with time dummies as well as region-occupation and time-state fixed effects. Because the main explanatory variable, RSH_r does not vary within regions, standard errors are clustered at the level of local labor markets (Moulton, 1986). The wage estimates are summarized in Panel B of Table 6. Most importantly, the pronounced increase in female service employment coincides with significant wages losses in this employment category. The coefficient of -.161 translates into a 1.2 log points larger decline in wages in a region at the 85th percentile of the distribution compared to the 15th percentile. These countervailing developments of employment and wages provides no evidence for increasing demand for personal services which contradicts findings for the United States. In contrast, employment gains in construction occupations realized by male workers are accompanied by significantly stronger wage growth in routine-intensive regions. A 7.4 point higher routine share in 1979 translates into larger wage growth by 1.8 log points.

Surprisingly, employment declines in routine-intensive occupations coincide with wage gains for male workers, although the estimates are rather small in size and imprecisely estimated. A potential explanation for this opposite movement of employment and wages are the pronounced within-occupational task shifts from routine to non-routine cognitive tasks (Senftleben-König and Wielandt, 2014). Hence, the remaining workers may be a selective group with higher average skill and wage levels. For production occupations, a strong exporting sector in Germany offers a further explanation for stable wages (Dauth, 2013).

Altogether, our analysis provides robust evidence for a technology-related reallocation of labor supply from routine to non-routine manual tasks, a finding that is consistent with results obtained for the US by Autor and Dorn (2013). Although this development has been observed for males and females, we find some gender-specific adjustment patters when considering occupational shifts, which are dissimilar to the United States. In particular, our analysis shows that female employees cluster in service occupations, while male employees experience increases in construction occupations. Further, in contrast to findings for the US, employment growth in service occupations was accompanied by significant wage *losses* of this occupational group. One interpretation of this pattern is that the rising supply of service occupations was not met by sufficient demand increases in Germany, which might be depressed by higher payroll taxes, eventually resulting in more home- than market-based production (Freeman et al., 2005; Burda et al., 2007). This argument is in line with several other studies which document that many European countries seem to be missing personal services such as retail trade or hotel and restaurant employment (Piketty, 1997).

3.4 Alternative Adjustment Mechanisms

In this section, we complement our analysis of employment and wage changes and consider the impact of technological progress on other labor market outcomes. First, we explore whether technological change induced a reallocation of employees towards regions that are less affected by computerization. If labor flows are perfectly mobile across regions, workers should adjust to regional technology shocks by relocating between regions. Then, the impact of technological change would unfold through regional migration patterns instead of occupational shifts. To test for technology-induced population shifts, we regress the change in regional net migration shares of low- and medium-skilled employees between 1979 and 2006 on the routine share measure.[12] The model is estimated for the overall sample as well as separately by gender. The negative coefficients in the first two columns of Panel A in Table 7 suggest that regions that were prone to technological change experienced higher outward-migration. The negative coefficient of -.023 suggests a differential outward migration of .17 percentage points in a region at the 85th percentile of the routine share distribution compared to a region at the 15th percentile. The coefficients for male workers (columns 3 and 4) are considerably larger than their female counterpart, indicating that adjustments along the margin of migration are more pronounced for males. However, the coefficients for both subsamples are imprecisely estimated, presumably due to small sample sizes.

One further margin of adjustment to technological change is selection into unemployment. We test for this possibility by exploring the relationship between technology exposure and subsequent changes in the regional unemployment rate between 1981 and 2004.[13] The positive coefficients for the overall sample in Table B of Table 7 imply a differential increase in the unemployment rate in regions that were initially routine-intensive. Yet, with the inclusion of additional covariates (column 2), the magnitude of the point estimate declines by about half of its size and turns insignificant.[14] The separate results for male and female employees reveal no gender-specific differences in unemployment effects. Both coefficients are similar in magnitude and insignificant at conventional levels when the control variables are included.

These findings, in combination with the results on occupational changes, suggest that the adjustment to technological change mainly occurred via the margin of employment, while there have been little or no technology-related shifts in migration patterns or unemployment. These findings are in line with existing literature on regional adjustments to labor market shocks, which shows that responses in regional mobility are relatively slow and incomplete, particularly among less-educated workers (Glaeser and Gyourko, 2005; Notowidigdo, 2011; Dauth et al., 2014). Furthermore, it has been shown that internal migration in Europe is much lower than in the US (Decressin and Fatàs,

[12] We use the information from the SIAB-R to compute regional net migration shares for the years 1979 and 2006. In this context, migration is defined as a job change when the new job is in a different labor market than the previous one. As our definition builds upon job changes, and not simply changes of the place of residence, it fits well with the purpose of our analysis. Further details are discussed in the Data Appendix.

[13] The unemployment rate is computed using the benefit recipient history included in the SIAB-R. Due to data limitations we are restricted to the shorter time period. See the Data Appendix for details on the construction of the unemployment rate and robustness checks.

[14] Employment changes for the shorter time period from 1981 to 2004 are similar in magnitude and significance to our previous results for the longer time span between 1979 and 2006.

Table 7: Estimated Impact of Technology Exposure on Net Migration and Regional Unemployment

	I. All		II. Males		III. Females	
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Δ Net migration share 1979-2006					
Routine Share 1979	-.018	-.023	-.022	-.035	-.005	.001
	(.026)	(.025)	(.037)	(.038)	(.028)	(0.030)
R^2	.063	.121	.050	.097	.039	.049
	B: Δ Unemployment rate 1981-2004					
Routine Share 1979	.095**	.053	.090*	.060	.111**	.052
	(.042)	(.040)	(.050)	(.051)	(.044)	(.043)
R^2	.343	.391	.342	.392	.216	.276
Regional covariates	no	yes	no	yes	no	yes

Notes: $N = 204$ labor market regions. All regressions include a constant, dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer), and regional covariates listed in Table 4 as indicated. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

1995; Nahuis and Parikh, 2002) and that adjustment processes to shocks occur mainly via lower participation rates.

4 Conclusion

In recent decades, the employment structures of many industrialized countries have undergone substantial changes. This paper examines the relation between technological progress and employment and wage polarization in Germany at the level of local labor markets. To do so, we exploit variation in the degree to which regions are exposed to technological change, as determined by local task structures.

Our results suggest that regions that were initially specialized in routine tasks adopted information technology faster and witnessed a larger displacement of routine employment. At the same time, these regions experienced a differential growth of occupations in which non-routine manual tasks are prevalent. We show that among these occupations, particularly the growth of the personal service sector contributed to the twisting of the lower tail of the employment distribution. Yet, our results suggest that the growth of service employment is gender-specific and exclusively attributable to employment growth of female workers. Men, instead, relocate towards construction occupations. While the employment results are generally consistent with findings for the US, our wage analysis has shown that supply increases in service occupations were accompanied by significant wage losses of this group. Hence, our results highlight the importance of demand side factors when exploring the impact of technological change on the wage structure. We also investigated the possibility of inter-regional mobility and selection into unemployment as a response to technological change, but find no robust support for adjustments along these margins.

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A Data Appendix

A.1 Processing SIAB Data and Sample Description

All information concerning local employment and wages are obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies that provides detailed information on daily wages for employees subject to social security contributions. We express employment in full-time equivalents, following the weighting procedure as proposed by Dauth (2013) and weigh part-time employment using information on whether an individual works full-time, major part-time or minor part-time: labor supply of individuals working minor part-time (less than 18 hours) is multiplied with 16/39 and major part time (18 to less than 39 hours) is multiplied by 24/39, respectively.

In our analysis we exclude marginal employment as this information is only available from 1999 onwards and delete parallel employment spells. If available, missing values for nationality, occupation and location of an individual are imputed based on the most recent spells of the same individual. Workers are classified based on their vocational education using the imputation algorithm developed by Fitzenberger et al. (2006) and education levels are aggregated into three groups: employees with no occupational training are considered as having a *low* level of education; employees with a vocational occupation who have completed an apprenticeship or graduated from a vocational college are classified as *medium* educated and employees holding a university or technical college degree are considered *highly* educated.

In our wage analysis we restrict the sample to full-time employment as employment and wage information is reported on a daily basis and lacks information on hours worked. Therefore, wages for part-time employment are measured less accurately. All wages are converted in Euros at constant 2000 prices using the German consumer price index (CPI) for all private households. As price level data and price indices are not available at the regional level we are forced to use a common deflator for all labor market regions. We correct for the right-censoring of wage records at the social security contribution threshold by imputing and replacing the topcoded wages following Gartner (2005). We run a series of tobit regressions of log wages in each year, separately by gender and the three education groups, including age and its square, a vector of region fixed effects and a set of industry and occupational fixed effects. Topcoded wages are then replaced by draws from normal distributions that are truncated and whose moments are determined from the tobit estimation. Since 1984, one-time and bonus payments have been included in the wage measure, resulting in a spurious increase in earnings inequality (Steiner and Wagner, 1998). We account for this structural break by correcting the wage observations before 1983 following Fitzenberger (1999) and Dustmann et al. (2009). As the additional payments generally only affect relatively high wages, it is assumed that only wages above the median need to be corrected. Hence, we run a linear regression of wage growth, where wage growth up to the median is assumed to be constant. The percentage difference between the quantile from the upper half of the distribution and the median can be interpreted as “excessive” wage growth and is used to correct wages before 1983. We thank Bernd Fitzenberger and Christian Dustmann for making the correction program available to us. Results of these regressions are available upon request.

Due to data protection reasons the SIAB-R is anonymized and occupational information is aggregated to 120 occupation groups. However, occupations are unambiguously assignable to the three-digit 1988 occupational classification which we use to construct occupational task information in the BIBB/IAB qualification and career survey.

A.2 Computing Regional Unemployment and Migration Rates using SIAB-R

Unemployment Rates

For the construction of regional unemployment rates separately by gender we rely on the benefit recipient history included in the SIAB-R, which provides information on periods during which individuals receive earnings-replacement benefits (unemployment benefit, unemployment assistance and maintenance allowance) from the Federal Employment Agency (Bundesagentur für Arbeit, BA). Due to data limitations we are forced to conduct our analysis on unemployment responses for the shorter time period 1981 to 2004. On the early end we are limited because the benefit receipt data up to and including 1980 are only partially recorded (Dorner et al., 2011). A change in legislation in 2005 limits a consistent analysis of unemployment trends after this year.

We measure the regional unemployment rate as the sum of days residents were registered as unemployed relative to total days worked in a given year and a given region. With the data stemming from the SIAB-R, we are restricted to unemployment information of workers who were previously employed subject to social security contributions. To validate the robustness of our results, we compare our self-computed unemployment rate with administrative records provided by the Statistics Department of the German BA that publishes a time series on district level data on the overall unemployment rate starting in 1985. Unfortunately, further splits by age groups, gender and citizenship are only available at the district level from 1998 onwards. Our self-computed measure and the official unemployment rate are highly correlated in the years after 1985, with the correlation coefficient varying between .81 and .92. In addition, we regress the change in the unemployment rate for the pooled sample between 1985 and 2004 (were we have reliable data from both sources) on the routine share in 1979 using both definitions of the unemployment rate and obtain similar coefficients from both specifications. All results are available from the authors upon request.

Migration Rates

Unfortunately, official data on the number of inward- and outward-migrants on the regional level separately for males and females is not fully available from 1979 on. Therefore, we construct migration shares for the years 1979 and 2006 using information on the workplace location available in the SIAB-R. Total regional inmigration is defined as the sum of workers, who have changed job from some region into a certain region. Analogously, total outmigration is defined as the sum of workers in one region, who have changed their jobs towards a workplace that is located in a different region.

B Table Appendix

Table 1: Estimated Impact by Age, Education and Working Time, 1979 - 2006

	Outcome measures among:					
	Age<40	Age≥40	Low-skilled	Medium-skilled	Part-time	Full-time
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Services			
Routine Share 1979	.097	.160**	.143	.037	.313	.114**
	(.070)	(.079)	(.132)	(.060)	(.201)	(.056)
R^2	.170	.109	.139	.129	.167	.177
			Panel B: Construction			
Routine Share 1979	.126**	.307***	.227***	.191***	.002	.186***
	(.062)	(.085)	(.086)	(.062)	(.030)	(.058)
R^2	.257	.293	.217	.291	.078	.259
			Panel C: Professional, Managerial, Technical			
Routine Share 1979	.026	-.006	-.021	.012	.088	.015
	(.054)	(.067)	(.047)	(.062)	(.148)	(.051)
R^2	.150	.108	.220	.164	.108	.145
			Panel D: Clerical, Sales			
Routine Share 1979	-.074	-.077	.075	-.137*	-.044	-.063
	(.083)	(.093)	(.108)	(.076)	(.185)	(.075)
R^2	.147	.263	.194	.222	.296	.198
			Panel E: Production, Operators			
Routine Share 1979	-.175	-.385***	-.423**	-.103	-.360*	-.251**
	(.112)	(.107)	(.199)	(.106)	(.218)	(.101)
R^2	.189	.222	.200	.215	.461	.229

Notes: $N = 204$ labor market regions. All models include a constant, dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer) as well as the covariates listed in Table 4. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

C Figure Appendix

Figure 1: Distribution of Routine Share 1979