Technological Change, Polarization and Inequality: Employment and Wage Patterns in German Local Labor Markets

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Abstract

This thesis studies the role of technological change as a determinant of employment and wage trends in Germany over the past 30 years. The econometric analysis exploits spatial variation in the exposure to technological progress which arises due to initial regional specialization in routine task-intensive activities. The empirical evidence suggests that the occupational structure of labor markets that were particularly susceptible to technological change has polarized, as employment shifted from middle-skilled routine clerical and production occupations not only to high-paying professional occupations but also to low-paying service and construction occupations. Building on these results, the second essay explores whether and to what extent increasing labor market inequality within and across regions is driven by technological change and establishes a positive link between intra-regional wage inequality and computerization. Because of substantial variation in the degree of technology exposure across German regions, technological change can also in part explain rising inter-regional wage inequality. The third essay investigates the interaction between polarization in the native labor market and employment opportunities of immigrant workers in Germany. The findings are consistent with a technology induced reallocation of labor from middle-paying routine tasks towards lower-paying non-routine manual tasks inducing additional competitive pressure in this labor market segment in which immigrant workers are typically employed. Finally, the fourth essay provides an empirical analysis of the diverging patterns of employment in temporary help services across labor markets in Germany over the last 30 years. The differential growth pattern both at the level of occupations and across regional labor markets are found to be related to the initial intensity of routine and non-routine manual tasks.

Keywords:
Labor economics, local labor markets, polarization, job tasks, technological change, wage inequality, immigration, temporary help services

Zusammenfassung

Die vorliegende Dissertation umfasst vier Essays, in denen die Rolle von technologischem Fortschritt für die Beschäftigungs- und Lohnentwicklung in Deutschland in den vergangenen 30 Jahren untersucht wird. Die empirische Analyse nutzt die räumliche Variation in der Verteilung der Beschäftigungsanteile von Routinetätigkeiten, die durch Informationstechnologien substituierbar sind. Die Ergebnisse zeigen, dass Arbeitsmärkte, die besonders durch Automatisierung betroffen sind, eine stärkere Polarisierung der Berufsstruktur zwischen 1979 und 2006 erfahren haben, d.h. eine Verschiebung der Beschäftigung von Routineberufen (Büro- und Produktionsberufe) hin zu kognitiven und manuellen Nicht-Routineberufen (Fach- und Führungskräfte bzw. Dienstleistungsberufe). Aufbauend auf diesen Ergebnissen zeigt der zweite Aufsatz, dass technologischer Fortschritt positiv zu intra- und interregionaler Lohnungleichheit beiträgt. Der dritte Aufsatz untersucht die Wechselwirkung zwischen dem durch technologischen Wandel getriebenen Beschäftigungsanstieg am unteren Ende der Lohnverteilung und Beschäftigungschancen von Arbeitnehmern mit Migrationshintergrund. Die Ergebnisse stehen im Einklang mit der Hypothese, dass der technologisch bedingte Rückgang in der Nachfrage nach Routinetätigkeiten und die damit verbundene Reallokation in Berufe mit geringem Qualifikationslevel zu einem Anstieg des Wettbewerbsdrucks im Niedriglohnsektor führt, in dem ausländische Arbeitnehmer oftmals Beschäftigung finden. Der vierte Aufsatz beschäftigt sich mit der langfristigen Entwicklung der Zeitarbeit in den regionalen Arbeitsmärkten in Deutschland in den vergangenen 30 Jahren und zeigt, dass die anfängliche Verteilung der Beschäftigungsanteile für manuelle Nicht-Routinetätigkeiten und insbesondere für Routinetätigkeiten eine starke Vorhersagekraft für das regionale Beschäftigungswachstum von Zeitarbeit in Deutschland besitzt.

Schlagwörter:
Arbeitsmarktökonomik, lokale Arbeitsmärkte, Polarisierung, Tätigkeiten, Technologischer Wandel, Lohnungleichheit, Einwanderung, Zeitarbeit

To my family

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1 Introduction

"Innovation, the elixir of progress, has always cost people their jobs. In the Industrial Revolution artisan weavers were swept aside by the mechanical loom. Over the past 30 years the digital revolution has displaced many of the mid-skill jobs that underpinned 20th-century middle-class life. Typists, ticket agents, bank tellers and many production-line jobs have been dispensed with, just as the weavers were."

Economist (Jan 18th, 2014)

1.1 Technological Change, Employment Polarization and Inequality

This dissertation attempts to develop a deeper understanding of technological progress as one determinant shaping employment and wage patterns and the resulting challenges for local labor markets in Germany. The rapid diffusion of technological innovation is an ongoing source of interest both to policymakers and researchers in many academic disciplines. Over the past decades, technological progress in general and advances in information and communication technologies in particular have altered the division of labor. The production process can now be divided into a series of tasks (Bresnahan et al., 2002; Autor et al., 2003) whereby tasks that are well-defined and follow explicit rules are particularly susceptible to substitution by computer technology (Autor et al., 2003). Using US data, Frey and Osborne (2013) predict which jobs are most likely to be automated within the next two decades and show that about 47 percent of total US employment is at risk. Building on a seminal paper by Autor et al. (2003), Frey and Osborne distinguish the tasks along two dimensions: routine versus non-routine and cognitive versus manual. So far, routine-intensive occupations (e.g. blue-collar manufacturing, accounting and bookkeeping jobs) are most susceptible to automation. Meanwhile, jobs that depend on non-routine cognitive and manual tasks such as high-skilled professional jobs involving high complexity and problem-solving but also low-paying service occupations that require environmental and interpersonal adaptability may continue to exist. Accordingly, Frey and Osborne (2013) forecast that telemarketers, salespersons and accountants face a very high probability that computerization will lead to job losses in their profession, while dentists, recreational therapists and editors do not. Certainly, tasks that cannot be replaced by computers right now might be in the future and the pace of technological innovation is in fact accelerating (Brynjolfsson and McAfee, 2014). Google's robotic car Stanley is rolling around California driver-free, an evolution that seemed very unlikely only ten years ago. Consider two other examples in the race man versus machine: In 1996, Deep Blue - a chess-playing computer developed by IBM - won against the grandmaster at chess Garri Kasparow. In 2011, former winners Brad Rutter and Ken Jenning were defeated by IBM's supercomputer Watson on the American television game show "Jeopardy!" that not only requires general knowledge but also natural language processing and syntactic understanding.[1] Given these rapid changes, understanding how technology is shaping the modern workplace and how it affects employment structures, employment prospects and wages is worthwhile pursuing. Further, heterogeneous labor implies that technological progress will not benefit all workers in the same way which has implications for labor market inequality. As the market value of certain tasks changes due to technological innovation especially cognitive abilities and personnel skills will become even more relevant. However, despite better education the abilities will still be unevenly distributed. Understanding these links is crucial for designing targeted and needs-oriented skills development for the population of all ages, migration background and gender.

There has always been a vivid discussion about the impact of technological change. The idea that technological progress can lead to rising inequality and higher unemployment dates back to the 1930's when British economist John Maynard Keynes (1930, p. 3) suggested that "[...] our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor [will result in] technological unemployment". Nowadays, the consensus view is that technological change has been skill-biased in that it complements high-skilled work and increases the demand for skilled jobs relative to unskilled jobs resulting in monotone employment and wage growth along the wage (skill) distribution. A recent wave of research has challenged the traditional skill-biased technological change (SBTC) hypothesis and illustrated that the diffusion of computer technology brought about by tremendous real price declines is related to another stylized fact in many industrialized countries: employment is becoming increasingly concentrated at the tails of the occupational skill distribution. A series of papers has linked this hollowing out of the employment structure to the displacement of middle-paying routine-intensive occupations and the title of a seminal paper by Goos and Manning (2007) "lousy and lovely jobs" captures the essence of this trend.[2] Due to their substitutability with computer capital, routine tasks are most affected by technological changes. Driven by real price declines, the task-based framework predicts a reallocation of employment away from routine task-intensive occupations that are typically located in the

[1] See Brynjolfsson and McAfee (2014) for those and more examples.

[2] Autor and Acemoglu (2011) provide an extensive literature overview. The polarizing pattern of employment has been documented for the United States (Autor et al., 2006, 2008), Germany (Spitz-Oener, 2006; Dustmann et al., 2009), Great Britain (Goos and Manning, 2007) and other industrialized countries in general (Goos and Manning, 2007; Michaels et al., 2014; Goos et al., 2014).

middle of the wage distribution towards non-routine tasks that are located at both tails of the distribution, thereby inducing employment polarization. In contrast to the traditional SBTC hypothesis, the task-based framework especially allows for employment increases in low-skilled non-routine manual activities that are neither a substitute nor a complement to computer capital.

The concept of tasks has initially been applied to study technological progress and its role for wage and employment patterns. The concept that routine tasks are not only easily codified and computerized, but also easy to explain and easy to monitor, has inspired further research on the tradeability of tasks and has complemented the existing trade literature (Blinder, 2006; Grossman and Rossi-Hansberg, 2008). Similar, Peri and Sparber (2009) advance the literature on the impact of immigration on native employment and wages by adopting the task framework. The authors empirically show that task specialization according to comparative advantages can explain why wage consequences of immigration are only modest for low-skilled natives. So far, the link between technological progress and wage and employment outcomes is largely unstudied for Germany. The four essays that form this dissertation intend to close this gap and are concerned with different aspects of technological change and its role for employment and wage changes in German local labor markets as well as employment opportunities of underrepresented groups. The spatial approach adopted in this dissertation builds on recent work by Autor and Dorn (2013) and advances the existing literature on technological change and its consequences for labor market outcomes that has so far mainly focused on trends at the aggregate level.

1.2 Outline Of This Thesis

The first essay of this thesis (chapter 2) analyzes the link between changes in the task structure as a consequence of technological progress and recent employment and wage trends at the lower tail of the German wage distribution. The study exploits spatial variation in the exposure to technological change which arises due to initial regional specialization in routine task-intensive activities on the level of local labor markets. The results suggest that regions that were initially specialized in routine tasks adopted information technology faster and witnessed a larger decline of routine employment. Empirical evidence confirms 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 not only to high-skilled professional occupations but also to less-skilled non-routine manual and service occupations. The empirical findings reveal that occupational shifts are gender-specific, with gains in service employment being exclusively realized by female employees. Yet, the overall polarization phenomenon as well as the relationship between the task structure and service sector employment on the regional level is less pronounced compared to findings for the United States. The empirical findings further suggest that technological change contributes to a dispersion of the wage structure rather than wage polarization as documented for the US.

The analysis in chapter 3 extends the research focus of the previous chapter by relating technological progress to spatial changes in labor market inequality over the last 30 years. The rapid diffusion of computer capital coincides with increasing wage inequality in Germany both within and across regions. Building on concepts of the task-based approach, this study explores whether and to what extent these developments are related. The study first presents novel evidence of spatial variation in task supply and task compensation. It further establishes a positive link between technological change and increasing wage inequality which is driven by increases in the compensation for non-routine cognitive tasks that are prevalent at upper percentiles of the wage distribution combined with decreases in the compensation for non-routine manual tasks that are located at lower percentiles. Because there exists substantial variation in the degree of technology exposure across German regions, technological change can also in part explain rising inter-regional wage inequality.

In the study that forms the basis of chapter 4, I expand the perspective and explore the interaction between employment polarization of the native labor market and employment and wage opportunities of immigrant workers. The empirical results suggest that, since 1981, employment rates of immigrant workers fell more in labor market regions for which the share of natives in low-paying occupations increased the most. The findings are consistent with a model of local labor markets for which the reduction in the demand for routine tasks and the associated reallocation of natives towards low paying occupations induces stronger competition in the low-skill labor market, a segment in which foreign workers are typically employed. The findings show that this relationship is more relevant for recent immigrants who have been in Germany for less than 5 years and that approximately one third of the decline in employment rates could be associated with occupational polarization of native employment.

Chapter 5 is concerned with the question whether diverging patterns of the use of temporary help services (THS) across local labor markets in Germany can be traced back to long run differences in the structure of local labor demand. Building upon concepts of the task and trade-in-task literature, it first documents that the task content of occupations is a strong predictor whether some type of work can be shifted into temporary help services. At the level of regional labor markets, the results suggest that long-run differences in the intensity of routine and non-routine manual tasks in local employment have some robust explanatory power for the differential spread of THS employment across Germany in the last 30 years.

All four subsequent chapters are supposed to be self-containing and can be read independently. Chapter 2 and 3 are based on joint work with Charlotte Senftleben-König. Chapter 5 is co-authored with Jan Peter aus dem Moore and Alexandra Spitz-Oener.

2 The Polarization of Employment in German Local Labor Markets

2.1 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. This has been documented for the US (Autor et al., 2006, 2008) and many other industrialized countries (Spitz-Oener, 2006; Goos and Manning, 2007; Goos et al., 2009b, 2014; Michaels et al., 2014).[1] As illustrated in Figure 2.1, 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 chapter 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 produc-

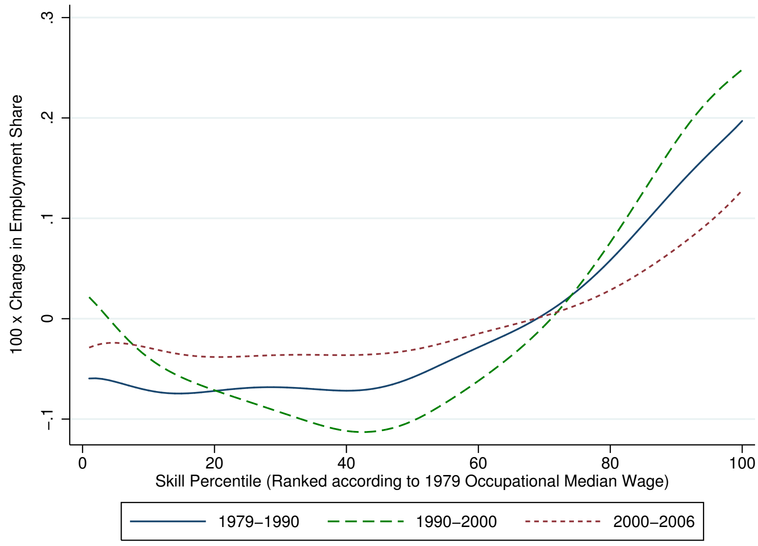
[1]For the US, Autor et al. (2006) show that medium-skilled employment has deteriorated relative to low- and high-skilled employment starting in the 1990's, corroborating the conjecture that technological change is rather task- than skill-biased. Goos and Manning (2007) find similar trends for Great Britain, showing that employment in occupations with the lowest and highest median wages in 1979 grew in subsequent decades, while employment in the middle of the distribution declined. Goos et al. (2009b, 2014) provide evidence for labor market polarization based on a cross-country comparison using data from the European Union Labour Force Survey.

tivity 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 2.2 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, while routine and non-routine manual tasks are mainly performed by less-skilled workers.

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.

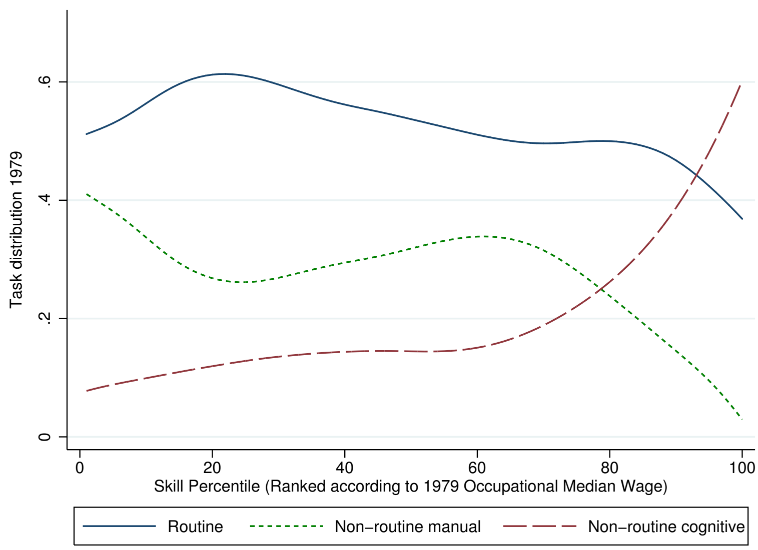
To our knowledge, we are the first to test the implications of the model proposed by Autor and Dorn (2013) for the German labor market. We show that local labor markets differ substantially in the degree to which they employ routine task performing labor. Given the initial task specialization, regions 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 employment 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

Figure 2.1: 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 2.2: Task Inputs by Skill Percentile



Notes: Shares of workers performing routine, non-routine manual and non-routine cognitive tasks. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.. Occupations are ranked according to their 1979 median wage using the SIAB-R. Task intensity is derived from the QCS wave 1979 and defined as in equation 2.3.

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 evidence for wage dispersion rather than compression at the lower tail of the wage distribution (Dustmann et al., 2009; Kohn, 2006; Antonczyk et al., 2010b, 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 chapter proceeds as follows. In section 2.2, we describe the empirical approach, the data set and the variables used in our analysis. Section 2.3 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 2.4 concludes.

2.2 Data and Methods

2.2.1 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:

$$\Delta Y_r = \alpha + \beta_1 RSH_r + \mathbf{X_r'}\beta_2 + \gamma_s + e_r. \tag{2.1}$$

Depending on which of the aforementioned hypotheses is tested, the dependent variable Y_r represents the change in one of the following measures in region r 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.

2.2.2 Data and Construction of Variables

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 and 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 (males and females) between 20 and 60 years

[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 Table 2.5, section 2.3.2.

[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.

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 (Gruhl et al., 2012). 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 2.1.

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 (Rohrbach-Schmidt, 2009). 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):

$$TM_i^j(1979) = \frac{\text{\# of activities in category } j \text{ performed by } i \text{ in 1979}}{\text{total \# of activities performed by } i \text{ over all categories in 1979}} \times 100, \quad (2.2)$$

where $j = C$ (non-routine cognitive), R (routine) and 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 $L_{ik}(1979)$:

$$TI_k^j(1979) = \left(\sum_i \left[L_{ik}(1979) \times TM_{ik}^j(1979) \right] \right) \left(\sum_i L_{ik}(1979) \right)^{-1}. \quad (2.3)$$

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:

$$T_r^j(t) = \left(\sum_k \left[L_{kr}(t) \times TI_k^j(1979)\right]\right)\left(\sum_k L_{kr}(t)\right)^{-1}, \tag{2.4}$$

where $L_{kr}(t)$ is employment in occupation k in labor market r at 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 2.1. 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 2.1 confirms that the prevalence of personal computers at the workplace has increased tremendously from 5% in 1979 to 75% in 2006.

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:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI_k^R > TI_k^{R,P66}\right]\right)\left(\sum_k L_{kr}\right)^{-1}, \tag{2.5}$$

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 6.1 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 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 2.1: Descriptive Statistics for 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.

[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.

2.3 Results

2.3.1 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 2.6:

$$\Delta PC_r = \alpha + \beta_1 RSH_r + \beta_2 dens_r + \gamma_s + e_r. \tag{2.6}$$

The results, displayed in the first column of Table 2.2, 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 2.6, 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 2.2 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

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

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 workers who formerly engaged in routine tasks.

Table 2.2: 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 chapter 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, 2014a).

[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.

2.3.2 The Growth of Personal Service Sector Employment

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 2.1, 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 2.3 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 2.3 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 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 2.3. 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

[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 2.3: 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: based on SIAB-R. 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).

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.

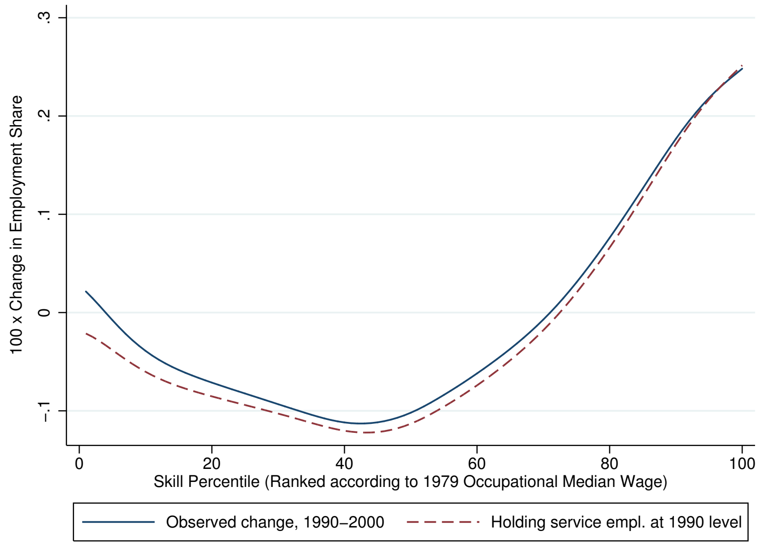
Baseline Estimates

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 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 2.1, where the dependent variable is the change in the share of service employment in overall employment between 1979 and

[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.

Figure 2.3: 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-R. To construct the counterfactual we keep service employment at its 1990 level. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.

2006. The positive and significant estimate, displayed in column 1 of Table 2.4, 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 employment, the model is augmented step-by-step by additional control variables as displayed in the remaining columns of Table 2.4. 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

Table 2.4: 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%.

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 supports 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 compared to male workers and higher levels of non-routine manual task inputs (see Table 2.3), 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 2.4. 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 regional routine share 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.

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 2.5. 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]

[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

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.

Table 2.5: 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)
Continguity weighting	.100*	.026	.247***
	(.053)	(.062)	(.075)
Panel 4: Stacked first differences	.052*	.000	.148***
($N = 612$)	(.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 (unless stated otherwise). 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 2.4. Regressions in Panel 4 additionally include time dummies. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

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

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.

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

2.3.3 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 2.6. 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.

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

Table 2.6: 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 2.4. 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 6.2. 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 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 2.3, which shows that clerical and sales occupations have on average higher education levels

[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.

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:

$$\ln w_{irkts} = \alpha + \beta_1 \left(RSH_r \times \mathbb{I}\left[t = 2006\right] \right) + \mathbf{X_i'}\beta_2 + \phi_{rk} + \gamma_{ts} + e_{irkt}. \tag{2.7}$$

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 2.6. Most importantly, the pronounced increase in female service employment coincides with significant wage 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 provide 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, 2014a). 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 et al., 2014).

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* in 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., 2013). 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, 1998).

2.3.4 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 2.7 suggest that regions that were prone to technological change experienced higher outward-migration. The negative coefficient of -.023 suggests a .17 percentage points larger outward migration in a region at the 85th percentile compared to a region at the 15th percentile of the routine share distribution. 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

[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 6.1.1.

[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 6.1.1 for details on the

positive coefficients for the overall sample in Table B of Table 2.7 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.

Table 2.7: 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 2.4 as indicated. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

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, 1995; Nahuis and Parikh, 2004) and that adjustment processes to shocks occur mainly via lower participation rates.

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.

2.4 Conclusion

In recent decades, the employment structures of many industrialized countries have undergone substantial changes. This chapter 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. 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 interregional mobility and selection into unemployment as a response to technological change, but find no robust support for adjustments along these margins.

3 Spatial Wage Inequality and Technological Change

3.1 Introduction

The increase in wage inequality in many industrialized countries during the last decades has attracted considerable attention from economists, policy makers and the general public alike. A consensus view in the literature is that rising inequality is linked to differential demand shifts for high- and low-skilled workers.[1] Existing studies on the determinants of these shifts have mainly focused on explaining developments at the aggregate level. However, there are substantial differences in the evolution of wages across spatial units. To illustrate this fact, Figure 3.1 shows the evolution of the mean and standard deviation of the composition-adjusted Gini-coefficient for wages in the 204 West German labor market regions. Between 1979 and 2006, the Gini-index rose by almost a quarter from .19 to .24. At the same time, the standard deviation almost doubled, indicating that this average rise occurs to varying degrees in different regions. These spatial disparities are sizable, for example, the difference between the region with the lowest and the highest Gini-coefficient amounted to .16 in 2006, while it was only .08 in 1979.[2] Hence, the presence of rising regional dispersion suggests that demand and supply shifts for skilled and unskilled workers also occur differentially across spatial units.

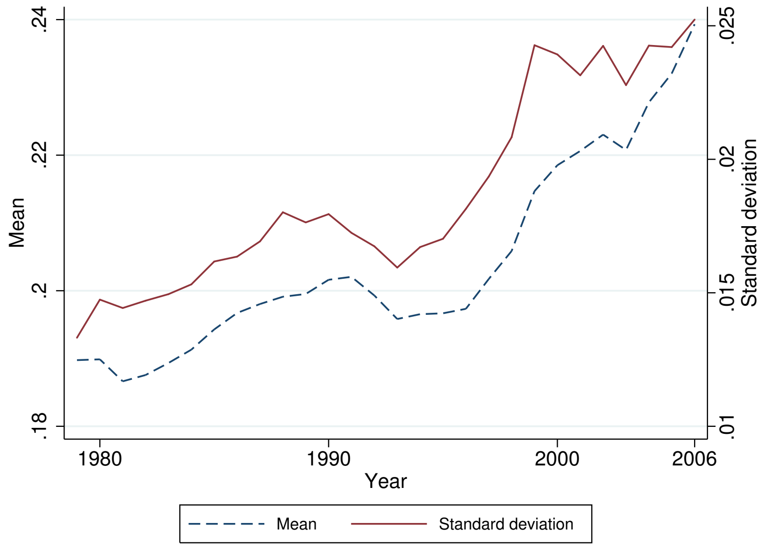
This chapter explores the spatial dimension of rising wage inequality in Germany between 1979 and 2006 and its determinants. We focus on the role of technological change which has proven a successful explanation for recent wage developments at the aggregate level. Our analysis builds upon a recent paper by Autor and Dorn (2013), who use the task-based approach to technological change to explain employment and wage dynamics. They argue that technological progress is non-neutral with respect to different job tasks that employees perform at the workplace (Autor et al., 2003).[3] Technological progress reduces the cost of automating codifiable, *routine* job tasks, which can be performed either by computer capital or low-skilled labor. This induces substitution from routine labor to computer capital and leads displaced workers to supply *non-routine manual* tasks instead. These do not

[1] Katz and Autor (1999) and Acemoglu and Autor (2011) offer an exhaustive overview of the facts.

[2] The same observation holds for alternative wage inequality measures, such as the Theil-index and the P85/P15 wage ratio.

[3] Acemoglu and Autor (2011) define a task as a unit of work activity, that produces goods and services. Workers allocate their skills to different tasks, depending on their comparative advantage in supplying them.

Figure 3.1: Evolution of Wage Inequality Over Time



Notes: N=204 labor market regions. In order to abstract from changes in the workforce composition we hold constant relative employment shares of demographic groups as defined by gender, education, nationality and potential experience. Gini-coefficients are calculated using the average labor supply share for each subgroup over 1979 to 2006 as fix weights.

require a high skill level but situational adaptability and personal interaction, and are thus unsuitable for substitution by technology. Simultaneously, technological progress increases the productivity of workers who perform problem-solving, *non-routine cognitive* tasks which are complemented by technology as they rely on information as an input. Technological change drives down the wages paid to routine tasks, and increases the compensation for non-routine cognitive tasks. The impact of technology on the wages paid for non-routine manual tasks is ambiguous, depending on whether the demand for these tasks rises enough to offset adverse wage effects stemming from additional supply.

This chapter studies the implications of the task-based approach for regional wage inequality at the level of local labor markets. To do so, we exploit variation in the regional endowment of routine task performing labor, resulting from regional differences in industry structures. This chapter makes a number of contributions to the existing literature. To our knowledge, we are the first to directly relate technological change to developments in task-specific compensation patterns. Building upon the results of this analysis, we provide novel evidence on the link between technological change and developments of intra- and inter-regional wage inequality. Previewing our key results, we first report that regions with high technology exposure experienced a greater relocation from routine to non-routine employment. The rise in non-routine cognitive tasks was accompanied by an increase in their compensation, while the decline in routine tasks came along with decreases in their compensation. Further, increases in non-routine manual tasks coincided with a decline in their pay.

Given the fact that non-routine cognitive tasks are prevalent at the upper tail of the wage distribution, while routine and non-routine manual tasks are most commonplace at the lower parts of the distribution, changes in the compensation structure of tasks should manifest in an increase of overall wage inequality. We present evidence that local labor markets that were initially specialized in routine intensive employment witnessed significant increases in local wage inequality as measured by the Gini-coefficient. Our estimates suggest that a region at the 85th percentile of the routine share distribution increases its Gini-coefficient by 21% more than a region at the 15th percentile.

We then address the question whether the spatial differences of technology exposure are an important determinant for the development of *inter-regional* inequalities. To this end, we compare wage developments, when hypothetically only one determinant of wage inequality is allowed to vary across regions, while all other factors remain constant. This dispersion analysis suggests that technology exposure is a relevant source of spatial disparities.

Our study combines literature on the labor market effects of technology with work in urban economics on spatial dispersion of wages and skill premia. On the one hand, an extensive body of research has highlighted the importance of technological progress in explaining changes in the aggregate wage and employment structure. Autor et al. (2006, 2008) show that both employment and wage growth has been u-shaped across the skill distribution in the Unites States. Similar employment patterns have been also detected in other industrialized countries (Spitz-Oener, 2006; Goos and Manning, 2007; Goos et al., 2009a; Michaels et al., 2014; Senftleben-König and Wielandt, 2014b). Yet, in contrast to the US, these countries have witnessed increases in wage inequality throughout the entire wage distribution (Gernandt and Pfeiffer, 2007; Antonczyk et al., 2010b). So far, existing studies for the German labor market did not establish a relationship between technological change and rising wage inequality (Antonczyk et al., 2009, 2010a). Instead, they emphasize the role of composition effects and labor market institutions (Dustmann et al., 2009; Antonczyk et al., 2010b).

At the same time, a number of studies documents spatial persistence of wage differentials (Combes et al., 2008; Moretti, 2011; Combes et al., 2012), where research primarily focuses on the impact of agglomeration and urban wage premia (see Duranton and Puga (2004) and Rosenthal and Strange (2004) for an overview of the existing literature). Other explanations for regional wage differences are related to the impact of international trade (Hanson, 1997; Autor et al., 2013), and, more broadly, to the role of market access and infrastructure (Redding and Venables, 2004; Breinlich et al., 2014). Yet, evidence on the connection between wage inequality and technology at the regional level is sparse. One notable exception is a recent paper by Lindley and Machin (2014), who investigate spatial variation in the college wage premium across US states and report that relative demand increases for high-skilled labor are larger in states with higher increases in R&D spending. Further, a study by Autor and Dorn (2013), which is most closely related to our analysis, explores the role of technology for occupational employment and wage changes at the commuting zone level. They find that regions that were particularly prone to computerization experienced differential increases in non-routine occupations which coincided with wage gains in these occupations, leading to job and wage polarization.

The remainder of the chapter proceeds as follows: Section 3.2 shortly presents the theoretical model developed by Autor and Dorn (2013) (henceforth AD), a model of unbalanced productivity growth upon which our empirical analysis is based, and its key implications. Further, we describe the empirical approach used to test the model predictions and their consequences for the evolution of spatial labor market inequality. Section 3.3 introduces the datasets employed and describes how we construct our main explanatory variable, a measure to capture the impact of recent technological progress, as well as measures of regional task inputs and compensation. In Section 3.4, we assess the relationship between technology exposure and regional developments in task supplies and task compensation patterns. Based upon these results, we explore the role of technology for the evolution of overall regional wage inequality in section 3.5. Section 3.6 concludes.

3.2 Theoretical Model and Estimation Strategy

3.2.1 Theoretical Model and Implications

Our analysis is based on a model of unbalanced productivity growth by AD. In their model, technological change takes the form of a decline in prices for computer capital which replaces routine-task labor. The model features three task inputs, non-routine manual (L_m), routine (L_r) and non-routine cognitive (L_c) tasks, either supplied by high-skilled (H) or low-skilled workers (L), employed in the goods or the services sector ($j = g, s$). High-skilled workers solely perform non-routine cognitive tasks (L_c) while low-skilled workers supply routine and non-routine manual tasks (L_r, L_m). In addition, capital (K), that can be used to substitute for routine tasks, is used as an input in the production of goods. The production of goods (Y_g) combines non-routine cognitive and routine labor as well as computer capital using the following technology:

$$Y_g = L_c^{1-\beta}\left[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu}\right]^{\beta/\mu}, \tag{3.1}$$

where α_r and α_k reflect efficiency parameters. The service sector only employs non-routine manual labor as an input factor:

$$Y_s = \alpha_m L_m \tag{3.2}$$

Consumers/workers have identical CES utility functions defined over the consumption of goods and services:

$$u = (c_s^\rho + c_g^\rho)^{1/\rho} \tag{3.3}$$

The elasticity of substitution between goods and services is given by $\sigma = 1/(1-\rho)$. As the price of computer capital falls to zero asymptotically, the allocation of low-skill labor between non-routine manual and routine tasks is determined as follows:

$$L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \overline{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}. \end{cases} \tag{3.4}$$

The allocation crucially depends upon the relative magnitude of the consumption $(\sigma = 1/\,(1-\rho))$ and the production elasticities $(1/\,(1-\mu))$, scaled by the share of the routine task input in goods production (β). That is, if the production elasticity exceeds the consumption elasticity, technological change raises the relative demand for low-skill labor in service employment. Yet, if the reverse is true, low-skilled labor concentrates in the goods sector performing routine tasks.

The dynamics of the relative compensation paid to non-routine cognitive versus routine $\left(\frac{w_c}{w_r}\right)$ and routine versus non-routine manual tasks $\left(\frac{w_m}{w_r}\right)$ mirror the dynamics of labor flows between goods and services. If the production elasticity exceeds the consumption elasticity, the compensation for non-routine manual tasks rises relative to the wage paid to routine tasks. If instead, the consumption elasticity is larger, demand for non-routine manual tasks does not rise sufficiently to increase compensation paid to these tasks. In addition, the ratio between the compensation paid for non-routine cognitive to routine tasks always goes to infinity as computer prices fall to zero.

$$\frac{w_m}{w_r} = \begin{cases} \infty & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -log(1-L_m*) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}, \end{cases} \tag{3.5}$$

$$\frac{w_c}{w_r} = \infty. \tag{3.6}$$

The AD model is then extended to a spatial equilibrium setting with a large set of regions $j \in J = (1,....,|J|)$. The key feature is that technology has differential effects on local labor markets depending on the amount of routine task inputs employed in regional goods production (β_j). The results from this spatial model closely resemble the closed economy model.

This theoretical framework provides a number of predictions for the evolution of task requirements and task compensation patterns and thus for regional wage inequality. Firstly, the model predicts a general downward trend in routine task inputs, as these are subject to substitution by computer capital, where regions that were particularly exposed to technological change should experience greater declines in routine task requirements. Secondly, the model makes predictions about task compensations: decreases in routine tasks should come along with declines in the wages paid for these tasks. Because technological change increases the productivity of employees performing non-routine cognitive tasks, wages paid to these tasks should rise. The consequences for the non-routine manual task compensation is ambiguous as these depend on consumer preferences. More specifically, if consumers do not admit close substitutes for services (provided by non-routine manual tasks), technological change raises aggregate demand for non-routine manual tasks and hence their compensation. Yet, if consumer preferences are different, the model predicts that the compensation for non-routine manual tasks declines. Thus, the model is consistent with wage polarization, as recently documented in the United States for example by Autor et al. (2008) as well as a monotonous increase of wage inequality throughout the skill distribution, a development that has been observed in Germany during the last decades (Dustmann et al., 2009). In that case, the model predictions are similar to the traditional skill-biased technological change hypothesis (Acemoglu and Autor, 2011).

3.2.2 Empirical Approach

In order to empirically test the relationships identified by the theoretical model in AD, we proceed in three steps. First, we assess the relationship between technology exposure and changes in task supplies across regions. Then, we explore the effects of computerization on the compensation of tasks. Finally, we quantify the role of technology for the evolution of overall regional wage inequality. To do so, we set up an empirical model of the following form:

$$\Delta Y_r = \alpha + \beta_1 RSH_r + \mathbf{X'}_r \beta_2 + \gamma_s + e_r. \tag{3.7}$$

The dependent variable ΔY_r represents the first difference of the variable of interest in region r between the base year 1979 and some subsequent year t. Depending on which hypothesis is tested, it represents (1) the regional supply of routine, non-routine manual and non-routine cognitive tasks, (2) the region specific compensation of routine, non-routine manual and non-routine cognitive tasks, and (3) the regional Gini-coefficient to reflect wage inequality within a region.[4]

[4]Autor and Dorn (2013) employ stacked first differences over three time periods to estimate the relationship between regional routine intensity and subsequent employment changes. In contrast, we restrict our analysis to the single difference based on the routine shares and regional covariates in 1979 as the explanatory variables to focus on the long-run component of differences in regional task structures and thus circumvent the endogeneity problem related to the use of subsequent routine shares. If we follow the approach of AD, we obtain very similar results in terms of effect size and statistical significance.

The parameter of interest, β_1, is the coefficient on the main explanatory variable, RSH_r. This measure is defined as the share of routine intensive employment in region r in 1979 as reflects the degree to which a specific region is exposed to technological change. It should be largely unaffected by technological progress as computerization only started to spur during the 1980's.[5] All regressions include state dummies, γ_s, that control for mean differences in employment and wages across states. In addition, all regressions are weighted by the regional population size.

In order to control for potentially confounding factors, we augment the model with a vector of additional covariates X_r, reflecting differences in urbanity between regions, the local human capital and demographic composition as well as local economic conditions in 1979.

3.3 Data, Construction of Variables and Descriptive Evidence

3.3.1 Data Sources: Employment and Wages

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 at the Federal Employment Agency. This highly reliable administrative dataset comprises marginal, part-time and regular employees as well as job searchers and benefit recipients covering the years 1975 to 2008 (for details, see Dorner et al. (2011)). It provides detailed information on daily wages for employees subject to social security contributions (wages of civil servants and 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. For our analysis, we restrict the sample to full-time workers between 20 and 60 years of age working in West Germany. Whenever we construct aggregate or average outcomes, we weight each employment spell by the number of days worked.[6]

For the analysis it is crucial to consider functionally delineated labor market regions. Hence, we aggregate the 324 administrative districts in West Germany (excluding Berlin) 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 1979, these labor market regions have an average population of around 300,000 individuals, although this varies from 55,000 to 2,5 million.

We use the wage information in the SIAB-R to compute the Gini-idex, an inequality

[5] 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.

[6] See the Data Appendix 6.2.1 for more details on the sample selection and the basic processing of the SIAB-R.

measure commonly used in the literature (e.g. by Kopczuk et al. (2010)). The index ranges from 0 (total equality) to 1 (total inequality) and is computed for every region and year. To test the robustness of our results, we alternatively consider the Theil-index and the ratio of wages at the 85th percentile relative to the 15th percentile of the wage distribution. The upper Panel of Table 3.1 summarizes the unconditional evolution of the different wage inequality measures across labor market regions between 1979 and 2006.[7] 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 (Gruhl et al., 2012). The additional covariates are chosen to control for the qualification structure as well as for the structural (firm size and industry composition) and demographic (gender and nationality) composition at the local level. Further, we include information on three basic area types (districts in urban, conurban and rural areas), following a classification scheme by the German Federal Office for Building and Regional Planning (BBR). Descriptive statistics for the regional covariates are summarized in the lowest Panel of Table 3.1.

3.3.2 Measuring Task Supplies

Construction and Trends

The information on task requirements of employees is derived from the BIBB/IAB Qualification and Career Survey (QCS). The BIBB comprises five cross sections launched in 1979, 1985, 1992, 1998 and 2006, each covering approximately 30,000 individuals (Rohrbach-Schmidt, 2009). 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 and time t according to the definition of Antonczyk et al. (2009):

$$TM_{it}^{j} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } t}{\text{total number of activities performed by } i \text{ over all categories in } t} \times 100, \qquad (3.8)$$

where $j = C$ (non-routine cognitive), R (routine) and M (non-routine manual) and $t = 1979$, 1985, 1992, 1998 and 2006. 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 at time t is weighted by its respective weekly working hours (L_{ikt}):

$$TI_{kt}^{j} = \left(\sum_i \left[L_{ikt} \times TM_{ikt}^{j} \right] \right) \left(\sum_i L_{ikt} \right)^{-1}. \qquad (3.9)$$

[7] These numbers are similar to data provided by official OECD and EU statistics.

Table 3.1: Descriptive Statistics on the Regional Level of Variables Employed

Variable	1979	1985	1992	1998	2006
Wage inequality measures					
Gini coefficient	.213	.219	.229	.242	.281
	(.010)	(.017)	(.017)	(.022)	(.028)
Theil index	.080	.086	.094	.106	.142
	(.014)	(.014)	(.014)	(.019)	(.028)
Log mean wage	4.181	4.195	4.334	4.339	4.331
	(.083)	(.086)	(.089)	(.087)	(.103)
Log P85/P15 ratio	1.181	1.186	1.182	1.189	1.231
	(.019)	(.020)	(.019)	(.020)	(.026)
Average task shares					
Non-routine cognitive (T^C)	.072	.021	.076	.136	.219
	(.011)	(.022)	(.020)	(.028)	(.026)
Non-routine manual (T^M)	.416	.406	.386	.388	.388
	(.025)	(.020)	(.023)	(.017)	(.014)
Routine (T^R)	.512	.574	.538	.475	.393
	(.020)	(.020)	(.024)	(.028)	(.022)
Relative task compensation					
Non-routine cognitive (W^C)	1.359	1.334	1.402	1.405	1.398
	(.123)	(.117)	(.139)	(.119)	(.196)
Non-routine manual (W^M)	.920	1.013	.995	.884	.693
	(.085)	(.108)	(.114)	(.141)	(.211)
Main explanatory variable					
Routine share	.416	–	–	–	–
	(.038)	–	–	–	–
Covariates					
Fraction female employees	.330	.328	.332	.325	.323
	(.045)	(.043)	(.038)	(.037)	(.038)
Fraction foreign employees	.081	.066	.090	.080	.108
	(.048)	(.039)	(.044)	(.041)	(.052)
Share manufacturing	.439	.428	.416	.385	.354
	(.125)	(.127)	(0.120)	(0.116)	(0.118)
Fraction high-skilled employees	0.027	0.035	0.046	0.059	0.074
	(.014)	(.017)	(0.022)	(0.027)	(0.034)
Fraction medium-skilled employees	0.679	0.724	0.759	0.783	0.804
	(.054)	(.051)	(0.044)	(0.041)	(0.041)
Fraction low-skilled employees	0.294	0.242	0.195	0.158	0.122
	(.058)	(.054)	(0.045)	(0.039)	(0.036)
Fraction small firms (<25 employees)	0.339	0.354	0.345	0.374	0.377
	(.083)	(.085)	(0.076)	(0.074)	(0.077)
Average region population	297,494	296,688	305,698	308,443	313,296
	(376,437)	(393,948)	(374,855)	(348,248)	(359,030)
Population density	301	299	311	316	317
	(418)	(403)	(415)	(408)	(400)

Notes: $N = 204$ labor market regions. Standard deviations in parentheses. Descriptives are depicted for years in which task information is available from the QCSs. All employment variables are based upon full-time employment subject to social security contributions for a given region. Fractions are computed with respect to total full-time employment. Task compensation is in constant 2000 Euro, corresponds to log daily returns and is expressed relative to the compensation for routine tasks.

Table 3.2 provides an overview of the occupations with the highest non-routine cognitive, routine and non-routine manual task contents in 1979. The most routine intensive occupations include clerical and administrative occupations as well as blue-collar production occupations. Non-routine manual task intensive occupations include less-skilled service occupations (e.g. nursing assistants, waiters) as well as construction occupations (e.g. roofers). In contrast, occupations with a high non-routine cognitive task content include high-education occupations, such as teachers, engineers and scientists. Table 3.2 also shows the task shares of the respective occupations in 2006. Strikingly, the relative task intensities vary significantly over time. Particularly the group of routine intensive occupations witnesses substantial changes in the distribution, presumably as a consequence of technological progress itself. Due to this substantial variation that occurs within occupations, it bears notice that the natural dimension to test the predictions of the task-based framework is to explore direct changes in regional task inputs instead of occupational shifts.

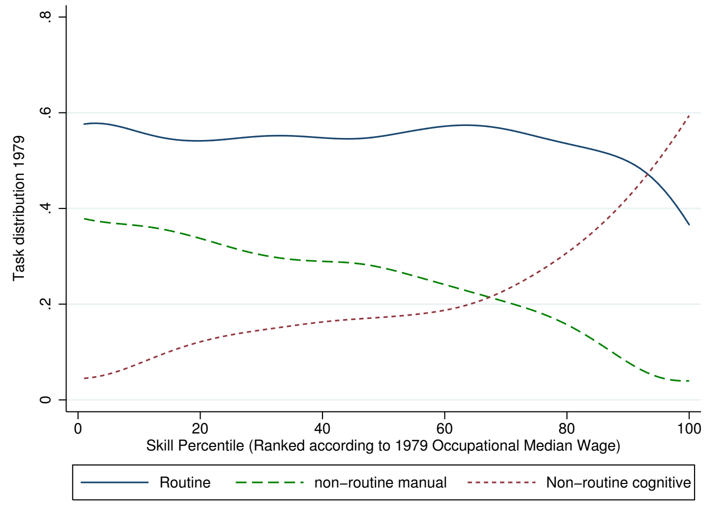
Table 3.2: Ranking of Occupations According to their Task Content in 1979 and their Task Intensities

	1979			2006		
Occupation	abstract	routine	manual	abstract	routine	manual
Five occupations with highest non-routine cognitive task intensity in 1979						
Technical draughtpersons	0.90	0.10	0.00	0.88	0.12	0.00
University teachers	0.76	0.20	0.04	0.82	0.09	0.09
Mechanical, motor engineers	0.75	0.20	0.05	0.84	0.13	0.03
Electrical engineers	0.69	0.26	0.05	0.72	0.20	0.08
Survey engineers	0.66	0.29	0.05	0.77	0.17	0.06
Five occupations with highest routine task intensity in 1979						
Cashiers	0.03	0.95	0.02	0.67	0.07	0.26
Office auxiliary workers	0.06	0.91	0.04	0.59	0.13	0.28
Stenographers, data typists	0.07	0.91	0.02	0.76	0.03	0.20
Cost accountants	0.09	0.90	0.01	0.81	0.10	0.09
Post masters	0.08	0.88	0.03	0.57	0.08	0.35
Five occupations with highest non-routine manual task intensity in 1979						
Household and building cleaners	0.01	0.09	0.90	0.19	0.05	0.75
Nurses, midwives	0.12	0.14	0.75	0.46	0.16	0.38
Nursing assistants	0.08	0.18	0.74	0.34	0.14	0.52
Mechanics	0.10	0.19	0.72	0.28	0.39	0.33
Attending on guests	0.07	0.21	0.71	0.48	0.22	0.30

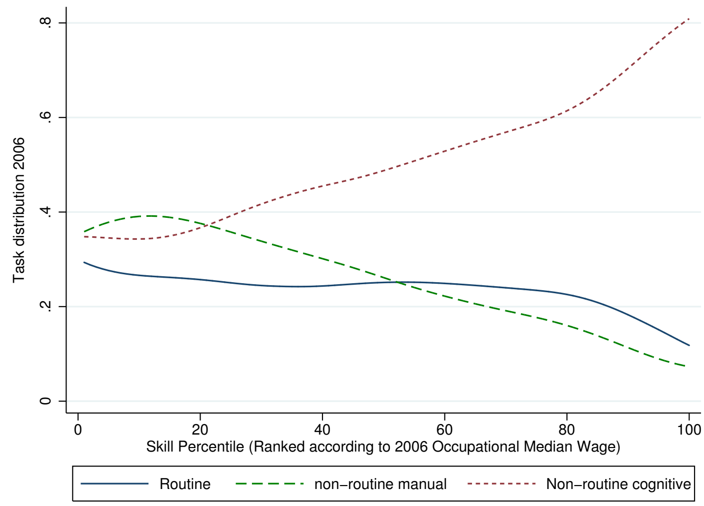
Notes: Task intensities are derived from the QCS waves 1979 and 2006 as defined in equation 3.9. The sample includes full-time employees between 20 and 60 years of age working in West-Germany, excluding agricultural and public sector employment.

Figure 3.2 provides stylized evidence on the systematic association between task intensities and their prevalence across the skill distribution. It plots the distribution of task usage across the skill distribution for 1979 and 2006, which is approximated by the occupational median wage in the respective year. The figure clearly shows that non-routine cognitive tasks are prevalent in occupations at the top of the skill distribution. In contrast, routine and non-routine manual tasks are mainly performed by less-skilled employees. Interestingly, apart from a large level shift, this distributional pattern remains relatively stable over the entire period.

Figure 3.2: Task Intensity Along the Wage Distribution, 1979 and 2006



(a) Task intensity 1979



(b) Task intensity 2006

Notes: Share of workers performing routine, non-routine manual and non-routine cognitive tasks in 1979 and 2006, respectively. Occupations are ranked according to their median wage in the respective year using the SIAB-R. Task intensity is derived from the QCS and defined as in equation 3.9.

Regional Quantities and Prices

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.[8]

[8]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

We construct composition-adjusted region-level task shares following Peri and Sparber (2009). That is, we clean the task information of demographic characteristics, which may affect regional task inputs and hence be correlated with the routine share. To do so, we regress separately by BIBB wave an individual's task input TI_{kt}^{j} (derived from the occupation) on a gender dummy, potential experience and its square, a set of education fixed effects and a dummy indicating German nationality.[9] The region-level averages of the predicted values, weighted by the length of the respective employment spell, constitute the task supplies T_{rt}^{j} for each region r and year t. Summary statistics of the three task shares are displayed in Table 3.1. In line with the predictions of the task-based approach, we observe a general downward trend of routine task input over time. Simultaneously, the share of labor that performs non-routine cognitive tasks is increasing, while non-routine manual task inputs remain relatively constant over time.

To obtain regional task compensation measures for each year, we follow a two step procedure proposed by Peri and Sparber (2009). First, we construct average log wages in each region that control for observable differences in demographic characteristics across local labor markets. To obtain these *cleaned* wages we regress separately for each BIBB wave log real daily wages on the same variables that are used for the adjustment of the task variables. The regressions further include occupation by region dummies whose coefficients represent the estimates for the average cleaned log-wage, $\ln(\tilde{w}_{krt})$, for occupation k, region r and year t. In a second step, these cleaned wages are transformed into levels and regressed on the occupation-specific task intensities TI_{kt}^{j}. By separately estimating the second-stage regression in equation 3.10 for each BIBB wave, we can identify the region and year-specific task compensations, w_{rt}^{C}, w_{rt}^{R} and w_{rt}^{M}, received for supplying one unit of non-routine cognitive, routine and non-routine manual tasks.

$$\tilde{w}_{krt} = w_{rt}^{C} \times TI_{kt}^{C} + w_{rt}^{R} \times TI_{kt}^{R} + w_{rt}^{M} \times TI_{kt}^{M} + e_{krt}. \tag{3.10}$$

Table 3.1 depicts the evolution of the compensation for non-routine cognitive and non-routine manual tasks relative to the compensation for routine tasks for each BIBB wave. As predicted by the AD framework, non-routine cognitive tasks experience relative wage gains over time. In contrast, the relative wages paid to non-routine manual tasks deteriorate after the 1980's.

3.3.3 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 AD: we use the occupational routine

classification.

[9] We calculate potential experience as current year minus year of birth minus age at the end of educational/vocational training. The average age for each education level is set at 15 for individuals "without completed education", 16 for those "without A-levels and without vocational training", 19 for those "without A-levels but with vocational training" or "with A-levels but without vocational training", 22 for those "with A-level and vocational training" and 25 for those "with a (technical) college degree".

task index in 1979 (TI^{R}_{k1979}) to identify the set of occupations that are in the upper third of the routine task distribution.[10] 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:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI^R_k > TI^{R,P66}_k\right]\right)\left(\sum_k L_{kr}\right)^{-1}, \tag{3.11}$$

where L_{krt} is employment in occupation k in labor market r in 1979, and $\mathbb{I}[\cdot]$ is an indicator function, which takes the value one if the occupation is routine intensive. The average population weighted regional routine share in 1979 is .42. A region at the 85th percentile of the routine share distribution has a 8.1 percentage points higher routine intensity compared to a region at the 15th percentile ($RSH^{P15} = .379$, $RSH^{P85} = .460$). To get an impression of the regional variation in routinization exposure, Figure 3.3a maps the geographic distribution of the regional routine intensity in 1979 across Germany. Routine intensive labor markets are industrial strongholds, such as Wuppertal and Wolfsburg, as well as human capital intensive regions, such as Düsseldorf, Bonn and Wiesbaden. Regions with a low routine share tend to be specialized in the tourism and hospitality industry, such as Husum or Garmisch-Patenkirchen and are located near the Alps or the sea. A potential concern is that the routine share largely reflects the degree to which labor markets are specialized in manufacturing industries. In this case, it would be difficult to disentangle the impact of technology from trade-related explanations. The simple population-weighted correlation coefficient between technology exposure and the manufacturing share is moderate and amounts to .255, indicating that the routine share is more related to the production technology than to industry specialization. As a visualization, Figure 3.3b shows the distribution of the manufacturing share across German regions.

3.4 Results

3.4.1 Technology and Task Inputs

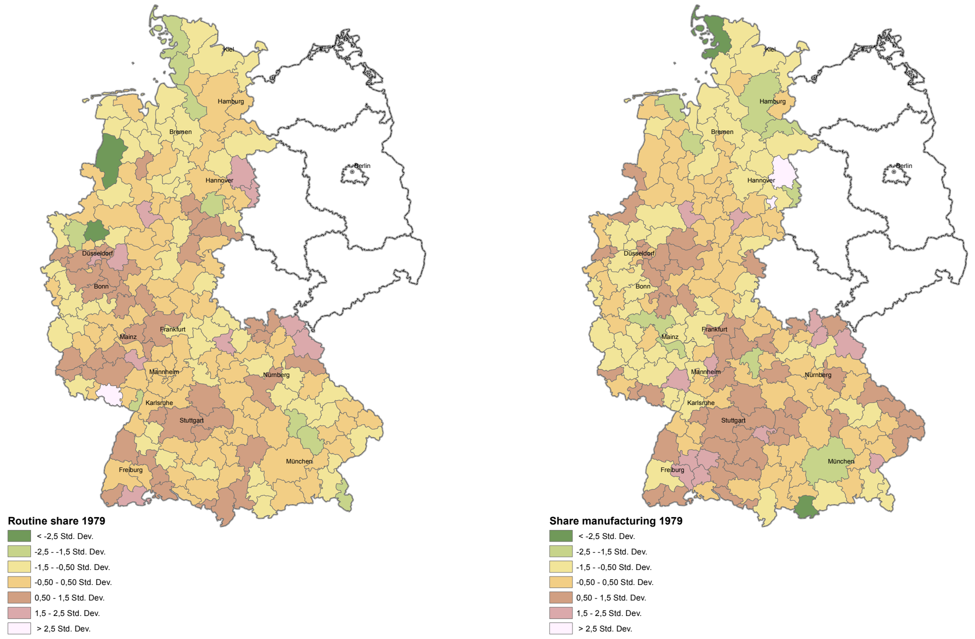
We now turn to the main estimates, where we assess the impact of technological change on regional task structures, compensation patterns and overall wage inequality. As a first step, we focus on changes in regional task structures by fitting the following variant of equation 3.7:

$$\Delta T^j_{r,1979-2006} = \alpha + \beta_1 RSH_r + \mathbf{X_r'}\beta_2 + \gamma_s + e_r. \tag{3.12}$$

The dependent variable is the change in the supply of task j between 1979 and 2006 in labor market r, where $j =$ R, C and M. The estimates from weighted-least squares regressions

[10]Our results remain unchanged if we instead use occupations in the upper quarter or upper half of the routine task distribution. Results are available from the authors upon request.

Figure 3.3: Distribution of Routine and Manufacturing Share in 1979



(a) Routine Share (b) Share Manufacturing

Notes: Routine Share as defined in equation 2.5. Occupational routine intensity is obtained from the QCS wave 1979 and the SIAB-R.

(WLS) are presented in Table 3.3. As a baseline, the first column presents a specification with the regional routine share as the variable of interest and a full set of state dummies. The estimated effect of technology on routine tasks is negative and significant at the 1 percent level, implying that regions that were particularly exposed to technology experienced greater declines in routine tasks.

To control for other factors that may explain regional changes in the task supplies, we augment the model step-by-step with a number of additional explanatory variables. In column 2, we control for differences in the degree of urbanization across regions by adding information on regions' area type. Numerous studies have found evidence for significant productivity differences between urban and rural areas due to agglomeration economies (Bacolod et al., 2009; Glaeser and Resseger, 2010; Davis and Dingel, 2012). Hence, it is likely that also task requirements evolve differently in regions of different types. Indeed, the decline in routine task inputs is significantly less pronounced in rural and conurban regions (as compared to urban areas which constitute the baseline category).

To capture differences in the regional human capital structure, column 3 adds the share of high-skilled and low-skilled employees in the local labor force. While regions with large shares of low-skilled employees witness smaller declines in routine task requirements, somewhat surprisingly, a greater initial supply of high-skilled employees predicts declining routine task inputs. In column 4, we further include two variables that reflect local economic

Table 3.3: Technology and Task Inputs, 1979-2006

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: ΔT^R			
RSH_{1979}	-.359***	-.315***	-.327***	-.439***	-.232***	-.401***
	(.070)	(.064)	(.054)	(.035)	(.063)	(.035)
Rural area		.032***				.007*
		(.006)				(.004)
Conurban area		.037***				.006
		(.007)				(.004)
High-skilled			-1.020***			-.356***
			(.126)			(.126)
Low-skilled			.119***			.016
			(.037)			(.033)
Manufacturing empl.				.161***		.133***
				(.015)		(.017)
Empl. in small estbl.				.236***		.101***
				(.022)		(.025)
Female employment					-.011	.115***
					(.054)	(.036)
Foreign employment					-.369***	-.161***
					(.071)	(.038)
R^2	.380	.520	.765	.783	.546	.848
			Panel B: ΔT^C			
RSH_{1979}	.091	.053	.063	.185***	-.040	.128***
	(.064)	(.063)	(.043)	(.035)	(.063)	(.036)
R^2	.160	.308	.681	.686	.374	.778
			Panel C: ΔT^M			
RSH_{1979}	.267***	.262***	.265***	.255***	.272***	.273***
	(.027)	(.026)	(.028)	(.024)	(.028)	(.026)
R^2	.603	.619	.605	.624	.619	.638

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and regional covariates as indicated as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

conditions: the share of small establishments (< 25 employees), which leads to regional productivity disparities (Agrawal et al., 2014) and the share of employment in manufacturing. Both variables enter with a positive sign, predicting an increase in the subsequent input of routine tasks. Finally, column 5 considers the share of female employees and the share of foreigners in the local labor force. Both variables are associated with declining regional routine task requirements, although the coefficient on female employment is imprecisely estimated.

Notably, the inclusion of additional explanatory variables leaves the significant, negative relationship between technology exposure and routine task inputs largely unaffected. When all control variables are simultaneously included (column 6), the point estimate increases slightly and the precision of the point estimate rises. To interpret the coefficient, we compare a region at the 85th percentile with a region at the 15th percentile of the routine share distribution in 1979 and predict their respective change in the input of routine tasks. The point estimate of -.401 implies a differential decline in routine tasks by 3.2 percentage points relative to a mean decrease of 11.9 percentage points between 1979 and 2006. Panel B and C present the results for the change in non-routine cognitive and non-routine manual tasks between 1979 and 2006. The estimates on both task inputs are positive and statistically significant.

Are the observed patterns consistent over time? To answer this question, we estimate models described by equation 3.12 separately for each outcome year and depict the results in Table 3.4. The year 1979 remains the base year, such that the coefficients reflect how the impact of technology accumulates over time. The effect of technology on routine tasks is negative and statistically significant in all sample years after 1979, and most pronounced during the 1990's. Similarly, both non-routine task inputs have experienced a differential growth in initially routine intensive regions throughout the observation period. The coefficients increase, indicating that the adaption in task supplies as a result of technological change is a continuous process. However, it is noteworthy that the impact of computerization on the regional task structure attenuates over time, since the coefficients on the routine task share remain relatively stable in the later periods (columns 3 and 4).

Table 3.4: Technology and Task Inputs, Subperiods

Time period:	1979-1985 (1)	1979-1992 (2)	1979-1998 (3)	1979-2006 (4)
		Panel A: ΔT^R		
RSH_{1979}	-.264***	-.283***	-.402***	-.401***
	(.028)	(.030)	(.040)	(.035)
R^2	.674	.693	.847	.848
		Panel B: ΔT^C		
RSH_{1979}	.098***	.114***	.159***	.128***
	(.023)	(.021)	(.033)	(.036)
R^2	.731	.706	.820	.778
		Panel C: ΔT^M		
RSH_{1979}	.166***	.169***	.243***	.273***
	(.022)	(.023)	(.026)	(.026)
R^2	.516	.330	.614	.638

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

In order to detect possible heterogeneous effects of technology exposure across demographic groups, Panel A of Appendix Table 6.3 depicts regressions bifurcated by gender, age and education level. The estimated coefficients indicate that the effects of computerization are similar in magnitude across all subsamples. One group exempted from the general pattern are high-skilled employees, among whom computerization has left the requirements for non-routine manual tasks unaffected. Instead, they exclusively increase their input of non-routine cognitive tasks, which is consistent with theoretical considerations in AD.

So far, the results of our analysis strongly support the key implications of the task-based approach, providing evidence for increasing specialization of employees in non-routine tasks as a consequence of routine task substituting technological change.

3.4.2 Technology and Tasks Compensation

In this section, we explore whether the changes in the regional task structure are accompanied by corresponding changes in the compensation paid to different tasks. To do so, we estimate the following model:

$$\Delta ln(\widehat{w}_r^j) = \alpha + \beta_1 RSH_r + \mathbf{X_r'}\beta_2 + \gamma_s + e_r. \tag{3.13}$$

The dependent variable represents the estimated change in the log compensation paid to task $j = R, C$ and M between the base year 1979 and each of the following BIBB waves. Task compensation estimates are acquired for each labor market and year according to the methodology described in section 3.3.2. To conserve space, Table 3.5 only reports the coefficient on the regional routine share and omits the results on the vector of control variables.

Table 3.5: Technology and Task Compensation, Subperiods

Time period:	1979-1985	1979-1992	1979-1998	1979-2006
	(1)	(2)	(3)	(4)
		Panel A: $\Delta ln(\widehat{w}^R)$		
RSH_{1979}	.015	-.202*	-.227*	-.362
	(.083)	(.109)	(.118)	(.272)
R^2	.298	.232	.343	.269
		Panel B: $\Delta ln(\widehat{w}^C)$		
RSH_{1979}	.198	.322**	.301**	.404**
	(.133)	(.137)	(.132)	(.174)
R^2	.367	.413	.522	.547
		Panel C: $\Delta ln(\widehat{w}^M)$		
RSH_{1979}	-0.216**	-0.208*	-0.260*	-.701
	(.094)	(.113)	(.133)	(.460)
R^2	.272	.354	.352	.396

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

In line with the theoretical model, the WLS estimates in Panel A of Table 3.5 indicate that technological change had an adverse effect on the compensation of routine tasks. The estimated coefficients are negative in the last three periods. However, it bears notice that this relationship is imprecisely estimated for the overall observation period from 1979 through 2006.

Panel B and C present complementary estimates for the wages paid to non-routine cognitive and non-routine manual tasks. Regions with a high technology exposure witnessed significant increases in the compensation of non-routine cognitive tasks. The coefficient of .404 implies a differential wage increase of 3.3% between a region at the 85th and the 15th percentile of the routine share distribution through 1979 to 2006. With respect to the dynamic pattern of the effect, the coefficients suggest that the effect was strongest until the beginning of the 1990's (columns 1 and 2) and increased only slightly thereafter (columns 3 and 4). The estimates in Panel C indicate that the compensation for non-routine manual tasks has decreased differentially in regions which were initially specialized in routine intensive employment. In contrast to the results obtained for the other tasks, the dynamic pattern reveals that the effect of technology has accelerated over time, although the estimate is statistically not different from zero when considering the entire period (column 4). The point estimate of -.701 implies a differential wage decrease of 5.7% in a region at the 85th relative to a region at the 15th percentile between 1979 and 2006. The result that computerization decreases the compensation for non-routine manual tasks suggests that the rise in the supply of non-routine manual tasks was not met by a sufficient increase in the demand for these tasks to offset negative wage effects. This finding stands in contrast to results for the US as presented by AD, who document employment *and* earnings growth for occupations that are characterized by a high non-routine manual task content.

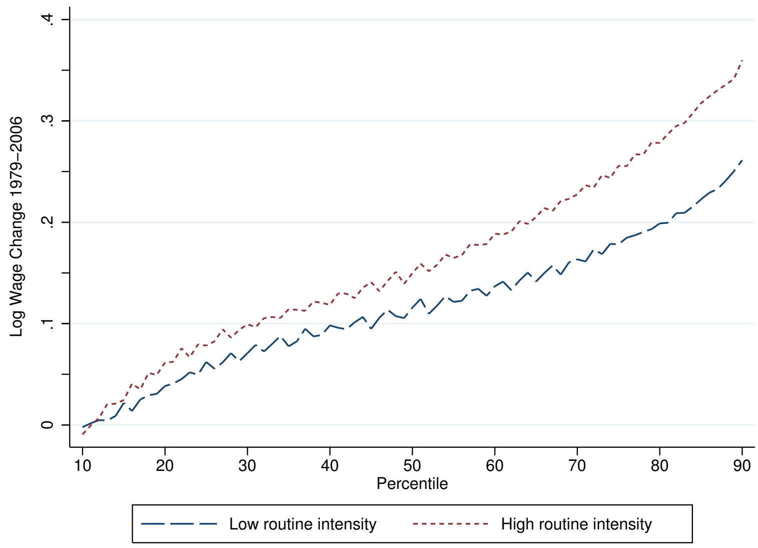
Panel B of Appendix Table 6.3 reports the coefficients of the models that are estimated separately by gender, age and education. In the case of high-skilled employees, some region-occupation cells have very few observations. Hence, we report the results for this subgroup only for the sake of completeness, but they are to be interpreted cautiously. While the results for older and younger employees are relatively similar, some substantial differences between changes in compensation patterns for males and females can be detected.

3.5 Regional Wage Inequality

So far, our empirical analysis has found a robust relationship between the historical exposure to technological change and subsequent changes in the structure and compensation of tasks across regions. Can these findings help understanding the roots of increasing wage inequality within and across regions? Recall that there exists a systematic association between the prevalence of tasks across the skill distribution. That is, non-routine cognitive tasks are prevalent at the upper tail of the wage distribution, whilst routine and non-routine manual tasks are predominantly performed at lower parts. Hence, technological change should lead to an increases in wage inequality within regions.

Prior to a regression analysis, we present some graphical evidence on this prediction. Figure 3.4 plots unconditional log wage changes between 1979 and 2006 at each percentile of the wage distribution for two sets of regions: those with an above average routine share in 1979 and those with a routine share below it. As the figure illustrates, wages have grown more at the upper part of the wage distribution in both sets of regions. Yet, it is noticeable that the increase in wage inequality is clearly more pronounced in routine intensive regions. For example, wages at the 85th percentile have grown 8 percentage points more over the observed period in routine intensive regions.

Figure 3.4: Wage Change by Percentile, 1979-2006



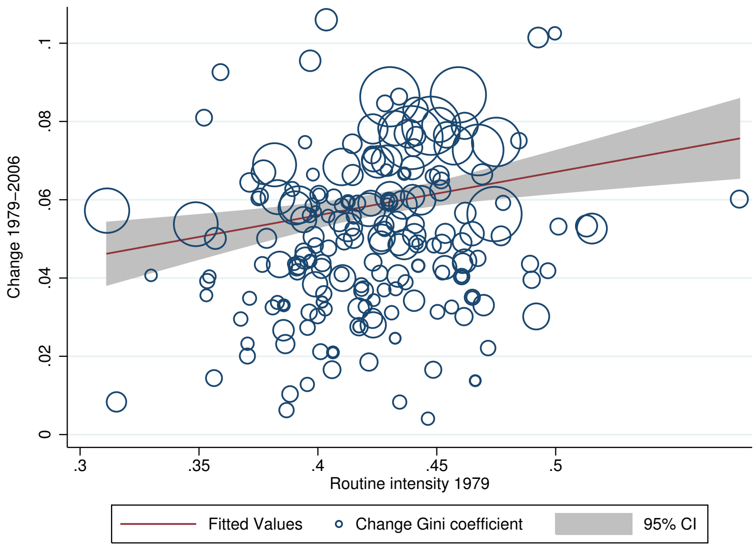
Notes: Figure plots unconditional log wage changes obtained from SIAB-R between 1979 and 2006 at each percentile of the wage distribution in regions with high and low routine intensities in 1979. Percentile numbers refer to wage distribution in 1979.

To inspect the link between technology exposure and wage inequality in more detail, we perform an econometric analysis, where income dispersion across local labor markets is measured by the Gini-index. The scatterplot in Figure 3.5 depicts the bivariate relationship between the local routine share in 1979 and changes in the Gini-coefficient over the subsequent 27 years and provides strong initial support for the prediction that technological change has contributed to rising wage inequality. The positively sloped regression line corresponds to the following WLS regression of the change in the Gini-coefficient between 1979 and 2006 on the routine share, where weights are equal to the regional population in 1979:

$$\Delta Gini_{r,1979-2006} = 0.01 + 0.11 \times RSH_r + e_r, \quad se = 0.032 \quad n = 204 \tag{3.14}$$

The positive coefficient implies that the Gini-index rose by 21.3% more in a region at the 85th percentile compared to a region at the 15th percentile, indicating that the economic

Figure 3.5: Change in Gini-Coefficient between 1979 and 2006 versus Routine Intensity in 1979



Notes: Figure plots routine intensity in 1979 against the change in Gini-coefficient for 204 local labor markets. The size of the circles is proportional to the regional population in 1979. The line is the predicted change in the Gini coefficient from a weighted OLS regression, where the weights are the regional population in 1979. The slope is .111 (.032).

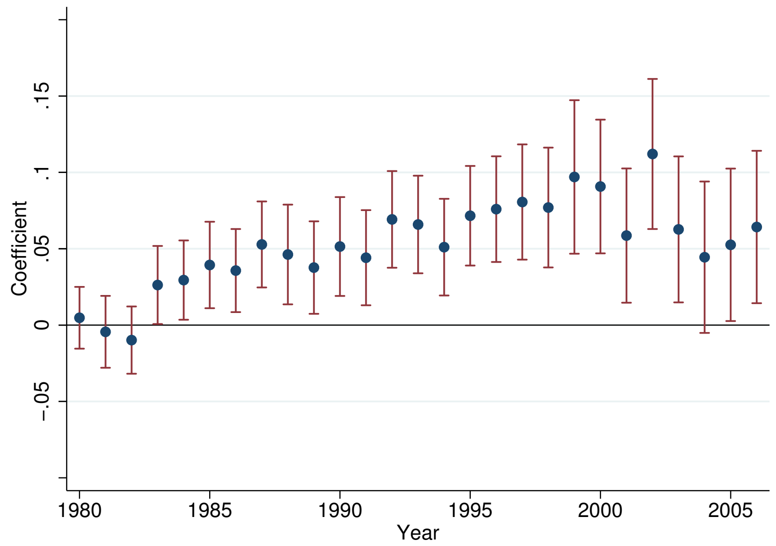
significance of the estimate is substantial.[11] Figure 3.6 provides some evidence on the dynamics of the routinization effect, plotting estimated coefficients on an annual basis for the years 1980 through 2006. The equations underlying this figure are identical to a version of equation 3.14, where the model is augmented by the full set of controls used in earlier specifications and estimated separately for each year. Until the mid 1980's, the estimated effect is small in magnitude and statistically not different from zero. Starting from that, the coefficient on technology exposure is positive and statistically significant in almost all years. With respect to the time pattern, the estimates reveal that the effect of technological change on the evolution of wage inequality roughly doubles during the 1990's, and decreases thereafter. In order to test the robustness of our results, we also estimated the computerization effect on alternative wage inequality measures, i.e. the Theil-index and the 85th/15th percentile wage ratio. The estimated coefficients are depicted in Appendix Figure 6.2 and reveal that the results do not hinge on a particular inequality measure.

3.5.1 Dispersion Analysis

As discussed in the introduction, wage inequality has not only increased within regions, but also to differential degrees across space. Thus, it is interesting to ask whether differences in

[11]This number is calculated by dividing the 85th/15th percentile difference of .9 percentage points by the predicted increase in the Gini-index at the 15th percentile of the distribution.

Figure 3.6: Estimated Impact of Technological Change on the Gini-Coefficient



Notes: The figure plots the regression coefficients and 90% confidence intervals obtained from up to 26 regressions. The regressions relate the Gini-index during the year indicated, to the regional technology exposure. All regressions include covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3.

technology exposure can help understanding the variation of wage inequality growth across German regions. To answer this question, we perform a simple counterfactual exercise. Specifically, we predict changes in the Gini-coefficient between 1979 and 2006, when only one component of regional wage developments is allowed to vary:

$$\Delta\widehat{Gini_r} = \alpha + \beta_1 RSH_r + \beta_2 \overline{X}. \tag{3.15}$$

Then, $\Delta\widehat{Gini_r}$ is the change in the Gini-index that would prevail if the considered region r differed from the regional average ($\overline{X}$) only with respect to its task structure. We perform this exercise analogously for the other explanatory variables in our model. Thus, we obtain predicted changes in wage inequality when we allow for variation in economic conditions (firm sizes and industry structure), the qualification structure and the demographic composition (share of female and share of foreign employees), as well as the area type.[12] For each of these variables, Table 3.6 displays the highest and the lowest predicted change in the Gini-coefficient as well as its difference.

The results indicate that most regional disparities in wage inequality are generated by the qualification structure, followed by the economic components. The contribution of technological change is the third most important source of wage dispersion across regions.

[12]It bears notice that since the effects are not orthogonal, the sum of the partial effects is not equal to the overall change in a region's Gini-coefficient.

Table 3.6: Results of the Dispersion Analysis

	Technology Exposure (1)	Qualification (2)	Economic (3)	Demographic (4)	Urbanity (5)
Min	.044	.034	.035	.048	.045
Max	.059	.073	.062	.052	.052
Range	.015	.039	.027	.004	.007

Notes: N=204 labor market regions. Each column represents the smallest and largest predicted change in the regional Gini-coefficient between 1979 and 2006 when only the indicated determinant of regional wage developments is allowed to vary.

Interestingly, the demographic composition and the area type of local labor markets are least important for explaining wage dispersion across spatial units.

3.6 Conclusion

This chapter examines the spatial dimension of labor market inequality in Germany in recent decades at the level of local labor markets focusing on the role of technological change. The analysis builds on concepts of the task-based view of technological progress which has proven to be successful in explaining wage and employment trends at the aggregate level. We document substantial differences in both, the evolution of labor market inequality across space and the degree to which regions are exposed to technology. We show that regions that were prone to computerization witnessed a more pronounced relocation from routine to non-routine task inputs together with differential changes in task compensation. Despite rising non-routine cognitive task inputs, wages paid to these tasks have increased suggesting that the demand for them has risen faster than the supply. On the contrary, increases in the input of non-routine manual tasks were accompanied by wage decreases. While the negative compensation effect of routine tasks is limited to the early 1980's and 1990's, it is attenuated over time and becomes insignificant thereafter. These developments translate into the regional wage structure resulting in an increase in wage inequality within and between labor markets, driven by opposing dynamics at both tails of the wage distribution. The findings of this study complement the existing empirical literature that has so far primarily focused on deunionization as the main explanatory factor for recent developments at the lower tail of the German wage distribution.

Our study underlines the importance of demand side factors when exploring the impact of technological change on wage and employment patterns. Contrary to the US, technological progress did not benefit low-paid employees in Germany which implies that demand for non-routine manual tasks has not risen sufficiently to offset declining wages.

4 Employment Polarization and Immigrant Employment Opportunities

4.1 Introduction

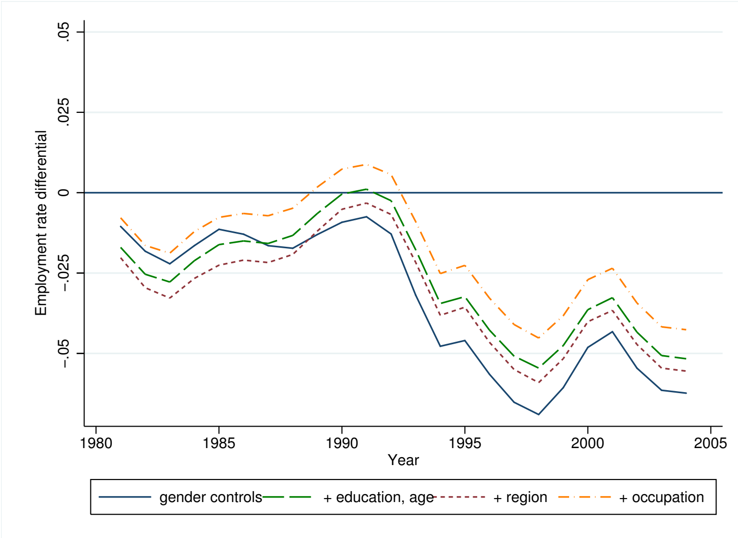
A significant and growing share of the population in many countries throughout the world is made up of immigrants and their descendants. According to OECD statistics, Germany has now become the largest destination for immigrants after the United States, and at least 10 percent of the population in Germany is of foreign origin (OECD, 2014). Naturally, the labor market situation of immigrants as well as the integration of immigrants into the German labor market has attracted large public and academic interest. One striking fact is the large difference in the labor market position of immigrant workers compared to natives and its deterioration in recent decades. Figure 4.1 depicts two key indicators of successful integration into a host country's labor market: employment and wage differentials between native and immigrant workers controlling for differences in the demographic composition, work location and occupational structure. The figure shows that up until the early 1990's, employment rates and wages of immigrant workers were close to those of natives but diverged thereafter. As Figure 4.1 illustrates, the divergence since the early 1990's can only in part be explained by differential initial endowments. Although education, age (dashed line) and occupational composition (dash-dotted line) explain a large part of the gap, a difference still remains.

This evolution is not unique to Germany and the deterioration in the labor market performance of immigrants has been studied for other industrialized countries including the United States, Canada and the UK.[1] So far, human capital differences, changes in the country of origin (Boudarbat and Lemieux, 2014; Borjas, 2015) as well as human capital accumulation and language proficiency (Borjas, 2015) have been found to be relevant in explaining a substantial part of the decline. International comparisons also highlight a higher sensitivity of immigrant workers compared to natives with respect to changes in economic conditions (OECD, 2005; Liebig, 2007; Dustmann et al., 2010).

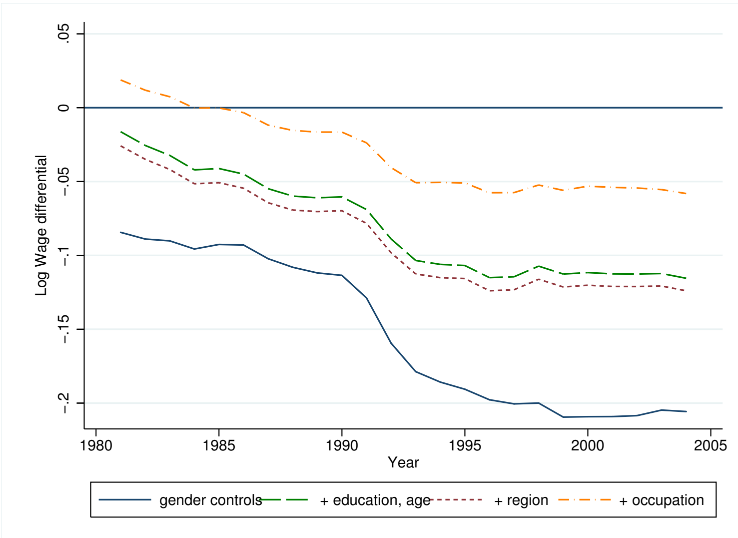
The deterioration of immigrant outcomes coincides with another stylized fact that has been documented in many industrialized countries: the increasing concentration of employment at

[1] See for the United States Chiswick (1978); Borjas (1985, 1995); Borjas and Friedberg (2009) and for Canada Baker and Benjamin (1994); Grant (1999). Dustmann et al. (2010) compare Germany and the UK documenting a long-term gradual decline in immigrant wages and a strong pro-cyclical pattern in unemployment probabilities of immigrants.

Figure 4.1: Conditional Wage and Employment Rate Differential, 1981-2004



(a) Conditional Employment Rate

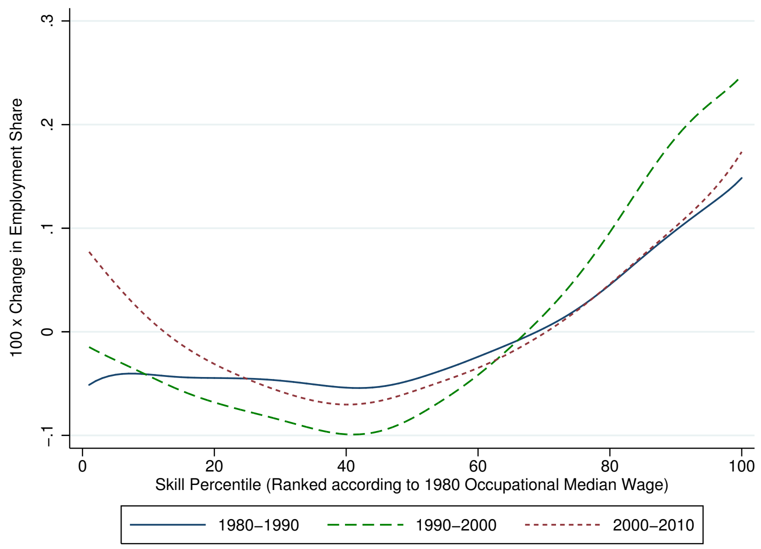


(b) Conditional Wage Differential

Notes: The figure is constructed using SIAB-R daily wage and employment information between 1981 and 2004. To obtain conditional employment rates and wages, models of the following form are estimated using the native population as a reference group: $Y_{it}^{g} = X_{it}^{g}\alpha + \sum_{t=t_1}^{T} \gamma_t^g T_t^g + \sum_{t=t_1}^{T} \gamma_t d_t + e_{it}^{g}$, where Y_{it}^{g} is either an employment indicator or log daily wage of individual i belonging to group g (natives, immigrants) in period t, additional controls such as gender, education, age, etc. are included in the vector X_{it}^{g}, and e_{it}^{g} is an error term. The variables T_t^g represent the interactions of the immigrant dummy and the year dummies d_t. Depicted are the estimated parameters γ_t^g that represent the mean employment rate of immigrants relative to the native population (picked up by γ_t) conditional on the demographic variables included in X_{it}^{g}.

the tails of the occupational wage (skill) distribution at the expense of employment declines in middle-income jobs (Autor and Acemoglu, 2011). This phenomenon is illustrated in Figure 4.2 that depicts smoothed employment changes in every percentile of the occupational distribution (ranked according to the occupational median wage in 1980) between selected years for the native workforce in Germany. While employment changes have been relatively monotone across the distribution in the 1980's, the occupational structure started to polarize during the 1990's. Since then, employment in occupations that are located in the middle of the wage or skill distribution has declined, while employment at both tails of the distribution has increased. Employment polarization has been documented primarily for the United States (Autor et al., 2006, 2008; Autor and Dorn, 2013) but also for Germany (Spitz-Oener, 2006; Dustmann et al., 2009; Senftleben-König and Wielandt, 2014b), the UK (Goos and Manning, 2007) and European countries in general (Goos et al., 2009a,b, 2014; Michaels et al., 2014).

Figure 4.2: Smoothed Employment Changes by Skill Percentile, 1980-2010



Note: Based on SIAB-R. Smoothed changes in employment by skill percentile using locally weighted smoothing regression with 100 observations and a bandwidth of 0.8. Occupations are ranked according to their 1980 median wage. Sample includes German employees subject to social security contributions aged 20-60 working in West Germany.

The purpose of this chapter is to explore the relationship between employment polarization of the native labor market - i.e. a technology driven change in labor demand inducing a gradual increase in native employment in the highest and lowest paying occupations - and employment opportunities of immigrant workers. Using high-quality administrative data, I document a negative relationship between technology induced polarization in the native labor market - as measured by the share of natives employed in traditionally low-paying occupations - and employment rates and wages of immigrant workers in local labor markets. First, I show that technological change partly drives native employment growth in lower-paying occupations that are typically held by immigrant workers. Second, I use cross-regional, over-time variation in the employment of natives in these occupations to document a negative relationship between polarization and immigrant employment rates and wages. To control for potential endogeneity, I apply a Bartik style instrument (Bartik, 1991) by interacting occupational employment growth at the national level with the regional start-of-period occupational composition to predict local outcomes. Depending on the specification, the results imply that around 12 per cent of the overall decline in immigrant employment rates of 8 percentage points is associated with polarization of native employment. The negative relationship between native employment polarization and employment rates & wages is more pronounced for recent immigrants who have resided in Germany for less than five years. For this sub-sample, employment polarization can account for approximately one third of the overall decline in employment rates.

The findings can be rationalized by applying a local labor market model introduced by Autor and Dorn (2013), that builds on the task-based framework and links employment polarization to technological progress.[2] The task-based approach suggests that technological progress in the form of declining prices of computer capital leads to a substitution of well-codifiable (routine) tasks which are mainly performed by medium-skilled employees while it benefits the productivity of non-routine cognitive tasks performed mainly by high-skilled workers. The model also explicitly leaves room for employment growth in occupations that are intensive in non-routine manual tasks which are typically lower-paying, service-sector jobs.[3] The decline in middle-skill employment especially during the 1990's and 2000's and the reallocation of those workers who were (or would be) in routine intensive occupations towards lower-skill, lower-paying non-routine manual occupations potentially induces additional competitive pressure, thereby influencing employment opportunities of workers who are traditionally employed in this labor market segment.

This research complements the literature on labor market polarization by shifting the focus from describing and explaining the phenomenon of polarization to exploring the effects of polarization on groups of workers who have traditionally been employed in lower wage occupations. Building on the task-based framework, a number of studies started to examine the differential impact of technological change on underrepresented groups. Black and Spitz-Oener (2010) and Bacolod and Blum (2010) show that changing skill demands particularly benefit women, and can explain a substantial fraction of the closing of the gender pay gap in Germany and the United States. In a similar way, Borghans et al. (2014) document that the growing importance of people-skills in the labor market (presumably driven by technology induced demand shifts) has contributed to the decline in the gender wage gaps in the United States, Great Britain and Germany. The study also argues that the stagnating white-black wage-gap in the U.S. can be explained by changing demand for people skills in the workplace. Smith (2011) explores the effect of the polarization of the adult labor market on employment

[2] See Acemoglu and Autor (2011) for an extensive literature overview.

[3] Studies for the United States (Autor and Dorn, 2013) and Germany (Senftleben-König and Wielandt, 2014b) verify that the declining demand for middle-paying occupations due to technological change indeed induces a reallocation of less-educated workers who were (or would be) in those middle-paying occupations towards lower-skilled non-routine manual occupations (e.g. service occupations).

outcomes of teenage workers showing that a higher share of adults in teen occupations is related to the decline in youth employment in the United States.

This research is also related to the work by Peri and Sparber (2009) who use occupational task requirements to study native task adjustments in response to immigration. The authors show empirically that inflows of low-educated immigrant workers cause comparably-educated natives to switch to more communication-intensive occupations, while immigrants specialize in occupations intensive in manual and physical labor skills. This imperfect substitutability in production between native and foreign-born workers can explain the small wage consequences of immigration for less educated natives. In contrast, changing task requirements due to technological progress and its relevance for immigrant performance, the results in this chapter point in the direction that comparably skilled immigrant and native workers are perfect substitutes.

The chapter continues as follows: section 4.2 discusses changes in the occupational structure over recent decades and documents the divergent evolution of immigrant outcomes. It also discusses the immigration structure in the German labor market. Section 4.3 lays out the empirical strategy, elaborates the instrumental variables approach, and describes the data set employed in the analysis. Section 4.4 interprets the empirical findings, first discussing the extent to which technological change can explain polarization as measured by cross-regional variation in native employment in low-paying occupations. Second, I analyze the link between measures of polarization and employment opportunities and average wages of immigrants. Section 4.5 concludes.

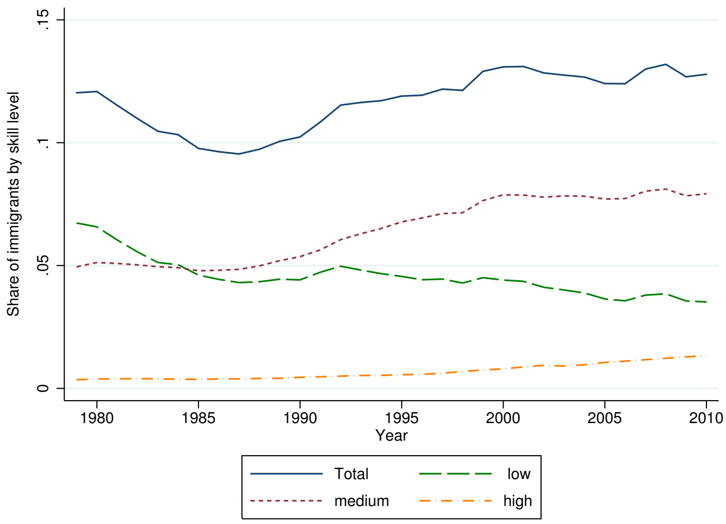
4.2 Immigration Structure in Germany and Employment Polarization

The foreign born population in West Germany excluding ethnic Germans increased from 4.6 million in 1980 to 6.2 million in 2013, making up approximately 10 percent of the total population. Germany is now the second most popular destination for immigrants after the United States recently attracting many job-seekers from Southern European countries driven from the ravages of the euro zone financial crisis (OECD, 2014). Several phases of immigration to West Germany can be distinguished (see Bauer et al. (2005) for detailed information on German migration). Between 1955 and 1973, Germany recruited so called "guestworkers" that mainly took unskilled and semi-skilled jobs to support Germany‘s postwar economic boom and alleviate labor shortages.[4] Since the breakdown of the Soviet

[4]Germany signed the first recruitment treaty with Italy in 1955. In the following years, agreements with Greece and Spain (1960), Turkey (1961), Morocco (1963), Portugal (1964), Tunisia (1965) and Yugoslavia (1968) followed (Liebig, 2007). Because of the oil crisis and the worsening economic situation, the government ordered a halt to recruitment in the early 1970's. Trend towards subsequent immigration of family members since the early 1970's, accelerating after the recruitment ban. Although recruitment halt, subsequent immigration because of family reunification visas was still possible so that immigrants from former guestworker countries account for around 60% of the foreign population in Germany today.

Union in 1989, immigration patterns have been dominated by inflows of ethnic Germans from Eastern Europe, asylum seekers, and refugees. Triggered by free-mobility flows for employment, new immigrants from Central and East European countries have entered the German labor market since 2004. Reflecting the migration history of Germany, the composition of immigrants is rather diverse. The largest group of immigrants are Turks, followed by immigrants from Yugoslavia and Italy. Figure 4.3 reports the share of days worked by workers with foreign citizenship in total employment (solid line) between 1980 and 2010 and reflects the slowdown of immigration during the 1980's due to the recruitment ban and the subsequent increase related to the breakdown of the Soviet Union. Further, Figure 4.3 is broken down by skill level and shows reflects the educational upgrading of immigrant workers since 1980. While immigrants were predominantly low-skilled (dashed line) in the early 1980's by now the vast majority has medium skill levels (dash-dotted line). Although the level of high-skilled immigrants (dotted line) is still low, growth has picked up since the mid 1990's.[5]

Figure 4.3: Share of Employees with Foreign Citizenship, 1980-2010, by Education Level



Notes: Calculation based on SIAB-R. Sample includes workers aged 20-60 subject to social security contribution working in West Germany.

Table 4.1 provides selected descriptive statistics for the native and immigrant workforce in 1981 and 2004, the first and the last year of the observation period in the subsequent analysis. Consistent with Figure 4.1, Table 4.1 documents rising employment rate and wage differentials between native and immigrant workers.[6] While employment rates and

[5]I classify workers educational attainment 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. The consistency of the education variable is improved using the imputation algorithm developed by Fitzenberger et al. (2006).

[6]Borjas (1994) and Altonji and Blank (1999) review the extensive literature on earnings differentials between

wages amongst natives and immigrants were largely similar in the early 1980's, by 2004 the employment rate for immigrants had fallen further than for natives, and wages had grown less. In terms of the demographic composition, the share of full-time working females is higher among natives compared to the immigrant sample, and follows a diverging trend. In comparison to natives, the majority of immigrants have very low education levels. While the share of foreign employees without completed education has declined from 55 per cent in 1981 to 30 per cent in 2004 it is still almost five times as large as in the native sample with only 7 per cent of native-born workers having such low educational levels. The table also illustrates the lower occupational status of immigrants that reflects the importance of blue-collar manufacturing jobs as well as non-routine manual intensive service occupations. Although the recent movement from production occupations to services is observable for both samples, the basic distribution and dominance of certain occupations has remained.

Table 4.1: Descriptive Statistics Labor Market Regions, 1981 and 2004

	Natives		Immigrants	
	1981	2004	1981	2004
Sample population (20-60)	1760	2096	220	292
	(2319)	(2096)	(467)	(581)
Log daily wage	4.188	4.348	4.154	4.185
	(.085)	(.102)	(.096)	(.105)
Empl./LF rate	.944	.906	.929	.844
	(.020)	(.025)	(.036)	(.056)
Share females	.329	.332	.274	.271
	(.042)	(.036)	(.104)	(.082)
Educational composition:				
Low skilled	.194	.066	.547	.300
	(.049)	(.018)	(.138)	(.088)
Medium skilled	.768	.829	.415	.634
	(.043)	(.043)	(.131)	(.088)
High skilled	.038	.105	.039	.067
	(.020)	(.043)	(.044)	(.045)
Occupational composition:				
Production	.344	.298	.591	.490
	(.063)	(.060)	(.137)	(.116)
Construction	.124	.080	.172	.090
	(.032)	(.022)	(.094)	(.045)
Service	.209	.256	.163	.266
	(.033)	(.038)	(.094)	(.094)
Admin/Sale	.228	.256	.046	.106
	(.040)	(.041)	(.041)	(.049)
Professional	.095	.110	.028	.048
	(.025)	(.021)	(.030)	(.030)

Note: Entries based on SIAB-R show means and standard deviations based on the 204 West German labor market regions. Sample includes individuals aged 20-60, working full-time, subject to social security contribution.

Besides discrimination (Becker, 1971), and differences in endowments, e.g. the lower educational attainment of immigrant workers (Dustmann and Glitz (2011) provide a com-

natives and immigrants. See Velling (1995) for the German case.

prehensive literature overview), worse labor market performance of immigrant workers is related to imperfect international transferability of human capital and less successful job matching. Findings indicate that for immigrants the transferability of occupational skills to their destination country is limited mainly by language proficiency leading to an initial mismatch in skill requirements that is larger for immigrants with less language proficiency.[7] Further, Chiswick (1978) spurred a large literature on immigrants' earnings assimilation, pointing out that the wage differential is most pronounced for recent immigrants while this difference fades out with the time migrants stay in the host country. Constant and Massey (2005) relate earnings differences between natives and guestworkers in Germany to initial occupational segmentation and differential job mobility and document that guestworkers are less able to transfer their human capital into a first job and face lower job mobility. Similarly, Dustmann et al. (2013) show that immigrants to the UK tend to work in occupations that do not correspond to their skills and require lower levels of education compared to their actual qualification. Imai et al. (2014) analyze migration to Canada and note that male immigrants find initial employment in occupations that require high levels of manual skills. Similarly, Ottaviano et al. (2013) document that occupations characterized by low cognitive intensity, low communication intensity, high manual intensity and low overall complexity have a lager share of hours worked by immigrants. Findings by Peri and Sparber (2009) suggest that immigrants are indeed disproportionately represented in non-routine manual intensive occupations. Especially recent immigrants (those who have been in the United States less than ten years) provide more manual tasks relative to communication tasks compared to long-term immigrants (those who live in the United States more than ten years) and low educated natives. Differences in labor market outcomes between natives and immigrants also arise among second-generation immigrants whose achievements are strongly related to parental characteristics (Dustmann et al., 2012; Riphahn, 2003).

4.3 Data and Empirical Approach

4.3.1 Empirical Approach and Estimation Strategy

The starting point of the analysis is the observation that the occupational structure in Germany has polarized, with declining employment opportunities in middle paying occupations accompanied by employment growth in low and high-paying jobs. The empirical strategy builds off of the general equilibrium model proposed by Autor and Dorn (2013) that explains employment and wage dynamics at the lower tail of the skill distribution in response to technological change using the task-based framework. In this model, human labor performing routine tasks (e.g. bookkeeping, operating machines) is substituted by computer capital, as

[7] Chiswick and Miller (1995) show that host-country language proficiency is significantly related to higher earnings in Australia, the United States, Canada, and Israel. Aldashev et al. (2009) document that language proficiency significantly increases employment probability and occupational choice for immigrants to Germany. Dustmann et al. (2010) show that employment rate and wage differentials in Germany and the UK are larger for immigrants from non-OECD countries.

the price for information technology declines. This induces a movement of employment from routine towards non-routine tasks, whereas the decline in routine employment is primarily offset by a reallocation of labor towards low-skill non-routine manual tasks (e.g. serving, accommodating, repairing). The model implies that regions that have a larger employment share in routine intensive occupations before computerization started to spur are more prone to occupational shifts induced by technological change. Therefore, I start by establishing a link between the regional variation in the exposure to technological progress and employment polarization of native workers as measured by the share of natives employed in the lower tail of the wage distribution. Specifically, I relate employment shifts in the lower tail of the wage distribution between the base year t and some year τ in region r to RSH_{rt}, a measure that reflects the regional exposure to technological progress in base year t:[8]

$$\Delta Share_r = \alpha + \beta_1 RSH_r + \beta_2 Production_r + \mathbf{X_r'}\beta_3 + \gamma_s + e_r. \tag{4.1}$$

$Share_{rt}$ is defined as the share of low- and medium skilled natives in region r at time t in typical immigrant occupations that combine low wage and skill levels with high non-routine manual task content.[9] Following the task-based approach, technological progress replaces routine cognitive (clerical) as well as routine manual (blue-collar manufacturing) tasks. To disentangle the direct effect of technological progress on the occupational structure, the share of production employment $(Production_r)$ in the base year is separately included since it is itself positively related to routine manual intensity. X_{rt} controls for the demographic and educational composition of the local workforce in the base year, γ_s represents state fixed effects.

In the next step, I use the region-year variation in the share of natives in immigrant occupations to analyze the relationship between employment polarization in the native labor market and employment opportunities of immigrants. Therefore, I relate Y_{rt} - either the regional employment rate or average log wages of immigrants - to the share of natives in

[8]To obtain this measure, I match occupational task information from the BIBB/IAB Qualification and Career Survey (QCS) in 1979 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. Following the approach of Autor and Dorn (2013), I 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, I calculate for each labor market r a routine employment share measure RSH_r for the year 1979, equal to:

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

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. Please refer to Senftleben-König and Wielandt (2014b) for more details on how the index is constructed and to Rohrbach-Schmidt (2009) for more information on the QCS.

[9]I define immigrant jobs in the following way: I rank occupations according to their share of immigrant employment and define immigrant occupations as those occupations in which 50 per cent of the immigrant workforce is employed. These jobs include: food preparation and service related occupations, sales and related occupations, stock clerks, grounds maintenance, locksmiths and metal related occupations, construction occupations and various personal service occupations.

immigrant occupations in the following way:

$$Y_{rt} = \alpha + \beta_1 SHARE_{rt} + \delta_t + \theta_r + \gamma_{st} + e_{rt}. \tag{4.2}$$

The specification includes region fixed effects (θ_r) to control for all time-invariant local characteristics and year fixed effects (δ_t) to control for cyclical trends. In some specifications the regression is augmented with state-year fixed effects (γ_{st}) to remove state-time unobservables.[10]

Although the fixed effects already control for some unobservables, the true effect is presumably more negative than the OLS estimates suggest. For instance, this could occur if technological change induced a reallocation of employees towards regions that are less affected by computerization. However, regional mobility in Germany is low and Senftleben-König and Wielandt (2014b) show that migratory responses to polarization are modest in size and significance. To address further threats to causal identification, I instrument for the share of natives in immigrant occupations using a Bartik-style instrument (Bartik, 1991) that has been used in many subsequent studies (Blanchard and Katz, 1992; Katz and Murphy, 1992; Bound and Holzer, 2000; Autor and Duggan, 2003). The basic idea is to use a set of region specific weights together with national level trends. In this case, the beginning-of-period employment share of natives in immigrant jobs within a region is interacted with the employment share in immigrant occupations at the national level in year t:[11]

$$\widehat{Share}_{rt} = Share_{r1981} \times Share_{\cancel{r}t} \tag{4.3}$$

The subscript $_{\cancel{r}\mathrm{kt}}$ in $Share_{\cancel{r}t}$ indicates that each region's employment is excluded in calculating the national employment share. Since year and region fixed effects are included, the estimates are identified from comparing regions with different initial levels of $Share_{r1981}$ and therefore differential scope for polarization. But, unlike the variation in the share variable, $\widehat{Share}_{rt}$ is only driven by nation wide changes due to employment polarization which should be orthogonal to local labor market conditions. Because regions that had a larger share in immigrant occupations in 1981 have less scope for polarization and therefore less pronounced growth of native employment in immigrant occupations, $Share_{rt}$ should be negatively related to the instrumental variable if its increase is indeed driven by polarization.

4.3.2 Data Sources

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 German Federal Employment Agency. It provides

[10]Including region specific time trends instead of state-year fixed effects does not alter the results.
[11]I define baseline as 1981, but the results are robust to this choice.

detailed information on daily wages for employees subject to social security contributions, as well as information on occupation, industry affiliation, workplace location and demographic information on age, gender, nationality and educational attainment.[12] As the data report daily wages yet lack information on hours worked, wages of part-time employees are measured less accurately. Therefore, the sample used in the analysis is restricted to full-time workers between 20 and 60 years of age working in West Germany. Due to data restrictions related to the unemployment spells that are required to calculate employment rates, the analysis is limited to the years 1981 to 2004. On the earlier end, reliable data on unemployment spells is only available from 1981 on, while a change in legislation and a redefinition of unemployment in 2005 yields a structural break in the data following this point.

As other official statistics in Germany, the SIAB only distinguishes between foreign and German citizenship and does not provide information on the place of birth. On the one hand, I will therefore over-count the number of immigrants due to individuals with foreign citizenship who were born in Germany. However, according to administrative statistics the share of second generation immigrants in the 20-65 age bracket, that have not themselves migrated, was only 12% in 2005 (Statistisches Bundesamt, 2009). On the other hand, I will identify workers who were born abroad but have German citizenship as Germans. In the remainder of the chapter, I will refer to the sample of workers with foreign citizenship as *immigrants* and the German workers as *natives*.

Since employment rate and wage differences between natives and immigrant workers may in part be explained by observable characteristics, I construct regional employment rates and average wages controlling for observable demographic characteristics. Regional employment rates and average wages for natives and immigrants are obtained by regressing an employment indicator or log daily wage on a vector of observable characteristics, including potential experience and a cubic of it, education fixed effects, region fixed effects and a gender dummy separately by year and nationality. In the analysis, I then use the estimated coefficients on the region dummies as dependent variables in the regressions of equation(4.2) to control for differences in observable demographic composition across regional labor markets. The analysis is executed at the level of 204 functionally delineated local labor markets in West Germany that take commuter flows into account and therefore reflect local labor markets most appropriately (Eckey et al., 2006; Eckey and Klemmer, 1991; Koller and Schwengler, 2000).[13]

[12] Civil servants, self-employed workers and military personnel are not included. In 2001, 77% of all workers in Germany were covered by social security and are recorded in the IAB data (Bundesagentur für Arbeit, 2007). For more details on processing the SIAB data and handling of right-censoring see the appendix. For more details on the data set, see Dorner et al. (2011).

[13] I focus on West Germany (excluding Berlin) since local labor markets in East Germany faced massive structural changes that are difficult to control for. Furthermore, the share of immigrants in the workforce in East Germany was only a mere 1.5% in 2006 (Bundesagentur für Arbeit, 2007).

4.4 Results

4.4.1 Occupational Employment Growth and Task Content

In the early 1980's, most immigrant workers were employed in low-skill, blue-collar jobs in the industrial sector (more than 40% in metal processing) which has faced massive employment declines due to technological progress. By now, immigrant workers are also predominantly employed in low-skilled service and construction occupations. Appendix Figure 6.1 illustrates combinations of average wages and non-routine manual task intensity for different occupation groups in which immigrant workers traditionally work: (i) what I define as typical *immigrant* occupations (as defined in footnote 9 on page 57), (ii) low-paying occupations (defined as occupations in the lowest decile of the wage distribution in 1980) and (iii) service occupations. The number in brackets represents the share of immigrant workers in these occupation groups. Those occupations that are predominantly held by immigrant workers combine low wage levels with high non-routine manual task content. hence, native employment growth in these occupations can be understood as a proxy for lower-tail employment polarization in the native labor market. In contrast, professional occupations have a very low share of immigrant employment and are associated with high wages and low non-routine manual task content.

To gauge the relevance of this relationship more rigorously, I combine data on the share of foreign employment by detailed occupation between 1981 and 2004 with information on the occupational skill and task content and average wages in 1981.[14] The correlation coefficient in the first column in Table 4.2 verifies that in 1981, immigrants are predominantly employed in occupations with low average wages, low skill levels and high manual task content. Appendix Table 6.1 provides a more detailed overview on average wages, skills and task content by occupational categories (*Berufsabschnitte*) and growth of immigrant employment between 1981 and 2004. The share of immigrants is generally larger in lower-paying occupations. Although the table reveals no clear picture on the employment growth pattern, low-paying occupations generally experience higher growth rates.

Using these data, I further explore whether task and skill composition are predictive of foreign employment growth. Specifically, I relate the growth in the employment share of foreign employment between 1981 and 2004 to occupational level variables in 1981:

$$\Delta Empl_j = \alpha + \beta_1 Wage_j + \beta_2 Low_j + \beta_3 Task_j + e_j, \tag{4.4}$$

where j indexes 110 detailed occupations and $\Delta Empl_j$ is the growth of foreign employment between 1981 and 2004. $Wage_j$ is the average wage level and Low_j the average share of low skilled employment in the occupation. Additionally, I control for the occupational task

[14]The information on the occupational task content is derived from the 1979 wave of the BIBB/IAB qualification and career survey (QCS). See the appendix for further information on data processing and construction of the task indices.

composition by including the share of non-routine cognitive, non-routine manual and routine tasks in $Task_j$. Estimates of equation 4.4 are found in Table 4.2. Columns 1 to 5 consider each of the variables separately, while the full set of explanatory variables is included in column 6. The results suggest that average wages and skill levels are a statistically and economically significant determinant of foreign employment growth. Relative to routine intensity, non-routine manual and non-routine cognitive task intensity predict employment growth. However, the occupational task content is not significant in the full specification in column 6.

Table 4.2: Relationship among Occupational Foreign Employment Growth, Job Tasks and Average Wages, 1981-2004

	Correlation with share immigrants in 1981	(1)	(2)	(3)	(4)	(5)	(6)
Average wage	-.318***	-.051***					-.092***
		(.014)					(.017)
Share low skilled	.806***		-.029				-.079***
			(.025)				(.024)
Share abstract tasks	-.429***			-.017			.035
				(.017)			(.029)
Share routine tasks	.172				-.025		
					(.020)		
Share manual tasks	.220**					.037*	.019
						(.020)	(.021)
Adj. R^2		.013	.111	-.003	.010	.032	.252

Note: N= 110 occupations. OLS estimates given, and robust standard errors are in parentheses. Task information is obtained from the QCS wave 1979 (see the appendix for details on the construction of the task indices). Remaining variables are calculated for 1981 and 2004, respectively. * Significant at 10%, ** at 5%, *** at 1%.

4.4.2 Technology Driven Labor Market Polarization

I now turn to the link between regional differences in native employment changes in the lower part of the occupational distribution and technological progress. The model proposed by Autor and Dorn (2013) suggests that regions that more heavily employ routine tasks experience a larger decline in demand for those routine tasks alongside a reallocation of employment towards non-routine manual and cognitive tasks. If technological progress indeed drives the decline in demand for routine occupations and reallocation towards lower paying non-routine manual occupations, we should observe a positive link between the measure of technology exposure (RSH_{rt}) and subsequent employment growth in immigrant occupations that combine low skill and wage levels with high non-routine manual task content.

This is verified in Table 4.3 that reports coefficient estimates according to equation 4.1, relating the change in the share of natives in immigrant occupations between 1981 and 2004 to routine intensity and the employment share in production occupations in the base year.

As other local labor market conditions affect native employment growth, regressions are augmented with additional covariates to control for demographic differences across regions as well as state fixed effects to control for unobservable differences across states.[15]

Table 4.3: Relationship Between Occupational Structure and Technology Exposure

	Change fraction natives in immigrant occ. (1981-2004)			Change in empl. rate (1981-2004)		
	(1)	(2)	(3)	(4)	(5)	(6)
Routine Intensity	.036*** (.011)		.037*** (.011)	-.015 (.016)		-.012 (.017)
Production empl.		.004 (.003)	-.000 (.003)		-.005 (.005)	-.004 (.006)
Adj. R^2	.227	.174	.227	.208	.207	.208

Note: N= 204. All models additionally include the share of high-skilled and low-skilled workers, a dummy indicating urbanity and dummies for the federal state in which the region is located. The dependent variable in the OLS regressions for columns 1-3 is the change in the share of natives employed in immigrant occupations (as defined in footnote 9, page 57) between 1981 and 2004. The dependent variable in the OLS regressions for columns 4-6 is the change in immigrant employment rates between 1981 and 2004, regression adjusted for observable differences in gender, education and experience. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

The results in column 1 support the hypothesis that routine intensive regions witnessed a differential increase of native employment in immigrant jobs. The coefficient implies that a one standard deviation increase in the routine share is associated with a 3.6 percentage point increase in the share of natives employed in immigrant occupations between 1981 and 2004. In contrast, column 2 suggests that the share of workers employed in production occupations does not predict native employment growth. Once routine intensity and the production share enter the regression simultaneously in column 3, the technology measure remains highly significant and similar in size while the production share becomes virtually meaningless.

Columns 4 to 6 report the coefficients from regressing the change in immigrant employment rates between 1981 and 2004 on initial routine intensity and the employment share in production occupations, respectively. A one standard deviation higher routine share in 1979 is associated with a 1.5 percentage point reduction in immigrant employment rates over the time period 1981 to 2004. However, the relationship is measured imprecisely. The share of production employment is also negatively related to the change in employment rates but is smaller in size and insignificant as well. The negative relationship between employment rates and technology exposure hints at the idea that declining demand for middle-paying occupations and a reallocation of employment towards lower-paying occupations potentially increases competitive pressure in the lower-skill labor market, a segment in which immigrants

[15] To make the coefficients comparable, the explanatory variables are standardized to have mean 0 and standard deviation 1.

are traditionally employed.

4.4.3 Polarization and Employment Opportunities of Immigrant Workers

The previous section established a link between technological change and polarization as measured by changes in the employment share of natives in immigrant occupations. This section turns to the question of how polarization of the native labor market relates to immigrant employment opportunities and average wages as described by equation 4.2. The estimates of β_1 from OLS and IV regressions are presented in Table 4.4. The coefficient of .133 in column 1 indicates that a 1 percentage point higher share of natives in immigrant occupations reduces the employment rate of immigrant workers by .13 percentage points. The point estimate increases with the inclusion of state-year fixed effects in column 2 and becomes significant. Column 3 presents the coefficient from the IV regression applying the instrument for the share of natives in immigrant occupations described by equation 4.3. As the first stage results in the lower panel of the table suggest, the instrumental variables approach leads to a strong predictor for local employment changes across regions. The significantly negative first-stage results imply that regions with a higher initial share of natives in immigrant occupations (and less scope for polarization) experienced lower growth in these occupations over the next 24 years. The results from the IV regressions confirm the OLS estimates but are in general more negative. Since the share of natives in immigrant occupations only modestly increased at the aggregate level by 2.1 percentage points between 1981 and 2004, the direct impact on immigrant employment is modest. Depending on the specification, the coefficient estimates suggest that native employment polarization can explain between 0.3 and 1 percentage points of the overall decline in immigrant employment rates of 8 percentage points. However, the aggregate trends mask extensive regional variation across labor markets ranging from a decline in native employment in immigrant occupations of 5% to an increase of 13%.

Columns 4 to 7 of Table 4.4 compare estimates of β_1 from regressions similar to equation 4.2, where the employment rate is bifurcated between recent and long-term immigrants.[16] The coefficient in column 4 suggests a negative and significant link between employment rates of immigrants who have been in Germany for less than five years and the share of natives in immigrant occupations. The coefficient from the IV regression (column 5) is even larger although less precisely estimated.[17] Although the implied effect is similar in size, the relationship is more relevant for this subsample since around 1 percentage point of the overall 3 percentage point decline in employment rates of recent immigrants may be related to polarization in the native labor market. For immigrants that have been in Germany longer than five years, the estimate from the OLS regression (column 6) is smaller in size

[16] To conserve space, I only display OLS results including state-year controls and the corresponding IV results. However, OLS results excluding state-year controls are in general more negative and have higher significance levels.

[17] One possible explanation is the smaller variation in the instrumental variable compared to the original variable.

and insignificant. However, the IV results (column 7) reveal a similar pattern as with the more recent immigrants. In contrast to these, employment rates of long-term immigrants declined by almost 10 percentage points. Therefore, the direct impact of native employment polarization for this sub-sample is negligible.

Table 4.4: Relationship between Employment Opportunities and Native Occupational Structure

	Dependent variable:	Immigrant employment rates (regression adjusted for observable characteristics)					
	All			recent		long-term	
Explanatory variable: Share natives in	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant occ.	-.133	-.196**	-.499**	-.479***	-.540*	-.159	-.560**
	(.088)	(.087)	(.196)	(.148)	(.303)	(.111)	(.244)
Adj. R^2	.870	.875		.713		.961	
Implied effect $\Delta 8104 = .021$	-.003	-.004	-.010	-.010	-.011	-.003	- .012
Method of estimation	OLS	OLS	IV	OLS	IV	OLS	IV
Additional controls							
Region & year FE	x	x	x	x	x	x	x
State-year FE		x	x	x	x	x	x
First stage			-38.07***		-38.07***		-38.07***
			(5.40)		(5.40)		(5.40)
F-test on excl. instruments			49.73		49.73		49.73

Note: $N = 4896$ (204 labor market regions x 24 years). Table displays regression coefficients from region-year level regressions for which the dependent variable is the employment rate of workers with foreign citizenship (and separated by years since migration). Employment rates are regression adjusted for observable differences in the age and education structure and gender. Each regression includes state and year fixed effects and state-year fixed effects in the indicated columns. Standard errors clustered at the regional level are in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

4.4.4 Polarization and Average Wages

Next, I turn to the question how wage patterns might be related to native employment polarization. Table 4.5 compares estimates of β_1 from regressions similar to 4.2 where the dependent variable is the average regional log wage of immigrant workers adjusted for observable characteristics. The findings for wages are much more inconclusive. In general, there is a negative relationship between the share of natives in immigrant occupations and average wages of immigrant workers. However, the coefficients are imprecisely estimated and not significantly different from zero. Nevertheless, the negative coefficient from the OLS regressions is consistent with the idea that declining demand for middle paying occupations results in higher competitive pressure in the low skill sector. In contrast, the coefficient from the IV regression in column 3 becomes positive but remains insignificant. Columns 4 to 7 display results bifurcated by years since migration and illustrate that the negative relationship is most pronounced for recent immigrants while average wages of long-term immigrants seem to be in part positively related to the share of natives in immigrant occupations. In light of endogeneity concerns as discussed in section 4.3.1, the IV models of columns 5 and 7 are preferred.

Table 4.5: Relationship Between Average Wages and Native Occupational Structure

	Dependent variable:	Average log real wages of immigrants (regression adjusted for observable characteristics)					
	All			recent		long-term	
Explanatory variable: Share natives in	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigrant occ.	-.115	-.209*	.047	-.288	-1.035*	-.301**	.137
	(.154)	(.126)	(.294)	(.205)	(.533)	(.141)	(.332)
Adj. R^2	.789	.812		.694		.855	
Implied effect $\Delta 8104 = .021$	-.002	-.004	.001	-.006	-.022	-.006	.002
Method of estimation	OLS	OLS	IV	OLS	IV	OLS	IV
Additional controls							
Region & year FE	x	x	x	x	x	x	x
State-year FE		x	x	x	x	x	x

Note: $N = 4896$ (204 labor market regions x 24 years). Table displays regression coefficients from region-year level regressions for which the dependent variable is the average log daily wage of workers with foreign citizenship (and separated by years since migration). Average wages are regression adjusted for observable differences in the age and education structure and gender. Each regression includes state and year fixed effects and state-year fixed effects in the indicated columns. Standard errors clustered at the regional level are in parentheses. First-stage as in Table 4.4. * Significant at 10%, ** at 5%, *** at 1%.

The results suggest that the growing earnings differential between natives and immigrants is not significantly related to native employment polarization. However, the evolution at the mean could hide a much larger influence at the low end of the wage distribution as shown for Canada by Boudarbat and Lemieux (2014). Because the German labor market is characterized by a high degree of unionized wage bargaining and generous unemployment benefits, employment dynamics are a better indicator for the labor market performance of immigrants than earnings.

4.4.5 Robustness

The results so far suggest a negative link between native employment polarization and employment opportunities and average wages of immigrant workers, especially those working in Germany less than five years. Table 4.6 summarizes different robustness checks of this relationship related to the sample selection. For comparison, panel I depicts the coefficient estimates of the base regression from panel I of Table 4.4.

Table 4.6: Robustness: Employment Opportunities and Occupational Structure - Sample Selection

	Dep. variable: Employment rates adjusted for observable characteristics					
Explanatory variable:	All		recent		long-term	
Share natives in immigrant occ.	(1)	(2)	(3)	(4)	(5)	(6)
I. Base	-.196**	-.499**	-.479***	-.540*	-.159	-.560**
	(.087)	(.196)	(.148)	(.303)	(.111)	(.244)
Adj. R^2	.875		.713		.961	
Implied effect ($\Delta 8104 = .021$)	-.004	-.010	-.010	-.011	-.003	- .012
II: Males only	-.178	-.601**	-.642***	-.525	-.077	-.648**
	(.113)	(.234)	(.149)	(.330)	(.150)	(.271)
Adj. R^2	.878		.652		.944	
Implied effect ($\Delta 8104 = .021$)	-.004	-.013	-.013	-.011	-.002	-.014
III: Low-skilled natives	-.138***	-.175	-.203***	-.232	-.138***	-.152
	(.038)	(.134)	(.071)	(.186)	(.043)	(.178)
Adj. R^2	.877		.686		.957	
Implied effect ($\Delta 8104 = .077$)	-.011	-.013	-.016	-.018	-.011	-.012
Additional controls	Region, year and state-year fixed effects					
Method of estimation	OLS	IV	OLS	IV	OLS	IV

Note: $N = 4896$ (204 labor market regions x 24 years). Table displays regression coefficients from region-year level regressions for which the dependent variable is the employment rate of workers with foreign citizenship (and separated by years since migration). Employment rates are regression adjusted for observable differences in the age and education structure and gender. Each regression includes state and year fixed effects and state-year fixed effects in the indicated columns. Standard errors clustered at the regional level are in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Since the labor force participation of women is very low and follows a reverse trend for the native and immigrant sample, I re-estimate the model restricting the sample to men only.[18] The point estimates presented in panel II are similar in size and imply that polarization potentially accounts for around 1.3 percentage points of the 6.5 percentage point decline in male employment rates. As before, relative to the overall employment decline the relationship is more relevant for recent immigrants. Instead of considering low- and medium skilled labor jointly, in the regressions in panel III the explanatory variable is restricted to native low skilled employment. The coefficients are smaller in magnitude but the overall effect is similar in size as the change in the share of low skilled natives in immigrant occupations over time is larger. Again, the link between the share of natives in immigrant occupations and employment rates is more pronounced for immigrants who have been in Germany for

[18] Since the number of immigrant women in the sample is rather small, there are not enough observations in region/year cells to perform the analysis for females only.

less than five years.

The results could also be driven by selective in- or out-migration. In regressions not shown here, I account for in-migration and select a sample composed of those immigrants who were already living in Germany prior to 1981. Although smaller in size and less precisely estimated, the results reveal the same pattern. Given the longitudinal nature of the data set, I can also control for out-migration by further restricting the immigrant sample to those that are observed in the data before 1981 and after 2004. This additional restriction reduces the sample size considerably but the general pattern remains.

Table 4.7: Robustness: Employment Opportunities and Occupational Structure - Alternative Definitions

	Dep. variable: Employment rates adjusted for observable characteristics					
Explanatory variable:	All		recent		long-term	
Share natives in immigrant occ.	(1)	(2)	(3)	(4)	(5)	(6)
I. Base	-.196**	-.499**	-.479***	-.540*	-.159	-.560**
	(.087)	(.196)	(.148)	(.303)	(.111)	(.244)
Adj. R^2	.875		.713		.961	
Implied effect ($\Delta 8104 = .021$)	-.004	-.010	-.010	-.011	-.003	- .012
II: Service occupations	-.378***	-.405	-.189	-1.327*	-.426***	-.013
	(.109)	(.564)	(.146)	(.776)	(.133)	(.643)
Adj. R^2	.876		.711		.957	
Implied effect ($\Delta 8104 = .047$)	-.018	-.019	-.009	-.062	-.020	-.001
III: Low-wage occupations	-.431***	-.513	-.256*	-1.551***	-.504***	-.062
	(.128)	(.430)	(.148)	(.597)	(.164)	(.469)
Adj. R^2	.876		.683		.957	
Implied effect ($\Delta 8104 = .017$)	-.007	-.009	-.004	-.026	-.009	-.001
IV. Share natives in	-.036	-.006	-.423***	-.156	.127	.138
production occupations	(.081)	(.310)	(.140)	(.409)	(.081)	(.313)
Adj. R^2	.875		.713		.961	
Implied effect ($\Delta 8104 = -.046$)	.002	.000	.020	.007	-.005	-.006
Additional controls	Region, year and state-year fixed effects					
Method of estimation	OLS	IV	OLS	IV	OLS	IV

Note: $N = 4896$ (204 labor market regions x 24 years). Table displays regression coefficients from region-year level regressions for which the dependent variable is the employment rate of workers with foreign citizenship (and separated by years since migration). Employment rates are regression adjusted for observable differences in the age and education structure and gender. Each regression includes state and year fixed effects and state-year fixed effects in the indicated columns. Standard errors clustered at the regional level are in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Table 4.7 continues the robustness checks and compares alternative definitions of $Share_{rt}$. Panel II re-estimates the model employing the share of natives in service occupations as a measure of lower-tail polarization. Research for the United States (Autor and Dorn, 2013) and Germany (Senftleben-König and Wielandt, 2014b) has shown that employment growth in service occupations is the main driver of the twisting of the lower tail of the employment and wage distribution. In line with these findings, panel II reports a significantly negative relationship between the share of natives in service occupations and employment opportunities of immigrants. The implied effect is slightly larger compared to the baseline specification since the share of natives in service occupations increased twice as much in comparison to the change in immigrant occupations. Panel III considers the share of natives in low-paying occupations (occupations in the bottom decile of the wage distribution in 1980) as a measure of lower-tail employment polarization. Again, the general pattern remains and the implied effect is similar in size. In panel IV, the explanatory variable is the share of low- and medium skilled native employment in production occupations which is not significantly related to employment outcomes of immigrants. This relationship becomes positive once the sample is restricted to long-term immigrants which is consistent with previous findings and in line with the task-based approach.

There is a large branch of the urban economics literature that is concerned with spatial inequality in employment growth. Although region fixed effects already pick up part of this variation, including native employment levels in the regression leaves the results unchanged. Furthermore, restricting the sample to urban or rural areas yields comparable results. While this study focuses on West German labor markets, the time period includes German reunification in 1990. For regions in close proximity to the former East-West border, results could be driven by exogenous increases in the labor supply due to migration flows following the fall of the wall. Excluding labor markets along the border in the regressions yields results consistent with the baseline specification. I further test the generality of the results by experimenting with alternative definitions of immigrant and low-paying occupations yet obtain similar results. Further, the conclusions of the analysis remain unaltered by the selection of different start and end dates.[19]

In summary, the presented results from this section suggest that there is a negative relationship between employment opportunities of immigrant workers and the share of natives in immigrant jobs. This relationship is robust to the sample selection, the choice of time period and how the share variable is defined. Although the results seem to be very robust, they probably hide considerable hetereogeneity according to country of origin and language proficiency, factors that have been proven to be important predictors of immigrant labor market outcomes. Unfortunately, the data at hand allow no further distinction by country of origin due to data protection reasons. However, tabulations using later QCS waves in which foreign-born workers are included suggest that non-EU country immigrants have a higher probability of working in manual intensive low-paying occupations in comparison to

[19]Results of all robustness checks not included in Table 4.6 and Table 4.7 are available upon request.

EU immigrants implying a higher risk for these workers.

4.5 Conclusion

With the caveats discussed above, the results presented in this chapter suggest that a portion of the decline in employment rates of immigrants are associated with a technology driven decline in demand for middle paying occupations associated with an increase of substitutable labor in low paying occupations. From the empirical investigation, the following findings stand out: first, technological change has explanatory power for employment changes of natives in the lower tail of the wage distribution. Second, employment polarization in the native labor market is negatively related to employment opportunities of immigrant workers while wages are generally found to be unresponsive to native employment levels. The reallocation of natives towards low paying occupations has not been dramatic over the period and the share of natives in immigrant occupations has increased on average by 2 percentage points. Therefore, the implied effects are only modest, and depending on the specification, polarization potentially explains around 12 per cent of the decline in immigrant employment rates. Third, this relationship is more relevant for recent immigrants that have been in Germany for less than five years. For this sub-sample, polarization potentially accounts for up to one third of the decline in employment rates. Employment opportunities of immigrants that have been in the country for longer periods of time do not seem to be affected as much.

The presented results are consistent with the possibility that declining employment rates of immigrant workers are in part related to increased labor market competition from natives. The results support the idea that the technology driven declining demand for routine task occupations and the reallocation of employment towards lower-paying jobs induces competitive pressure in the lower-paying segment of the labor market causing foreign employment and wages to decline. Due to data limitations, the most recent changes in employment and wages cannot be considered. However, it seems that polarization is still a relevant factor related to immigrant labor market outcomes.

5 Regional Task Intensity and the Growth of Temporary Help Services

5.1 Introduction

The growth of temporary help services (THS) is an important stylized trend in many industrialized countries. In Germany, THS has increased tremendously in recent decades (see, e.g., Rudolph and Schröder, 1997; Deutscher Bundestag, 2009). This evolution has sparked a growing academic as well as public interest in the implications of THS for job stability, wage inequality and labor market segmentation.[1] However, most authors argue that THS is still a minor part of overall employment and thus not relevant as a key explanation for the secular trends of employment and wage polarization. While this assessment seems to be appropriate for the national aggregate, the overall share masks an already much higher impact of THS employment in regional labor markets. For Germany as a whole, THS employment constituted a share of 2 percent of overall employment and 3 percent of dependent employment in 2008 (cf. Deutscher Bundestag, 2009; Jahn and Bentzen, 2012). In our data for 2008, some regions exhibit THS employment shares larger than 8 percent. In this chapter, we adopt the task-based approach to study the heterogeneous pattern in regional growth of THS employment, and hence shed further light on the question if THS constitute a boon or bane for regional labor markets.

An important insight of the task-based framework is that the classification of employment by its task content (e.g. routine or non routine tasks) enables a deeper understanding of many trends that shape modern labor markets. Autor et al. (2003) first argued that especially routine tasks which are easily codified are substituted by computer capital.[2] The key idea is that these routine intensive occupations are in the middle of the wage distribution, and that the substitution by computer capital leads to a decline in the demand for those medium skilled occupations, while demand for high- and low-skilled labor increases. The task-based approach therefore predicts a polarization of employment and wages, a stylized fact that has been analyzed and documented for many industrialized countries (see Autor et al., 2006 for the U.S., Goos and Manning, 2007 for the UK, Dustmann et al., 2009; Senftleben-König and Wielandt, 2014b for Germany; Goos et al., 2009a,b; Michaels et al., 2014 present evidence of labor market polarization for European countries). Recent research by Autor and Dorn (2013)

[1] See, e.g., Nonnenmann (2011); Möller (2011).

[2] See Autor and Acemoglu (2011) for a comprehensive overview of the task literature and Weiss (2008) for a model of the substitution of human routine tasks by computer capital.

extends the analysis of the impact of nuanced skill-biased technical change on employment and wages to local labor markets. Regions that were initially specialized in routine intensive occupations saw a substantial decline in employment in these occupations, but a growth in low-skilled service sector employment which is in line with the idea of employment and wage polarization.

The concept that routine tasks are not only easily codified and computerized, but also easy to explain and easy to monitor, has inspired further research on the tradeability of tasks.[3] Grossman and Rossi-Hansberg (2008) first proposed a model of tradeable tasks and established a positive relationship between factor productivity and the decline in costs of trading the task, which makes the task easier to offshore. Using firm level data on US multinationals, Oldenski (2012) confirms that routine intensive tasks are indeed more likely to be offshored. This finding is also supported by empirical evidence for Germany using industry-level data presented by Baumgarten et al. (2013).

Our research project links this task and "trade-in-tasks" literature to the existing studies of employment services. In their seminal paper for the US, Segal and Sullivan (1997) use CPS data to study the changing nature of temporary work and first documented a shift in the composition of workers in this sector away from office and administrative support occupations towards blue-collar occupations. Furthermore, they argue that labor market outcomes of temporary workers are worse: their job stability is reduced, they gain lower wages and have a higher probability of getting unemployed. Subsequently, most studies on THS employment have further analyzed the impact of THS employment from the perspective of the temp workers, in particular whether temp work provides a "stepping stone" out off unemployment into regular employment[4]

From the perspective of the firm recurring to THS, three key types of potential explanations for their THS use have been set forth in the literature (cf. Abraham, 1990; Abraham and Taylor, 1996; Segal and Sullivan, 1997; Houseman, 2001; Autor, 2001; Burda and Kvasnicka, 2006). First, the use of THS may allow firms to gain *flexibility* to adjust the extensive margin more easily in response to business cycle and/or seasonal fluctuations and also replace permanent employees in cases of (long-term) sickness. Second, firms might employ temps as a way to improve *screening* of prospective permanent employees. Third, the use of THS might provide firms with *cost savings* if the total cost to the employer is lower for a temp worker than for a permanent employee. The empirical evidence on the relative importance of these three motives is still relatively scarce. While the flexibility argument is regularly

[3]However, it is not a priori clear which tasks are most likely to being offshored. Following Autor et al. (2003), Levy and Murnane (2004) have classified tasks into routine and non routine tasks. Blinder (2006) on the other hand argues that regional proximity and face-to-face contact are important determinants for the tradeability of tasks.

[4]See, among others, Autor and Houseman (2010) who exploit the unique structure of a job placement program in Detroit and find no evidence for the "stepping stone"-effect of temporary-help work, as placement in temporary help jobs does not improve labor market outcomes of low-skilled workers. For Germany, Kvasnicka and Werwatz (2003), Kvasnicka (2009), and Jahn and Rosholm (2014) analyze the transitions into and out of THS work and the associated wage gaps and reach similar conclusions.

brought forward by representatives of THS firms and several studies have confirmed that THS employment is indeed procyclical, this argument alone does not seem to explain the secular rise in THS employment, at least in the absence of a commensurate trend towards more aggregate volatility.[5] The appeal of the screening motive seems to be limited to the small group of temp workers that possess higher and more specialized skills, as the empirical absence of a pervasive "stepping stone"-effect into permanent employment at least for the large majority of low qualified temp workers suggests. Due to the lack of representative micro data on the detailed personnel cost structure of employers, the empirical analysis of the cost saving motive relies either on employer surveys or on case studies on a small number of firms. Houseman (2001) reports evidence from a representative survey of US companies conducted in 1996: while only a small share of employers cited cost-savings when asked directly about their motives for the use of temps, a large majority of them still indicated that the total hourly billed rate for temp workers would be equal or lower relative to the hourly compensation including benefits for their comparable permanent employees. Houseman et al. (2003) analyze and compare the use of temp workers in a sample of six hospitals and five auto suppliers. Their analysis of the relative cost of temp workers reveals a split pattern: while the bill rate for high-skilled specialized temps is higher than the average total employer costs of regular employees, the use of temps for low-qualified jobs is associated with cost savings of 10 to 30 percent. For Germany, Oberst et al. (2007) provide a rare inside perspective on the use of temp workers by a service sector company and estimate a cost saving of 29 percent per hour of work for the use of temp workers relative to permanent employees with similar characteristics.[6]

While the lack of data precludes the opportunity of establishing the exact magnitude of potential cost savings for a more representative set of firms that use THS, several studies have pointed to institutional factors that could have made THS use look more attractive to firms in search of opportunities to lower their wage bill. Autor (2003) establishes a causal link between the presence of restrictive employment protection legislation associated with high firing costs to employers and the growth of THS employment over time and across U.S. states. Houseman (2001) points to the level of unionization, leading to permanent workers enjoying rents from non-competitive wages, as a potential explanation for the prevalence of THS use in manufacturing. Dey et al. (2012) find some empirical support for this claim by constructing a unique panel data set on employment by occupation by industry for the years 1989 to 2004, and showing that US manufacturers increasingly use employment services to outsource low-skilled manual and clerical occupations.[7]

[5] Note that the time periods under consideration in almost all existing studies on THS still exclude the current Great Recession that might constitute a turning point towards an era of increased volatility and uncertainty.

[6] Mitlacher (2007) also compares the use of temp work in the US and in Germany and reports cost savings in the German automotive industry of 8.55 EUR per hour and of 10-15 percent per hour in the catering industry for unskilled temp workers.

[7] Based on a smaller sample of US manufacturing companies in Wisconsin, Vidal and Tigges (2009) also find evidence of a "systematic use" of temp workers, which they characterize as a trend towards "permanently tempting out entire positions".

Against the backdrop of these strands of the literature, our study proposes a fresh look at the demand-driven explanation of the growth of THS employment by incorporating the data and methodology of the task and trade-in-task literature into the analysis of the evolution of THS employment. Our research questions are twofold: first, do firms outsource primarily manual tasks into THS employment, as predicted by the task framework? Second, does THS employment hence grow faster in local labor markets that are initially more intensive in manual labor? Our results indicate that the share of THS employment indeed rises particularly strongly for occupations that were initially intensive in manual tasks, but not for those intensive in non routine interactive or routine cognitive tasks. Taken to the regional level, the initial routine manual share of a region is a strong predictor of the subsequent regional growth in THS employment: a 1 percentage point higher routine manual share in a region in 1979 is associated with an increase in the growth rate of THS employment between 1979 and 2008 by 50 percentage points. This result is robust to the inclusion of a number of regional covariates and alternative levels of regional aggregation. The chapter proceeds as follows: the next section spells out the empirical approach and describes the datasets that are used. Section 5.3 reports the results from the descriptive analysis and the regression estimates. Section 5.4 summarizes the conclusions and details avenues for further research.

5.2 Methods and Data

5.2.1 Empirical Approach and Estimation Strategy

Starting point of our analysis is the observation that occupations differ in their skill requirements and task structure (Autor et al., 2003; Spitz-Oener, 2006). Taken these differences as given, occupations witness a differential growth of THS provision depending on their initial task structure. However, it is not a priori clear which task are more likely of being outsourced into THS employment. The offshoring and trade-in-tasks literature (Blinder, 2006; Grossman and Rossi-Hansberg, 2008) hypothesizes that firms can realize cost savings by relocating impersonal/routine tasks into countries with a wage advantage. However, the degree of offshorability is limited by the amount of labor that requires regional proximity or the direct integration into the production process at the firm's own plant (including the use of firm-specific assets). Following this line of reasoning, outsourcing into THS employment would provide employers with an additional mechanism to lower their labor costs for these tasks or in cases when offshoring is not feasible due to other strategic considerations.[8] In line with the observation at the occupational level, regional differences in industry specialization and therefore the task structure should have differential effects on regional THS employment growth. In our econometric analyses, we therefore test two closely related predictions: (1) firms primarily outsource manual tasks into THS employment and (2) THS employment grows faster in manual intensive labor markets.

[8]This argument has also been put forward in recent studies on re-shoring (Baldwin and Venables, 2011).

In order to analyze the relationship between the occupational task intensity in 1979 and subsequent growth in THS penetration, we set up an empirical model of the following form:

$$\Delta(THSshare_{k,1979-2008}) = \alpha + \beta_1 TI^j_{k1979} + e_k \tag{5.1}$$

where $\Delta(THSshare_{k,1979-2008})$ is the change in the share of occupational employment provided by THS between 1979 and 2008, j indexes the task categories and k the detailed occupations. TI^j_{k1979} measures the fraction of occupational employment allocated to the respective task in 1979 and the associated coefficient β_1 reveals which tasks are most prone to substitution by THS employment. Estimates are weighted by the average fraction of national employment in each occupation between 1979 and 2008.

In our main analysis at the regional level, we regress the log difference of regional THS employment for a given region and period on the initial task share according to the following specification:[9]

$$\Delta(Y_{rt,t+1}) = \alpha + \beta_1 TSH^j_{r1979} + \mathbf{X'_{r1979}}\beta_2 + e_r. \tag{5.2}$$

Our main parameter of interest, β_1, is the coefficient on the measure of the initial task share in 1979, TSH^j_{r1979}. The vector X_{r1979} includes additional variables aimed at controlling for heterogeneity in the regional distributions of employment. All regressions use robust standard errors and are weighted by start of the period regional total population.[10]

5.2.2 Data and Construction of Variables

Our measure of regional task intensity as the main explanatory variable is constructed from the combination of two datasets, the Sample of Integrated Labor Market Biographies (SIAB) and the BIBB/IAB Qualification and Career Survey (QCS). The information on the task content of occupations comes from the QCS, which is an employment survey carried out by the German Federal Institute for Vocational Training (*Bundesinstitut für Berufsbildung; BIBB*) and the Research Institute of the Federal Employment Service (*Institut für Arbeitsmarkt- und Berufsforschung; IAB*). It consists of five cross-sections in the years 1979, 1985, 1992, 1998 and 2006, each covering about 30.000 individuals, including men and women (see Rohrbach-Schmidt, 2009). The dataset contains information on workplace characteristics and educational attainment and is particularly well suited for our research, as it includes detailed information on the activities individuals perform at the workplace and

[9] 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. In contrast, we restrict our analysis to the single difference based on the routine shares and regional covariates in 1979 as the explanatory variable to focus on the long-run component of differences in regional task structures and thus circumvent the potential endogeneity problem related to the use of subsequent task shares. For ease of interpretation and comparison across periods, the outcome variables are adjusted for the length of the different time periods and represent 10 x annual changes.

[10] To correct for outliers, we exclude the regions "Pirmasens" and "Garmisch-Partenkirchen" from our regressions as their manual task shares in 1979 are more than one standard deviation larger compared to the second largest regional task share. Figure 5.4 provides a graphical illustration.

on the tools and machines employees use at work. These activities are pooled into five task groups. In the assignment of tasks, we follow Spitz-Oener (2006) and construct individual task measures TM^j_{i1979} for task j according to the definition of Antonczyk et al. (2009):

$$TM^j_{i1979} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } 1979}{\text{total number of activities performed by } i \text{ over all categories in } 1979} * 100, \quad (5.3)$$

where j = A, I, RC, RM and M represents the five task groups non-routine analytic (A), non-routine interactive (I), routine cognitive (RC), routine manual (RM) and non-routine manual (M).[11] The individual task measures are aggregated to construct average task indices for each occupation k, where L_{ik1979} is the number of individuals working in occupation k in 1979:

$$TI^j_{k1979} = \left(\sum_i TM^j_{ik1979}\right)\left(\sum_i L_{ik1979}\right)^{-1}. \quad (5.4)$$

TI^j_{k1979}, the task intensity of occupation k in 1979 is matched to the SIAB employment sample, which is a two percent random sample of administrative social security records in Germany covering the years 1975 to 2008 (Dorner et al., 2011). The sample consists of about 200.000 employment spells per year and provides detailed information on employment spells for dependent employees who contribute to the social security system (civil servants and self-employed workers are not included). The data set also contains information on the individuals' age, gender, educational attainment as well as information on the employer such as industry affiliation, firm size and location. The occupational titles used in the two datasets are categorized according to the 1988 classification constantly throughout time and the datasets are therefore well suited to analyze the development of skill requirements within occupations.

Furthermore, the SIAB provides a time-consistent definition of administrative districts in Germany, which can be used to construct the regional task shares. Since administrative regions in Germany have developed as a result of historical circumstances they do not necessarily depict regional economic entities (Eckey et al., 2006). For the analysis of regional employment changes functional labor markets that exhibit few commuter flows are more suited. A delineation by Eckey et al. (2006) is particularly adequate as it derives labor market regions that consist of one or more administrative districts across state borders and take commuter flows into account. This feature is particularly relevant for our analysis as it limits the potential measurement error if employees of THS firms located in one district are leased to companies in other districts. Following Eckey et al. (2006), we therefore further aggregate the administrative districts into 150 labor market regions (with 113 in West and 37

[11] The sample to construct the individual indices includes West German employees aged 20-60, excluding public sector and agricultural employment.

in East Germany). For each region r the task share TSH^{j}_{r1979} is given as:

$$TSH^{j}_{r1979} = \left(\sum_{k=1}^{K} L_{kr1979} * TI^{j}_{k1979}\right)\left(\sum_{k=1}^{K} L_{kr1979}\right)^{-1}, \qquad (5.5)$$

where j indexes the respective task and L_{rk1979} is the employment in occupation k in labor market r in 1979. For example, TSH^{RM}_{r1979} thus represent the share of routine manual labor in total employment on the regional level in 1979.[12]

As for our main outcome variable, regional THS employment, we use data for the time period 1975-2008 from the Establishment History Panel (BHP) provided by the German Institute for Employment Research (IAB) (see Hethey-Maier and Seth (2010) for details and e.g., Dauth (2013) for the use of the BHP in an analysis of employment in the context of regional externalities). The BHP data is a cross-section of the complete universe of all establishments that employ at least one employee subject to social security contributions on June 30th of a given year. Based on the mandatory individual social security notifications, the BHP provides for each establishment information on the total number of employees as well as several breakdowns, e.g. the number of employees by gender, age, citizenship, education, and working hour categories. In addition, it details the district (NUTS-3 region) where the establishment is located, the year the establishment was founded (i.e. the starting year of the first employment contract subject to social security contributions) and the detailed 5-digit industry classification.

The BHP data is particularly adequate for the study of the THS employment at the regional level. As it covers the total employment at the granular establishment level, it provides a more complete picture of the regional importance of THS employment than survey data with sampling error or data based on firm statistics. It is also highly accurate due to its official use for the social security administration. However, these advantages come at three types of cost. First, the aggregate nature of the data precludes the use of information at the level of the individual employee in the analysis. Second, the BHP data does not entail additional information at the establishment level on productivity, type of assets etc. Third, the employment information is restricted to the number of full-time employees, as the number of part-time employees is only incompletely recorded until a change in the social security legislation in 1999. However, as part-time work is only a minor share of overall THS employment[13], the last caveat is only of minor importance for our analysis.

In constructing our panel of the regional level of THS employment, we proceed similar to Kvasnicka and Werwatz (2003) to identify all THS establishments via their registration

[12]Our measure of regional task intensity improves on that in Autor and Dorn (2013) by exploiting the task intensity of all occupations. Hence, we measure the share of all regional routine employment instead of using only the top third most routine intensive occupations. See Senftleben-König and Wielandt (2014b) for further details on the construction of the index.

[13]See, e.g., Rudolph and Schröder (1997), who find that the shares of part-time workers in 1995 are only .3 percent (5 percent) for males (females), compared to 2 percent (27 percent) in overall employment.

with the industry code exclusively dedicated to THS.[14] One drawback of this approach is that the THS workers that are leased to other companies cannot be easily differentiated from the permanent workforce of the THS firm, i.e. the managerial and administrative staff that organizes the temporary work mission. Again, we rely on Kvasnicka and Werwatz (2003) who cite additional evidence that the permanent workforce of the THS firm only constitutes a minor part (less than 8 percent) of the total staff of the THS establishments.[15]

We aggregate the THS employment data from the establishment level to the level of the 113 labor markets and merge them with the measures of the regional routine share in 1979. We further augmented our panel of region-by-year observations by aggregating information from the BHP on the overall composition of the regional employment distribution with regard to the fraction of female employees, the share of young employees (defined as being less than 25 years old), the share of high and low skilled employees, the share of foreign employees and the distribution of employment by three firm size categories.[16]

5.3 Results

5.3.1 Occupational THS Growth and Job Tasks

Temp-workers are mainly employed as laborers, in low-skilled blue-collar or administrative support occupations (Jahn and Pozzoli, 2013; Dey et al., 2012). Figure 5.1 depicts aggregate trends in the growth of occupational employment provided by THS between 1979 and 2008 for 6 broad occupational groups.[17] THS penetration increased over time for all occupational groups but accelerated particularly for manual occupations in the mid 1990's. Unskilled manual occupations (e.g. miners, rockbreakers, welders, unskilled workers) witnessed the largest growth in THS penetration as well as to a smaller extent skilled manual occupations (e.g. glassblowers, bookbinders, precision instrument makers, carpenters). In contrast, the increase in THS employment between 1979 and 2008 in high-skilled occupations such as professionals, managers and engineers is minuscule in size.

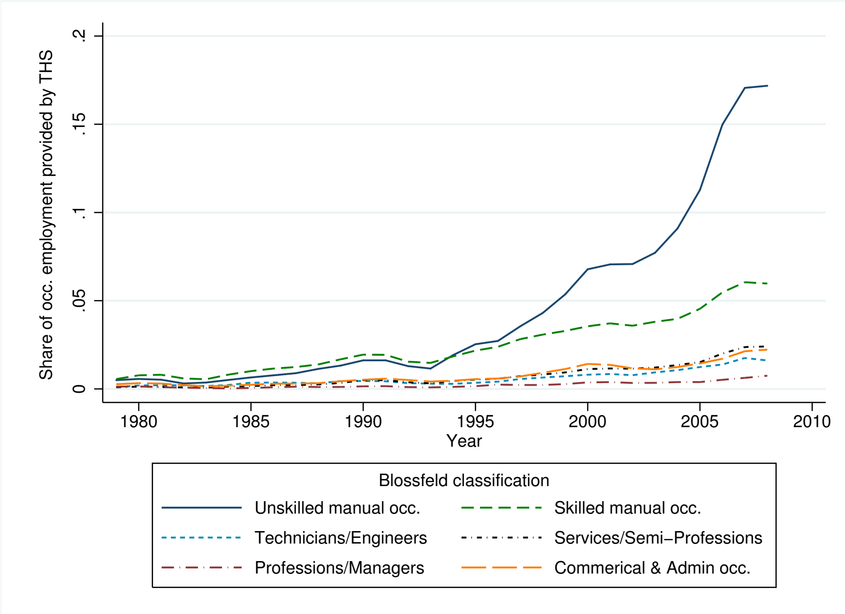
[14]For the industry classification 1973, this industry category is labeled at the 3-digit-level with the code 865 "Arbeitnehmerüberlassung/Leiharbeitskräfte", and for the industry classification 2003, the respective code is 74.50.2 "Überlassung von Arbeitskräften". Kvasnicka and Werwatz (2003) provide supplementary evidence that the establishments in this industry category make up for the large majority of THS employment in Germany.

[15]In a robustness check, we also subtracted at the THS establishment level the number of employed managers from the total full-time employment, as we assume most of these high-skilled employees to be *permanent* staff since the market for the temporary lease of managers is miniscule in size. Our preliminary results are not sensitive to this change.

[16]The additional covariates which will be used in the regression analysis and that are listed in Table 5.4 are chosen according to Autor and Dorn (2013). We also considered the share of employment concentrated in manufacturing as potential covariate. However, the manufacturing share is highly correlated with our measures of regional routine intensity and therefore likely a "bad control".

[17]In an effort to build homogeneous occupational groups with respect to their educational requirements and occupational assignments, occupations are aggregated into 6 major occupational groups following Blossfeld (1985). Occupations are classified according to the industrial sector (production, service, administration) and further subdivided by qualification.

Figure 5.1: Share of occupational employment provided by THS, 1979-2008



Notes: Occupations are aggregated into 6 major occupational groups following Blossfeld (1985). Source: IAB-QCS data; own calculations. See text for details.

For the same 6 occupational groups, Table 5.1 displays aggregate skill inputs in 1979. In line with the task-literature, manual and service occupations are characterized by a high routine and non routine manual task content while interactive and analytic tasks are more prevalent in high-skilled occupations.[18]

Table 5.1: Aggregate Skill Inputs in 1979 by Occupational Group

Occupation	Non-routine analytic	Non-routine interactive	Routine cognitive	Routine manual	Non-routine manual
Unskilled manual occupations	.019	.060	.093	.544	.285
	(.110)	(.195)	(.245)	(.450)	(.407)
Skilled manual occupations	.045	.107	.075	.312	.460
	(.161)	(.237)	(.195)	(.398)	(.431)
Services/Semi-Professions	.027	.197	.101	.160	.515
	(.118)	(.320)	(.221)	(.297)	(.433)
Commercial & Admin occupations	.025	.254	.346	.354	.022
	(.106)	(.322)	(.310)	(.299)	(.111)
Technicians/Engineers	.320	.250	.157	.166	.106
	(.370)	(.303)	(.245)	(.291)	(.229)
Managers/Professions	.102	.459	.255	.122	.062
	(.205)	(.336)	(.275)	(.197)	(.181)

Notes: Occupational task information on the three-digit level of the classification of occupational titles 1988 is derived from the QCSs. Occupations are then further aggregated into 6 major occupational groups following Blossfeld (1985). Sample includes West German workers aged 20-60 excluding agricultural and public sector employment.

[18]Looking at the data from a different angle, Table 6.2 in Appendix 6.4 lists the ten three-digit occupations with the highest share of THS employment in 2008 and their task content in 1979. Consistent with previous evidence, those occupations are characterized by a high routine and non routine manual task content.

We now further explore analytically which tasks are most prone to substitution by THS employing the empirical strategy described by equation 5.1. Table 5.2 summarizes the results for the five task measures. The negative albeit insignificant coefficient in column 1 suggests that occupations with a high non-routine analytic task content in 1979 witnessed a slower growth of THS employment between 1979 and 2008. This negative relationship holds also true for occupations with a high non-routine interactive task content as indicated by the negative an highly significant coefficient in column 2. As those tasks in our data are mainly performed by high-skilled employees, this finding seems to square with the fact that the large majority of temp workers is employed in rather low qualified occupations. While routine cognitive tasks seem to be less prone to substitution by THS employment as well (column 3), a high routine manual task intensity predicts a much faster growth in occupational THS penetration (column 4). The positive and highly significant coefficient suggests that occupations with a high routine manual share in 1979 indeed witnessed a stronger growth in THS employment between 1979 and 2008. Based on the coefficient estimate of 8.574 a one standard deviation higher routine manual task content in 1979 is associated with a 200 percent larger growth in the occupational THS share. In other words, occupations with a one standard deviation higher routine manual share witnessed an increase in THS penetration twice as large compared to the mean occupational THS growth of 225 percent between 1979 and 2008. The coefficient estimate in column 5 predicts a positive but insignificant relationship between non routine manual task intensity and subsequent occupational THS penetration.

Table 5.2: Task Content and Growth of THS Share by Occupation 1979-2008

Task share	Means (SD)	Dependent variable: 100 x Δ share of occupational employment provided by THS (1)	(2)	(3)	(4)	(5)
Non routine Analytic	.090	-6.945				
	(.142)	(4.843)				
Non routine Interactive	.198		-10.570***			
	(.175)		(3.124)			
Routine Cognitive	.150			-6.692*		
	(.126)			(3.507)		
Routine Manual	.305				8.574***	
	(.225)				(2.564)	
Non routine manual	.258					2.194
	(.252)					(1.879)
R^2		.011	.059	.019	.057	.007

Notes: N=186 occupations. Occupations are defined according to the three-digit level of the classification of occupational titles 1988. Each cell reports the results from a separate OLS regression and its standard errors in parentheses. Estimates are weighted by the average fraction of national employment in each occupation over the years 1979-2008.

To summarize, occupations that are most likely to being outsourced into THS employment are those characterized by a high routine and non-routine manual task content which are mainly low-skilled blue collar occupations. In contrast, non-routine analytic and interactive tasks offer less potential for substitution by THS. We therefore expect a positive relationship between the initial share of manual employment in a region and subsequent THS employment growth and will focus on the relationship in the remainder of our analysis.

5.3.2 Regional Distribution of Manual Tasks and THS Employment

We start our empirical description at the regional level by looking at the top 10 regions with the highest manual shares of employment in 1979. Table 5.3 lists these regions, with a separate ranking for the routine manual and the non-routine manual share. The two rankings reveal distinct regional distributions: while the top regions in terms of routine manual share in 1979 correspond to industrial strongholds across Germany, the non-routine manual share is highest in regions that are characterized by tourism and hospitality.[19]

Table 5.3: Top 10 Regions with Highest Manual Shares in 1979

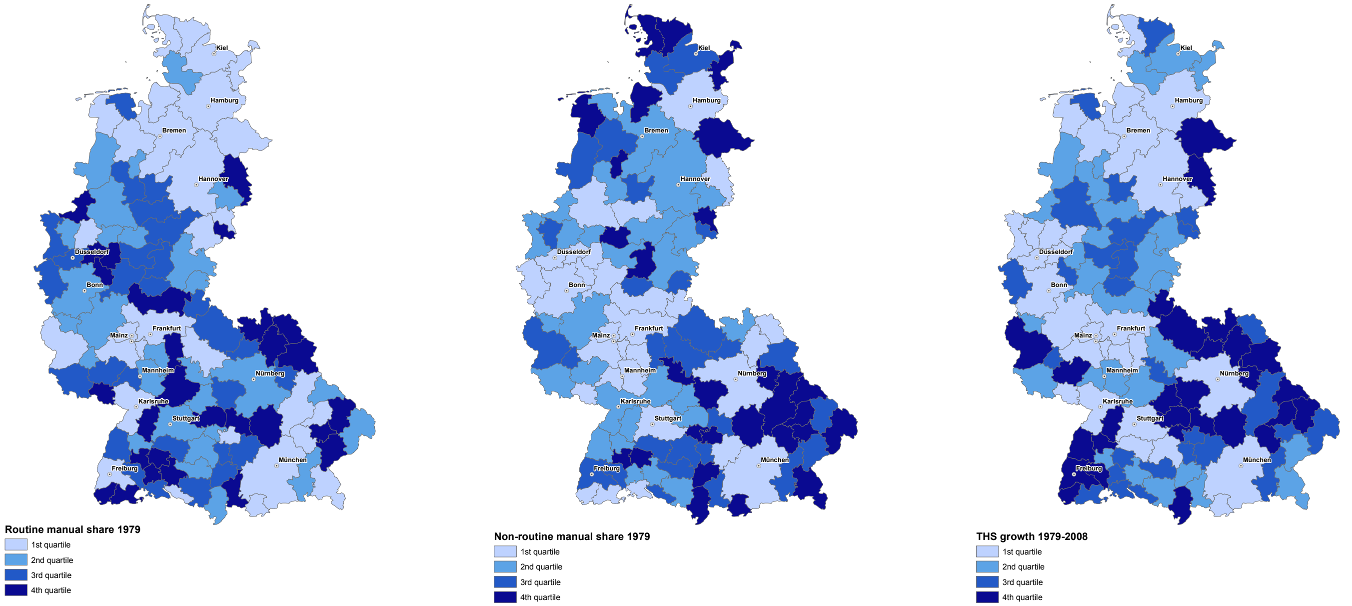
Panel A: Regional ranking in 1979					
Region	State †	Routine man.	Region	State †	Non-routine man.
Hof	BY	.384	Straubing	BY	.330
Dingolfing	BY	.373	Passau	BY	.323
Waldshut	BW	.364	Nordfriesland	SH	.318
Märkisch	NRW	.362	Cham	BY	.317
Tuttlingen	BW	.360	Landshut	BY	.317
Wolfsburg	NDS	.359	Traunstein	BY	.312
Lörrach	BW	.357	Heidenheim	BW	.311
Deggendorf	BY	.356	Ansbach	BY	.307
Rottweil	BW	.350	Waldeck	HE	.305
Coburg	BY	.349	Flensburg	SH	.305
Zollernalb	BW	.348	Emden	NDS	.305
Panel B: Descriptive statistics, manual shares 1979					
Mean		.322	Mean		.274
Std. Deviation		.020	Std. Deviation		.022

Notes: N=111. †The federal states are: Baden-Württemberg (BW), Bavaria (BY), Hessen (HE), Lower-Saxony (NDS), North Rhine-Westphalia (NRW), Schleswig-Holstein (SH).

Figure 5.2 further illustrates the geographic distributions by mapping the two manual shares in 1979. While a small number of regions do figure in the upper quartiles of both the routine manual as well as the non-routine manual share distribution, the overall correlation between the two manual shares is negative, with a correlation coefficient of -.2432.

[19] These regions are mainly located at the coast of the North and Baltic Sea, in the Bavarian Forest, and the Alps.

Figure 5.2: Routine task share and THS growth in West Germany, 1979-2008
left: Routine Manual Task Share *center:* Non-routine Manual Task Share *right:* THS Employment Growth by Region, 1979-2008



Source: IAB-QCS data; own calculations. See text for details.

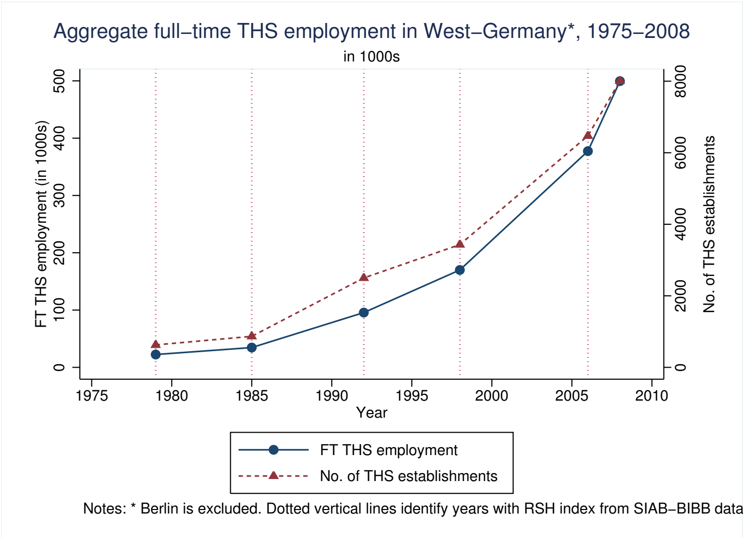
Table 5.4: Descriptive Statistics for Regions in West Germany, 1979-2008

	1979	1994	2002	2008
Full-time THS employment	202	780	1,986	4,491
	(536)	(1,398)	(2,852)	(5,540)
Full-time employment	148,692	152,520	147,654	143,999
	(190,734)	(191,655)	(188,467)	(182,643)
Fraction of THS in total employment	.0006	.0035	.0116	.0303
	(.0009)	(.0029)	(.0067)	(.0141)
Number of THS establishments	6	21	51	72
	(13)	(36)	(75)	(95)
Fraction employed/pop.	.262	.255	.242	.238
	(.048)	(.053)	(.050)	(.049)
Fraction female employees	.330	.330	.329	.320
	(.034)	(.026)	(.027)	(.029)
Fraction young (< 25) employees	.149	.112	.086	.082
	(.017)	(.018)	(.015)	(.016)
Fraction high to low skill employees	.032	.062	.086	.109
	(.015)	(.028)	(.040)	(.050)
Fraction manufacturing employment	.120	.102	.093	.089
	(.040)	(.031)	(.033)	(.034)
Fraction foreign employees	.084	.083	.070	.066
	(.044)	(.036)	(.032)	(.030)
Fraction small firms (<25 employees)	.319	.348	.358	.345
	(.061)	(.055)	(.055)	(.054)
Fraction medium firms (25-100 employees)	.211	.218	.224	.227
	(.036)	(.028)	(.029)	(.029)
Fraction large firms (>100 employees)	.471	.433	.418	.429
	(.091)	(.075)	(.077)	(.075)
Average unemployment rate[a]	-	.086	.081	.064
	-	(.022)	(.023)	(.024)
Average region population	539,585	558,864	568,901	570,161
	(625,945)	(608,124)	(618,137)	(626,555)
Population density	245	260	263	262
	(260)	(258)	(255)	(250)
Number of regions	111	111	111	111
Number of regions with THS employment $\geq$1	61	99	111	111

Notes: [a]The regional unemployment rate is only available from 1985 on.
All employment variables are based upon full-time employment subject to social security contributions for a given region. Fractions are computed with respect to total full-time employment.

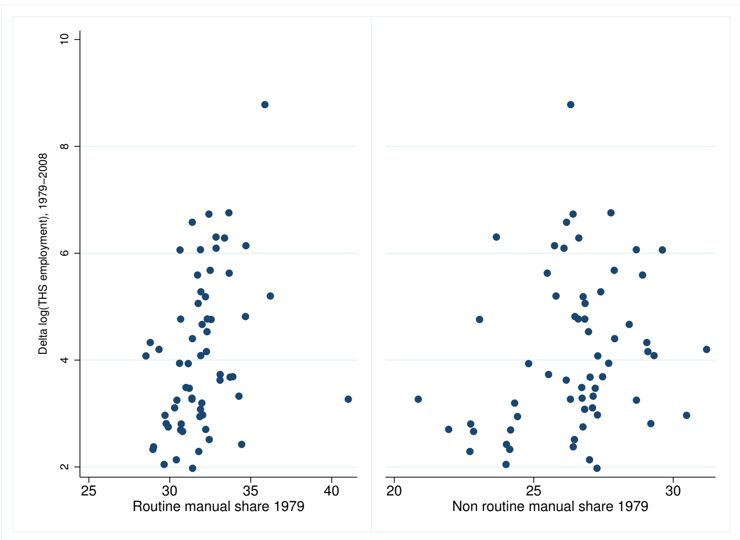
Table 5.4 summarizes the main characteristics of employment by region for the time period under consideration. The first row shows that full-time employment in THS was at very low levels until the beginning of the 1980's, with only 200 THS employees on average in a given region, and has started to grow especially since the mid 1990's. A similar development can be observed for the fraction of THS in total regional employment and the number of THS establishments, alike. While in 1979 still around 50 percent of the regions did not exhibit any THS employment, all regions had at least some THS employment in 2008. The tremendous growth in THS employment is most visible in Figure 5.3 which depicts aggregate full-time THS employment and the number of THS establishments in West-Germany for the years 1975 to 2008. In accordance with Table 5.4, THS employment increased only little until the early 1990's, but has accelerated afterwards. As noted earlier, even if the average share of THS employment in total employment seems to be rather small, it can be significantly larger for particular regions. The top five regions had a share of THS employment of around 8 per cent in 2008. Analytically, Figure 5.4 plots the routine manual and routine cognitive task shares in 1979 along with regional THS employment growth and reveals a positive relationship. Taken together, the first descriptive evidence provides encouraging results for the following regression analysis.

Figure 5.3: Aggregate Full-Time THS Employment (in 1000s) and Number of THS Establishments in West-Germany, 1975-2008



Source: IAB data; own calculations. See text for details.

Figure 5.4: Routine Manual Task Share and Regional THS Employment Growth, 1979-2008



Source: IAB-QCS data; own calculations. See text for details.

5.3.3 Regression Estimates for Relationship between Regional Manual Intensity and THS Employment Growth

Baseline estimates

As a first pass to analyzing the relationship between regional task intensity and THS employment, we relate the long difference in regional log THS employment between 1979 and 2008 to the initial manual shares of employment in 1979. The first column of Table 5.5 reports a coefficient estimate of .177 for the routine manual share, indicating that a 1 percentage point higher regional routine share in 1979 would translate into an increase in regional THS employment growth by 17.7 log points (∼17.8 percentage points) relative to the mean THS growth across all regions over 10 years. As to be expected from the earlier analysis on the differential penetration of THS by occupations intensive in non routine manual tasks, the relationship at the regional level also exhibits a significant positive relationship. Apparently, regions with high shares of non routine manual work witnessed a relatively faster expansion of THS employment. Column 2 adds a measure of the population density (number of inhabitants per square kilometer) to control for differences in urbanity between the regions. While the coefficient on the population density enters with a negative sign, the coefficient on the routine manual share remains unchanged compared to a slightly smaller coefficient on the non routine manual share than in the base result. In Column 3, the regression is further augmented with the share of the population active in social security employment. This variable that serves as a proxy for the employment rate is negatively associated with later THS employment growth. Next, columns 4-8 add alternative measures for the initial structure of employment in a region. The relative share of female employment enters with a positive and significant sign. This result seems to be consistent with the idea that THS employment could thrive in regions with a large workforce with relatively lower labor force attachment and less initial human capital. Similarly, the initial share of young workers below 25 years is positively (but insignificantly) related to the subsequent growth of THS, indicating that regions employing a greater regional pool of young workers (who are also less likely to have already obtained a large amount of firm-specific human capital) could be a fertile ground for the spread of THS work. The specification in column 6 aims to evaluate the effect from the variation in the human capital intensity of the regional workforce more directly by including the ratio of high- to low-skilled employment as a measure of formal educational attainment. Surprisingly, a higher relative share of high-skilled workers in a region is related to comparatively faster growth of regional THS employment. However, the coefficient is not statistically different from zero. Column 7 includes the relative share of foreign employees. If THS are used by firms to realize labor cost savings, a larger relative supply of foreigners (that could potentially market their skills at lower wages compared to natives) could have a moderating effect on THS growth. Indeed, the share of foreign employees exhibits a negative but insignificant coefficient and it leaves the coefficient on the routine manual share almost unaltered while the coefficient on the non routine manual share further declines. We also added the share of employment in large firms (defined as having more than 100 full-time employees) in column 8. Based on the literature on THS, there are two contradictory arguments regarding the expected effect of this explanatory variable: on the one hand, large firms might create relatively more demand for THS if they enjoy economies of scale in the outsourcing process, particularly if the use of THS requires a certain degree of sophistication in the management of HR processes. On the other hand, large firms in Germany are subject to more union influence due to the co-determination rights of works councils. Based on the partial correlation that we can observe in our regression analysis, the latter effect seems to dominate, as the coefficient estimate on this variable is negative but insignificant. Reassuringly, when the full set of explanatory variables is included (column 9), the point estimate on the routine manual share remains robust and still retains almost 98 percent of the size reported in the base specification in column 1. However, the point estimate on the non routine manual share is only 40 percent of its initial size and is no longer significant.

Table 5.5: Estimated Impact of Manual Task Shares on Regional THS Employment Growth, 1979-2008

10 x annual Δ log(THS employment)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Routine manual share 1979	.177***	.177***	.171***	.176***	.152***	.181***	.175***	.170***	.173***
	(.029)	(.024)	(.024)	(.024)	(.027)	(.034)	(.024)	(.025)	(.043)
Non-routine manual share 1979	.150***	.115***	.103***	.106***	.071**	.113***	.093***	.095***	.056
	(.018)	(.017)	(.020)	(.019)	(.029)	(.033)	(.025)	(.023)	(.038)
Population density		-.0005***	-.0005***	-.0004***	-.0005***	-.0005***	-.0005***	-.0005***	-.0003***
		(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Share employed/pop.			-.012*	-.015*	-.008	-.013*	-.008	-.009	-.010
			(.007)	(.008)	(.007)	(.007)	(.008)	(.008)	(.010)
Share female/empl.				.033**					.063***
				(.016)					(.023)
Share young (<25 years)/empl.					.069				.108**
					(.043)				(.046)
High to low-/medium-skilled empl.						.019			.015
						(.046)			(.062)
Share foreign empl./empl.							-.012		-.031**
							(.012)		(.015)
Share empl. large firms/empl.								-.006	.013
								(.010)	(.013)
R^2	.465	.568	.577	.597	.591	.578	.580	.580	.642

Notes: N=111. All models include a constant and are weighted by start of period regional population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Estimates for Subperiods

To get a better understanding of the underlying determinants of THS employment growth we further subdivide the long period 1979-2008 into three subperiods 1979-1994, 1994-2002 and 2002-2008. Since the early 1980's temporary agency employment in Germany underwent major deregulation and continuous liberalization, increasing the flexibility of THS use. Jahn and Bentzen (2012) point out that relaxing the regulations will affect the demand for THS employment as it decreases the quasi-fixed cost component of employment. Reforms in 1985, 1994 and 1997 gradually extended the maximum period of assignment from initially 3 months to 12 months and up to two years in 2002. The prohibition of THS employment in the construction sector (introduced in 1982) was abolished in 1994 and the re-employment and synchronization ban were relaxed from 1997 on. In order to improve the labor market situation of temp workers, the most recent reform in 2004 stipulated the equal pay and equal treatment principle between temp workers and the permanent workforce. Nevertheless, the temp agency can circumvent the new regulation by signing a sectoral collective agreement which makes the equal treatment principal obsolete.[20]

Table 5.6: Estimated Impact of Manual Task Shares on Regional THS Employment Growth, subperiods

Dependent variable:	Time Period					
10 x annual	1979-1994		1994-2002		2002-2008	
Δlog(THS employment)	(1)	(2)	(3)	(4)	(5)	(6)
Routine manual share 1979	.191***	.120	.178***	.253**	.142***	.113**
	(.049)	(.094)	(.063)	(.106)	(.032)	(.052)
Non-routine manual share 1979	.151***	-.022	.179***	.149*	.115***	.044
	(.035)	(.077)	(.042)	(.087)	(.037)	(.060)
Regional covariates	no	yes	no	yes	no	yes
R^2	.187	.326	.130	.189	.225	.265

Notes: N=112. Each cell reports the results from a separate regression. All regressions include a constant and are weighted by start of period regional population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

For our empirical analysis on the regional growth pattern of THS, these deregulation steps that amended the German national labor laws should only affect the posited secular relationship of the regional routine share if they in some way interacted with regional characteristics. We try to explore this possibility by re-estimating the regression model for three subperiods that each cover one or more of the aforementioned liberalization steps.[21] Table 5.6 presents the results for the base specification (column 1,3 and 5) and a specification including the regional covariates (columns 2,4 and 6) for each of the three subperiods,

[20] Mitlacher (2005) documents that while this regulation led to an increase in temp worker wages, their average remuneration is still far below the minimum pay stipulated in many industry collective wage agreements, and thus likely has not eradicated potential savings from THS use altogether.

[21] As THS employment is strongly affected by business cycle fluctuations, start and end points of the subperiods should be comparable with respect to their location in the economic cycle. Apart from the base year 1979 we therefore select 1994, 2002 and 2008. Figure 6.2 in the Appendix depicts the evolution of the output gap in Germany between 1979 and 2010 and underlines the appropriateness of the selected subperiods.

respectively. The results in Panel A confirm the positive relation between the manual routine share in 1979 and subsequent THS employment growth for all three subperiods, providing some further support for the notion that our previous estimates indeed capture a long-run secular relationship. As previously, a higher non routine manual share in 1979 also seems to predict a faster growth of THS employment throughout all subperiods, as presented in Panel B of Table 5.6. However, consistent with our previous estimates for the long difference from 1979 to 2008, the inclusion of covariates vastly reduces the coefficient estimates on the non routine manual share and renders them insignificant in nearly each period.

Robustness Checks

As a first step to test the robustness of our results we repeat the OLS estimates using an alternative definition of regional labor markets following a delineation of the "Gemeinschaftsaufgabe *Verbesserung der regionalen Wirtschaftsstruktur*" (Koller and Schwengler, 2000). This classification is based on a less rigorous provision for commuter flows than the one used in our baseline and aggregates the administrative districts into 204 labor market regions for West Germany.[22] It is therefore somewhat finer compared to the definition previously employed, but for administrative reasons does not allow for broader labor market regions that span across state borders. However, as argued before, temp workers are frequently assigned to firms that are not necessarily located in the same district which might lead to an underestimation of the relation between regional routine intensity and subsequent THS employment growth and thus rather favors the use of the broader classification following Eckey et al. (2006) for the purpose of our analysis. In any case, while the coefficient estimates in columns 1 and 2 of Table 5.7 are somewhat smaller, their overall pattern is consistent with the earlier results.

Table 5.7: Estimated Impact of Manual Task Shares on Regional THS Employment Growth, 1979-2008

Dependent variable:	Alternative regional		Spatial Error Model			
10 x annual	specification		Contiguity		Inverse Distance	
Δlog(THS employment)	(1)	(2)	(3)	(4)	(5)	(6)
Routine manual share 1979	.131***	.115***	.151***	.107**	.153***	.107**
	(.017)	(.034)	(.028)	(.041)	(.027)	(.042)
Non routine manual share 1979	.127***	.064**	.130***	.031	.132***	.031
	(.015)	(.028)	(.021)	(.040)	(.021)	(.040)
Regional covariates	no	yes	no	yes	no	yes
R^2	.342	.458				
Wald-Test			1.410	.008	.157	.000
p-value			(.235)	(.927)	(.692)	(.999)
N	202	202	111	111	111	111

Notes: Each cell reports the results from a separate regression. Regressions in columns 1 and 2 are weighted by start of period regional population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

[22] As before, we exclude the region "Südwestpfalz" which is part of the outlier region "Pirmasens" and "Garmisch-Partenkirchen", see footnote 10 on page 75 for details.

We also considered the possibility that outcomes in the regional labor market regions in our baseline analysis are potentially still spatially correlated and re-estimated spatial error models with contiguity and inverse distance weighting. 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. However, as the results for the base specification in columns 3 and 5 suggest, both weighting methods yield very similar, but somewhat smaller coefficients compared to previous results. The coefficient on the routine manual share for 1979 further decreases with the inclusion of additional control variables (columns 4 and 6) but remains highly significant. The non routine manual share becomes insignificant with the inclusion of the regional covariates just like in the earlier analysis. Moreover, there is no evidence of significant spatial autocorrelation as suggested by the Wald test statistic and the associated p-value.

Many additional tests further confirm the robustness of our results. In results not tabulated here, we tested alternative time periods in case our results are sensitive to the chosen end point of 2008. If we repeat our analysis with the time periods 1979-2006 or 1979-2007, the results remain virtually unchanged. We further experimented with different subsamples depending on the size and the region type of the specific labor market. We obtain similar result if we only consider urban or rural regions separately or if we estimate separate models for large (population >500 T in 1979) and small (population < 500 T in 1979) regions. Finally, we also tested specifications that included the initial share of THS employment in 1979 and the total employment growth rate between 1979 and 2008 as additional covariates to ensure that our results are not driven by a mere form of "catch up growth" or general differences in employment growth across regions. While these covariates enter with the expected sign (i.e. the initial share has a negative effect on the subsequent growth rate whereas the total employment growth rate has a positive effect), they are only marginally significant and leave the size and significance of our estimates on the regional manual shares unaltered.

Instrumental Variable Estimates

To shed some more light on the potential origin of the heterogeneous diffusion of THS employment across German regions, we exploit historical cross-regional differences in the production structure similar to the analysis by Autor and Dorn (2013) who relate the growth in local service sector employment since 1980 back to the regional industry structure in the U.S. in 1950. While this is not a true IV estimation in the sense that the instrument is completely exogenous, the approach should mitigate concerns about the endogeneity of the regional differences at the beginning of the sample period by isolating the long-run structural component of the regional employment composition. For this approach we use historical workplace and employee data (Arbeitsstätten- und Berufszählung) published by the Statistical Federal Office which includes the number of employees and workplaces by industry and region and is available for several years just after the second world war (Statistisches Bundesamt, 1953). Similar to the task shares we generate the fraction of manufacturing in regional employment in 1950. For the share of manufacturing in 1950 to serve as a valid instrument, it must be (at least to some degree) exogenous and correlated with the routine manual share in 1979, conditional on the other covariates. The manufacturing share in 1950 is indeed highly correlated with the routine manual share in 1979 (correlation coefficient of .669).[23]

Panel II of Table 5.8 presents first-stage estimates for the IV model.[24] The first-stage coefficients are positive and highly significant and the high partial r-squared and F-statistics in the first-stage regression confirm the validity of the instrument. The first panel of Table 5.8 presents the main estimates for the growth of temporary help service employment using the IV model and reveals a similar pattern. The coefficient estimates are somewhat larger compared to the OLS results but highly significant and robust to the inclusion of additional covariates. In the specification including all regional covariates the coefficient from the IV estimation is .172 as against .134 in a comparable OLS model.

[23] We also require the instrument to be correlated with our dependent variable, the growth of THS employment, but only via its correlation with the routine manual share 1979. Indeed, the share of manufacturing in 1950 has only little explanatory power for the growth of THS employment between 1979 and 2008.

[24] As before, we leave out the outlier regions "Garmisch-Partenkirchen" and "Pirmasens" in the regressions. In addition, the region "Saarland" is excluded as it was reintegrated into the Federal Republic of Germany only in 1957 and thus is absent from the historical data in 1950.

Table 5.8: Estimated Impact of Routine Manual Task Share on Regional THS Employment Growth, 1979-2008: IV estimates

10 x annual Δ log(THS employment)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel I: IV estimates				
Manual routine share 1979	.149**	.121**	.146***	.133***	.144***	.113**	.209***	.144***	.172***
	(.063)	(.048)	(.040)	(.040)	(.032)	(.046)	(.034)	(.038)	(.059)
Population density		-.0008***	-.0007***	-.0006***	-.0006***	-.0006***	-.0007***	-.0005***	-.0004***
		(.0002)	(.0002)	(.0002)	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)
Share employed/pop.			-.027***	-.031***	-.011*	-.014*	-.010	-.016*	-.009
			(.009)	(.011)	(.006)	(.008)	(.007)	(.008)	(.009)
Share female/empl.				.028					.074***
				(.020)					(.022)
Share young (<25 years)/empl.					.132***				.142***
					(.030)				(.038)
High to low-/medium-skilled empl.						-.107***			-.014
						(.039)			(.076)
Share foreign empl./empl.							-.038***		-.040**
							(.012)		(.019)
Share empl. large firms/empl.								-.020**	.016
								(.010)	(.014)
R^2	.212	.415	.486	.494	.566	.532	.519	.513	.631
					Panel II: First stage				
Share manufacturing 1950	.113***	.115***	.124***	.133***	.123***	.108***	.153***	.124***	.104***
	(.020)	(.020)	(.016)	(.015)	(.014)	(.013)	(.013)	(.016)	(.016)
F-statistic	32.335	32.726	57.228	73.675	72.180	72.994	141.946	57.384	40.010
Partial R^2	.437	.443	.508	.565	.541	.503	.550	.510	.292

Notes: N=110. All models include a constant and are weighted by start of period regional population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Estimates for East Germany

We complete our empirical analysis on regional THS employment trends by extending our focus to regions in East Germany from 1992 onwards (the first year with data available). The perspective on East Germany is of particular interest as the use of THS employment has also increased tremendously since reunification and, according to some recent reports for the German Federal Labor Agency, the overall average of 2.8 per cent of employment in 2010 even exceeds the West-Germany average (2.6 percent).[25]

Table 5.9: Estimated Impact of Manual Task Shares on Regional THS Employment Growth in East Germany, 1992-2008

Dependent variable:	Time Period							
10 x annual	1992-2008		1992-1994		1994-2002		2002-2008	
Δlog(THS employment)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R manual share 1992	-.178	-.054	-2.254***	-1.141	.092	.135	.160**	.051
	(.110)	(.162)	(.818)	(.957)	(.100)	(.131)	(.077)	(.089)
NR manual share 1992	.211	.236	1.239	2.268	.071	-.085	.050	.057
	(.146)	(.255)	(.933)	(1.503)	(.121)	(.134)	(.054)	(.093)
Regional covariates	no	yes	no	yes	no	yes	no	yes
R^2	.107	.250	.215	.294	.035	.287	.205	.399

Notes: N=36 labor markets in East Germany excluding Berlin. Each cell reports the results from a separate regression. All regressions include a constant and are weighted by start of period regional full-time employment. Due to data availability, population density is replaced by a dummy variable indicating urban or rural areas. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Analogous to our previous analyses, we relate the growth in THS employment for the long difference from 1992 to 2008 as well as separately for the three subperiods 1992-1994, 1994-2002 and 2002-2008 to the initial regional routine and non routine manual share in 1992.[26] Results are presented in Table 5.9. Note that as the sample for East Germany only consists of 36 regions, the coefficients on the manual shares in 1992 are estimated with less precision. At first glance, the results for the long difference 1992-2008 and the first subperiod 1992-1994 in columns 1 to 4 seem to follow a somewhat diverging pattern from the results for West German regions as the coefficient estimates on the routine manual share have a negative sign, but are insignificant, whereas the positive coefficient estimates for the non routine manual share are larger in absolute size. However, it is important to note that our empirical approach suffers from an important caveat for East Germany. Measured in 1992 only two years after reunification, the regional task shares for East German regions are much less likely to capture stable differences in regional production structures as the differences at the time were still strongly affected by the ongoing massive transformation of the entire East German economy.[27] The results for the later subperiods from 1994-2002 and

[25] Cf. Jahn and Wolf (2005); Fuchs (2009b,a). For some regions especially in Thuringia, THS employment is reported to constitute for more than 9 per cent of overall regional employment.

[26] See Figure 6.3 in the Appendix for the graphical mapping of the regional manual shares and the THS growth rates.

[27] See, e.g., Sinn and Sinn (1994) and Burda and Hunt (2001) on the many facets of this process.

2002-2008 again reveal relationships that seem to be more similar to the pattern observed for West Germany.

5.4 Conclusion

In this study, we have argued that the notion of the routine task intensity of labor that forms a centerpiece of the task and trade-in-task literature also provides a useful framework for the understanding of the secular rise of THS employment, a feature of growing importance for many labor markets in industrialized countries. We start out by confirming that employment in occupations that were initially intensive in routine manual tasks are indeed particularly prone to being outsourced into THS. This positive relationship is observed for non routine manual tasks as well, but with less significance. In our main analysis, we apply this concept in the spirit of Autor and Dorn (2013) to the level of regional labor market differences and find that the growth of employment by temporary help services has been particularly pronounced in regions that initially were specialized in routine manual labor. The economic magnitude of this relationship is large and robust to the inclusion of variables that control for alternative explanations due to regional differences in labor supply and demand conditions as well as alternative model specifications. The initial non routine manual task intensity is also positively related to subsequent THS employment growth, but looses explanatory power after controlling for relevant covariates.

Our study aims to contribute to the emerging literature on the patterns of polarization in regional labor markets. We would like to conclude by stressing that while our results suggest an important role for THS employment in this development, several questions about the fundamental connection between THS use and employment and wage polarization have to be left open at this stage and should deserve further scrutiny in future research. In particular, we think that more empirical evidence at the firm level of the determinants for and the connections between the use of alternative forms of mediated labor market arrangements that include offshoring, (business process) outsourcing as well as temporary help services is highly warranted. At the regional labor market level, it would be interesting to see to what extent the differential penetration of THS also has repercussions on the wage bargaining process and could therefore contribute to regional wage inequality.

6 Appendix

6.1 Appendix to Chapter 2: The Polarization of Employment in German Local Labor Markets

6.1.1 Data Appendix

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 shares in the BIBB/IAB Qualification and Career Survey (QCS).

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.

6.1.2 Replication using the German Microcensus

In an earlier version of this chapter, the analysis was complemented with results stemming from the German Microcensus. Because the empirical setup has changed in the course of this dissertation, these results are not included in the chapter anymore due to their limited comparability with the current setup. Nevertheless, the result complement the analysis and yield additional insight and are therefore presented in the appendix of this dissertation.

The Microcensus is a representative one percent sample survey of all persons in private households and community accommodation in Germany provided by the Federal Statistical Office and covers approximately 370,000 households with 800,000 individuals. It has been collected for West Germany since 1957 and extended to the new Federal States in 1991. In 2005 the survey design changed from data collection during a fixed reference week (usually the last holiday-free week in April) to a continuous survey design. It contains detailed information on the demographical background (age, sex, nationality etc.), the labor market status (employment status, employment characteristics, job search), education and training, income and the household and family context (children, living conditions). The sample is restricted to the West German civil labor force population from the age of 20 to 60 excluding agricultural and public sector employment in 1982 and 2006. Labor supply is measured as the number of hours worked and includes full-time and part-time employment as well as marginally employed workers. Due to data security regulation, the regional information available in the data is limited. The Microcensus only provides information on the level of 97 German planning districts (Raumordnungsregionen, ROR) that are defined according to commuting ranges and comprise labor market regions that are relatively self-contained. A reallocation of districts in 1996 resulted in a new assignment of planning districts and unfortunately, the statistical office does not provide a time consistent definition of this regional classification. As a result, some ROR's are grouped together in order to ensure comparability over time. In addition, the region "Northern Schleswig-Holstein" is excluded from the regressions as its routine share is more than one standard deviation larger compared to the second largest regional routine share. Out of the 74 ROR in West Germany, 69 planning districts excluding Berlin remain. To construct the regional routine share on the level of planning districts, the occupational task information from the 1979 QCS wave is used and weighted with regional employment in 1982 using the detailed occupational employment information entailed in the Microcensus.

A major advantage of the Microcensus is the fact that it not only entails employment subject to social security contributions but also marginal employment (which cannot be considered in the SIAB-R).[1] If employment possibilities are mainly created among marginally employed, the results stemming from the SIAB-R will underestimate the relation between routine intensity and service sector employment growth as the sample lacks information on marginal employment. In order to test for this possibility, the model is re-estimated using data from the Microcensus and the results of the baseline estimation (column 1) and the specification including regional covariates (column 2) are depicted in Table 6.1. Consistent with expectations, the coefficient estimates are slightly larger compared to the (former) results obtained with the SIAB-R, suggesting that additional labor is partly generated among non-standard employment. The point estimate is less precisely measured, which can be ascribed to a much smaller sample size. To make the results comparable, a similar set of regional covariates is included together with the elderly share of the population (> 65 years) which is considered to be a potential demand shifter. Most covariates enter with the expected sign: positive for fraction of high to low and medium skilled, share of foreign employees, female labor force participation, elderly share of population but negative for the share of working population. However, the coefficient estimates are not individually significant in the specification including all regional covariates and are not tabulated in Table 6.1 to conserve space.

An additional advantage of the Microcensus data it the detailed occupational classification that allows a further refinement of service occupations into unskilled (all unskilled personal services) and skilled (essentially order and security occupations as well as skilled service occupations) services. The definition of service occupations that we employ in the main analysis does not coincide 1:1 with the U.S. census classification adopted by Autor and Dorn (2013), which mainly comprises unskilled personal services. Although a confinement to low-skilled services does not seem appropriate for the German setting, it is still interesting to further narrow down the group of occupations driving the employment changes at the lower tail of the wage distribution. Results are presented in columns 3 to 6 in Table 6.1 and reveal a positive and significant relationship between regional routine intensity and the growth

[1] German law defines employment relationships as "marginal" if individuals work less than 50 days per calendar year or their monthly paycheck does not exceed 400 Euro (mini-job).

of unskilled personal services (columns 3 and 4) and a rather weak association with the growth of more skilled services (columns 5 and 6). This is in line with findings for the U.S. and suggests that the relation between a region's routine share and subsequent employment growth is more pronounced for unskilled services.

Table 6.1: Estimated Impact of Routine Task Intensity on Service Sector Growth (Microcensus Results)

Dependent variable:	All services		Unskilled services		Skilled services	
Δ employment 1982-2006	(1)	(2)	(3)	(4)	(5)	(6)
Routine Share 1982	0.280*	0.304*	0.287**	0.300**	-0.007	0.004
	(0.148)	(0.156)	(0.139)	(0.147)	(0.071)	(0.077)
Regional covariates	no	yes	no	yes	no	yes
R^2	0.066	0.245	0.084	0.272	0.012	0.059

Notes: N=69 planning districts excluding Northern Schleswig-Holstein and Berlin. The routine share in 1982 is constructed using occupational task information from the QCS wave 1979 and regional employment by occupation from the Microcensus of 1982. All regressions include regional covariates as discussed in the text as well as a constant. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

6.1.3 Table Appendix

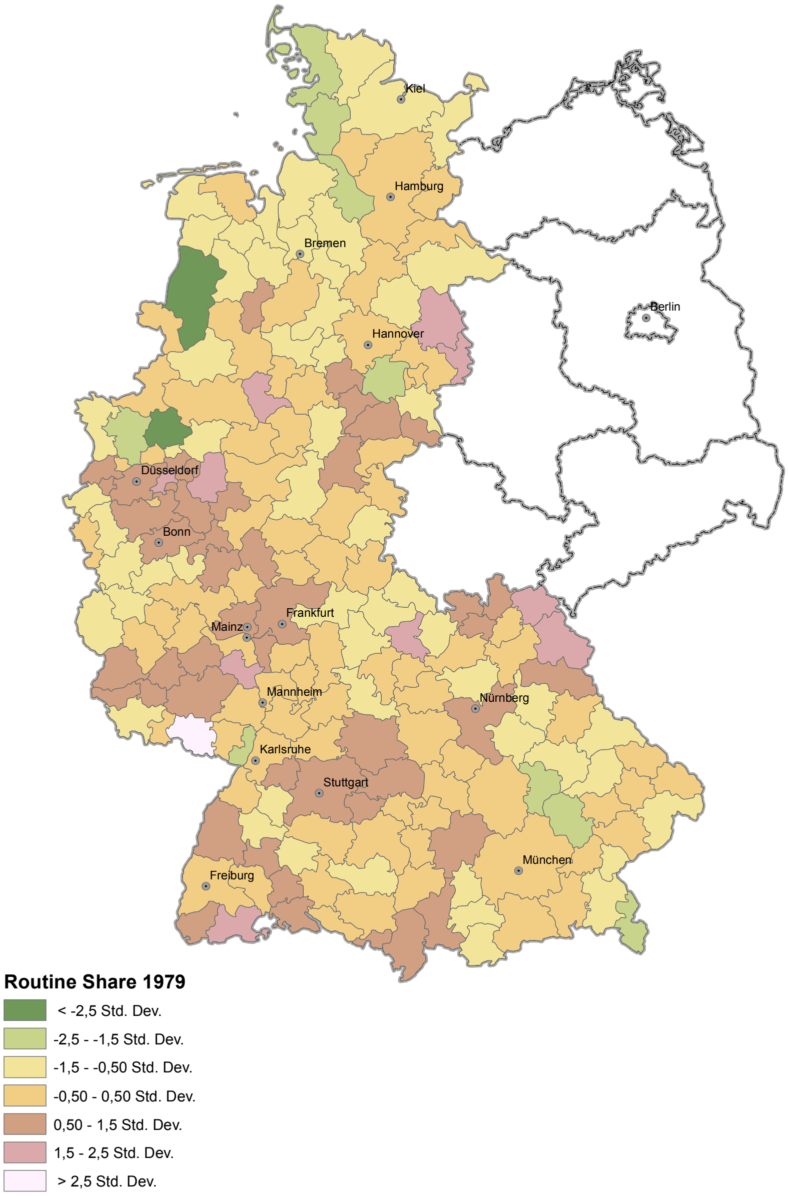
Table 6.2: Estimated Impact by Age, Education and Working Time, 1979 - 2006

	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 2.4 in chapter 2. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

6.1.4 Figure Appendix

Figure 6.1: Distribution of Routine Share 1979



Notes: Routine Share as defined in equation 2.5 in chapter 2. Occupational routine intensity is obtained from the 1979 wave of the QCS and combined with employment information from the SIAB-R.

6.2 Appendix to Chapter 3: Spatial Wage Inequality and Technological Change

6.2.1 Data Appendix: Processing SIAB Data and Sample Description

All information concerning local employment and wages were 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. We exclude public sector and agricultural workers from our sample and focus on full-time employment only. As employment and wage information is reported on a daily basis and lacks information on hours worked, wages for part-time employment are measured less accurately. Furthermore, we exclude marginal employment as this information is only available from 1999 onwards and delete parallel employment spells. If available, missing values for the nationality of an individual are imputed based on the most recent spells of the same individual. 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. Workers are classified based on their vocational education using the imputation algorithm proposed by Fitzenberger (1999).

All wages are converted to Euros at constant year 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 et al. (2006) 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.

6.2.2 Table Appendix

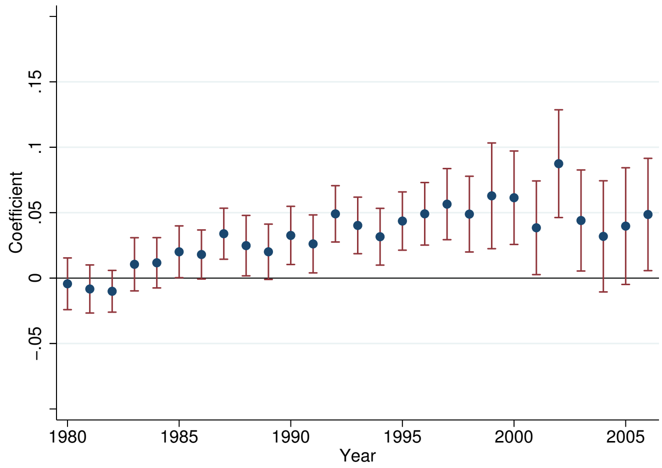
Table 6.3: Technology and Task Inputs, 1979 - 2006

	Outcome Measures Among:						
	All	Males	Females	Age<40	Age>40	Less-skilled	High-skilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Results for Task Supplies							
				ΔT^R			
RSH_{1979}	-.401***	-.382***	-.439***	-.404***	-.395***	-.397***	-.474***
	(.035)	(.040)	(.050)	(.044)	(.038)	(.036)	(.111)
R^2	.848	.765	.696	.797	.811	.854	.444
				ΔT^C			
RSH_{1979}	.128***	.126***	.115**	.125***	.126***	.116***	.448***
	(.036)	(.038)	(.045)	(.048)	(.035)	(.037)	(.109)
R^2	.778	.707	.733	.712	.720	.796	.342
				ΔT^M			
RSH_{1979}	.273***	.256***	.324***	.279***	.269***	.281***	.026
	(.026)	(.029)	(.043)	(.032)	(.035)	(.026)	(.045)
R^2	.638	.555	.402	.577	.496	.623	.122
Panel B: Results for Task Compensation							
				$\Delta ln(w^R)$			
RSH_{1979}	-.362	-.265	-.360	-.312	-.495*	-.389	-.516
	(.272)	(.292)	(.407)	(.313)	(.277)	(.243)	(1.636)
R^2	.269	.386	.248	.311	.296	.330	.120
				$\Delta ln(w^C)$			
RSH_{1979}	.404**	.202	1.079***	.383	.495**	.444**	.426
	(.174)	(.177)	(.284)	(.236)	(.208)	(.199)	(.407)
R^2	.547	.367	.412	.438	.476	.439	.155
				$\Delta ln(w^M)$			
RSH_{1979}	-.701	-.230	-2.895***	-.990	-.750	-1.850**	3.740
	(.460)	(.764)	(.910)	(.955)	(.736)	(.884)	(4.028)
R^2	.396	.393	.334	.283	.229	.471	.297

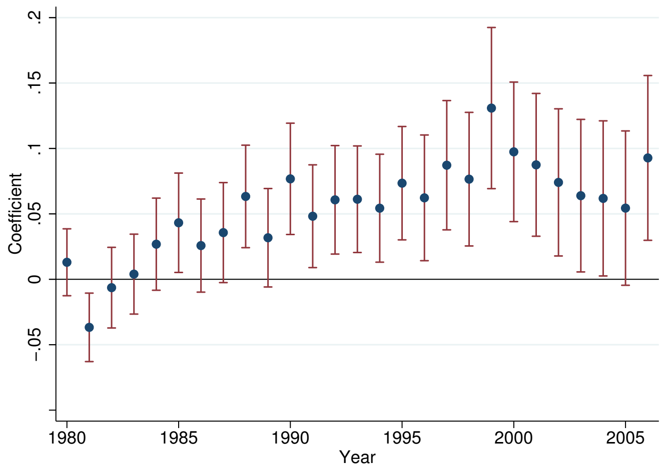
Notes: $N = 204$ labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3, chapter 3 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

6.2.3 Figure Appendix

Figure 6.2: Dynamic Wage Patterns of the Routinization Effect



(a) Estimated Impact of Technological Change on the Theil-Index



(b) Estimated Impact of Technological Change on the P85/P15-Ratio

Notes: Each panel plots the regression coefficients and 90% confidence intervals obtained from up to 26 regressions. The regressions relate each outcome measured during the year indicated, to the regional technology exposure. All regressions include covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3, chapter 3.

6.3 Appendix to Chapter 4: Employment Polarization and Immigrant Employment Opportunities

6.3.1 Processing SIAB and BIBB Data

The Sample of Integrated Labor Market Biographies Regional File (SIAB-R) is 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. To ensure consistency over the years, the analysis excludes workers in marginal employment as this information is only available from 1999 onwards and 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. The sample is restricted 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. Whenever I construct aggregate or average outcomes, each employment spell is weighted by the number of days worked. For the analysis of wages I use information on real gross daily wages of employees. 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, a common deflator for all labor market regions is applied. I correct for the right-censoring of wage records at the social security contribution threshold by imputing and replacing the topcoded wages following Gartner (2005). 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). I account for this structural break by correcting the wage observations before 1983 following Fitzenberger (1999) and Dustmann et al. (2009).

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 (see Rohrbach-Schmidt (2009) for details). The dataset is particularly well suited for this line of research as it includes detailed information on the activities individuals perform at the workplace. For each individual i, these activities are pooled into three categories: (1) non-routine cognitive, (2) routine and (3) non-routine manual tasks. The assignment of tasks follows Spitz-Oener (2006) and individual task measures TM_i^j for task j in the base year 1979 are constructed according to the definition of Antonczyk et al. (2009):

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

where $j = C$ (non-routine cognitive), R (routine) and M (non-routine manual). To obtain task intensities on the occupational level, the individual task measures are aggregated, where the task input of individual i in occupation k in 1979 is weighted by its respective weekly working hours $L_{ik}(1979)$:

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

6.3.2 Table Appendix

Table 6.1: Average Wages, Share Immigrants and Task Structure 1981, Employment Growth 1981-2004

Occupational category (KldB-88 *Berufsabschnitte*)	Log Wage	Task Structure non-routine cognitive	Task Structure routine	Task Structure non-routine manual	Share Immi.	Empl. Growth
General services	3.73	7.92	28.81	63.27	18.36	8.22
Textile and apparel occupations	3.85	11.51	54.02	34.47	20.38	3.06
Food Preparation	3.98	14.43	66.22	19.35	17.45	7.39
Merchants	4.03	22.32	70.72	6.96	2.79	4.72
Inspectors and distribution workers	4.05	14.72	65.14	20.15	16.19	1.76
Machine operators & related occupations	4.07	3.57	67.87	28.56	28.51	-3.79
Assemblers and metalworking	4.07	9.22	65.32	25.46	34.15	-8.89
Ceramicist, glassmakers	4.10	25.83	74.17	0.00	16.59	2.73
Woodworking occupations	4.10	5.88	83.31	10.81	22.55	-1.72
Chemical and plastic processing	4.16	14.65	74.84	10.51	24.38	-3.86
Security and public order	4.17	19.87	34.33	45.80	5.85	2.05
Health professions	4.18	20.57	68.01	11.42	14.68	1.13
Paper processing, printing	4.19	9.03	39.43	51.54	14.18	1.70
Transportation	4.19	17.20	30.24	52.56	4.36	5.92
Painters, lacquerers	4.19	14.58	52.16	33.26	9.38	4.69
Construction	4.22	15.93	36.31	47.76	18.68	-2.36
Administrative and office workers	4.26	21.26	75.48	3.26	2.42	3.17
Interior decorators, carpenters, upholsterers	4.26	14.87	43.89	41.24	10.04	1.20
Electricians	4.27	16.65	27.48	55.87	6.23	1.19
Metal producers, processors	4.28	8.21	74.06	17.73	28.03	-4.17
Locksmiths, mechanics	4.29	13.07	40.28	46.65	7.98	1.43
Miners, brick/concrete block makers	4.31	7.67	57.55	34.78	22.85	-5.01
Education, social sciences	4.32	62.91	22.32	14.77	5.15	0.85
Generator machinists; machine attendants	4.35	10.00	54.42	35.58	8.19	3.63
Service merchants and related occupations	4.37	32.20	64.39	3.42	2.07	2.51
Writers and producers of art	4.40	51.14	38.03	10.84	9.29	-0.03
Technicians	4.54	49.18	38.94	11.87	2.74	2.12
Engineers, scientists, mathematicians	4.93	65.96	29.10	4.95	5.18	1.21

Note: Entries based on information from the SIAB-R. Shaded occupations combine above average level of task intensity, employment share of immigrants and below median wages. Task structure refers to the 1979 wave of the QCS (see the data appendix for details on the construction). English names of all KldB-88 categories are own translations by the author.

6.3.3 Figure Appendix

Figure 6.1: Wage Level and Manual Task Intensity by Occupation Group

Notes: Numbers in brackets represent the share of immigrant workers in the respective occupation group. The occupation groups are not exclusive and therefore overlap. Manual task intensity is obtained from the 1979 wave of the QCS (see the data appendix for details on the construction of this variable).

6.4 Appendix to Chapter 5: Regional Task Intensity and the Growth of Temporary Help Services

6.4.1 Table Appendix

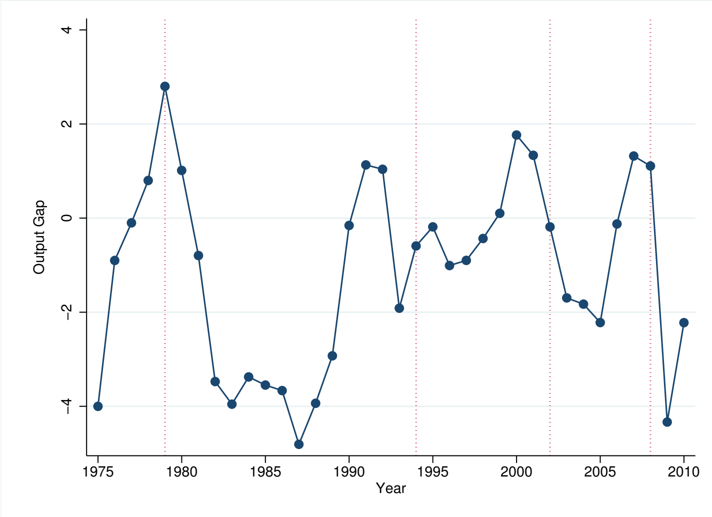
Table 6.2: Top 10 Occupations with Highest THS Share in 2008 and their Task Content in 1979

Occupation	THS Share 2008	Δ THS Share 1979-2008	Non-routine analytic	Non-routine interactive	Routine cognitive	Routine manual	Non-routine manual
Laborers	.545	.510	.009	.035	.060	.600	.296
Welders	.213	.196	.002	.084	.076	.441	.397
Transport equipment drivers	.195	.194	.000	.058	.091	.522	.329
Storekeeper	.166	.158	.007	.129	.150	.380	.334
Building fitters	.148	.131	.028	.049	.057	.250	.616
Painters	.145	.138	.028	.150	.030	.293	.499
Clothing sewers	.135	.135	.040	.132	.064	.295	.469
Data typists	.124	.119	.000	.042	.165	.761	.031
Electrical fitters	.096	.087	.080	.138	.070	.145	.568
Telephonists	.093	.091	.031	.155	.190	.624	.000

Notes: Occupations are defined according to the three-digit level of the classification of occupational titles 1988. Occupational task information derived from the QCS, share of THS employment derived from SIAB. Sample includes West German workers aged 20-60 excluding agricultural and public sector employment.

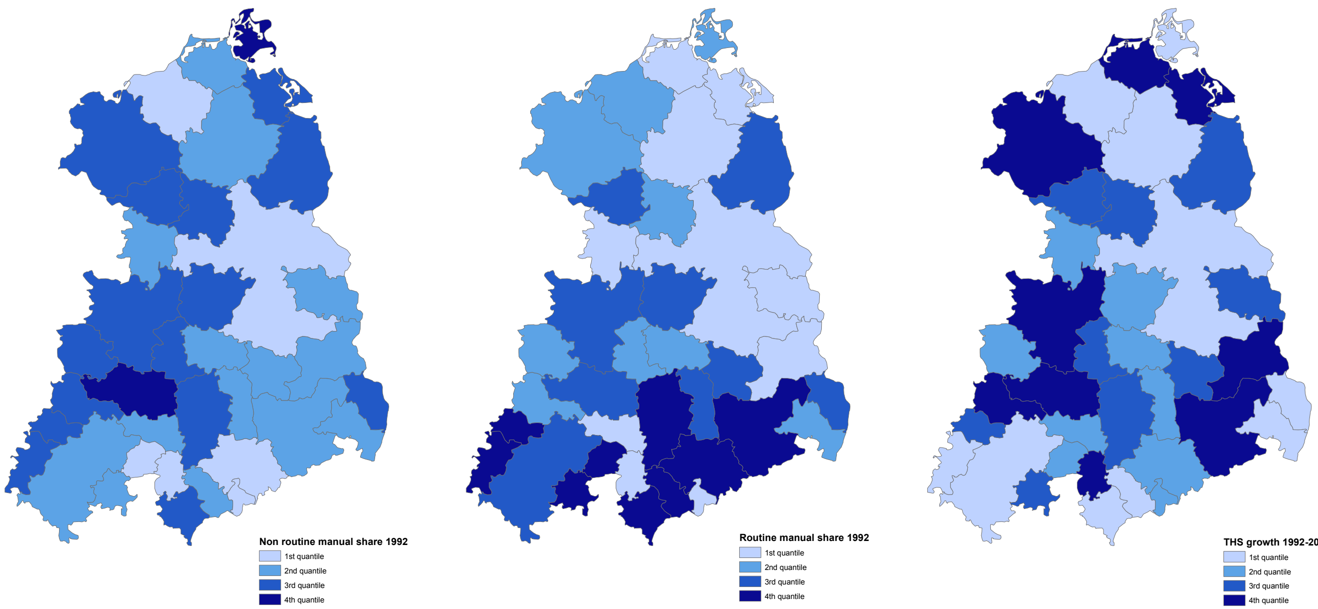
6.4.2 Figure Appendix

Figure 6.2: Output Gap, 1975-2010



Source: International Monetary Fund, World Economic Outlook Database, September 1999, October 2010.
Notes: Output gap in percent of potential GDP. Dotted vertical lines indicate years used for the analysis.

Figure 6.3: Routine Task Share and THS Growth in East Germany, 1992-2008
left: Routine Manual Task Share *center:* Routine Cognitive Task Share *right:* THS Employment Growth by Region, 1992-2008



Source: IAB-QCS data; own calculations. See text for details.

Bibliography

Abraham, K. and Taylor, S. (1996) Firms' Use of Outside Contractors: Theory and Evidence., *Journal of Labor Economics*, 14, 394–424.

Abraham, K. G. (1990) Restructuring the Employment Relationship: The Growth of Market-Mediated Work Arrangements, in *New Developments in the Labor Market: Toward a New Institutional Paradigm* (Eds.) K. Abraham and R. McKersie, MIT Press; Cambridge, MA, pp. 85–120.

Acemoglu, D. and Autor, D. (2011) Skills, Tasks and Technologies: Implications for Employment and Earnings, in *Handbook of Labor Economics* (Eds.) O. Ashenfelter and D. Card, Elsevier Science B.V., Amsterdam. 1 Ed., Vol. 4, Chapter 12, pp. 1043–1171.

Agrawal, A., Cockburn, I., Galasso, A. and Oettl, A. (2014) Why are Some Regions More Innovative than Others? The Role of Small Firms in the Presence of Large Labs, *Journal of Urban Economics*, 81, 149–165.

Aldashev, A., Gernandt, J. and Thomsen, S. L. (2009) Language Usage, Participation, Employment and Earnings: Evidence for Foreigners in West Germany with Multiple Sources of Selection, *Labour Economics*, 16, 330–341.

Antonczyk, D., DeLeire, T. and Fitzenberger, B. (2010a) Polarization and Rising Wage Inequality: Comparing the U.S. and Germany, IZA Discussion Paper 4842, Institute for the Study of Labor (IZA).

Antonczyk, D., Fitzenberger, B. and Leuschner, U. (2009) Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?, *Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik)*, 229 (2+3), 214–238.

Antonczyk, D., Fitzenberger, B. and Sommerfeld, K. (2010b) Rising Wage Inequality, the Decline of Collective Bargaining, and the Gender Wage Gap, *Labour Economics*, 17 (5), 835–847.

Autor, D. (2001) Why Do Temporary Help Firms Provide Free General Skills Training?, *The Quarterly Journal of Economics*, 116, 1409–1448.

Autor, D. (2003) Outsourcing at Will: Unjust Dismissal Doctrine and the Growth of Temporary Help Employment, *Journal of Labor Economics*, 21 (1), 1–42.

Autor, D. and Acemoglu, D. (2011) Skills, Tasks and Technologies: Implications for Employment and Earnings, in *Handbook of Labor Economics, Volume 4* (Eds.) O. Ashenfelter and D. Card, Elsevier-North Holland, Amsterdam, pp. 1043–1171.

Autor, D. and Dorn, D. (2009) This Job is "Getting Old": Measuring Changes in Job Opportunities Using Occupational Age Structure, *American Economic Review: Papers & Proceedings*, 99 (2), 45–51.

Autor, D. and Dorn, D. (2013) The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review*, 103 (5), 1553–1597.

Autor, D., Dorn, D. and Hanson, G. (2013) The China Syndrome: Local Labor Market Effects of Import Competition in the United States, *American Economic Review*, 103, 2121–2168.

Autor, D. and Houseman, S. (2010) Do Temporary Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from "Work First", *American Economic Journal: Applied Economics*, 2, 96–128.

Autor, D., Katz, L. and Kearney, M. (2006) The Polarization of the U.S. Labor Market, *American Economic Review*, 96 (2), 189–194.

Autor, D., Katz, L. and Krueger, A. (1998) Computing Inequality: Have Computers Changed the Labor Market?, *The Quarterly Journal of Economics*, 113 (4), 1169–1213.

Autor, D., Levy, F. and Murnane, R. (2003) The Skill Content of Recent Technological Change: An Empirical Exploration, *The Quarterly Journal of Economics*, 118 (4), 1279–1333.

Autor, D. H. and Duggan, M. G. (2003) The Rise In The Disability Rolls And The Decline In Unemployment, *The Quarterly Journal of Economics*, 118, 157–205.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2008) Trends in U.S. Wage Inequality: Revising the Revisionists, *The Review of Economics and Statistics*, 90, 300–323.

Bacolod, M., Blum, B. S. and Strange, W. C. (2009) Skills in the City, *Journal of Urban Economics*, 65, 136–153.

Bacolod, M. P. and Blum, B. S. (2010) Two Sides of the Same Coin: U.S. Residual Inequality and the Gender Gap, *Journal of Human Resources*, 45, 197–242.

Baker, M. and Benjamin, D. (1994) The Performance of Immigrants in the Canadian Labor Market, *Journal of Labor Economics*, 12, 369–405.

Baldwin, R. and Venables, A. J. (2011) Relocating the Value Chain: Off-shoring and Agglomeration in the Global Economy, Economics Series Working Papers 544, University of Oxford, Department of Economics.

Bartik, T. J. (1991) *Who Benefits from State and Local Economic Development Policies*, W.E. Upjohn Institute for Employment Research: Kalamazoo, Michigan.

Bauer, T., Dietz, B., Zimmermann, K. F. and Zwintz, E. (2005) German Migration: Development, Assimilation, and Labour Market Effects, in *European Migration: What Do We Know?* (Ed.) K. F. Zimmermann, Oxford University Press, pp. 197–261.

Baumgarten, D., Geishecker, I. and Görg, H. (2013) Offshoring, Tasks, and the Skill-Wage Pattern, *European Economic Review*, 61, 132–152.

Becker, G. S. (1971) *The Economics of Discrimination*, Univ. Chicago Press, 2nd edn.

Black, S. E. and Spitz-Oener, A. (2010) Explaining Women's Success: Technological Change and the Skill Content of Women's Work, *Review of Economics and Statistics*, 92 (1), 187–194.

Blanchard, O. and Katz, L. (1992) Regional Evolutions, *Brookings Papers on Economic Activity*, 1992 (1), 1–75.

Blinder, A. (2006) Offshoring: The Next Industrial Revolution?, *Foreign Affairs*, 85(2), 113–128.

Blossfeld, H.-P. (1985) *Bildungsexpansion und Berufschancen: Empirische Analysen zur Lage der Berufsanfänger in der Bundesrepublik*, Campus Verlag, Frankfurt/New York.

Borghans, L., ter Weel, B. and Weinberg, B. A. (2014) People Skills and the Labor-Market Outcomes of Underrepresented Groups, *Industrial and Labor Relations Review*, 67, 287–334.

Borjas, G. J. (1985) Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants, *Journal of Labor Economics*, 3, 463–489.

Borjas, G. J. (1995) Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?, *Journal of Labor Economics*, 13, 201–45.

Borjas, G. J. (2015) The Slowdown in the Economic Assimilation of Immigrants: Aging and Cohort Effects Revisited Again, *Journal of Human Capital*, forthcoming.

Borjas, G. J. and Friedberg, R. M. (2009) Recent Trends in the Earnings of New Immigrants to the United States, NBER Working Papers 15406, National Bureau of Economic Research (NBER).

Boudarbat, B. and Lemieux, T. (2014) Why Are the Relative Wages of Immigrants Declining? A Distributional Approach, *Industrial and Labor Relations Review*, 67, 1127–1165.

Bound, J. and Holzer, H. J. (2000) Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980's, *Journal of Labor Economics*, 18 (1), 20–54.

Breinlich, H., Ottaviano, G. I. and Temple, J. (2014) Regional Growth and Regional Decline, in *Handbook of Economic Growth* (Eds.) P. Aghion and S. Durlauf, Elsevier Science B.V., Amsterdam. 1 Ed., Vol. 1, Chapter 4, pp. 683–779.

Bresnahan, T. (1999) Computerisation and Wage Dispersion: An Analytical Reinterpretation, *The Economic Journal*, 109 (456), 390–415.

Bresnahan, T. F., Brynjolfsson, E. and Hitt, L. M. (2002) Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence, *The Quarterly Journal of Economics*, 117, 339–376.

Brynjolfsson, E. and McAfee, A. (2014) *The Second Machine Age - Work, Progress, and Prosperity in a Time of Brilliant Technologies*, New York: W. W. Norton & Company, 2014.

Bundesagentur für Arbeit (2007) *Arbeitsmarkt 2006*, Amtliche Nachrichten der Bundesagentur für Arbeit.

Burda, M. and Hunt, J. (2001) From Reunification to Economic Integration: Productivity and the Labor Market in Eastern Germany, *Brookings Papers on Economic Activity*, 32, 1–92.

Burda, M. and Kvasnicka, M. (2006) Zeitarbeit in Deutschland: Trends und Perspektiven, *Perspektiven der Wirtschaftspolitik*, 7, 195–225.

Burda, M. C., Hamermesh, D. S. and Weil, P. (2013) Total Work and Gender: Facts and a Possible Explanations, *Journal of Population Economics*, 26 (1), 239–261.

Chiswick, B. R. (1978) The Effect of Americanization on the Earnings of Foreign-born Men, *The Journal of Political Economy*, 86, 897.

Chiswick, B. R. and Miller, P. W. (1995) The Endogeneity between Language and Earnings: International Analyses, *Journal of Labor Economics*, 13, 246–88.

Combes, P.-P., Duranton, G. and Gobillon, L. (2008) Spatial Wage Disparities: Sorting Matters!, *Journal of Urban Economics*, 63, 723–742.

Combes, P.-P., Duranton, G., Gobillon, L. and Roux, S. (2012) Sorting and Local Wage and Skill Distributions in France, *Regional Science and Urban Economics*, 42, 913–930.

Constant, A. and Massey, D. (2005) Labour Market Segmentation and the Earnings of German Guestworkers, *Population Research and Policy Review*, 24, 489–512.

Cortes, P. (2008) The Effects of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data, *Journal of Political Economy*, 116 (3), 381–422.

Dauth, W. (2013) Agglomeration and Regional Employment Dynamics, *Papers in Regional Science*, 92, 419–435.

Dauth, W., Findeisen, S. and Südekum, J. (2014) The Rise of the East and the Far East: German Labor Markets and Trade Integration, *Journal of the European Economic Association*, 12 (6), 1643–1675.

Davis, D. R. and Dingel, J. I. (2012) A Spatial Knowledge Economy, NBER Working Papers 18188, National Bureau of Economic Research (NBER).

Decressin, J. and Fatàs, A. (1995) Regional Labor Market Dynamics in Europe, *European Economic Review*, 39 (9), 1627–1655.

Deutscher Bundestag (2009) Elfter Bericht der Bundesregierung über Erfahrungen bei der Anwendung des Arbeitnehmerüberlassungsgesetzes - AÜG -, Deutscher Bundestag, 17. Wahlperiode.

Dey, M., Houseman, S. and Polivka, A. (2012) Manufacturers' Outsourcing to Eployment Services, *Industrial & Labor Relations Review*, 65 (3), 533–559.

Dorner, M., König, M. and Seth, S. (2011) Sample of Integrated Labour Market Biographies Regional File 1975-2008 (SIAB-R 7508), FDZ Datenreport 07/2011, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Duranton, G. and Puga, D. (2004) Micro-foundations of Urban Agglomeration Economies, in *Handbook of Regional and Urban Economics* (Eds.) V. J. Henderson and J. Thisse, Elsevier Science B.V., Amsterdam. 1 Ed., Vol. 4, Chapter 48, pp. 2063–2117.

Dustmann, C., Frattini, T. and Lanzara, G. (2012) Educational Achievement of Second Generation Immigrants: An International Comparison, *Economic Policy*, 27, 143–185.

Dustmann, C., Frattini, T. and Preston, I. (2013) The Effect of Immigration along the Distribution of Wages, *Review of Economic Studies*, 80 (1), 145–173.

Dustmann, C. and Glitz, A. (2011) Migration and Education, in *Handbook of the Economics of Education* (Eds.) E. A. Hanushek, S. Machin and L. Woessmann, Amsterdam: Elsevier, vol. 4, pp. 327–439.

Dustmann, C., Glitz, A. and Vogel, T. (2010) Employment, Wages, and the Economic Cycle: Differences between Immigrants and Natives, *European Economic Review*, 54, 1–17.

Dustmann, C., Ludsteck, J. and Schönberg, U. (2009) Revisiting the German Wage Structure, *The Quarterly Journal of Economics*, 124 (2), 843–881.

Eckey, H.-F. and Klemmer, P. (1991) Neuabgrenzung von Arbeitsmarktregionen für die Zwecke der regionalen Wirtschaftspolitik, *Informationen zur Raumentwicklung*, 9 (10), 569–577.

Eckey, H.-F., Kosfeld, R. and Türck, M. (2006) Abgrenzung deutscher Arbeitsmarktregionen, *Raumforschung und Raumordnung*, 64, 299–309.

Fitzenberger, B. (1999) *Wages and Employment Across Skill Groups: An Analysis for West Germany*, Physica/Springer, Heidelberg.

Fitzenberger, B., Osikominu, A. and Völter, R. (2006) Imputation Rules to Improve the Education Variable in the IAB Employment Subsample, *Schmollers Jahrbuch: Journal of Applied Social Science Studies / Zeitschrift für Wirtschafts- und Sozialwissenschaften*, 126 (3), 405–436.

Freeman, R., Schettkat, R., Duflo, E. and Jappelli, T. (2005) Marketization of Household Production and the EU-US Gap in Work, *Economic Policy*, 20 (41), 7–50.

Frey, C. and Osborne, M. (2013) The Future of Employment: How Susceptible are Jobs to Computerisation?, OMS Working Paper, Oxford Martin School.

Fuchs, M. (2009a) Zeitarbeit in Sachsen-Anhalt, IAB-Regional 4/2009, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Sachsen-Anhalt-Thüringen.

Fuchs, M. (2009b) Zeitarbeit in Thüringen, IAB-Regional 2/2009, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Sachsen-Anhalt-Thüringen.

Gartner, H. (2005) The Imputation of Wages Above the Contribution Limit with the German IAB Employment Sample, FDZ Methodenreport 02/2005, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Gernandt, J. and Pfeiffer, F. (2007) Rising Wage Inequality in Germany, *Journal of Economics and Statistics (Jahrbücher für Nationalökonomie und Statistik)*, 227, 358–380.

Glaeser, E. and Gyourko, J. (2005) Urban Decline and Durable Housing, *Journal of Political Economy*, 113 (2), 345–375.

Glaeser, E. L. and Resseger, M. G. (2010) The Complementarity Between Cities and Skills, *Journal of Regional Science*, 50, 221–244.

Goos, M. and Manning, A. (2007) Lousy and Lovely Jobs: The Rising Polarization of Work in Britain, *Review of Economics and Statistics*, 89 (1), 118–133.

Goos, M., Manning, A. and Salomons, A. (2009a) Recent Changes in the European Employment Structure: The Roles of Technology and Globalization, *The American Economic Review*, 99 (2), 58–63.

Goos, M., Manning, A. and Salomons, A. (2009b) The Polarization of the European Labor Market, *American Economic Review: Papers & Proceedings*, 99, 58–63.

Goos, M., Manning, A. and Salomons, A. (2014) Explaining Job Polarization: Routine-Biased Technological Change and Offshoring, *American Economic Review*, 104, 2509–2526.

Grant, M. L. (1999) Evidence of New Immigrant Assimilation in Canada, *The Canadian Journal of Economics / Revue canadienne d'Economique*, 32, 930–955.

Grossman, G. and Rossi-Hansberg, E. (2008) Trading Tasks: A Simple Theory of Offshoring, *American Economic Review*, 98, 1978–1997.

Gruhl, A., Schmucker, A. and Seth, S. (2012) The Establishment History Panel 1975-2010, FDZ-Datenreport 04/2012, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Hanson, G. (1997) Increasing Returns, Trade and the Regional Structure of Wages, *The Economic Journal*, 107, 113–133.

Hethey-Maier, T. and Seth, S. (2010) The Establishment History Panel (BHP) 1975-2008, Handbook Version 1.0.2, FDZ Datenreport 04/2010, Institut für Arbeitsmarkt und Berufsforschung (IAB), Nürnberg.

Houseman, S. (2001) Why Employers Use Flexible Staffing Arrangements: Evidence from an Establishment Survey, *Industrial and Labor Relations Review*, 55, 149–170.

Houseman, S., Kalleberg, A. and Erickcek, G. (2003) The Role of Temporary Agency Employment in Tight Labor Markets, *Industrial and Labor Relations Review*, 57, 105–127.

Imai, S., Stacey, D. and Warman, C. (2014) From Engineer to Taxi Driver? Language Proficiency and the Occupational Skills of Immigrants, Working Papers 040, Ryerson University, Department of Economics.

Jahn, E. and Pozzoli, D. (2013) The Pay Gap of Temporary Agency Workers - Does the Temp Sector Experience Pay Off?, *Labour Economics*, 24, 48–57.

Jahn, E. and Rosholm, M. (2014) Looking Beyond the Bridge: How Temporary Agency Employment Affects Labor Market Outcomes, *European Economic Review*, 65 (1), 108–125.

Jahn, E. and Wolf, K. (2005) Entwicklung der Leiharbeit und regionale Disparitäten, Kurzbericht 14/2005, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Jahn, E. J. and Bentzen, J. (2012) What Drives the Demand for Temporary Agency Workers?, *LABOUR*, 26, 341–355.

Katz, L. and Murphy, K. (1992) Changes in Relative Wages, 1963-1987: Supply and Demand Factors, *The Quarterly Journal of Economics*, 107 (1), 35–78.

Katz, L. F. and Autor, D. H. (1999) Changes in the Wage Structure and Earnings Inequality, in *Handbook of Labor Economics* (Eds.) O. Ashenfelter and D. Card, Elsevier Science B.V., Amsterdam. Vol. 3, Chapter 26, Handbook of Labor Economics, pp. 1463–1555.

Keynes, J. M. (1930) Economic Possibilities for our Grandchildren, [Online] available at: http://www.econ.yale.edu/smith/econ116a/keynes1.pdf [Accessed 13 March 2015].

Kohn, K. (2006) Rising Wage Dispersion After All! The German Wage Structure at the Turn of the Century, ZEW Discussion Paper, 06-031, Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim.

Koller, M. and Schwengler, B. (2000) *Struktur und Entwicklung von Arbeitsmarkt und Einkommen in den Regionen*, Beiträge zur Arbeitsmarkt- und Berufsforschung, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.

Kopczuk, W., Saez, E. and Song, J. (2010) Earnings Inequality and Mobility in the United States: Evidence from Social Security Data since 1937, *The Quarterly Journal of Economics, MIT Press*, 125, 91–128.

Kvasnicka, M. (2009) Does Temporary Help Work Provide a Stepping Stone to Regular Employment?, in *Studies of Labor Market Intermediation* (Ed.) D. Autor, University of Chicago Press, Studies of Labor Market Intermediation, pp. 335–372.

Kvasnicka, M. and Werwatz, A. (2003) On the Wages of Temporary Help Service Workers in Germany, Labor and Demography, EconWPA.

Levy, F. and Murnane, R. (2004) *The New Division of Labor*, Princeton University.

Liebig, T. (2007) The Labour Market Integration of Immigrants in Germany, OECD Social, Employment and Migration Working Papers No. 47, OECD Publishing, Paris.

Lindley, J. and Machin, S. (2014) Spatial Changes in Labor Market Inequality, *Journal of Urban Economics*, 79, 121–138.

Manning, A. (2004) We Can Work It Out: The Impact of Technological Change on the Demand for Low-Skill Workers, *Scottish Journal of Political Economy*, 51 (5), 581–608.

Mazzolari, F. and Ragusa, G. (2013) Spillovers from High-Skill Consumption to Low-Skill Labor Markets, *The Review of Economics and Statistics*, 95, 74–86.

Michaels, G., Natraj, A. and Van Reenen, J. (2014) Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty–five Years, *Review of Economics and Statistics*, 96 (1), 60–77.

Mitlacher, L. (2005) Equal-Pay - Das Ende der Zeitarbeit? Eine ökonomische Ana-lyse der Wirkungen des Urteils des Bundesverfassungsgerichts zur Zeitarbeit, *Sozialer Fortschritt*, 54, 97–103.

Mitlacher, L. (2007) The Role of Temporary Agency Work in Different Industrial Relations Systems - A Comparison between Germany and the USA, *British Journal of Industrial Relations*, 45, 581–606.

Möller, J. (2011) Das Normalarbeitsverhältnis verschwindet - stimmt's?, [Online] SPIEGEL Online 08.06.2011, available at: http://www.spiegel.de/karriere/berufsleben/0,1518,767232,00.html [Accessed 29 July 2011].

Moretti, E. (2011) Local Labor Markets, in *Handbook of Labor Economics* (Eds.) O. Ashenfelter and D. Card, Elsevier Science B.V., Amsterdam. Vol. 4, Chapter 14, pp. 1237–1313.

Moulton, B. R. (1986) Random Group Effects and the Precision of Regression Estimates, *Journal of Econometrics*, 32, 385–397.

Nahuis, R. and Parikh, A. (2004) Factor Mobility and Regional Disparities: East, West, Home's Best?, Economics Working Papers 026, European Network of Economic Policy Research Institutes.

Nonnenmann, J. (2011) Verleih mich!, [Online] SPIEGEL Online 25.05.2011, available at: http://www.spiegel.de/karriere/berufsleben/0,1518,764000,00.html [Accessed 29 July 2011].

Nordhaus, W. D. (2007) Two Centuries of Productivity Growth in Computing, *The Journal of Economic History*, 67 (01), 128–159.

Notowidigdo, M. J. (2011) The Incidence of Local Labor Demand Shocks, NBER Working Papers 17167, National Bureau of Economic Research (NBER).

Oberst, M., Schank, T. and Schnabel, C. (2007) Interne Arbeitsmärkte und Einsatz temporärer Arbeitsverhältnisse: Eine Fallstudie mit Daten eines deutschen Dienstleistungsunternehmens, *Zeitschrift für Betriebswirtschaft*, 77, 1159–1177.

OECD (2005) *Trends in International Migration. 2004 Edition*, OECD Publications, Paris.

OECD (2014) *International Migration Outlook 2014*, OECD Publications, Paris.

Oldenski, L. (2012) The Task Composition of Offshoring by U.S. Multinationals, *International Economics: The Quarterly Journal in International Economics founded in 1980 by the CEPII*, 131 (3), 5–21.

Ottaviano, G. I. P., Peri, G. and Wright, G. C. (2013) Immigration, Offshoring, and American Jobs, *American Economic Review*, 103, 1925–59.

Peri, G. and Sparber, C. (2009) Task Specialization, Immigration, and Wages, *American Economic Journal: Applied Economics*, 1, 135–169.

Piketty, T. (1998) L'Emploi dans les Services en France et aux États-Unis: Une Analyse Structurelle sur Longue Période , *Economie et Statistique*, 318, 73–99.

Redding, S. and Venables, A. J. (2004) Economic Geography and International Inequality, *Journal of International Economics*, 62, 53–82.

Riphahn, R. T. (2003) Cohort Effects in the Educational Attainment of Second Generation Immigrants in Germany: An Analysis of Census Data, *Journal of Population Economics*, 16, 711–737.

Rohrbach-Schmidt, D. (2009) The BIBB/IAB - and BIBB/BAuA - Surveys of the Working Population on Qualification and Working Conditions in Germany - Data and Methods Manual, BIBB-FDZ Daten- und Methodenberichte Nr. 1/2009, Bundesinstitut für Berufsbildung (BIBB), Bonn.

Rosenthal, S. S. and Strange, W. C. (2004) Evidence on the Nature and Sources of Agglomeration Economies, in *Handbook of Urban and Regional Economies* (Eds.) V. J. Henderson and J. Thisse, Elsevier Science B.V., Amsterdam. Vol. 4, Chapter 49, pp. 2119–2171.

Rudolph, H. and Schröder, E. (1997) Arbeitnehmerüberlassung: Trends und Einsatzlogik, *Mitteilungen aus der Arbeitsmarkt- und Berufsforschung*, 30, 102–126.

Segal, L. M. and Sullivan, D. G. (1997) The Growth of Temporary Services Work, *Journal of Economic Perspectives*, 11, 117–36.

Senftleben-König, C. and Wielandt, H. (2014a) Spatial Wage Inequality and Technological Change, BDPEMS Working Paper 2014-08, Humboldt-Universität zu Berlin.

Senftleben-König, C. and Wielandt, H. (2014b) The Polarization of Employment in German Local Labor Markets, BDPEMS Working Paper 2014-07, Humboldt-Universität zu Berlin.

Sinn, G. and Sinn, H. (1994) *Jumpstart: The Economic Unification of Germany*, vol. 1 of *MIT Press Books*, The MIT Press.

Smith, C. (2011) Polarization, Immigration, Education: What‘s Behind the Dramatic Decline in Youth Employment?, Finance and Economics Discussion Series 2011-41, Divisions of Research & Statistics and Monetary Affairs Federal Reserve Board, Washington, D.C.

Spitz-Oener, A. (2006) Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure, *Journal of Labor Economics*, 24 (2), 235–270.

Statistisches Bundesamt (1953) *Statistik der Bundesrepublik Deutschland, vol. 46.1-7. Die nichtlandwirtschaftlichen Arbeitsstätten in den Ländern und deren Verwaltungsbezirken nach der Zählung vom 13.9.1950.*

Statistisches Bundesamt (2009) Bevölkerung und Erwerbstätigkeit: Bevölkerung mit Migrationshintergrund – Ergebnisse des Mikrozensus 2005, Fachserie 1 Reihe 2.2.

Steiner, V. and Wagner, K. (1998) Has Earnings Inequality in Germany Changed in the 1980’s?, *Zeitschrift für Wirtschafts- und Sozialwissenschaften*, 118 (1), 29–59.

Velling, J. (1995) Wage Discrimination and Occupational Segregation of Foreign Male Workers in Germany, ZEW Discussion Papers 95-04, Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim.

Vidal, M. and Tigges, L. (2009) Temporary Employment and Strategic Staffing in the Manufacturing Sector, *Industrial Relations*, 48, 55–72.

Weiss, M. (2008) Skill-Biased Technical Change: Is there Hope for the Unskilled?, *Economics Letters*, 100 (3), 439–441.

Selbstständigkeitserklärung

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

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

Berlin, den 09.04.2015 Hanna Wielandt