Spatial Wage Inequality and Technological Change*

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Abstract

During the last decades, wage inequality in Germany has considerably increased both within and across regions. Building on concepts of the task-based approach, this paper studies whether and to what extent these developments are driven by technological change. We present novel evidence that technological change is positively related to intra-regional wage inequality. This 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, which are located at lower percentiles. Because there exists substantial variation in the degree of technology exposure across German regions, technological change can also explain part of the rise in inter-regional wage inequality.

Key Words: Spatial Changes, Wage Inequality, Job Tasks, Technological Change.

JEL Classifications: J31, O33, R23.

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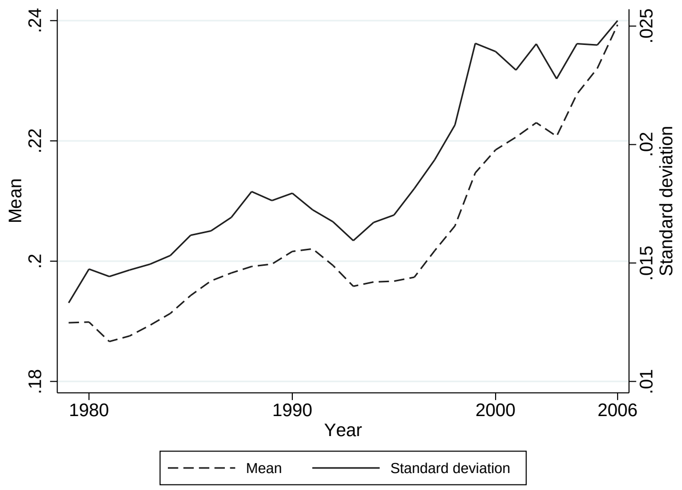
1 Introduction

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 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.

Figure 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.

This paper 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,

[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

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 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 paper 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 paper 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 16% 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; Michaels et al., 2013; Senftleben-König and Wielandt, 2014). 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 Rosen-

allocate their skills to different tasks, depending on their comparative advantage in supplying them.

thal 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 paper proceeds as follows: Section 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 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 task supply and compensation. In Section 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 5. Section 6 concludes.

2 Theoretical Model and Estimation Strategy

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:

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

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

(2) $$Y_s = \alpha_m L_m$$

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

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

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:

$$(4) \qquad L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \overline{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}. \end{cases}$$

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.

$$(5) \qquad \frac{w_m}{w_r} = \begin{cases} \infty & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -log(1-L_m*) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}, \end{cases}$$

$$(6) \qquad \frac{w_c}{w_r} = \infty.$$

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 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 shuold 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 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 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).

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:

$$\Delta Y_{rs} = \alpha + \beta_1 RSH_r + \mathbf{X}'_r \beta_2 + \gamma_s + e_{rs}. \tag{7}$$

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]

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 X_r that includes additional covariates, reflecting differences in urbanity between regions, the local human capital and demographic composition as well as local economic conditions in 1979.

3 Data, Construction of Variables and Descriptive Evidence

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 or self-employed workers are not included), as well as information on occupation, industry affiliation, workplace location and demographic information on age, gender, nationality and educational attainment. 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

[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.

[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 for more details on the sample selection and the basic processing of the SIAB-R.

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 data in the SIAB-R to compute the Gini-index, an inequality measure commonly used in the literature (e.g. by **?**). 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 of the wage distribution and the 15th percentile. Table 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. 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 Table 1.

3.2 Measuring Task Supplies

3.2.1 Construction and Trends

The information on task requirements of employees is derived from the BIBB/IAB Qualification and Career Survey. The BIBB comprises five cross sections launched in 1979, 1985, 1992, 1998 and 2006, each covering approximately 30,000 individuals. The dataset is particularly well suited for our research, as it includes detailed information on the activities individuals perform at the workplace. For each individual i, these activities are pooled into three task categories: (1) non-routine cognitive, (2) routine and (3) non-routine manual tasks. In the assignment of tasks, we follow Spitz-Oener (2006) and construct individual task measures TM_i^j for task j and time t according to the definition of Antonczyk et al. (2009):

$$(8) \qquad TM_{it}^j = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } t}{\text{total number of activities performed by } i \text{ over all categories in } t} \times 100,$$

where $j = C$ (non-routine cognitive), R (routine), 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}):

$$(9) \qquad TI_{kt}^j = \left(\sum_i \left[L_{ikt} \times TM_{ikt}^j \right] \right) \left(\sum_i L_{ikt} \right)^{-1}.$$

Table 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 (nursing assistants, waiters) as well as construction occupations (roofers). In contrast, occupations with a high non-routine

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

Table 1: Descriptive statistics 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 BIBB/IAB data. 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.

cognitive task content include high-education occupations, such as teachers, engineers and scientists. Table 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 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 BIBB-IAB data in 1979 and 2006 as defined in equation 8. The sample includes full-time employees between 20 and 60 years of age working in West-Germany, excluding agricultural and public sector employment.

Figure 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.

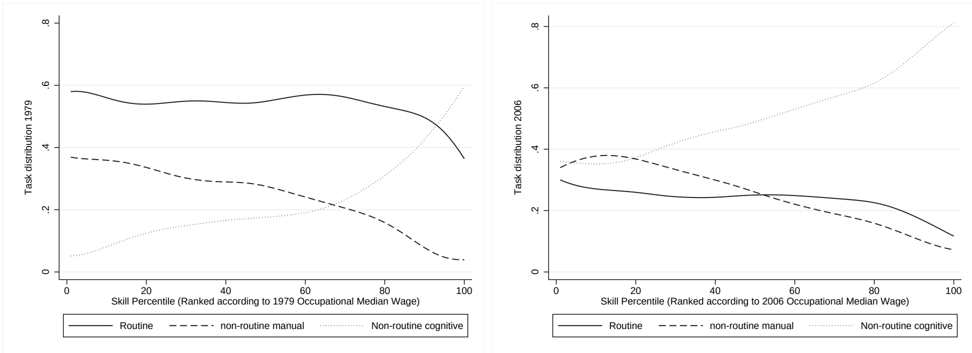
3.2.2 Regional Quantities and Prices

To obtain task measures at the regional level, the occupational task information from the BIBB data 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]

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 supply and hence be correlated with the routine share. To do so, we regress separately by BIBB

[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 classification.

Figure 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 BIBB and defined as in equation 9.

wave each TI^j_{kt} 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 respective employment spell, constitute the task supplies T^j_{rt} for each region r and year t. Summary statistics of the three task shares are displayed in Table 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^j_{kt}. By separately estimating the second-stage regression in equation 10 for each BIBB wave, we can identify the region and year-specific task compensations, w^C_{rt}, w^R_{rt} and w^M_{rt}, received for supplying one unit of non-routine cognitive, routine and non-routine manual tasks.

$$\tilde{w}_{krt} = w^C_{rt} \times TI^C_{kt} + w^R_{rt} \times TI^R_{kt} + w^M_{rt} \times TI^M_{kt} + e_{krt}. \tag{10}$$

Table 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.

[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".

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 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:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI^R_k > TI^{R,P66}_k \right] \right) \left(\sum_k L_{kr} \right)^{-1}, \tag{11}$$

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 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 3b shows the distribution of the manufacturing share across German regions.

4 Results

4.1 Technology and Task Supply

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 7:

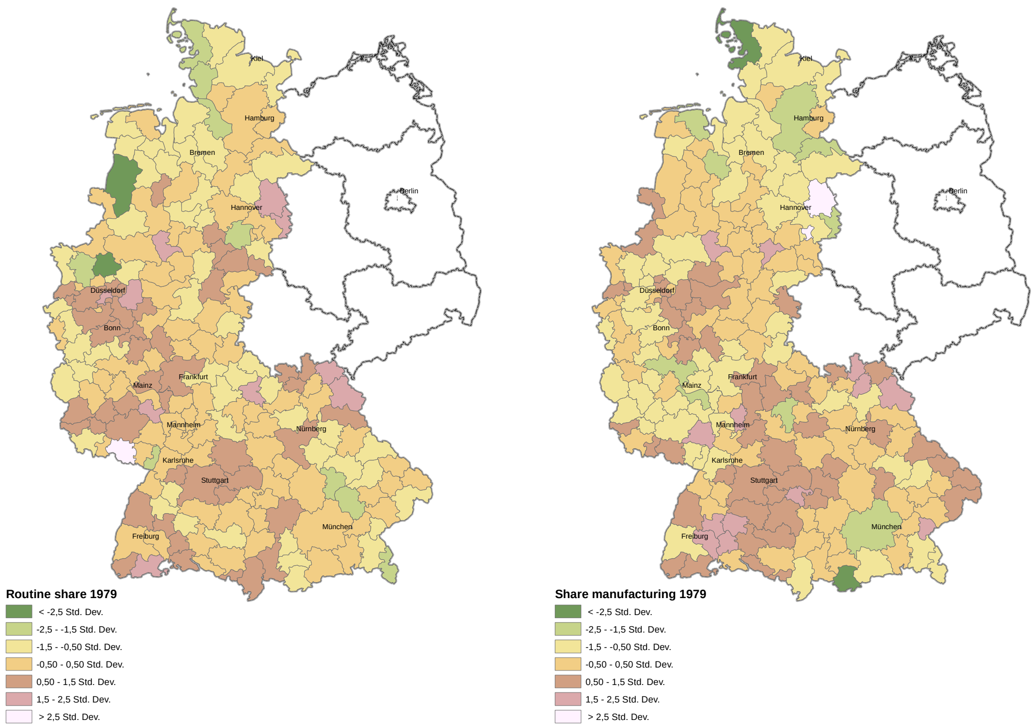
$$\Delta T^j_{r,1979-2006} = \alpha + \beta_1 RSH_r + X'_r \beta_2 + \gamma_s + e_r. \tag{12}$$

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 (WLS) are presented in Table 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.

[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: Distribution of Routine and Manufacturing Share in 1979



(a) Routine Share

(b) Share Manufacturing

Table 3: Technology and Task Supply, 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%.

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 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 over 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 12 separately for each outcome year and depict the results in Table 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 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 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 **??** 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 tasks-based approach, providing evidence for increasing specialization of employees in non-routine tasks as a consequence of routine task substituting technological change.

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:

$$\Delta ln(\widehat{w}_r^j) = \alpha + \beta_1 RSH_r + \beta_2 X_r + \gamma_s + e_r. \tag{13}$$

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 3.2.2. To conserve space, Table 5 only reports the coefficient on the regional routine share and omits the results on the vector of control variables.

Table 5: Technology and Task Compensation, Subperiods

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

Appendix Table **??** 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.

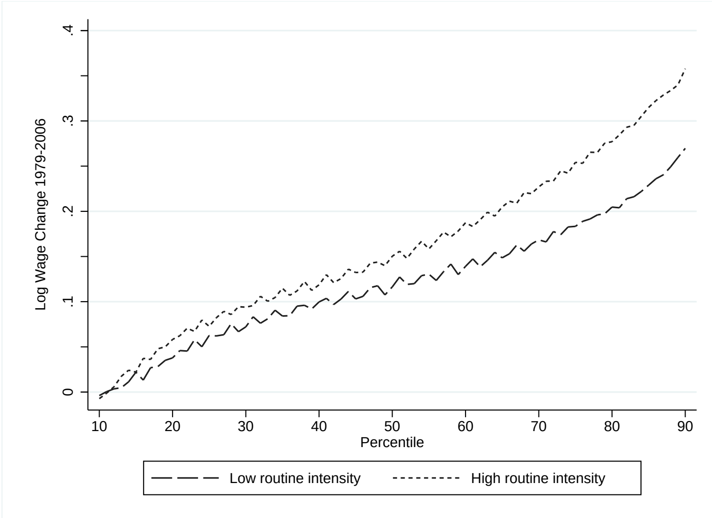
5 Regional Wage Inequality

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 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.

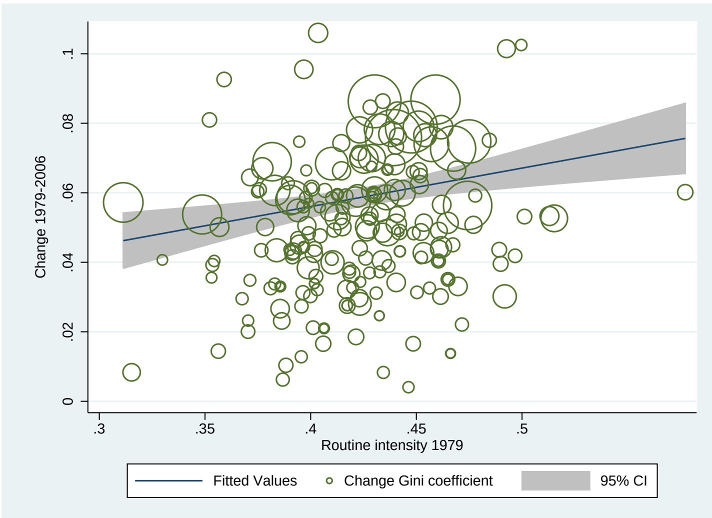
To inspect the link between technology exposure and wage inequality in more detail, we perform an econometric analysis, where income dispersion across local labor markets is measured by the Gini-index. The scatterplot in Figure 5 depicts the bivariate relationship between the local routine share in 1979 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.

Figure 4: Wage Change by Percentile, 1979-2006



Notes: Percentile numbers refer to wage distribution in 1979.

Figure 5: Change in Gini-Coefficient between 1979 and 2006 versus Routine Intensity in 1979



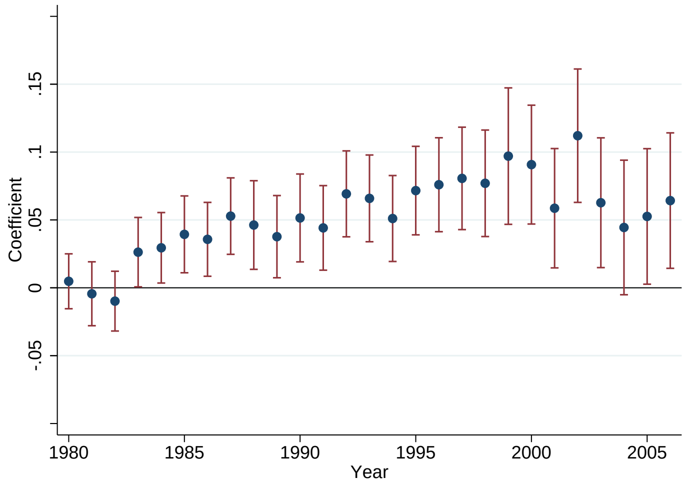
Notes: Figure plots routine intensity in 1979 against the change in Gini-coefficient for 204 local labor markets. The size of the circles is proportional to the regional population in 1979. The line is the predicted change in the Gini coefficient from a weighted OLS regression, where the weights are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

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:

$$\Delta Gini_{r,1979-2006} = 0.01 + 0.11 \times RSH_r + e_r, \quad se = 0.032 \quad n = 204 \tag{14}$$

The positive coefficient implies that the Gini-index rose by 16% more in a region at the 85th percentile than a region at the 15th percentile, indicating that the economic significance of the estimate is substantial.[11] Figure 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 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 **??** and reveal that the results do not hinge on a particular inequality measure.

Figure 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.

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 technology exposure can help understanding the variation of wage inequality growth across Germany 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.

$$\Delta\widehat{Gini_r} = \alpha + \beta_1 RSH_r + \beta_2 \overline{X}. \tag{15}$$

[11] This number is calculated by dividing the 85th/15th percentile difference of .9 percentage points by the average predicted increase in the Gini-index of 5.6 percentage points.

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 6 displays the highest and the lowest predicted change in the Gini-coefficient as well as its difference.

Table 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.

The results indicate that most regional disparities in wage inequality are generated by the economic component, followed by the qualification component. The contribution of technological change is the third most important source of wage dispersion across regions. Interestingly, the demographic composition and the location of local labor markets are least important for explaining wage dispersion across spatial units.

6 Conclusion

This paper 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. 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.

[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.

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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 (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.

Table Appendix

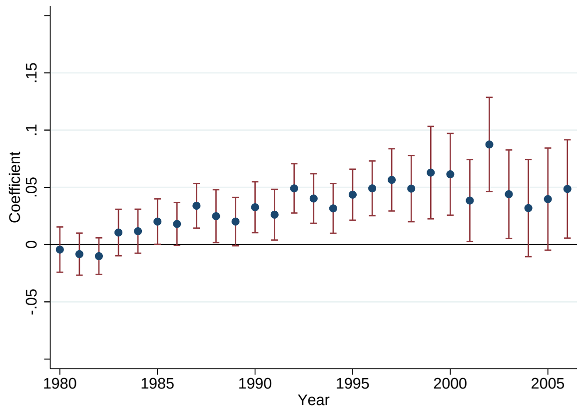
Table 1: Technology and Task Inputs, 1979 - 2006

	Outcome Measures Among						
	All (1)	Males (2)	Females (3)	Age<40 (4)	Age>40 (5)	Less-skilled (6)	High-skilled (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

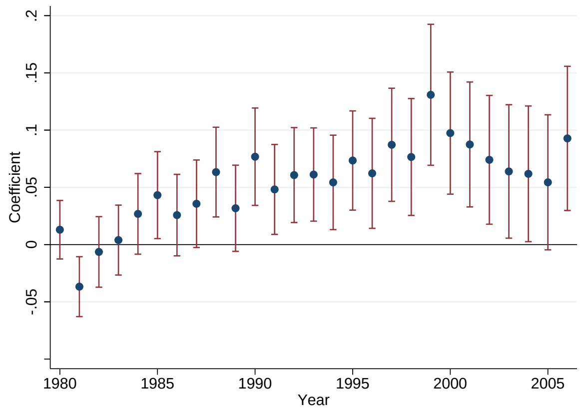
Notes: $N = 204$ labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 1 as well as a constant. Models are weighted by start of period share of national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

Figure Appendix

Figure 1: Dynamic Wage Patterns of the Routinization Effect



(a) Theil-Index



(b) 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 1.