RUHR
ECONOMIC PAPERS

Uwe Neumann

Regional Adaptability to Digital Change – May the Swabian Force Be with You

rwi #1004

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #1004

Responsible Editor: Ronald Bachmann

ISSN 1864-4872 (online) – ISBN 978-3-96973-170-3

Ruhr Economic Papers #1004

Uwe Neumann

Regional Adaptability to Digital Change – May the Swabian Force Be with You

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973170
ISSN 1864-4872 (online)
ISBN 978-3-96973-170-3

Uwe Neumann[1]

Regional Adaptability to Digital Change – May the Swabian Force Be with You

Abstract

The study explores to what extent adaptation to digital change has affected regional employment growth and regional disparities in Germany over the past decade. Using data from administrative sources the analysis finds no evidence for a net decline in employment in connection with technological progress during this period. On the contrary, labour market regions where many employees perform occupational tasks susceptible to automation have fared comparatively well so far. After all, these regions often comprise strong manufacturing clusters, e.g. in rural parts of Southern Germany. In regions dominated by less prosperous industries, however, implementation of job creation potentials may turn out to be a much greater challenge.

JEL-Code: E24, J21, J23, J24, R11

Keywords: Digital change; productivity growth; occupational tasks; regional convergence

February 2023

1 Uwe Neumann, RWI. *– Most of all, I thank Yujie Qin for discussing the theoretical background and empirical approach with me while she prepared her Master´s Thesis (M.A. Urban Culture, Society and Space, University of Duisburg-Essen). I thank Ronald Bachmann and Christina Vonnahme for helpful comments. I also thank Lukas Hörnig, Matthias Kaeding, Janin Marquardt and a group of undergraduate students from the Management & Economics degree programme at Ruhr University Bochum for supporting this research.* *– All correspondence to: Uwe Neumann, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: uwe.neumann@rwi-essen.de*

1. Introduction

In the current debate about the labour market outcomes of technological progress, concerns arise that labour may be replaced by machines due to decreasing costs of computing power and advances in artificial intelligence and robotics. In particular, it is expected that differentials in job perspectives and income by occupation may increase considerably given further rapid progress in automation and substitution of manual work (Autor et al. 2003, Autor 2015). With respect to current digital change it is uncertain to what extent positive employment effects, for example due to creation of new tasks and as an outcome of price reductions made possible by productivity increases, might outweigh the risks of automation (Acemoglu and Restrepo 2016, Bessen 2020).

The following study examines the potential effects of automation on employment growth in different occupations from a regional perspective. It draws on data from the German Employment Office and further administrative statistics characterising local economies at the level of municipal districts and labour market regions. The empirical framework derives from a model of change in labour demand in the light of technological progress, which was developed by Appelbaum and Schettkat (1999) and applied to regional analysis by Blien and Ludewig (2017). Specifically, following a task operationalisation for occupations in Germany provided by Dengler et al. (2014), the analysis will assess the role of the local occupational susceptibility to digital change among the determinants affecting regional employment growth.

Whereas theoretical considerations and empirical findings in regional economics until fairly recently implied that regions in North America and Europe tend to converge to respective common levels of prosperity, current research appears to deny such intra-continental convergence. Given the likely disparate consequences of digitalisation across regional labour markets the digital transformation might reinforce economic divergence between national and sub-national economies. After all, whereas the digital transformation will mitigate some of the disadvantages faced by peripheral areas, it may also enhance the agglomeration advantages characterising the most prosperous regions preferred as workplace by highly qualified personnel (Haefner and Sternberg 2020).

Using Germany as a case study three closely connected basic questions motivate the following research:

1. To what extent (and in which direction) has regional-level employment growth been affected by industry-specific productivity increases due to technological progress over the past decade?
2. In particular, have automation potentials connected to digitalisation already been put into effect and has the resulting job (task) displacement outpaced the creation of new jobs?
3. Have regional disparities in terms of job growth increased in response of local labour and product markets to automation?

2. Literature review

The study is motivated by a debate on the labour market impact of digitalisation, in which a number of studies have predicted striking job losses in occupations that are susceptible to current automation (e.g. Arntz et al. 2017, Frey and Osborne 2017). With a view to the first two research questions the literature suggests that the regional outcomes of productivity increases regarding employment will depend on the way in which they affect the relation between the costs of capital and labour and on the demand for the goods and services provided by the local stock of industries (Neisser 1942, Combes et al. 2004, Cingano and Schivardi 2004).

Acemoglu and Restrepo (2016) argue that if the long-run cost of capital relative to wages is low, eventually all tasks will be automated. However, if productivity gains reduce the costs of labour in relation to a firm´s output, jobs will not simply be wiped away as the creation of new tasks is encouraged, in which labour has a comparative advantage. Since digitalisation is likely to enhance market transparency the probability that workers are unconstrained in their labour supply increases, which in turn encourages utilisation of the emerging comparative advantages of labour in case of productivity boosts. All in all, while it is undisputed that new technologies can lead to job displacement when they are introduced, there is little evidence showing that their introduction has resulted in widespread unemployment across the past centuries (Hötte et al. 2022).

For Germany, Bachmann et al. (2019) demonstrate that for workers engaged mainly in routine tasks, job stability has decreased and the likelihood of unemployment increased significantly during the past four decades. Blien et al. (2021) reveal that between 1980 and 2010 workers employed in routine-intensive occupations suffered larger, more persistent and increasing earnings losses from mass layoffs. On the other hand, Bachmann et al. (2022) highlight that in Germany occupations with a decreasing routine intensity experienced stable or even increasing wages over the past 25 years. In addition, Hensvik and Skans (2023) argue that between 2001 and 2013 in Sweden at every wage level, employment in occupations that employed workers with higher skills (conditional on the wage) tended to grow more. This was particularly true at the lower end of the distribution.

The debate about the employment effects of digitalisation also provides new perspectives to the study of the regional economic outcomes of longer-term technological progress, which are in the focus of the third basic question motivating the analysis. Neoclassical theory expects regional economies to converge to a "steady state" of prosperity, which may be region-specific or common to all regions, in the long run (Solow 1956; Swan 1956). Lower costs of production and less obstacles with respect to the introduction of new technology are among the reasons why peripheral regions may benefit from comparative advantages, which help them to catch up with the more prosperous regions.

On the other hand, in line with current thinking in regional economics (Krugman 1991, Fujita et al. 1999, Fingleton and Fischer 2010) a variety of recent studies tend to reject regional convergence within the U.S., in Europe as a whole or within European countries (Phillips and Sul 2007, Mazzola and Pizzuto 2020). Rather, these studies imply “club convergence” among groups of regions that may but do not need to be located in close proximity to one another (Quah 1996). Given the importance of the industrial structure with respect to the adaptability of regional economies to digital change it is not surprising that several papers find disparate employment effects of current technological progress across sectors and regions. Mann and Püttmann (2021), for example, reveal job increases in services but decreases in manufacturing among U.S. commuting zones between 1976 and 2014. Autor et al. (2015) highlight that local U.S. labour markets, which were more susceptible to automation, did not experience net employment decline between 1990 and 2007. Akerman et al. (2015) demonstrate diverging employment effects according to skills as a result of broadband internet adoption by firms in Norway over the period 2001–2007, i.e. growth among skilled workers but no effect on the employment rates of unskilled workers. Similarly, evidence on the employment effects of industrial robots is mixed (Acemoglu and Restrepo 2017, Dauth et al. 2017, Graetz and Michaels 2015, Koch et al. 2019).

The empirical framework of the following analysis derives from a model of employment growth developed by Appelbaum and Schettkat (1999), who argue that given a price-elastic demand for the output provided by an industrial sector, above-average productivity gains in this sector will be accompanied by expanding rather than diminishing employment. After all, demand for output is assumed to increase as a result of the decrease in relative prices due to an above-average productivity growth in this sector. An increase in employment due to a rising demand for sector-specific output further presupposes a sufficiently elastic labour supply (Combes et al. 2004).

Blien and Ludewig (2017) elaborate on these considerations in their model of regional change in labour demand in the light of technological progress. They demonstrate that basic assumptions regarding the employment effects of technological progress hold both on a micro and macro (regional) level, thus making it possible to utilise considerations regarding the labour demand of individual firms with a view to regional analysis. In their empirical study they estimate industry-specific price and income elasticities for Germany and use these in order to evaluate the job growth effects of productivity increases in the respective sectors. They demonstrate that regional employment growth between 1970 and 2004 corresponded closely with the price elasticities of demand characterising the local stock of industries and – due to a prevalence of sectors facing price elastic demand – productivity increases coincided with job growth rather than decline.

3. Data and methods

3.1 Empirical Framework

The empirical framework as explained derives from Appelbaum and Schettkat (1999) and Blien and Ludewig (2017). In order to answer the research questions posed above, in a first step the respective price and income elasticities of demand for the output provided by economic sectors need to be retrieved. These will subsequently be interacted with productivity and income growth respectively in order to be introduced to a model of regional employment growth.

Since it is not feasible to account for the prices and income elasticities of all other goods when estimating the demand for one specific good it is assumed that the products provided by each manufacturing or service industry are substitutes against a composite good representing all other goods. Further, as Möller (2001) points out, if it is assumed that each industry is small compared to the total economy a suitable estimation approach derives from the following Marshallian type demand function:

$$q_{it} = \beta_i + \varepsilon_i(p_{it} - p_t) + \eta_i y_t + u_{it} \quad (1)$$

q_{it} is the industry real output in year t, y_t the average disposal income per household, p_{it} is the industry price level and p_t represents the national price level in year t and u_{it} is a disturbance term. Estimates for ε_i provide the industry-specific price elasticities and those for η_i the income elasticities. Equation (1) will be estimated for five German industries with a pooled set of annual data for the period 2011–2019, in which all variables are indexed with base year 2015 (100) and taken in logarithms. As the industry real output might be determined endogenously by prices, p_{it} and p_t will be instrumented with their lagged values and the lagged values of y_t and q_{it}. Three-year lags will be used for each variable.

One would expect the price elasticities ε_i to be typically negative, with inelastic demand corresponding to values between 0 and -1 and elastic demand to values below -1. Industries with an income elasticity $\eta > 1$ face income elastic demand. It can be argued that the products or services provided by these industries are superior goods; those with $0 \leq \eta \leq 1$ sell relatively inferior and those with $\eta < 0$ inferior products.

It is an important basic characteristic of the empirical strategy to assume Hicks neutrality, i.e. a constant ratio of the marginal products of capital and labour. This implies that the productivity of labour will rise in line with investment in new technology. Under these circumstances new technologies will not simply wipe away jobs but affect labour demand via the way in which product demand responds to productivity boosts and on the relation between the costs of capital and labour.

With a view to the second research question, the assessment of the susceptibility to automation derives from a procedure developed by Dengler et al. (2014) that follows a task-based approach suggested by Autor et al. (2003) for the U.S. The definition of a job´s automation potential draws on expert knowledge about competencies and skills, which are usually required for performing an occupation. Dengler et al. (2014) provide an alternative task operationalisation for the occupational classifications used in German employment statistics (i.e. the German classification of occupations from 2010, KldB 2010 for 36 occupational groups (3-digit codes), Federal Employment Agency 2022).

Using a typology suggested by Spitz-Oener (2006), the tasks accounting for jobs in each occupational group are allocated to five categories: analytical non-routine, interactive non-routine, cognitive routine, manual routine and manual non-routine tasks. For each category the share among all tasks typically performed in this group of occupations is defined, the five shares adding up to 1. A high automation potential is expected, most and for all, with respect to manual and cognitive routine tasks, e.g. accounting, measuring (cognitive), operating of machines (manual). The regional susceptibility to automation will be defined in terms of the total share of routine tasks among all occupations performed by employees in the region. Fonseca et al. (2018) uncover a sharp decline in routine manual employment, but only a modest decline in routine cognitive employment for the period 1986-2007 in Portugal. They argue that this distinction may be due to relatively slow computer capital adoption in the Portuguese service industry. For Germany rapid implementation of automation potentials can be expected with respect to all routine tasks.

It is assumed that the share of routine tasks typically performed by workers in an occupational group correlates with the share of jobs prone to be replaced by computer technology in the near future (Bennewitz et al. 2016). The jobs (i.e. full-time equivalents) susceptible to automation per occupational group thus defined add up to a total number per region:

$$AP_{rt} = \sum_{KldB=1}^{Kldb=36} RT_{rt}/L_{rt}\,. \tag{2}$$

In (2), AP_{rt} represents the regional automation potential in terms of the share of employees prone to be substituted by computer technology in year t, RT_{rt} comprises the regional sum of jobs expected to be in danger of automation, calculated as the share of routine tasks performed by each occupational group (KldB) in relation to the number of employees in the respective occupation in region r in year t, divided by the total number of jobs in the region, L_{rt}.

Basic model (3), which refers to all research questions, incorporates the elasticities deriving from estimations of (1) and the regional automation potential AP_{rt}, as retrieved from (2):

$$\Delta L_{i,rt} = \alpha_0 + \alpha_1 \varepsilon_i \Delta Q_{i,rt} + \alpha_2 \eta_i \Delta Y_{rt} + \alpha_3 X_{rt} + v_{i,rt}. \quad (3)$$

$\Delta L_{i,rt}$ captures the annual employment growth rate in industry i of region r between years $t-1$ and t, for $t = 2012, \ldots., 2019$. The independent variables include the interaction of the industry-specific price demand elasticity ε_i and the productivity growth rate $\Delta Q_{i,rt}$ among industry i of region r, the interaction of the income elasticity η_i and the regional growth rate of per capita income, ΔY_{rt}. X_{rt} comprises a set of regional-level control variables, which include wage growth, two measures representing urbanisation, i.e. the existing concentration of economic activity (employment density) and accessibility and our indicator of the regional occupational susceptibility to automation, AP_{rt}. Both agglomeration indicators and AP_{rt}, which are measured in levels, enter the equation as one-year lags, i.e. at $t-1$, corresponding to the base years of the variables measured as growth rates. Regional unemployment is accounted for implicitly, as wages are expected to respond inversely to unemployment rates. $v_{i,rt}$ captures the industry-by-region level disturbances. Growth is measured in terms of log differences.

It is thereby considered that the overall effects of technological progress on employment depend on the interplay between displacement of old and creation of (most likely, higher-qualified and higher-paid) new jobs in the light of productivity increases. In this context estimations of equation (3) explore to what extent the interplay of automation and job creation has affected the regional-level demand for labour.

The first urbanisation indicator, the employment density, is measured as the ratio between the number of employees and the total number of inhabitants. The second indicator, i.e. accessibility, is defined as the proximity from administrative units to the nearest railway station providing access to long-distance travel (measured by the average commuting time to this railway station by car).

OLS estimations will serve as base model. Robustness checks comprise two types of estimation as suggested by Blien and Ludewig (2017), i.e. an outlier robust regression, which weights each industry by the inverse of the residual in an iterative process and a weighted regression, which weights each industry by the inverse of the width of the 95% confidence interval for the point estimates of the respective price elasticity according to equation (1). Further robustness checks include a fixed-effects estimation and an instrumental variable estimation, in which the regional automation potential indicator AP_{rt} will be instrumented by its annual rank. After all, in contrast to all other independent variables accounted for by equation (3) it is less certain whether endogeneity regarding the regional occupational structure can be ruled out.

In close connection with the analytical steps motivated by the first and second research question the third question, which is concerned with whether regional disparities have increased in response of local labour markets to automation, will be examined from different perspectives. The most straightforward answer to this question derives from indicator AP_{rt} in (3). A negative coefficient would indicate that regions with a comparatively higher share of occupations susceptible to automation performed considerably worse in terms of job growth during the past decade, given sector-specific productivity increases and other determinants of local employment growth. A positive coefficient, on the other hand, would imply that job creation outpaced automation in the regions most likely to face automation. However, a high share of occupations prone to automation need not necessarily characterise lagging regions, as regions with a strong and prosperous manufacturing base may represent a relatively high share of manual occupations susceptible to automation. Indicator AP_{rt} will thus not necessarily evaluate convergence regarding regional prosperity in general. For this purpose as explained two urbanisation indicators will be taken into account, which capture broad differentials in prosperity and accessibility.

Further robustness checks will explore whether any impact of regional characteristics also applies to employment growth among urban and rural regions, if these are taken into view separately. An additional set of robustness checks comprises estimations, which (i) utilise the expected elasticities (-1 for prices and 1 for income) instead of the estimated counterparts and (ii) weight by the annual industry employment share. All estimations include year fixed effects and fixed effects for East Germany (excluding Berlin). Alternatively, an estimation that separates between urban and rural regions will incorporate fixed effects for macro-regions comprising a combination of federal states (North, i.e. Bremen, Lower Saxony, Hamburg, Schleswig-Holstein; South West, i.e. Hesse, Saarland, Rhineland-Palatinate) or single states (North Rhine-Westphalia, Baden-Württemberg, Bavaria). In these estimations Berlin and East Germany add up to the reference group.

Controlling for macro-regions at the level of states represents an important robustness check, yet will not be part of the main empirical strategy, since considerable variation across labour market regions within states can be assumed, e.g. between the old industrialised Ruhr and the very prosperous Rhineland metropolises of North Rhine-Westphalia (Bonn, Cologne, Düsseldorf) or between urban and rural regions.

A final robustness check investigates to what extent spatial autocorrelation in the annual cross-sectional regional variation of industry-specific employment growth among all labour market regions might affect the analysis. After all, if potential spillovers between regions remain unaccounted for, the regional-level relation between the independent variables and employment growth may be overestimated. The main analysis will not incorporate such controls for spatial dependence, since it is assumed that labour market regions, which will represent the territorial level, account for the main regional interdependencies. In order to verify this assumption, the analysis applies a spatial autoregressive (SARAR) model according to equations (4) and (5) that allows for spatial effects among the dependent variable and the error term, i.e. accounting for potential spatial interdependence in the regional-level automation potential AP_{rt} and the other independent variables

$$\Delta L_{ir} = \lambda \sum_{l=1}^{n} w_{rs} \; \Delta L_{ir} \; + \sum_{p=1}^{P} x_{rs} ß_P \; + u_{ir} \tag{4}$$

$$u_{ir} = \rho \sum_{p=1}^{P} m_{rs} u_s \; + \; \varepsilon_{ir} \, . \tag{5}$$

In equations (4) and (5) w_{rs} and m_{rs} represent spatial weights, which are inversely related to the distance (in kilometres) between the geographic centre of districts r and s, x is a set of P independent variables as in equation (3). ß comprises the corresponding parameters, u_{ir} is a spatial autoregressive error term, such that disturbances ε_{ir} are assumed to be independent and identically distributed, the parameter λ measures the extent of spatial interaction in the outcomes of the dependent variable and ρ measures spatial dependence in the error term. In the case of our study it is of particular interest whether spatial autocorrelation among the occupational structure affects the estimations, which is captured by ρ. The spatial-autoregressive model implemented in this analysis uses a generalised spatial two-stage least-squares (GS2SLS) estimator allowing for endogenous covariates (Drukker et al. 2013). The regional automation potential indicator AP_{rt} will again be instrumented by its annual rank.

The analysis will refer to two different regional levels, (i) municipal districts (Kreise und kreisfreie Städte), the territorial unit for which regional-level administrative statistics is compiled, and (ii) labour market regions as defined for the purposes of regional policy. Labour market regions do not represent territorial units in public administration and their layout is subject to revision (RWI 2018). Yet, as they are delineated in order to encompass commuting zones, they represent the main level of reference for the following analysis, comprising 258 regions defined in order to determine areas eligible for regional aid by the German Federal Government and the federal states during the period 2014–2020 (Schwengler and Bennewitz 2013). They consist of individual districts or groups among 401 German municipal districts. Selected additional analyses will refer to the level of municipal districts for reasons of comparison with previous research.

3.2 Data Sources

According to the empirical strategy outlined in the previous subsection, a dataset will be constructed from different sources, comprising

(1) annual data on national industry nominal and real output and prices compiled by the Federal Statistical Office (2022), which is required to estimate the industry-specific price elasticities ε_i and the industry-specific income elasticity of product demand η_i (equation 1);

(2) annual data on regional-level nominal industry output (which is required to calculate industry-specific regional productivity growth $\Delta Q_{i,rt}$ in equation 3), income and population (required to calculate per capita income Y_{rt} in equation 3) from the Federal Statistical Office and Statistical Offices of the Federal States (2022);

(3) annual regional-level data on wages and accessibility from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR 2022), which is required to construct the covariates X_{rt} in equation 3;

(4) annual regional-level data on employment by sectors and occupations deriving from the statistics of the Federal Employment Agency (2022)[1], which provides the basis for the dependent variables $\Delta L_{i,rt}$ in equation 3 and for calculation of the share of jobs susceptible to

[1] Data on tasks by occupational group for 2013 was provided by the Institute for Employment Research (2014) as a documentation supplement to Dengler et al. (2014). It is assumed that the task shares remained constant over one year. They were thus applied in order to calculate the regional susceptibility to automation for 2013 and 2014. For 2016, updated information about the occupational automation potential was provided by Bennewitz et al. (2016). The respective shares of routine tasks by occupation were used to calculate the regional automation susceptibility in 2015 and 2016. The time series for 2013-2016 was used to impute the respective data for 2011-2012 and 2017-2019 by linear extrapolation.

automation, AP_{rt}, in equations 2 and 3; this statistics, which refers to all research questions, covers all employees liable to the social security system, i.e. the total workforce except for self-employed persons, marginally employed persons (below an income threshold of currently 450 Euro per month) and civil servants; around 75% of all economically active persons in Germany are liable to social security; regional statistics on employment are given in terms of full-time equivalents, i.e. part-time employed persons are counted as 0.5; and

(5) own calculation of the geographical centres of municipal districts using the ETRS89 / UTM zone 32N Coordinate Reference System in order to derive spatial distance weights w_{rs} and m_{rs} in the robustness checks drawing on SARAR models (equations 4 and 5).

4. Analysis and results

4.1 Industry-specific price and income elasticities of demand

The first step of the analysis estimates elasticities according to equation (1), assuming they are constant over the study period and apply to Germany as a whole. The interactions of the elasticities with productivity and income, however, vary across time and regions. Since the analysis refers to market mechanisms, activities which are arguably state-driven or non-profit-oriented will be excluded. These include agriculture, public administration and defence, social security and private households (Blien and Ludewig 2017).

As explained, due to potential endogeneity of prices with respect to output estimations of industry-specific price and income elasticities according to equation (1) will draw on an instrumental variable approach. Elasticities will be instrumented using lagged variables (see above). Price and income elasticities will be estimated with respect to five (profit-oriented) sectors, which can be distinguished among regional-level statistics on industry output. The chi^2 statistics shows that the probability of the price elasticity for manufacturing to be different from (the expected value) -1 is not higher than (but exactly) 90% (Table 1).

In the following estimations the price elasticity for manufacturing will therefore be set to -1 whereas the estimated elasticities will be used for all other sectors. Inelastic prices, i.e. elasticities below 0 but above -1, are found to characterise service industries (trade, catering, information, logistics, finance and real estate) and positive elasticities result from the estimations for construction and mining.

Table 1
Estimated price and income elasticities (IV estimations)

sector[1]	price elasticity		income elasticity	
	elasticity	chi²-value[2]	elasticity	chi²-value[3]
mining, energy and water supply	0.389	0.000	1.467	0.001
manufacturing	0.056	0.100	0.750	0.628
construction	0.278	0.005	0.818	0.840
trade, catering, information, logistics	-0.158	0.000	0.640	0.144
financial & business services, real estate	-0.086	0.002	0.339	0.024

Author´s calculations. [1]Sectors classified according to European NACE 2 (rev. 2) system; [2]probability that estimated coefficient is different from -1. [3]probability that estimated coefficient is different from 1

Price elasticities are expected to be positive only in special cases comprising either luxury or strongly inferior goods. As such characteristics would not apply to the mining and construction sectors, robustness checks will comprise estimations, in which all price elasticities will be set to -1. Demand for output from mining, energy and water supply appears to react income elastic, whereas it is inelastic concerning financial services. Regarding the other sectors the probability that the income elasticity is different from 1 is below 90%. For these sectors an income elasticity of 1 will be assumed.

4.2 Regional job growth and determining variables – descriptive statistics

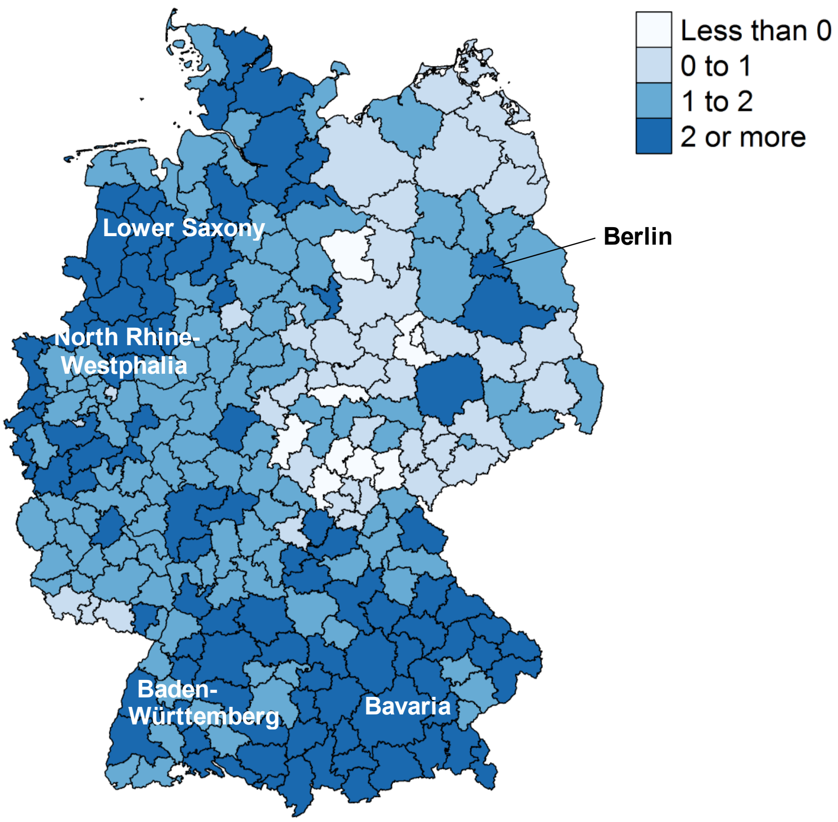
The study period was characterised, on average, by an annual regional growth of employment by around 2% in construction and the service sectors and by around 1% in manufacturing and in mining, energy and water supply (Table 2). Productivity increased at a higher annual rate among in the mining, energy and water supply and construction sectors (+4%) than in manufacturing and services (+ 1%). Per capita income increased by around 2% on average, wages by 3%.

Table 2
Descriptive statistics – municipal districts and labour market regions

	municipal districts		labour market regions	
	mean	standard deviation	mean	standard deviation
*annual employment growth**				
mining, energy, water supply	0.01	0.08	0.01	0.08
manufacturing	0.01	0.04	0.01	0.06
construction	0.02	0.04	0.01	0.08
trade, catering, information	0.02	0.03	0.02	0.06
financial/real estate services	0.02	0.06	0.02	0.08
*annual productivity growth**				
mining, energy, water supply	0.04	0.18	0.04	0.15
manufacturing	0.01	0.09	0.01	0.09
construction	0.04	0.08	0.04	0.10
trade, catering, information	0.01	0.04	0.01	0.07
financial/real estate services	0.00	0.06	0.01	0.09
annual growth of income	0.02	0.02	0.02	0.01
annual wage growth	0.03	0.01	0.03	0.01
employment density	0.37	0.12	0.36	0.06
rail accessibility	22.04	15.07	24.07	14.01
automation potential	0.40	0.03	0.40	0.03
Observations (max.)	3,609		2,313	

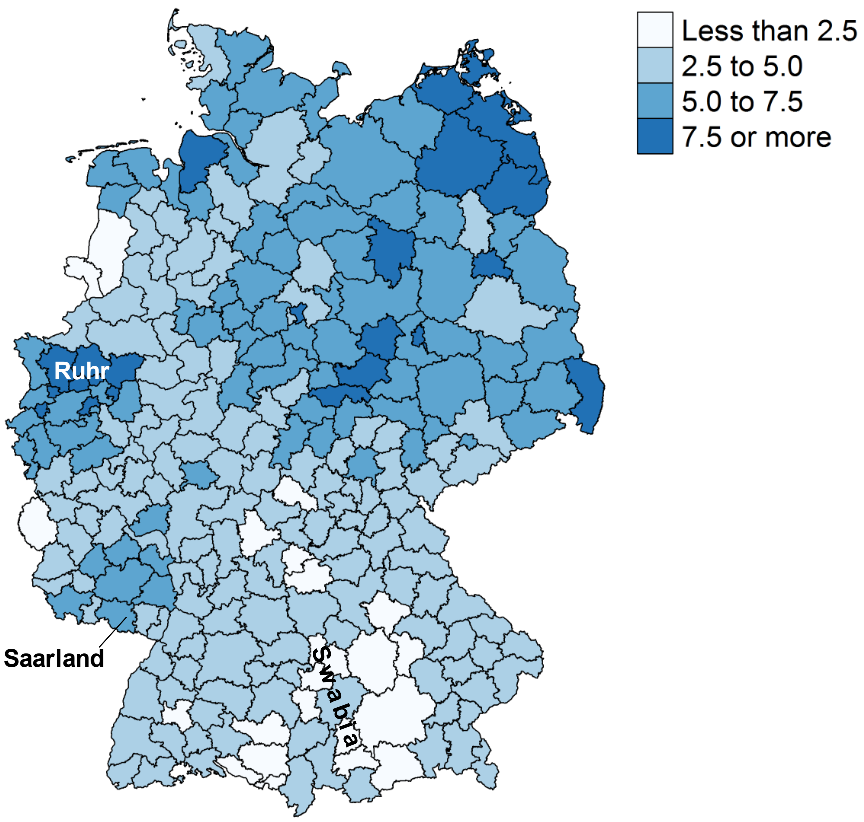
Author´s calculations; *log differences

Figure 1
Average annual employment growth, 2012-2019 (in %)
Labour market regions*



Author´s calculation using data provided by the Federal Employment Agency (2022) *labour market regions as defined by Schwengler and Bennewitz (2013)

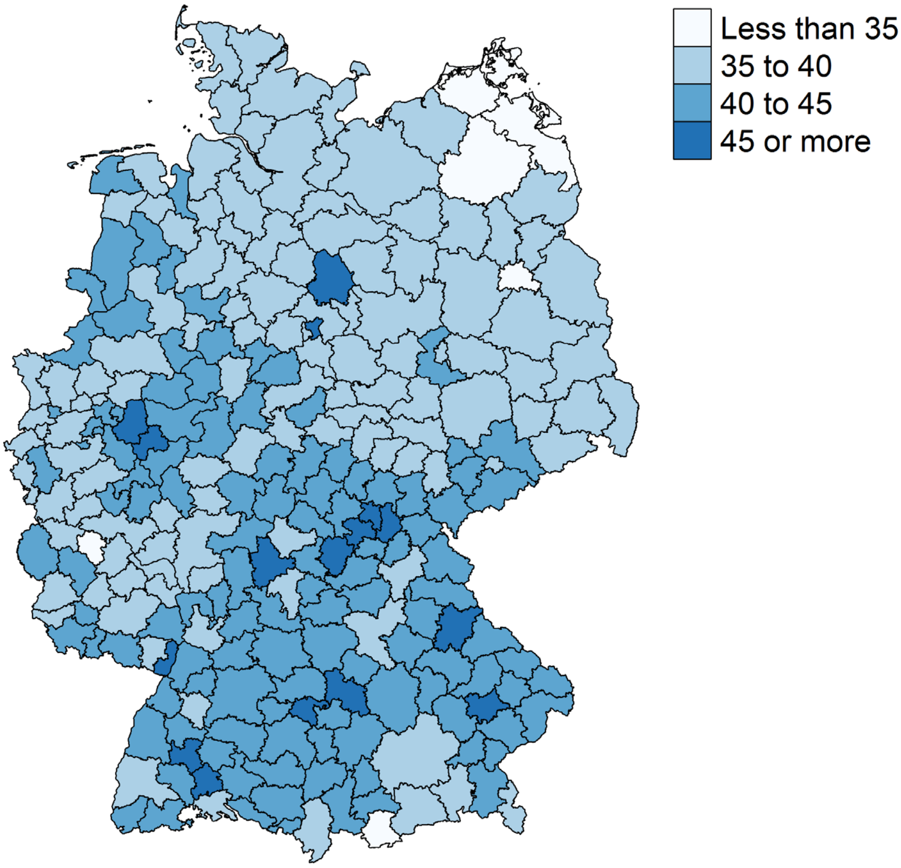
Figure 2
Unemployment rate, 2019 (in %)[1]
Labour market regions*



Author´s calculation using data provided by the Federal Employment Agency (2022). [1]Share of unemployed persons among the civilian labour force; *labour market regions as defined by Schwengler and Bennewitz (2013)

Whereas at the regional level there is obviously a strong correlation between employment growth and unemployment rates, as regions characterised by high growth during the past decade typically report low unemployment rates (Figures 1 and 2), the interrelation between employment growth and the occupational structure is less straightforward. The share of employees performing tasks at risk of automation is comparatively high in many prosperous regions of Southern Germany and the northwest of Lower Saxony, where unemployment is low and the number of jobs has increased (Figure 3).

Figure 3
Share of employees performing tasks at risk of automation (in %)
2016, labour market regions*



Author´s calculation using data provided by the Federal Employment Agency (2022)); *labour market regions as defined by Schwengler and Bennewitz (2013)

In 2016, for example, Bavaria and Baden-Württemberg accounted for 12 labour market regions, in which over 45% of all employees were found to be at risk of substitution by computer technology. In all other states altogether there were only 4 further regions with a share similarly high above the annual average among all regions (40.4%) (Olpe and Lüdenscheid in North Rhine-Westphalia, Salzgitter and Wolfsburg in Lower Saxony). On the other hand, the share of jobs, which are susceptible to automation, is relatively high also in Saarland, a federal state representing an old industrial region of West Germany.

4.3 Technological progress and local automation potential as determinants of job growth

4.3.1 Base model

As explained, in the analysis labour market regions will represent the main territorial reference. Yet, for reasons of comparison with previous research the base model will be estimated at both regional levels, municipal districts and labour market regions. With respect to the first research question, the basic OLS estimations carried out at the level of municipal districts, first of all, find negative coefficients for the interaction of price elasticity and productivity growth. Since the demand elasticity is negative regarding three out of five sectors considered in the analysis (see above), a positive employment effect in this case derives from a negative coefficient. In line with the results by Blien and Ludewig (2017) at the level of municipal districts this result is robust against variation in the variables included in the model (Table 3). The interaction between the income elasticity and income, however, is insignificant. In line with expectations, the coefficient of wage growth is positive, i.e. total employment growth may be assumed to gain from creation of new (high-skilled) tasks in line with technological progress. The base model further outlines negative job growth effects associated with urban agglomeration as indicated by negative coefficients assigned to employment density.

Regarding the second research question the analysis reveals that a statistically significant and positive job growth effect, however, is connected to a high share of occupations prone to automation (estimation 6 in Table 3). While this suggests that during the past decade job loss due to automation has been outpaced by job creation, the results need to be interpreted with some caution. After all, the job growth performance of regions with a high local occupational susceptibility to automation has been characterised by significant urban-rural differentials, which will be examined in greater detail below.

Table 3
Employment growth per region (municipal districts) and industry (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
price elasticity*	-0.111***	-0.111***	-0.110***	-0.111***	-0.111***	-0.111***
productivity growth	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
income elasticity*income		-0.024	-0.026	-0.036	-0.039	-0.040
		(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
wage growth			0.154***	0.158***	0.155***	0.156***
			(0.045)	(0.046)	(0.045)	(0.045)
employment density[1]				-0.007***	-0.006**	-0.007***
				(0.002)	(0.002)	(0.002)
accessibility					0.000	0.000
					(0.000)	(0.000)
automation potential						0.036**
						(0.019)
year fixed effects	yes	yes	yes	yes	yes	yes
East/West fixed effect	yes	yes	yes	yes	yes	yes
constant	0.015***	0.016***	0.012***	0.005*	0.004*	-0.010
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.008)
observations	15,722	15,722	15,722	15,722	15,722	15,722
R^2	0.026	0.026	0.027	0.028	0.029	0.029

Author´s calculations. Robust standard errors (clustered by labour market regions) in parentheses; */**/***: significant at 0.1/0.05/0.01-level

Table 4
Employment growth per region (labour market regions) and industry (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
price elasticity*	0.007	0.007	0.007	0.003	0.002	0.002
productivity growth	(0.167)	(0.167)	(0.168)	(0.164)	(0.164)	(0.164)
income elasticity*income		-0.005	-0.012	-0.029	-0.022	-0.024
growth		(0.055)	(0.055)	(0.056)	(0.055)	(0.055)
wage growth			0.236**	0.244**	0.248**	0.248**
			(0.103)	(0.103)	(0.104)	(0.104)
employment density				-0.040**	-0.043**	-0.049**
				(0.016)	(0.017)	(0.019)
accessibility					-0.000*	-0.000**
					(0.000)	(0.000)
automation potential						0.083*
						(0.043)
year fixed effects	yes	yes	yes	yes	yes	yes
East/West fixed effect	yes	yes	yes	yes	yes	yes
constant	0.012***	0.013***	0.007*	-0.033*	-0.033*	-0.070**
	(0.002)	(0.001)	(0.003)	(0.017)	(0.17)	(0.034)
observations	10,192	10,192	10,192	10,192	10,192	10,192
R^2	0.009	0.010	0.011	0.017	0.018	0.019

Author´s calculations. Robust standard errors in parentheses; */**/***: significant at 0.1/0.05/0.01-level

At the level of labour market regions, the estimations confirm the significant and positive job growth effects associated to wage growth, negative agglomeration effects (employment density, accessibility) and the positive effect of the automation potential (Table 4). The coefficients of the elasticities interacted with productivity and income growth respectively, however, both turn out insignificant. Apparently among the larger and more disparate labour market regions some of the variability in productivity and job growth characterising the districts is levelled out. None the less, the coefficient of automation again turns out positive.

4.3.2 Robustness checks I – alternative estimations for all regions

In the weighted and outlier robust OLS estimations the coefficients on the price and income elasticities are insignificant. In the weighted regression (which weights the industries by the inverse of the width of the 95% confidence interval of the point estimates for the price elasticity in the respective sector-specific estimation) the agglomeration indicators (employment density, accessibility) turn out negative, whereas the coefficients on wage growth and on the automation potential are significant and positive. By contrast, in the outlier robust estimation the coefficient of the employment density turns positive and the coefficients on wage growth and automation negative (estimations 1 and 2 in Table 5).

These seemingly contradictory results arise from opposite weightings assigned to sectors. In the weighted regression the weighting for manufacturing assumes a high value, since the bandwidth of the point estimate is comparatively small. In the outlier robust estimation, however, the weights are high for services due to smaller residuals yielded by the respective estimations. The robustness checks thus point at disparate employment effects by productivity increases and automation between manufacturing and services. It appears that in manufacturing creation of high-skilled (and well-paid) jobs has outpaced job losses due to automation, while service industries have lost jobs in regions where the automation potential is high. It needs to be kept in mind that this does not indicate job destruction among services in general, as regions with a high local automation potential are usually manufacturing strongholds. Nevertheless, it can be argued that in regions with strong manufacturing clusters these industries have generally fared well in terms of job growth over the past decade, whereas services have performed worse in these regions than in those (urban) regions, where they agglomerate.

Table 5
Employment growth per region (labour market regions) and industry – alternative estimation approaches

	(1)	(2)	(3)	(4)	(5)	(6)
model	OLS - weighted	OLS - outlier robust	fixed effects	IV	OLS – urban regions	OLS – rural regions
price elasticity*	0.171	0.019	-0.071	-0.188***	-0.206**	0.094
productivity growth	(0.170)	(0.038)	(0.094)	(0.057)	(0.081)	(0.214)
income elasticity*income	-0.051	0.085	0.033	-0.011	-0.062	-0.004
growth	(0.065)	(0.091)	(0.047)	(0.048)	(0.053)	(0.085)
wage growth	0.326***	-0.403***	0.138	0.212**	0.195	0.296**
	(0.111)	(0.152)	(0.096)	(0.102)	(0.142)	(0.142)
employment density[1]	-0.050**	0.019**	-1.000***	-0.004	-0.003	-0.094**
	(0.023)	(0.009)	(0.144)	(0.007)	(0.006)	(0.038)
accessibility[1]	-0.000**	0.000	-	-0.000	0.000	-0.000**
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
automation potential[1]	0.129***	-0.142***	-0.060	0.077*	0.005	0.204**
	(0.042)	(0.046)	(0.114)	(0.043)	(0.041)	(0.098)
year fixed effects	yes	yes	yes	yes	yes	yes
East/West fixed effects	yes	yes	yes	yes	yes	yes
constant	-0.095**	0.082**	-0.965***	-0.025	0.007	-0.167***
	(0.040)	(0.020)	(0.153)	(0.021)	(0.017)	(0.074)
observations	10,192	10,192	10,192	8,929	4,600	5,929
R^2 (within)	0.058	0.157	0.180	0.024	0.036	0.036
F (1, 8916)				6,539.80		

Author´s calculations. Robust standard errors in parentheses; */**/***: significant at 0.1/0.05/0.01-level

In the fixed effects estimations controlling for year effects all coefficients are insignificant – arguably due to relatively moderate within-regional changes regarding the covariates - , except for the coefficient of the employment density, which is significant and negative (estimation 3). The IV model, in which the automation potential is instrumented by its annual rank, confirms the coefficients of the base model, yet the coefficient of the interaction between the price elasticity and productivity growth is negative and significant (estimation 4). It implies that a 1 point higher annual growth of productivity has been associated to a 0.18 percentage points higher growth of employment. The coefficient of automation is significant and positive (+0.077). In this and further IV estimations the F statistics confirm that the instrument is not weak.

4.3.3 Robustness checks II – urban and rural regions

With a view to the regional dimensions of digital change the analysis according to the base model suggests that during the past decade regions with a higher susceptibility to automation in general have not been affected by below-average job growth or above-average total job-losses. From this perspective, therefore it appears that adaptation to digital change in Germany so far has not coincided with an acceleration of regional disparities.

If we separate between urban and rural regions (using a classification of regions provided by BBSR (2018)) the separate OLS regressions, first of all, find a significant (and positive) impact from productivity growth on job growth in urban regions (estimation 5 in Table 5). Among rural regions the results confirm the results from the base model, i.e. finding a positive coefficient of wage growth and negative coefficients of the employment density and accessibility but no effects deriving from industry-specific productivity increases. The coefficient on automation is significant, positive and higher in magnitude than in the base model (implying a 0.2 point higher job growth in case of a 1 point higher share of employees in danger of automation) (estimation 6).

Further robustness checks pursue whether the significant and positive coefficient on the automation potential in rural regions holds in OLS estimations using a predefined price elasticity of product demand (-1) or weighting by the industry employment share and in fixed effects and IV estimations. In both OLS models the coefficient on productivity growth is significant and positive (estimations 1-2 in Table 6), revealing that in a price inelastic market environment (or in case the elasticity is -1) among rural regions an increase in productivity has in fact resulted in employment decline. The agglomeration indicators are negative in both of these estimations, whereas the coefficient on automation is significant and positive in the weighted regression. In the fixed effects panel estimation the automation coefficient is insignificant (estimation 3). In the IV model the coefficient of productivity growth adopts a negative value and the coefficient on automation is confirmed to be positive (estimation 4).

Table 6
Employment growth per region (labour market regions) and industry – urban/rural regions[1]

	(1)	(2)	(3)	(4)	(6)	(7)
model	OLS –price elasticity -1	OLS – industry weighting	fixed effects	IV	OLS – macro-region fixed effects	
	rural	rural	rural	rural	urban	Rural
price elasticity*	0.485***	0.335*	-0.010	-0.156**	-0.206**	0.093
productivity growth	(0.049)	(0.172)	(0.115)	(0.071)	(0.081)	(0.212)
income elasticity*income	0.286***	-0.022	0.016	0.058	-0.061	-0.002
	(0.064)	(0.053)	(0.078)	(0.077)	(0.053)	(0.085)
wage growth	0.236**	0.293***	0.156	0.196	0.183	0.241*
	(0.109)	(0.107)	(0.124)	(0.135)	(0.145)	(0.139)
employment density	-0.045**	-0.081**	-1.066***	-0.007	-0.007	-0.108***
	(0.019)	(0.032)	(0.142)	(0.017)	(0.006)	(0.040)
accessibility	-0.000**	-0.000***	-	-0.000	0.000	-0.000**
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
automation potential	0.084	0.162**	-0.211	0.157*	-0.013	0.094
	(0.057)	(0.082)	(0.213)	(0.082)	(0.054)	(0.083)
year fixed effects	yes	yes	yes	yes	yes	yes
East/West fixed effects	yes	yes	yes	yes	no	no
Instrument for Automation	no	no	no	yes	no	no
macro-regions (reference categories: Berlin and East Germany)[2]						
North					0.008*	-0.001
					(0.004)	(0.004)
NRW					0.008**	0.005
					(0.004)	(0.006)
South-West					0.010***	-0.003
					(0.004)	(0.006)
Baden-Württemberg					0.014***	0.019***
					(0.004)	(0.003)
Bavaria					0.015***	0.018***
					(0.004)	(0.003)
constant	-0.071*	-0.137**	-1.012***	-0.061	0.000	-0.146**
	(0.039)	(0.064)	(0.172)	(0.046)	(0.021)	(0.069)
observations	5,592	5,592	5,592	4,904	4,600	5,592
R^2	0.477	0.127	0.263	0.016	0.037	0.043
F (1, 4890)				2,936.14		

Author´s calculations. Robust standard errors in parentheses; */**/***: significant at 0.1/0.05/0.01-level; [1]urban and rural regions as defined by BBSR (2018); [2]North: Bremen, Lower Saxony, Hamburg, Schleswig-Holstein; South-West: Hesse, Rhineland-Palatinate, Saarland

Additional robustness checks incorporate fixed effects for state-level macro-regions. The results are displayed for both urban and rural regions (estimations 5 and 6 in Table 6). As explained, due to within-state disparities state fixed effects are not used in the base model, yet when separating between urban and rural regions it is feasible to account for variation at the macro-regional level. Among urban regions apart from the coefficients of the macro-regional fixed effects (and several year fixed effects, for which the results are not displayed) only the coefficient of productivity growth turns out significant (and negative). The coefficients of all macro-regions are positive due to stronger employment growth among West German cities compared to the entirety of Berlin and East Germany. Of course, among all urban regions in Germany during the study period employment growth was strongest in Berlin (see above). Yet, in the reference region altogether urban job growth was slower than in any of the West German macro-regions.

It is remarkable that among rural regions the coefficients of agglomeration (i.e. employment density and accessibility) turn out significant and negative, if macro-regional differentials are considered. Among macro-regions, the rural areas of Baden-Württemberg and Bavaria dominated in terms of job growth during the past decade, accounting for a 1.9 percentage points (Baden-Württemberg) or 1.8 points (Bavaria) higher annual job growth than rural labour market regions with similar features of other states. In the Bavarian part of Swabia, for example, many manufacturing industries which account for an above-average share of employees (in comparison to Germany as a whole), e.g. mechanical engineering, experienced a remarkable period of job growth between 2011 and 2019. Employment in the aerospace industry, which is among the strongly represented manufacturing sectors in the region, even increased by 57%, comprising around 15,200 jobs in 2019. At the same time, employment in knowledge-intensive service industries increased by remarkable 79%, accounting for over 43.000 jobs altogether (Prognos 2020).

The coefficient of the automation potential remains positive among rural regions yet wanes in significance. Apparently job growth in rural regions of Baden-Württemberg and Bavaria exceeded that in rural regions of other states to such an extent that within-state differentials according to the local automation potential are small in comparison. On the other hand, the positive coefficient of the automation potential among all regions is driven to a large extent by strong growth in rural regions of Baden-Württemberg and Bavaria, where jobs in prosperous manufacturing industries are nevertheless characterised, among other things, by a high susceptibility to automation.

4.3.4 Robustness checks III –testing for spatial autocorrelation

The final robustness check incorporates a spatial autoregressive IV model, which is estimated separately for annual cross-sections by industry. It is the purpose of this step to examine whether spatial autocorrelation in the variation of the automation potential across labour market regions affects the analysis and whether the coefficients on the automation potential turn out significant.

Table 7
Employment growth per region (labour market regions), spatial autoregressive IV model (SARAR), GS2SLS, marginal effects, total impact of automation potential, spatial autocorrelation in error term, selected years

	mining, energy, water supply	manufacturing	construction	trade, catering, information, logistics	finance, business services, real estate
	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
2015					
automation potential	-0.184	0.076**	0.071	-0.060	0.105**
	(0.195)	(0.033)	(0.088)	(0.046)	(0.046)
ρ	-0.442	0.606**	-1.351	0.446	-2.072*
	(1.322)	(0.308)	(1.174)	(0.728)	(1.165)
2016					
automation potential	-0.097	0.009	-1.230	-0.215	0.180**
	(0.223)	(0.074)	(3.238)	(0.314)	(0.089)
ρ	-4.146***	-1.645	-0.207	1.484***	0.286
	(1.535)	(1.521)	(0.786)	(0.287)	(0.681)
2019					
automation potential	-0.522	0.023	-0.095**	0.005	0.071
	(1.452)	(0.051)	(0.041)	(0.052)	(0.182)
ρ	-1.211	0.425	3.573***	-0.433	-1.485
	(1.444)	(0.551)	(1.223)	(0.832)	(1.292)

Author´s calculations. Standard errors allowing for heteroscedasticity in parentheses. ***/**/* = significant at 0.01/0.05/0.1-level; [1]no significant coefficients on the automation potential in other years; ρ: spatial autocorrelation in error term

The coefficients of the automation potential, AP_{rt}, are significant and positive with respect to manufacturing and finance services in 2015, concerning finance services also in 2016 and for the construction sector it is negative in 2019 (Table 7). The automation coefficient in the estimation for manufacturing in 2015 corresponds to the coefficient in the base model in magnitude, suggesting a 0.08 percentage point job growth increase in case of a 1 point higher share of occupations in danger of replacement. The coefficient of finance services is higher in magnitude (+0.105 in 2015, +0.180 in 2016). In 2015 the analysis is affected by spatial autocorrelation among the covariates in both sectors and in the analysis for the construction sector in 2019.

The cross-sectional models accounting for spatial spillovers between regions confirm that the impact of the occupational structure on job growth varied over time and across sectors during the past decade. As expected, in an analysis focussing on selected industries the automation potential is shown to have affected job growth in manufacturing, where the susceptibility of jobs to automation continues to be high. Moreover, the local automation potential has also coincided (positively) with job growth in financial services, i.e. a sector comprising many highly qualified jobs. Altogether, as the impact of spatial autocorrelation among the cross-sectional analysis is limited to selected years and sectors, it can be assumed that labour market regions provide a sound territorial basis for the analysis.

5. Conclusions

The analysis utilises a variety of methodological approaches in order to pursue the role of industry-specific productivity increases and job automation potentials among the determinants of regional employment growth over the past decade in Germany. Regarding the first research question the basic model referring to labour market regions suggests no significant statistical association between productivity growth and employment. Yet, robustness checks employing an instrumental variable for the share of jobs susceptible to automation or restricting the analysis to rural regions find a positive employment effect of productivity increases. With respect to the first basic research question the analysis would thus suggest that job losses due to technological progress were counterbalanced by the creation of new tasks.

With a view to the second research question the analysis finds positive coefficients of the automation potential, suggesting that there is no inverse association between a high regional occupational susceptibility to automation and job growth, as might have been expected. Quite the contrary, OLS and IV estimations both suggest that employment grew more rapidly in regions with a comparatively high automation potential. Apparently, demand for the goods and services provided by industries with a high automation potential and by industries with rising productivity increased sufficiently so as to support above-average job growth.

In addition, positive coefficients on wage growth emphasise that overall job growth in the past decade was associated with the emergence of rather high-skilled jobs, apparently providing labour with a competitive advantage over capital. Even though job creation in line with productivity increases may vary to a great extent between firms, the average industry-by-region perspective suggests that firms are doomed to utilise the productivity increases made possible by digitalisation in order to innovate and create new tasks.

With respect to the third question the analysis finds that local automation potentials were no drivers of economic divergence in terms of job growth, at least not in the sense that lower growth would have been a specific characteristic of regions with a high occupational susceptibility to automation. Rather, a group of remote regions with strong manufacturing clusters - characterised by relatively high automation potentials - have experienced high rates of job growth. In terms of the current literature on regional convergence these rural regions of Baden-Württemberg and Bavaria – corresponding roughly to the cultural macro-region known as Swabia – represent a specific “convergence club” set apart from other rural regions in Germany. As a whole, job growth during the past decade did proceed at a faster pace in urban regions, even in Baden-Württemberg and Bavaria.

If state-level fixed effects are accounted for, the positive coefficient of the local automation potential wanes but does not turn negative. The study thus finds no evidence suggesting that automation potentials have been put into effect to such an extent that they would have induced net regional employment losses during the past decade in Germany. Yet, since the automation potential does not appear to be highly correlated with overall regional prosperity the findings should not be misinterpreted as good news for lagging regions. Around the locations of strong manufacturing clusters such as in rural southern Germany, there is certainly no need to be overly afraid of the short-term employment effects of digitalisation. In regions dominated by less prosperous industries, however, implementation of the job creation potentials arising from the digital transformation may turn out to represent a much more difficult challenge.

After all, even the continuation of the success story of the "Swabian force" will depend to a large extent on whether further productivity boosts will be met by a corresponding rise in product demand among this regions´ industrial base and whether the creation of new tasks will continue to outpace automation. Regarding the job perspectives connected to specific occupations in the face of ongoing digital change it will play an important role in all regions to what degree local industries adapt to changing conditions, much likely resulting in a continuing reduction of routine activities.

References

Acemoglu, D. and P. Restrepo (2016), The race between machine and man: implications of Technology for Growth, Factor Shares and Employment. *NBER WP* 22252. Cambridge, MA: NBER.

Acemoglu, D. and P. Restrepo (2017), Robots and jobs: evidence from US labor markets. *NBER WP* 23285. Cambridge, MA: NBER.

Akerman, A., I. Gaarder and M. Mogstad (2015), The skill complementarity of broadband internet. *Quarterly Journal of Economics* 130(4): 1781–1824.

Appelbaum, E. and R. Schettkat (1999), Are Prices Unimportant? *Journal of Post-Keynesian Economics* 21(3): 387-398.

Arntz, M., T. Gregory and U. Zierahn (2017), Revisiting the risk of automation. *Economics Letters* 159: 157–160.

Autor, D.H., D. Dorn and G.H. Hanson (2015), Untangling trade and technology: evidence from local labor markets. *Economic Journal* 125(584): 621–646.

Autor, D.H. (2015), Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives* 29(3): 3-30.

Autor D.H., F. Levy and R.J. Murnane (2003), The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics* 118(4): 1279–1333.

Bachmann, R., M. Cim and C. Green (2019), Long-run patterns of labour market polarisation: Evidence from German micro data. *British Journal of Industrial Relations* 57(2): 350-376.

Bachmann, R., G. Demir, C. Green and A. Uhlendorff (2022), The role of within-occupation task changes in wage development. *Ruhr Economic Papers* #975. Essen et al.; RWI.

Bennewitz, E., J. Kislat, T. Buch and K. Dengler (2016), Digitalisierung der Arbeitswelt. Auswirkungen auf den Arbeitsmarkt in Hessen. *IAB-Regional. IAB Hessen* 3/2016. Nürnberg: IAB.

BBSR Federal Institute for Research on Building, Urban Affairs and Spatial Development (2018), Siedlungsstrukturelle Kreistypen, Tabelle. Internet: https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/downloads, last accessed 08.06.2022.

BBSR Federal Institute for Research on Building, Urban Affairs and Spatial Development (2022), Tabellen. Arbeitsmarktregionen; Bruttoverdienst; Erreichbarkeit von IC/EC/ICE-Bahnhöfen. Internet: www.inkar.de, last accessed 09.06.2022.

Bessen, J. (2020), Automation and jobs: when technology boosts employment. *Economic Policy* 34(100): 589-626.

Blien, U., W. Dauth, and D.H.W. Roth (2021), Occupational routine intensity and the costs of job loss: evidence from mass layoffs. *Labour Economics* 68: 101953.

Blien, U. and O. Ludewig (2017), Technological progress and (un)employment development. *IZA DP* 10472. Bonn: IZA.

Cingano, F. and F. Schivardi (2004), Identifying the sources of local productivity growth. *Journal of the European Economic Association* 2(4): 720– 742.

Combes, P.-P., T. Magnac and J.-M. Robin (2004), The dynamics of local employment in France. *Journal of Urban Economics* 56(2): 217–243.

Dauth, W., S. Findeisen, J. Südekum and N. Woessner (2017), German robots-the impact of industrial robots on workers. *CEPR Discussion Paper*s 12306. London.

Dengler, K., B. Matthes und W. Paulus (2014), Berufliche Tasks auf dem deutschen Arbeitsmarkt. *FDZ Methodenreport 12/2014*. Nürnberg: IAB.

Drukker, D.M., P.H. Egger and I.R. Prucha (2013) On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. *Econometric Reviews* 32: 686–673.

Federal Employment Agency (2022), Tabellen, Regionalreport über Beschäftigte (Quartalszahlen). Internet: http://statistik.arbeitsagentur.de, last accessed 05.09.2022.

Federal Statistical Office (2022), Tabellen. Preise, VGR des Bundes. Internet: https://www-genesis.destatis.de/genesis/online, last accessed 31.08.2022.

Federal Statistical Office and Statistical Offices of the Federal States (2022), Tabellen. Bevölkerung; VGR der Länder: Entstehungsrechnung, Umverteilungsrechnung. Internet: www.regionalstatistik.de, last accessed 01.09.2022.

Fingleton, B. and M.M. Fischer (2010), Neoclassical theory versus new economic geography: competing explanations of cross-regional variation in economic development. *Annals of Regional Science* 44(3): 467-491.

Fonseca, T., F. Lima, and C.B. Pereira (2018), Job polarization, technological change and routinization: Evidence for Portugal. *Labour Economics* 51: 317-339.

Frey, C.B. and M.A. Osborne (2017), The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change* 114: 254–280.

Fujita, M., P. Krugman, and A.J. Venables (1999), The spatial economy. Cities, regions, and international trade. Cambridge, MA: MIT Press.

Graetz, G. and G. Michaels (2015), Robots at work. *Review of Economics and Statistics* 100(5): 753-768.

Haefner, L. and R. Sternberg (2020), Spatial implications of digitization: State of the field and research agenda. *Geography Compass* 14(12): e12544.

Hensvik, L. and O.N. Skans (2023), The skill-specific impact of past and projected occupational decline. *Labour Economics* 81: 102326

Hötte, K., M. Somers and A. Theodorakopoulos (2022), Technology and jobs: a systematic literature review. *Oxford Martin Working Paper Series on Technological and Economic Change. WP 2022-2*. Oxford.

Institute for Employment Research (2014), FDZ Methodenreport 12/2014. Dokumentation. Internet: http://doku.iab.de/fdz/reporte/2014/MR_12-14_data.zip. Nürnberg: IAB.

Koch, M., I. Manuylov and M. Smolka (2019), Robots and firms. *Aarhus University Department of Economics WP* 2019–5. Aarhus.

Krugman, P. (1991), Geography and Trade. Cambridge, MA: MIT Press.

Mann, K. and L. Püttmann (2021), Benign effects of automation: new evidence from patent texts. *Review of Economics and Statistics* (forthcoming).

Mazzola, F. and F. Pizzuto (2020), Great Recession and club convergence in Europe: a cross-country, cross-region panel analysis (2000–2015). *Growth and Change* 51(2): 676-711.

Möller, J. (2001), Income and price elasticities in different sectors of the economy. An analysis of structural change for Germany, the UK and the US. In: ten Raa, T. and R. Schettkat (2001), The Growth of Service Industries. The Paradox of Exploding Costs and Persistent Demand. Cheltenham: Edward Elgar: 167-208.

Neisser, H.P. (1942), "Permanent" technological unemployment. Demand for commodities is not demand for labor. *American Economic Review* 32(1): 50–71.

Phillips, P.C.B. and D. Sul (2007), Transition modeling and econometric convergence tests. *Econometrica* 75(6): 1771-1855.

Prognos (2020), Branchenportfolios des IHK-Bezirks Schwaben. Internet: https://www.prognos.com, last accessed 11 October 2022.

Quah, D.T. (1996), Empirics for economic growth and convergence. *European Economic Review* 40 (6): 1353-1375.

RWI (2018), Überprüfung des Zuschnitts von Arbeitsmarktregionen für die Neuabgrenzung des GRW-Fördergebiets ab 2021. Studie im Auftrag des Bundesministeriums für Wirtschaft und Energie (BMWi). *RWI Projektberichte*. Essen: RWI.

Schwengler, B. and E. Bennewitz (2013), Arbeitsmarkt- und Einkommensindikatoren für die Neuabgrenzung des GRW-Regionalfördergebietes ab 2014. Gutachten im Rahmen der Gemeinschaftsaufgabe „Verbesserung der regionalen Wirtschaftsstruktur" (GRW). Studie im Auftrag des Bundesministeriums für Wirtschaft und Technologie. *IAB-Forschungsbericht* 13/2013. Nürnberg: IAB.

Solow, R.M. (1956), A contribution to the theory of economic growth. *Quarterly Journal of Economics* 70(1): 65-94.

Spitz-Oener, A. (2006) Technical change, job tasks and rising education demands. *Journal of Labour Economics* 24(2): 235-270.

Swan, T.W. (1956), Economic growth and capital accumulation. *Economic Record* 32(2): 334-361.