The decline of routine jobs and occupational mobility

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Abstract: Technological change caused a secular decline in routine intensive occupations while non-routine occupations grew. We first document that this development happened also in Germany during the last 35 years. However, it remains an open question whether this development is mediated by occupational mobility or labour market exit and entry. We examine the detailed employment biographies of a large sample of German workers who were most affected by technological change: those who worked in declining routine intensive occupations at the onset of technological change. We follow their careers and analyze how individual and regional characteristics affect the transition into other types of occupations or into unemployment.

1 Introduction and background

The last couple of decades brought rapid changes to industrialized societies. Vast advances in technology changed the way that things are produced and how people interact with each other. While new technologies enhanced the productivity of workers in some jobs, other jobs were replaced by machines and became obsolete.

In a number of industrialized countries employment has grown predominately in jobs at the upper and lower tails of the wage distribution, while employment in the middle of the distribution has stagnated or declined (see Autor, Dorn 2013; Goos, Manning, Salomons 2014). In this paper we are interested in assessing the situation in Germany. Though a number of papers (Senftleben-König, Wielandt 2014; Rendall, Weiss 2016) has already concentrated on this country, we contribute to an assessment by exploiting an especially rich dataset with new classifications of occupations and tasks.

The term job polarization was popularized by Goos, Manning (2007). They build upon the hypothesis of Autor, Levy, Murnane (2003) that technological change is routine-biased. Jobs, which can be described by a limited number of rules, can be substituted by computer technology. Technological change is complementary to interactive tasks at the upper tail of the wage distribution whereas it erodes demand for routine tasks in the middle. It is also expected, that technological change is neutral to non-routine unskilled tasks, such as those in personal services or that the share of these jobs is also growing. When occupations are ranked according to their initial average wage, jobs at both ends grow more strongly than those in the middle of the distribution. The result is the U-shaped wage/employment profile familiar from recent studies.

Goos, Manning (2007) and Autor, Katz, Kearney (2006) find strong support for job polarization and its connection to routine-biased technological change (RBTC), both in the United Kingdom and the United States. Autor, Dorn (2013) derive an integrated model of how technological change leads to a decline in routine manual work but an increase in non-routine service occupations. Taking their model to US data on local labour markets, they find that regions with a high initial share of routine tasks are more inclined to adopt information technology and exhibit a relocation of routine workers to unskilled service jobs. Senftleben-König, Wielandt (2014) transfer this approach to the German labour market.

Many of the recent studies on the effects of technological progress on employment surprises by treating the general employment level as fixed. Influential theoretical models analyze equilibrium situations that exclude unemployment. The majority of empirical research concentrates on differential effects on occupations and skill groups and their employment development. This contrasts with popular publications that use recent assessments and forecasts prepared mainly outside mainstream economics (Brynjolfsson, McAfee 2011, 2014; Frey, Osborne 2013). In this context, severe employment losses are predicted as the consequence of recent technological developments. However, in the latter category of literature, interacting economic effects are not sufficiently integrated, and at least its popular reinterpretations follow the idea of 'technological determinism'. Authors using this approach assume implicitly that the production of an economy is carried out in proportions that are technologically fixed. Thus, if a task carried out by a worker is substituted by a machine, the consequence is that the worker is made redundant. No counteracting economic effects - e.g. by price decreases - are taken into account. These counteracting tendencies do not imply that job losses are not important. However, the complete picture shows a more complex structure.

Autor (2015 with reference to Bessen 2015) provides an example that shows the complex connection between the use of technology and employment dynamics: the number of automated teller machines (ATMs) in the US economy increased from about 100,000 (1995) to around 400,000 (2010). From the point of view of technological determinism the case is clear: human bank tellers can be expected to be made redundant due to the introduction of ATMs. In reality however, the number of human bank tellers increased from 500,000 to 550,000 between 1980 and 2010. On the one hand, this is due to a demand effect: a specific kind of technical progress, the introduction of ATMs, reduced the price of bank services, so demand for the services grew. On the other hand, in addition the job description of bank tellers changed, now emphasizing the interaction with customers.

Another interesting example goes further back in history: the introduction of Henry Ford’s Model T. Table 1 shows the price of the Model T and the sales figures following its market entry in 1908. Due to major technical innovations concerning mass production, especially the introduction of the assembly line, the price fell to about one third of its original price within only a few years. The last column of the table makes clear, that due to a productivity effect less workers were needed to produce a fixed number of cars. On the other hand, the sales figures exploded, and therefore Henry Ford’s factories employed far more workers in 1915 than in 1909.

As can be discussed on the basis of these examples, technological progress has two opposing effects on employment (see Sabadash 2013; Appelbaum, Schettkat 1999). The first one is a labour-saving effect, i.e. the direct substitution of labour by capital. According to technological determinism this is the only effect. The second effect, however, is a compensating one, which depends among other things on the price change generally triggered by technological progress. An increase in productivity leads to lower prices, to higher sales and to an additional demand for labour. Which effect dominates is an empirical question. The conclusion is that not even the direction of the employment effect can be directly attributed to the shock on productivity: technological progress might be disruptive and destructive, but it can also have welfare-increasing effects. The direction and strength of an employment effect depend on shaping economic factors (there are also shaping institutional factors – but that is another story).

Table 1: Prices and sold cars of Ford’s Model T

Year	Retail Price ($)	Produced cars per employee	Sales in thousands	Number of employees in thousands
1909	950	8.4	12	1.7

1910	780	7.5	19	2.8
1911	690	13.5	40	4.0
1912	600	12.0	79	6.9
1913	550	13.2	183	14.4
1914	490	17.9	261	12.9
1915	440	20.9	355	19.0
1916	360		577	

Source: Hounshell (1984: 224) and Beaudreau (2009: 71)

In this paper, we first document that since the late 1970s, routine-intensive occupations have declined, whereas non-routine occupations grew. This could be driven either by workers moving between occupations or by workers in routine occupations leaving employment more often while younger workers take up jobs in non-routine occupations. In any case, we find that this does not necessarily lead to employment polarization as those routine jobs are not always located in the middle of the German wage distribution. Our main focus is on the biographies of individual workers. We analyze which characteristics affect whether workers in declining routine occupations become unemployed or manage to change into growing occupations.

2 Data

The analysis of job polarization at the regional level requires comprehensive, detailed information about the labour force over a longer span of time. An ideal source of such information is the register data of the German Federal Employment Agency (BA), which originates from the compulsory notifications made by employers to the social security insurance. Specifically, we use the so-called Employment History file (BeH) provided by the Institute for Employment Research (IAB). From the full sample of this dataset, a cross-section 30 percent of all employees registered as employed on June 30 is drawn. These data are representative for all employees covered by social security, which accounts for about 80 percent of the German labour force (Dustmann, Ludsteck, Schoenberg 2008). The subset of economically active persons who are not included in this dataset comprises civil servants, the self-employed, and people who work for an income lower than a defined threshold (2010: € 400).

The data are very reliable, since they are used to calculate retirement pensions. The major caveat of the data is that wages are censored at the upper earnings limit for compulsory social security contributions (e.g. € 66,000 in Western Germany, 2010). We use an imputation procedure suggested by Gartner (2005) to correct the top-coded values.

Since job polarization is a process that takes place over a longer time period, we focus our analysis on Western Germany, where data is available continuously from 1978 to 2014. The resulting dataset contains approximately 16 million observations each year and provides information on daily wages (imputed), occupation, industry, qualification, place of work, as well as some social-demographic details. Information is available about whether a person works full-time, minor part-time (less than 18 hours) or major part-time (between 18 and 39 hours) but not about the exact working hours. We estimate full-time equivalents by weighting part-time with 0.5.

Our occupational classification consists of 85 items. While our data also provide occupational information at a much more detailed level, a high level of detail entails a risk of individual occupations not being separated in a meaningful way. Since we are ultimately interested in the relative growth and decline of occupations, it is important that the former occur for economic reasons and not as a result of arbitrary re-classifications. We thus use the time consistent 2-digit version of the German occupational classification (KldB) of 1988. This classification has one extremely large category containing all office occupations (Bürofach-, Bürohilfskräfte). We disaggregate this category into three sub-groups according to an individual's sector of employment (services, the public service and a residual category).

In measuring the routine content of occupations, we depart from the literature. Most analyses, especially from the USA, use data from O*NET, the Occupational Information Network or its predecessor, the Dictionary of Occupational Titles (DOT). Both draw their occupational information from surveys of workers and occupation experts (see https://www.onetcenter.org for more details on this data). Since O*NET is most commonly used in the exploration of career opportunities or human resources, strong efforts are made to keep this data up to date. However, in an analysis of the historic development of occupations, this currentness might actually pose a problem.

In Germany, the most reliable source of historic occupational information stems from the BiBB-IAB surveys. This scientific survey of a large number of German workers was conducted in the years 1979,1985,1991/92, 1999, 2006, and 2012. Workers were asked in detail about their jobs and the contents of the work they carry out. Several studies classify the answers to the survey items into meaningful tasks (see Spitz-Oener 2006). This becomes an almost impossible endeavor when looking at changes over time as the questions asked change radically between the survey waves. We thus rely solely on two questions that were asked in every wave:

- whether the contents of a job are minutely prescribed by the employer,
- whether the job's work sequence is repeating itself regularly.

We believe that these two items correspond closely to the basic idea on the substitutability of a task by computer technology and, therefore, these items provide a measure of the routine content of a job in a straightforward way.

In the subsequent analyses, we use the years of the first four BiBB-IAB surveys as the starting year and then examine the developments of either aggregate occupations or individuals over the subsequent 15 years.

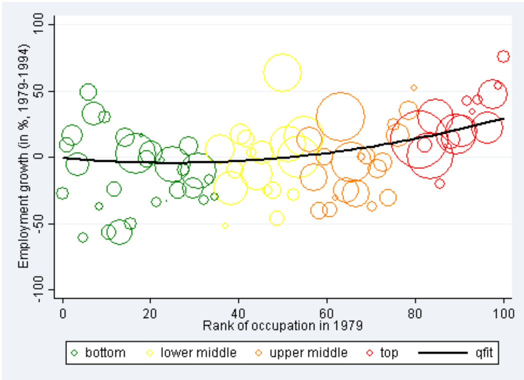
3 Empirical Analysis

3.1 Occupational level

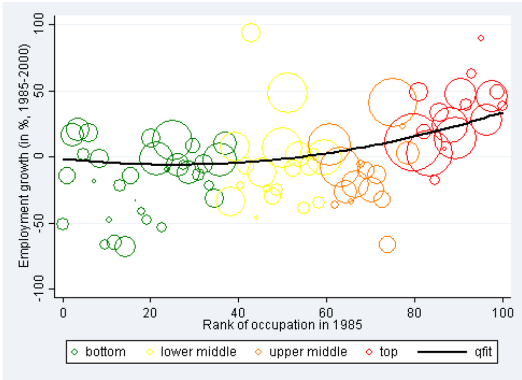
We begin by aggregating individual-level observations into occupations. For each occupation, we then compute the rate of employment growth over a 15-year period starting with each of the years in which a BiBB-IAB survey took place (1979, 1985, 1991 and 1999). For each of these years we also produce the ranking of occupations according to the median wage of male full-time workers.

Figure 1 plots an occupation's employment growth against its rank in the wage distribution. While growth is always largest for occupations at the top end the distribution, there is also some evidence for employment polarization as occupations at the bottom end appear to grow stronger than occupations in the lower middle quartile of the distribution. However, just looking at the quadratic fit yields an incomplete indicator for polarization since growth at the bottom is never statistically stronger than in the middle of the distribution.

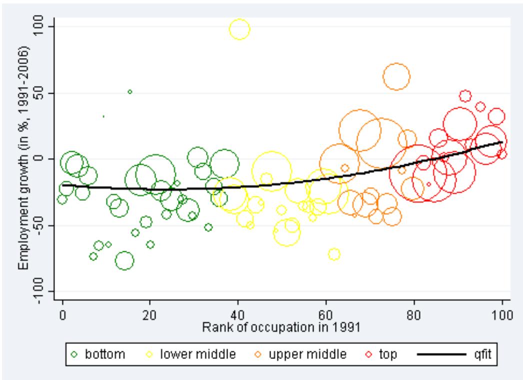
Figure 1: Employment growth with respect to wage rank of occupation



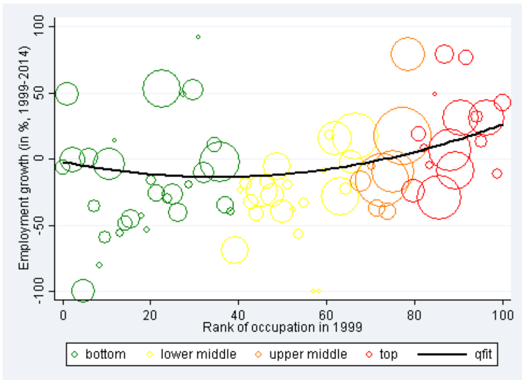
Panel A: 1979-1994



Panel B: 1985-2000



Panel C: 1991-2006

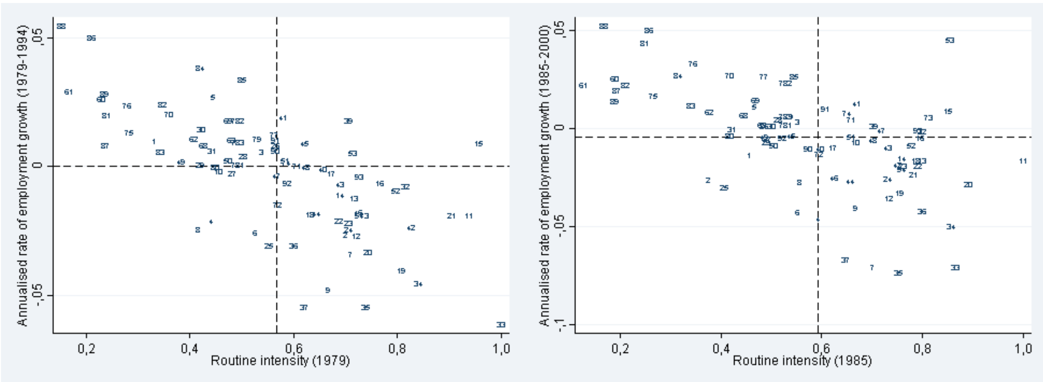


Panel D: 1999-2014

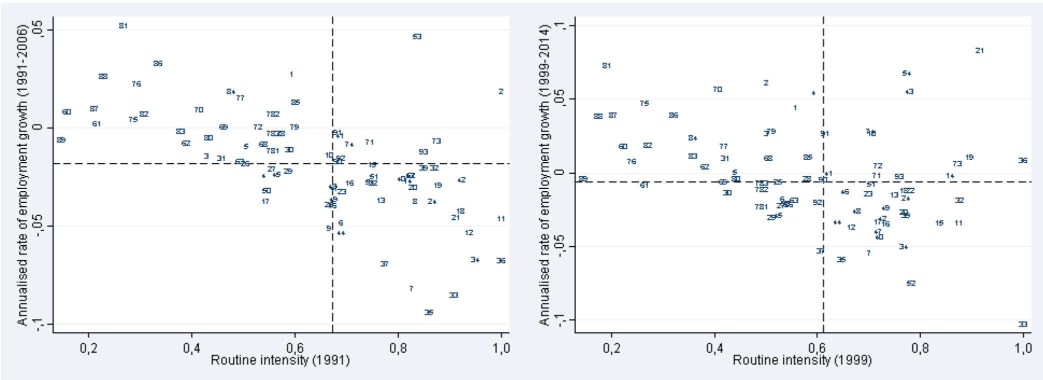
Table A1 presents more insights on employment growth of occupations. As expected, there is a strong correlation between the routine content of an occupation and its growth rate. Employment growth is stronger in non-routine occupations.

This is no contradiction to the absence of job polarization over the largest part of the observation period. Whether routine-replacing technological change leads to polarization or to the patterns depicted in Figure 1 depends on the ex-ante ranking of routine-intensive occupations in the wage distribution. In Germany, routine jobs are not necessarily concentrated in the middle of the wage distribution, likely because of institutions that have a strong impact on the German wage structure. Due to the developed unemployment insurance system, many low-skill service occupations usually found in Anglo-Saxon countries either do not exist in Germany or are paid a significantly higher wage. In addition, the collective bargaining system established a de-facto minimum wage in many industries. While both influence the ranking of occupations in the lower part of the distribution, routine-intensive jobs might still be declining.

Figure 2: Employment growth and routine intensity of occupations



Panel A: 1979-1994 Panel B: 1985-2000



Panel C: 1991-2006 Panel D: 1999-2014

Figure 2 visualizes the strong negative correlation of routine intensity and employment growth at the occupation level. Each number corresponds to an occupation code (see Table A2 for the occupations that relate to the respective codes). An open question is how the transition between routine and non-routine jobs takes place. One could conjecture that workers are laid off from declining routine intensive occupations. But do they change into growing non-routine occupations or are those occupations filled by labour-market entrants? To answer this question, we now look at the employment biographies of individual workers.

3.2 Worker level

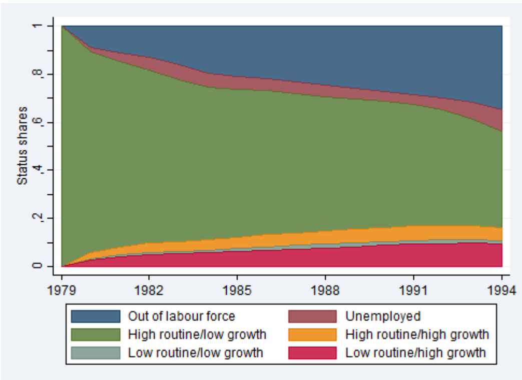
For each period, we use the medians to classify all occupations into high vs. low routine and high vs. low growth occupations. Figure 2 shows that most occupations are either high routine / low growth or low routine / high growth occupations. We then focus on workers on the bottom right quadrant of each figure, who start out in a high routine /

low growth occupation, and follow their careers for the subsequent ten years. Appendix Table A3 provides summary statistics for this sample of workers.

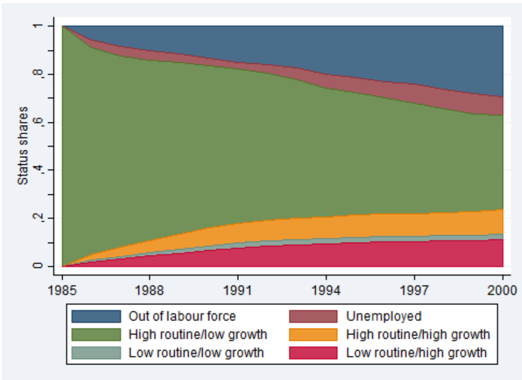
We summarize the employment status of workers that start out in high routine / low growth occupations over the subsequent 15 years. We distinguish between employment in four categories according to the job classification of high/low routine and high/low growth occupations, receiving unemployment benefits, and a residual category. The latter category comprises persons that are not registered as employed or unemployed at the federal employment agency. Reasons for not registering are usually withdrawal from the labour force, but also self-employment and long-term unemployment combined with receiving social security benefits (Sozialhilfe). Since self-employment plays a minor rule for former routine workers, we interpret this category as containing non-participants. The break in 2011 in panel D relates to a classification change in 2011 that led to a large number of invalid social security notifications in this year.

In each period, the probability to stay in a declining high routine occupation decreases over time. Most people either become unemployed or leave the labour force. Conditional on changing into a different occupational group, most workers change into low routine / high growth occupations. These occupations can be either interactive non-routine jobs or non-routine service jobs (cf. Autor/Dorn 2013). A substantial share becomes unemployed. In contrast, Figure 4 shows that a larger share of workers initially employed in low routine/high growth occupations remains in this group and that transitions into unemployment or into other types of employment are less prevalent.

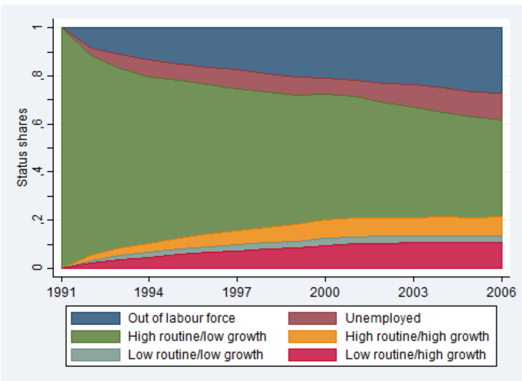
Figure 3: Employment status of workers originally in declining routine occupations



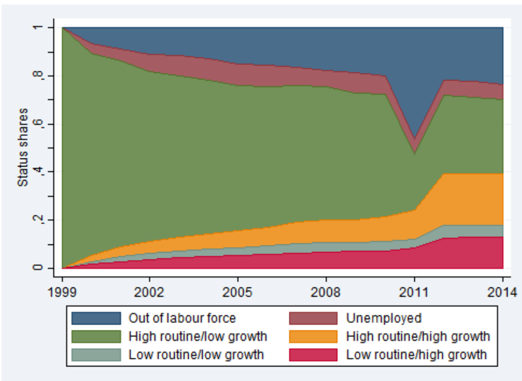
Panel A: 1979-1994



Panel B: 1985-2000

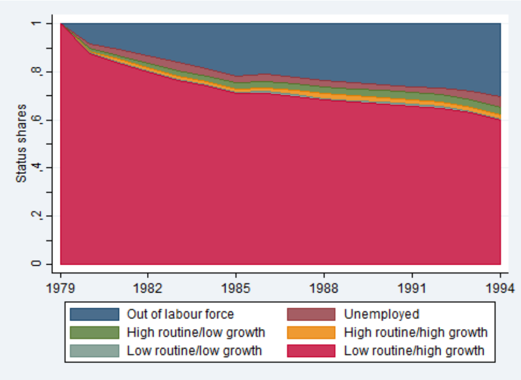


Panel C: 1991-2006

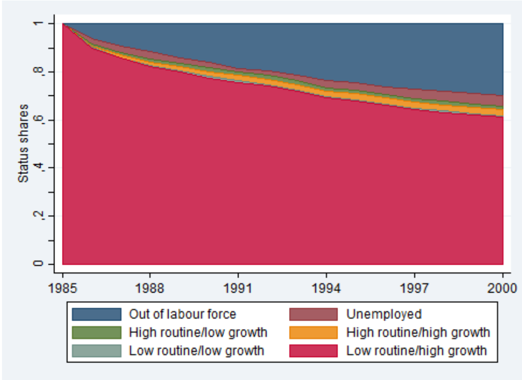


Panel D: 1999-2014

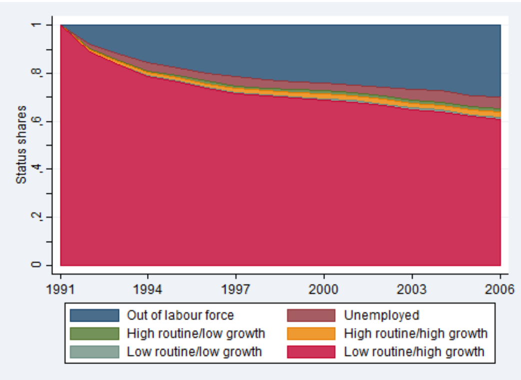
Figure 4: Employment status of workers originally in growing non-routine occupations



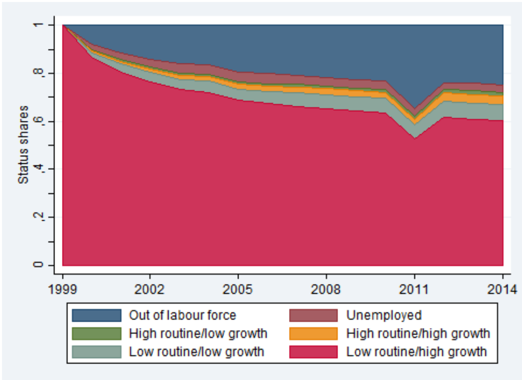
Panel A: 1979-1994



Panel B: 1985-2000



Panel C: 1991-2006



Panel D: 1999-2014

Next, we aim to shed light on how workers that are initially employed in high routine/low growth occupations adjust to technical change. To do so, we construct several outcomes measuring the fraction of years a worker spends in different types of employment: employment in low routine/high growth, low routine/low growth, high routine/high growth, high routine/low growth occupations as well as the total fraction of years spent in employment. These variables are then regressed on individual-level and region-specific variables (see Table A4). By construction, the estimated coefficients of the first four outcome variables add up to that of the final column.

On average, individuals spend 75% of each period in employment (see Table A3). We find that, ceteris paribus, males, older workers and workers with a completed apprenticeship training (as opposed to those without training) have significantly higher employment shares, while shares are smaller for foreigners and those with tertiary education. The effects on overall employment, however, mask the fact that the effects on group-specific employment can be different.

While on average, females have total employment share that are smaller by between 5 (1979-1994) and 11 percentage points (1985-2000), they accumulate significantly longer periods of employment in low routine/high growth occupations than males. Likewise, individuals with tertiary education also appear to be able to move into low routine/high growth occupations as evidenced by the significantly larger share of employment years spent in this occupational group. In contrast, the finding that individuals that are older at the start of the period of observation have realize longer employment durations is driven exclusively by employment in high routine/low growth occupations, whereas the time spent in all other types of employment is significantly shorter.

Do regional characteristics affect how routine workers adjust to technological change? Overall, workers that are initially employed in districts that are more densely populated spend less time in employment. The overall effect is, however, driven by contrasting effects on group-specific employment shares: while there is a larger negative effect on employment in high routine/low growth occupations, low routine/high growth employment is significantly larger. It is therefore possible that denser areas provide workers with better opportunities of transferring into occupations with a lower routine intensity.

4 Conclusion

Computer technology can most easily replace routine-intensive occupations, since computers are especially good with algorithms, which are made up of a fixed set of rules that also underlie routine jobs. In this paper, we have shown that this could be the explanation for the development of the labour market of Germany over the past 35 years. Whereas in other countries this process generated a polarized employment structure, in Germany there is only a weak form of polarization. The upper part of the distribution developed better than the middle part, however, employment in the lower part grew only weakly.

In a second step, we looked at the fates of workers replaced in this process. We examined the employment biographies of a large sample of German workers who were most directly affected by technological change: those who worked in declining routine-intensive occupations at the onset of technological change. We followed their careers and analyzed which individual or regional characteristics affect the chances of them leaving the labour market or moving into other groups of occupations.

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Appendix

Table A1: Regression results of employment growth models

Employment growth rate	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – 1979-1994						
Occupational ranking						
Bottom 25%	-12.9530	-2.6254	1.2913			
	(9.4026)	(7.3107)	(6.2998)			
Upper middle 25%	-5.3914	-7.6900	-7.9523			
	(11.2534)	(8.9387)	(9.1654)			
Top 25%	11.5357	-6.7408	-8.4711			
	(9.1744)	(9.4687)	(9.1654)			
Routine intensity		-112.0965***	-82.1679***	-104.3491***		-77.0911***
		(20.5417)	(29.6209)	(14.4003)		(27.6521)
Education						
% Unknown			-10.1553		33.0203	-3.9982
			(51.3990)		(62.4771)	(51.8618)
% Vocational training			20.6142		49.7984***	13.8670
			(18.8954)		(12.7103)	(18.2672)
% University degree			42.3813		92.7404***	32.9832
			(27.4624)		(12.8374)	(25.8290)
Constant	6.5414	71.6768***	40.9688	63.1569***	-30.9793***	38.4807
	(8.0943)	(15.8412)	(26.8379)	(8.6592)	(10.5024)	(26.3429)
Observations	83	83	83	83	83	83
R^2	0.1452	0.4230	0.4459	0.4083	0.3537	0.4232
Panel B – 1985-2000						
Occupational ranking						
Bottom 25%	-11.0828	-6.7994	-7.4697			
	(10.0240)	(9.9392)	(9.3611)			
Upper middle 25%	-3.9485	-6.6411	-6.1453			
	(13.8332)	(12.8183)	(13.4357)			
Top 25%	15.8353	1.4887	0.6050			
	(10.2484)	(11.3051)	(10.8221)			
Routine intensity		-68.6987***	-45.9686	-80.5500***		-51.4197
		(25.2585)	(37.2752)	(16.1049)		(36.1633)
Education						
% Unknown			64.7678		95.5271	62.7287
			(85.4262)		(76.0959)	(75.5201)
% Vocational training			13.7297		45.1830**	17.2628
			(28.9371)		(17.8654)	(28.5792)
% University degree			43.3885		97.1540***	48.9105
			(36.3774)		(14.5077)	(34.9593)
Constant						
Observations	83	83	83	83	83	83
R^2	0.1566	0.2481	0.2669	0.2320	0.2308	0.2524
Panel C – 1991-2006						
Occupational ranking						
Bottom 25%	1.9299	3.1588	-0.9431			
	(7.1497)	(8.0568)	(8.3298)			
Upper middle 25%	24.5716**	17.9273*	20.2202**			
	(9.9347)	(9.0439)	(8.4353)			
Top 25%	22.8485***	7.4600	6.7119			
	(7.7490)	(8.3456)	(7.2328)			
Routine intensity		-60.6707***	-52.8300	-71.4927***		-51.7868
		(21.3741)	(32.4903)	(16.2408)		(34.3850)
Education						
% Unknown			120.2174*		143.2516**	102.0664
			(62.5220)		(55.4324)	(65.5558)
% Vocational training			2.1546		50.3094**	17.5314
			(27.8919)		(19.2975)	(30.7196)

% University degree			31.2630 (35.4349)		98.5355*** (18.8497)	43.0108 (38.7807)
Constant	-23.8447*** (6.0646)	17.9927 (13.8989)	3.1305 (39.9817)	31.6066*** (10.1603)	-59.7833*** (16.7067)	-0.9150 (43.8895)
Observations	84	84	84	84	84	84
R^2	0.1988	0.2940	0.3431	0.2323	0.2308	0.2589
Panel D – 1999-2014						
Occupational ranking						
Bottom 25%	10.0769 (14.0860)	18.0551 (13.5115)	10.0722 (15.7826)			
Upper middle 25%	19.2862 (14.9568)	0.8139 (12.4881)	0.0354 (12.9432)			
Top 25%	21.5001 (13.1997)	-12.4738 (13.9436)	-18.8779 (12.9076)			
Routine intensity		-140.4731*** (35.7057)	-90.4809* (47.9743)	-98.0939*** (27.9760)		-71.1801 (51.2709)
Education						
% Unknown			131.8492 (112.6931)		242.5884*** (72.1108)	181.7669** (90.7627)
% Vocational training			36.3582 (46.2159)		83.1461** (35.3895)	32.7182 (49.6553)
% University degree			92.7044* (53.5056)		150.2489*** (34.1484)	72.4688 (60.8558)
Constant	-13.5800 (8.9406)	74.6330*** (23.5034)	7.1533 (63.4759)	53.0156*** (15.6714)	-90.7786*** (31.9434)	-5.9337 (69.3038)
Observations	77	77	77	77	77	77
R^2	0.0660	0.2926	0.3463	0.2280	0.2750	0.3040

***/**/* indicate significance at the 0.01/0.05/0.1 level, respectively. Standard errors are robust. Regressions are weighted by the number of full-time employee per occupation-year cell.

Table A2: Degree of routinisation and employment growth by occupation

Occupation	1979	1985	1991	1999
1 Farmers	lh	ll	lh	lh
2 Animal breeders; Fishermen	hl	ll	hh	lh
3 Managers, Advisors in agriculture and breeding	lh	lh	lh	lh
4 Land workers, Animal keeper	ll	hl	ll	lh
5 Gardeners	lh	lh	lh	lh
6 Forestry and Hunting occupations	ll	ll	hl	ll
7 Miners	hl	hl	hl	hl
8 Mineral, Oil, Natural gas quarries	ll	ll	hl	lh
9 Mineral preparers	hl	hl	ll	hh
10 Stone preparers	ll	hl	lh	hh
11 Building material makers	hl	hl	hl	hl
12 Ceramics workers	hl	hl	hl	hl
13 Glass makers	hl	hl	hl	hl
14 Chemical workers	hl	hl	hl	hh
15 Plastics processors	hh	hh	hl	hl
16 Paper makers	hl	hl	hl	hl
17 Printer	hl	hl	ll	hl
18 Wood preparers, Wood products makers, etc.	hl	hl	hl	hl
19 Metal producers, Rollers	hl	hl	hl	hh
20 Moulders, Mould casters	hl	hl	hl	hl
21 Metal moulders (non-cutting deformation)	hl	hl	hl	hh
22 Metal moulders (metal-cutting deformation)	hl	hl	hl	hl
23 Metal surface workers, heat-treating-plant op. etc.	hl	hl	hl	hl
24 Metal connectors	hl	hl	hl	hl
25 Smiths	ll	ll	ll	lh
26 Sheet metal workers	lh	lh	lh	ll
27 Locksmiths	ll	ll	ll	ll
28 Mechanics	lh	lh	lh	lh
29 Toolmakers	lh	ll	ll	ll
30 Precision fitters	lh	lh	lh	ll
31 Electricians	lh	lh	lh	lh
32 Assemblers and Metal workers (no further spec.)	hl	hh	hl	hl
33 Spinners	hl	hl	hl	hl
34 Textile makers	hl	hl	hl	hl
35 Textile processer	hl	hl	hl	hl

36 Textile finisher	hl	hl	hl	hh
37 Leather makers, Leather and Skin processing op.	hl	hl	hl	ll
39 Bakery goods makers, Confectioners (pastry)	hh	hh	hl	hl
40 Butchers, Fish processing operatives	hl	hl	hl	hl
41 Food preparers	hh	hh	hh	hh
42 Beverage makers, Luxury food makers	hl	hl	hl	hl
43 Other nutrition occupations	hl	hl	hl	hh
44 Bricklayers, Concrete workers	hl	hl	hl	hl
45 Carpenters, Roofers, Scaffolders	hh	lh	ll	ll
46 Road makers, Civil engineering workers	hl	hl	hl	hl
47 Building labourer, general	hl	hh	hl	hl
48 Building finishers	hl	hl	ll	hl
49 Room equippers, Upholsterers	lh	lh	hl	hl
50 Carpenters, Model maker	lh	ll	ll	ll
51 Painters, lacquerers and related occupations	hh	hl	hl	hl
52 Goods examiner, despatchers	hl	hl	hl	hl
53 Assistants (no further specification)	hh	hh	hh	hh
54 Machinists and related occupations	hl	hl	hl	hh
60 Engineers	lh	lh	lh	lh
61 Chemists, Physicists, Mathematicians	lh	lh	lh	ll
62 Technicians	lh	lh	lh	lh
63 Technical specialists	lh	lh	lh	ll
68 Wholesale and retail trade	lh	lh	lh	lh
69 Bank specialists, Insurance representatives	lh	lh	lh	ll
70 Other services agents and related occupations	lh	lh	lh	lh
71 Surface transport occupations	hh	hh	hh	hh
72 Water and Air transport occupations	hl	hl	lh	hh
73 Communication occupations	hl	hh	hh	hh
74 Warehouse managers, Stores, transport workers	hh	hh	hh	hh
75 Management consultants, Organisors, Accountants	lh	lh	lh	lh
76 Members of Parliament, Senior government officials	lh	lh	lh	lh
77 Accountants, Data processing specialists	lh	lh	lh	lh
79 Watchpersons and related workers	lh	lh	lh	lh
80 Protective services workers	ll	lh	lh	lh
81 Legal and related business associate professionals	lh	lh	lh	lh
82 Journalists, Interpreters, Librarians	lh	lh	lh	lh
83 Artists	lh	lh	lh	lh

84 Physicians, Pharmacists	lh	lh	lh	lh
85 Other health occupations	lh	lh	lh	lh
86 Social work associate professionals	lh	lh	lh	lh
87 Teachers	lh	lh	lh	lh
88 Humanities specialists, Scientists	lh	lh	lh	lh
89 Ministers of religion	lh	lh	lh	lh
90 Body care occupations	lh	ll	hh	hh
91 Attending on guests occupations	lh	hh	hh	hh
92 Housekeeping occupations	hl	ll	hh	ll
93 Cleaning occupations	hl	hh	hh	hh
78 A Office specialists / aux. workers (sector: other)	lh	lh	lh	ll
78 B Office specialists / aux. workers (sector: services)	lh	lh	lh	ll
78 C Office specialists / aux. workers (sector: public)	lh	lh	lh	ll

Occupation titles are from the *Klassifikation der Berufe 1988*. The occupation *Bürofach-, Bürohilfskräfte* is disaggregated into three sub-groups according to an individual's sector of employment (services, civil service and a residual category). The abbreviations l/h, l/l, h/h and h/l stand for low routine/high growth, low routine/low growth, high routine/high growth and high routine/low growth.

Table A3: Descriptive statistics

	Obs	Mean	Standard deviation	Max	Min
1979					
Fraction of years spent in employment	927,646	0.7498	0.3021	1.0000	0.0625
Fraction of years spent in low routine/high growth occupations	927,646	0.0670	0.1833	0.9375	0.0000
Fraction of years spent in low routine/low growth occupations	927,646	0.0123	0.0803	0.9375	0.0000
Fraction of years spent in high routine/high growth occupations	927,646	0.0458	0.1505	0.9375	0.0000
Fraction of years spent in high routine/low growth occupations	927,646	0.6246	0.3487	1.0000	0.0625
Age	927,646	33.0952	8.2440	45.0000	18.0000
Sex	927,646				
Female	314,494	0.3390	0.4734	1.0000	0.0000
Male	613,152				
Nationality	927,646				
German	725,536	0.7832	0.4121	1.0000	0.0000
Foreign	201,110				
Qualification	927,646				
No apprenticeship	512,975	1.4488	0.5009	3.0000	1.0000
Completed apprenticeship	413,017				
Tertiary education	1,654				
Imputed average daily wage	927,646	72.3317	25.1381	848.1284	12.9541
Population density (1,000 inhabitants/km^2)	927,646	0.9143	1.0055	4.1831	0.0398
1985					
Fraction of years spent in employment	598,294	0.7865	0.2739	1.0000	0.0625
Fraction of years spent in low routine/high growth occupations	598,294	0.0754	0.1913	0.9375	0.0000
Fraction of years spent in low routine/low growth occupations	598,294	0.0182	0.0961	0.9375	0.0000
Fraction of years spent in high routine/high growth occupations	598,294	0.0732	0.1848	0.9375	0.0000

Fraction of years spent in high routine/low growth occupations	598,294	0.6198	0.3432	1.0000	0.0625
Age	598,294	31.6715	8.1780	45.0000	18.0000
Sex	598,294				
Female	131,812	0.2203	0.4145	1.0000	0.0000
Male	466,482				
Nationality	598,294				
German	500,481	0.8365	0.3698	1.0000	0.0000
Foreign	97,813				
Qualification	598,294				
No apprenticeship	241,432	1.5992	0.4956	3.0000	1.0000
Completed apprenticeship	355,220				
Tertiary education	1,642				
Imputed average daily wage	598,294	77.1521	25.2350	753.7039	10.4402
Population density (1,000 inhabitants/km^2)	598,294	0.8131	0.9201	4.0764	0.0400
1991					
Fraction of years spent in employment	770,793	0.7545	0.2995	1.0000	0.0625
Fraction of years spent in low routine/high growth occupations	770,793	0.0753	0.1917	0.9375	0.0000
Fraction of years spent in low routine/low growth occupations	770,793	0.0225	0.1068	0.9375	0.0000
Fraction of years spent in high routine/high growth occupations	770,793	0.0572	0.1630	0.9375	0.0000
Fraction of years spent in high routine/low growth occupations	770,793	0.5995	0.3590	1.0000	0.0625
Age	770,793	31.4066	7.2971	45.0000	18.0000
Sex	770,793				
Female	192,712	0.2500	0.4330	1.0000	0.0000
Male	578,081				
Nationality	770,793				
German	631,943	0.8199	0.3843	1.0000	0.0000
Foreign	138,850				
Qualification	770,793				
No apprenticeship	324,293	1.5817	0.4981	3.0000	1.0000
Completed apprenticeship	444,643				

Tertiary education	1,857				
Imputed average daily wage	770,793	86.2249	26.7835	733.0995	11.2913
Population density (1.000 inhabitants/km^2)	770,793	0.7463	0.8644	3.9557	0.0407
1999					
Fraction of years spent in employment	504,094	0.7777	0.2785	1.0000	0.0625
Fraction of years spent in low routine/high growth occupations	504,094	0.0647	0.1625	0.9375	0.0000
Fraction of years spent in low routine/low growth occupations	504,094	0.0333	0.1179	0.9375	0.0000
Fraction of years spent in high routine/high growth occupations	504,094	0.0932	0.1786	0.9375	0.0000
Fraction of years spent in high routine/low growth occupations	504,094	0.5865	0.3237	1.0000	0.0625
Age	504,094	33.9824	6.6636	45.0000	18.0000
Sex	504,094				
Female	97,918	0.1942	0.3956	1.0000	0.0000
Male	406,176				
Nationality	504,094				
German	424,242	0.8416	0.3651	1.0000	0.0000
Foreign	79,852				
Qualification	504,094				
No apprenticeship	176,153				
Completed apprenticeship	325,916	1.6546	0.4839	3.0000	1.0000
Tertiary education	2,025				
Imputed average daily wage	504,094	89.2550	30.6431	2,449.7878	12.5444
Population density (1.000 inhabitants/km^2)	504,094	0.6814	0.8037	3.8447	0.0427

Table A4: Regression output for fractions of years spent in different types of employment

	Fraction of years spent in …				
	low routine / high growth occupations	**low routine / low growth occupations**	**high routine / high growth occupations**	**high routine / low growth occupations**	**Employ-ment**
			Panel A 1979-1994		
Age	-0.0026*** (0.0001)	-0.0005*** (0.0000)	-0.0014*** (0.0000)	0.0070*** (0.0002)	0.0025*** (0.0002)
Completed ap-prenticeship	0.0289*** (0.0009)	0.0023*** (0.0004)	-0.0165*** (0.0007)	-0.0019 (0.0018)	0.0128*** (0.0014)
Tertiary education	0.1724*** (0.0267)	-0.0108*** (0.0014)	-0.0250*** (0.0027)	-0.2491*** (0.0273)	-0.1125*** (0.0085)
Average daily wage	0.0002*** (0.0000)	0.0000 (0.0000)	-0.0004*** (0.0000)	0.0022*** (0.0001)	0.0020*** (0.0001)
Population density	0.0087*** (0.0015)	0.0000 (0.0004)	0.0006 (0.0008)	-0.0146*** (0.0023)	-0.0052* (0.0030)
Female	0.0210*** (0.0015)	-0.0163*** (0.0004)	-0.0484*** (0.0009)	-0.0083*** (0.0032)	-0.0520*** (0.0034)
Foreign	-0.0446*** (0.0015)	-0.0036*** (0.0004)	-0.0102*** (0.0010)	-0.0802*** (0.0037)	-0.1386*** (0.0032)
Constant	0.1176*** (0.0035)	0.0326*** (0.0011)	0.1498*** (0.0020)	0.2675*** (0.0075)	0.5675*** (0.0060)
N	927,646	927,646	927,646	927,646	927,646
R^2	0.0367	0.0127	0.0220	0.0747	0.1009

Panel B 1985-2000					
Age	-0.0029*** (0.0001)	-0.0006*** (0.0000)	-0.0018*** (0.0001)	0.0051*** (0.0002)	-0.0003 (0.0002)
Completed apprenticeship	0.0234*** (0.0009)	0.0033*** (0.0004)	-0.0309*** (0.0013)	0.0038* (0.0022)	-0.0004 (0.0015)
Tertiary education	0.1502*** (0.0219)	-0.0102*** (0.0015)	-0.0306*** (0.0072)	-0.2525*** (0.0130)	-0.1431*** (0.0111)
Average daily wage	0.0004*** (0.0000)	-0.0000 (0.0000)	-0.0007*** (0.0000)	0.0022*** (0.0001)	0.0019*** (0.0001)
Population density	0.0099*** (0.0015)	-0.0013*** (0.0003)	-0.0018 (0.0016)	-0.0158*** (0.0023)	-0.0091*** (0.0020)
Female	0.0306*** (0.0018)	-0.0137*** (0.0005)	-0.0331*** (0.0016)	-0.0908*** (0.0032)	-0.1069*** (0.0034)
Foreign	-0.0396*** (0.0010)	-0.0035*** (0.0005)	0.0020 (0.0016)	-0.0315*** (0.0025)	-0.0725*** (0.0026)
Constant	0.1125*** (0.0030)	0.0403*** (0.0011)	0.2152*** (0.0028)	0.3215*** (0.0085)	0.6895*** (0.0074)
N	598,294	598,294	598,294	598,294	598,294
R^2	0.0334	0.0074	0.0259	0.0841	0.0917
Panel C 1991-2006					
Age	-0.0028*** (0.0001)	-0.0006*** (0.0000)	-0.0009*** (0.0000)	0.0057*** (0.0002)	0.0014*** (0.0002)
Completed apprenticeship	0.0244*** (0.0008)	0.0026*** (0.0005)	-0.0189*** (0.0008)	0.0099*** (0.0017)	0.0181*** (0.0014)

Tertiary education	0.1677*** (0.0098)	-0.0150*** (0.0020)	-0.0202*** (0.0030)	-0.2733*** (0.0117)	-0.1407*** (0.0083)
Average daily wage	0.0004*** (0.0000)	0.0000** (0.0000)	-0.0005*** (0.0000)	0.0025*** (0.0001)	0.0023*** (0.0000)
Population density	0.0099*** (0.0015)	-0.0013*** (0.0005)	0.0037*** (0.0007)	-0.0222*** (0.0032)	-0.0098*** (0.0020)
Female	0.0436*** (0.0013)	-0.0224*** (0.0005)	-0.0179*** (0.0011)	-0.0722*** (0.0033)	-0.0690*** (0.0031)
Foreign	-0.0370*** (0.0009)	-0.0044*** (0.0005)	-0.0032*** (0.0011)	-0.0329*** (0.0025)	-0.0774*** (0.0024)
Constant	0.1068*** (0.0024)	0.0455*** (0.0013)	0.1448*** (0.0022)	0.2402*** (0.0059)	0.5372*** (0.0058)
N	770,793	770,793	770,793	770,793	770,793
R^2	0.0320	0.0122	0.0127	0.0827	0.0937
Panel D 1999-2014					
Age	-0.0025*** (0.0001)	-0.0010*** (0.0000)	-0.0011*** (0.0001)	0.0060*** (0.0002)	0.0013*** (0.0002)
Completed apprenticeship	0.0176*** (0.0008)	0.0080*** (0.0005)	-0.0334*** (0.0011)	0.0240*** (0.0019)	0.0163*** (0.0016)
Tertiary education	0.1626*** (0.0076)	0.0200*** (0.0037)	-0.0438*** (0.0040)	-0.2640*** (0.0102)	-0.1252*** (0.0088)
Average daily wage	0.0005*** (0.0000)	0.0000*** (0.0000)	-0.0004*** (0.0000)	0.0018*** (0.0001)	0.0018*** (0.0001)
Population density	0.0043***	0.0028***	0.0009	-0.0215***	-0.0135***

	(0.0014)	(0.0005)	(0.0016)	(0.0022)	(0.0024)
Female	0.0163***	0.0043***	-0.0217***	-0.0318***	-0.0328***
	(0.0011)	(0.0008)	(0.0014)	(0.0035)	(0.0031)
Foreign	-0.0295***	-0.0129***	-0.0022	-0.0221***	-0.0667***
	(0.0009)	(0.0006)	(0.0014)	(0.0029)	(0.0030)
Constant	0.0965***	0.0587***	0.1965***	0.2345***	0.5862***
	(0.0025)	(0.0015)	(0.0034)	(0.0067)	(0.0070)
N	504,094	504,094	504,094	504,094	504,094
R^2	0.0303	0.0067	0.0171	0.0622	0.0659

***/**/* denote significance at the 0.01/0.05/0.1 level. Standard errors are in parentheses and are clustered at the district level.