// NO.22-019 | 06/2022

DISCUSSION PAPER

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Regional Structural Change and the Effects of Job Loss

Leibniz Association

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Regional Structural Change and the Effects of Job Loss *

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May, 2022

Abstract

Routine-intensive occupations have been declining in many countries, but how does this affect individual workers' careers if this decline is particularly severe in their local labor market? This paper uses administrative data from Germany and a matched difference-in-differences approach to show that the individual costs of job loss strongly depend on the task-bias of regional structural change. Workers displaced from routine manual occupations have substantially higher and more persistent employment and wage losses in regions where such occupations decline the most. Regional and occupational mobility partly serve as an adjustment mechanism, but come at high cost as these switches also involve losses in firm wage premia. Non-displaced workers, by contrast, remain largely unaffected by structural change.

Keywords: routine-biased structural change, local labor markets, displacement, mass-layoffs, plant closures, matching, difference-in-differences, event study
JEL-Codes: J24, J63, J64, J65, O33, R11

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*We thank Wolfgang Dauth and André Diegmann for sharing code, data and helpful comments. We further thank Christina Gathmann, Eduard Brüll, Matthias Parey, Sarah McNamara, Friedhelm Pfeiffer, Nicolas Ziebarth and participants of the IWH/IAB-Workshop 2020, the IAB PhD Workshop "Perspectives on (Un)employment" 2021 and seminar participants at ZEW Mannheim, University of Heidelberg and IAB Nuremberg for comments and suggestions. We also give thanks to Leo Gaertner, Nargiza Ibragimova and Theresa Bolz for excellent research assistance. This paper was financially supported by the Leibniz Association through the Leibniz Professorship for Applied Labor Economics at the University of Heidelberg (P56/2017) and the SEEK-Project 2016: Fiscal and Labor Policy Institutions and Inequality at ZEW Mannheim. Address of correspondence: ZEW – Leibniz Centre for European Economic Research, L 7,1, D-68161 Mannheim, E-mail: melanie.arntz@zew.de, boris.ivanov@zew.de, laura.pohlan@iab.de

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1 Introduction

In many advanced economies, automation and the relocation of production to low-cost countries have substituted for workers in routine-intensive tasks, while spurring demand for labor in other complementary tasks (Autor et al., 2003; Autor et al., 2013a; Goos et al., 2014). Yet, these structural shifts are far from uniform across regions within a country (Autor, 2019; Davis et al., 2020) and should have implications for the career prospects of individual workers as they determine the composition of locally available jobs. This should be particularly relevant when individuals are hit by an unexpected job loss that terminates a previously stable employment relationship. Yet, little is known about how regional structural change affects worker's career path after displacement and how individuals adjust to structural change in this case.

In this paper, we use two decades of administrative data for West German regions and individuals to add novel evidence on this matter. We focus on workers displaced during mass layoffs and plant closures, because such separations are plausibly unrelated to individual employment and earnings prospects. We also document that these events are not systematically more common in regions with a stronger long-term decline in routine occupations. From the workers' point of view, job displacement can therefore be considered as an unexpected individual shock that exposes them to different degrees of local structural change. Comparing displaced workers' outcomes across regions while controlling for differences in worker composition allows us to analyze how local structural change and job loss interact to shape individual employment and earnings trajectories. We also study whether occupational and regional mobility serve as individual adjustment devices and identify worker groups that are most vulnerable to structural change.

In the first part of our analyses, we show that in West Germany, employment losses were strongly concentrated in initially routine manual (RM) intensive occupations between 1990 and 2010. The extent of these losses, however, varied greatly between regions and was most concentrated in urban centers with high initial employment shares in large manufacturing firms. Job growth in non-routine occupations and the service sector, in turn, was driven by more rural and initially less productive regions.

In the second part of the paper, we take this regional variation to an administrative data set of displaced workers. In order to identify the causal effects of job loss, we match each displaced worker with an observationally similar non-displaced worker from the same pre-displacement task specialization and from a region with a similar long-term structural change pattern. We then apply both an event study and a matched difference-in-differences (DiD) approach in the spirit of Schmieder et al. (2020). The first method focuses on how the costs of job loss within a specific occupation and region type change over time and provides results that are easily comparable to the job displacement literature. The matched DiD approach allows us to study effect heterogeneity along the entire distribution of regional structural change.

We obtain three key findings. First, our results show that even in the most exposed regions, workers specialized in RM tasks (henceforth: RM workers) are shielded from the potentially adverse effects of structural change unless they are hit by job loss. Upon displacement, however, RM workers' outcomes strongly depend on local structural change: One year after job loss, RM workers who got displaced in regions with the strongest decline in RM jobs have a 10pp lower re-employment probability and 14pp higher wage losses than comparable workers in regions where RM occupations grow the most. This regional gap remains significant even after six years. Workers with a task focus other than RM also suffer significant employment and wage losses upon displacement, but these losses are generally lower and not systematically related to RM-biased structural change. Second, the wage losses of RM workers are closely linked to switching occupations. RM workers who take up an occupation with a different main task suffer almost 50% higher initial wage losses than those who return to RM jobs. Again, these losses are strongly concentrated in regions with strongly declining RM employment. Our results suggest that this is driven by losses in establishment premia associated to RM jobs rather than losses in task-specific human capital. Third, regional mobility allows up to 30% of workers to re-enter an RM occupation by leaving strongly exposed regions. However, especially older and less skilled workers are locked in regions with poor RM job prospects and are thus more prone to long-term unemployment. Hence, especially for these workers, the regional context strongly determines the costs of job loss.

Our paper contributes to several strands of the literature. It relates to the literature on the impact of local labor demand shocks on labor market outcomes. Such shocks have been found to have long-run effects on local employment rates due to sluggish out-migration responses (see e.g. Bound and Holzer, 2000; Amior and Manning, 2018; Bartik, 2021), resulting also in higher inactivity levels (e.g. Bound and Holzer, 2000; Autor et al., 2013a; Yagan, 2019). We provide a complementary angle by studying how long-term shifts in the local employment structure affect workers who are hit by an individual-level displacement shock. While the existing literature suggests that aggregate shocks can have persistent negative labor market effects, our findings indicate that the persistence of individual shocks depends on local structural change. Moreover, our results echo the finding that economic inactivity is a major adjustment margin, partly due to limited regional and occupational mobility.

This paper also relates to numerous studies documenting that job displacement causes substantial and persistent individual earnings and employment losses (see e.g. Ruhm, 1991a; Ruhm, 1991b; Jacobson et al., 1993 for the U.S. and Eliason and Storrie, 2006; Huttunen et al., 2011; Schmieder et al., 2010; Schmieder et al., 2020 for Europe). Common explanations put forward are the loss of industry or occupation-specific human capital (e.g. Neal, 1995, Kletzer, 1996), and regional or occupational mobility (e.g. Carrington, 1993; Macaluso, 2019; Huttunen et al., 2018; Gathmann et al., 2020).[1] A growing literature also hints at the role of local labor markets. Haller and Heuermann (2020) show that local labor market thickness affects post-displacement outcomes. Gulyas and Pytka (2019) study earnings losses after job displacement in Austria and find that losses in firm wage premia and the (non-)availability of well-paying jobs in the local labor market are the two most important factors. Jacobson et al. (1993) demonstrate that displacement effects in the U.S. during the 1980s vary with the local unemployment rate at the time of displacement. Schmieder et al. (2020) provide similar evidence for Germany. However, these papers focus on the role of general labor demand during the business cycle for the costs of job loss, rather than the impact of long-term structural shifts in labor demand. Blien et al. (2021) and Goos et al. (2020), on the other hand, suggest that post-displacement employment and earnings losses increase with the prior routine intensity of work due to routine-replacing technological change, but they do not establish any direct link between structural change and post-displacement outcomes. Our study takes up both recent strands of the displacement literature and shows that the regional exposure to task-biased structural change is an important determinant of the costs of job loss.[2]

Our analysis thus also speaks to recent evidence on the regional heterogeneity of routine-biased structural change: Autor (2019) shows that in the U.S. both the substitution of mid-wage routine jobs and the growth of technical and service jobs was most pronounced in urban centers. Davis et al. (2020) provide similar evidence for France. Our results confirm that routine-biased structural change in West Germany was also far from uniform across regions, but we also describe some interesting differences: job losses in RM manufacturing occupations were mainly concentrated in urban industrial centers, while non-routine and cognitive service jobs were created in more rural regions. This is in line with other studies about the geography of sectoral composition shifts in West Germany (Findeisen and Suedekum, 2008; Dauth and Suedekum, 2016; Margarian and Hundt, 2019), but our paper is the first to analyze the role of regional structural change for individual level outcomes.

[1] Carrington and Fallick (2017) provide a review of the literature about the theory and evidence of different sources of post-displacement earnings losses.

[2] A few earlier papers analyzed how the costs of displacement are related to regional industry or occupation structure (Neal, 1995; Neffke et al., 2018; Macaluso, 2019).

We also contribute to the debate to what extent structural change poses a threat for incumbent workers. Recent studies show that workers in routine occupations experience lower wage growth (Cortes, 2016), job stability (Edin et al., 2019, Bachmann et al., 2019) and job finding probabilities after job loss (Schmidpeter and Winter-Ebmer, 2021). Moreover, evidence from the U.S. suggests that the disappearance of routine intensive jobs mainly occurs during economic downturns (Jaimovich and Siu, 2020) and is driven by lower return rates from unemployment or non-participation into these occupations (Cortes et al., 2020). This suggests that job displacement might be particularly disruptive if it exposes routine workers to a labor market with a decreasing demand for their specific skill set. In line with this, routine workers are generally more likely to experience sustained unemployment and larger earnings losses after displacement (Blien et al., 2021; Goos et al., 2020; Dauth et al., 2021). Complementing this evidence, we find that the detrimental effects of structural change are confined to individuals who are displaced from their current jobs and that the associated costs are strongest in regions hit hardest by structural change. Moreover, similar to other studies (Cortes, 2016; Cortes et al., 2017), our findings suggest that low-skilled and older workers are affected most by routine-biased structural change.

The rest of the paper is structured as follows. Section 2 describes the particular RM task-bias of structural change in West Germany between 1990 and 2010 and how it varies across local labor markets. Section 3 introduces our sample of displaced workers and their matched controls for the subsequent event study and matched DiD estimations. 4 presents results on how the displacement effects on employment and wages differ with local structural change, while Section 5 looks at patterns of regional and occupational mobility. Section 6 discusses our results and concludes.

2 Structural Change in West Germany

2.1 Data

For the analysis of regional structural change between 1990 and 2010, we draw on data from Dauth (2014), which measures employment by local labor market regions and occupations on June 30 in 1990, 2000 and 2010 as recorded in the Employment History File (BeH). The BeH is an administrative data set of the German Federal Employment Agency that covers information on all German employees subject to social security contributions and thus represents about 80% of the German labor force (Dustmann et al., 2009). After excluding employees in agriculture, mining and the public sector, each original cross section encompasses around 16 million regular employees in West Germany.[3] The data is aggregated to full-time equivalent employment in 315 KldB-1988 3-digit occupations at the level of 203 local labor market regions that correspond to major commuting zones. We further aggregate occupations to 52 occupational fields that are most similar in terms of their task structure.[4] Moreover, we use five waves of the German Qualifications and Career Surveys (GQCS) between 1986 and 2012 to characterize the time-varying task content of occupations.[5] For that purpose, we follow the literature and distinguish between routine manual, non-routine manual, routine cognitive, non-routine interactive and non-routine analytical tasks (e.g. Autor et al., 2003, Spitz-Oener, 2006). For most of our analyses, we will distinguish occupations by their broad main-tasks according to the task structure in the 1986 wave, i.e. prior to the structural shifts that our analysis focuses on and prior to major shifts related to computerization and globalization. Merging this information to the region-occupation-level employment data allows us to describe the task-bias of shifts in the overall West German occupation structure and how these shifts vary across regions.[6]

2.2 Routine Manual Bias of Structural Change

Figure 1 plots the growth rate of occupations in West Germany between 1990 and 2010, weighted by the initial employment shares in 1990. The colors of the bars mark the occupations' main tasks as given by the GQCS 1986.

About half of all declining occupations were initially dominated by RM tasks. This is especially true for occupations with the strongest employment contraction (see list of occupations in Table B.1 in Appendix B.1 for further details). Most of the declining occupations were low- and mid-wage manufacturing or construction occupations, representing about 65% of total employment in 1990. In contrast, almost all growing occupations were mid- or high-wage technical (e.g. engineers, IT specialists, natural scientists) or service occupations (e.g. health care, office occupations, management). In 1986, most of the growing occupations were specialized in analytical and interactive tasks and only some in non-routine manual tasks.

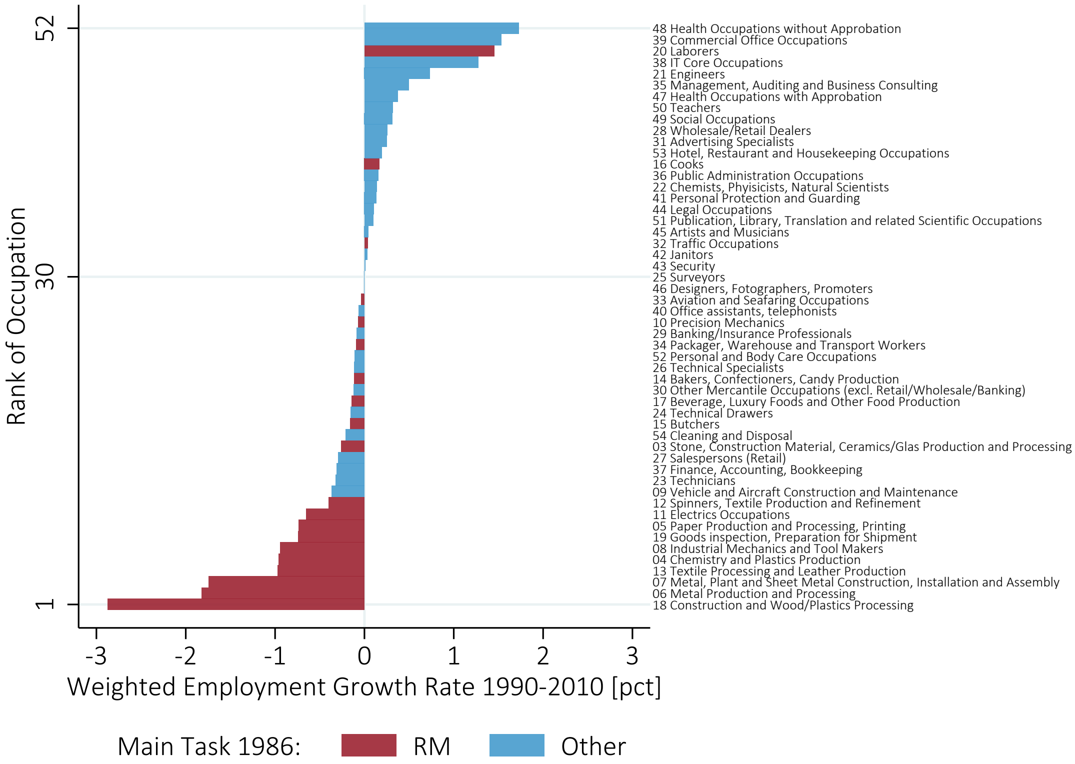
[3]The data also excludes self-employed persons, civil servants and military personnel as well as interns and employees in vocational training or partial retirement. East Germany is excluded due to its unique structural change after the fall of the Iron Curtain.

[4]See BBSR (2021) for the mapping of counties to labor market regions and Tiemann et al. (2008) for the mapping of KldB occupations to occupational fields.

[5]BIBB/IAB and BIBB/BAuA Erwerbstätigenbefragung (Qualification and Career Survey, GQCS), waves from 1979 to 2012, DOI: http://dx.doi.org/doi:10.4232/1.1243, http://dx.doi.org/doi:10.42, http://dx.doi.org/doi:10.4232/1.2565, http://dx.doi.org/doi:10.4232/1.12247, http://dx.doi.org/doi:10, http://dx.doi.org/doi:10.7803/501.12.1.1.40.

[6]For a more detailed description of how we prepare and combine the BeH and GQCS in order to construct indicators of local structural change, see Appendix A.1.

Figure 1: Aggregate Occupational Change in West Germany 1990-2010

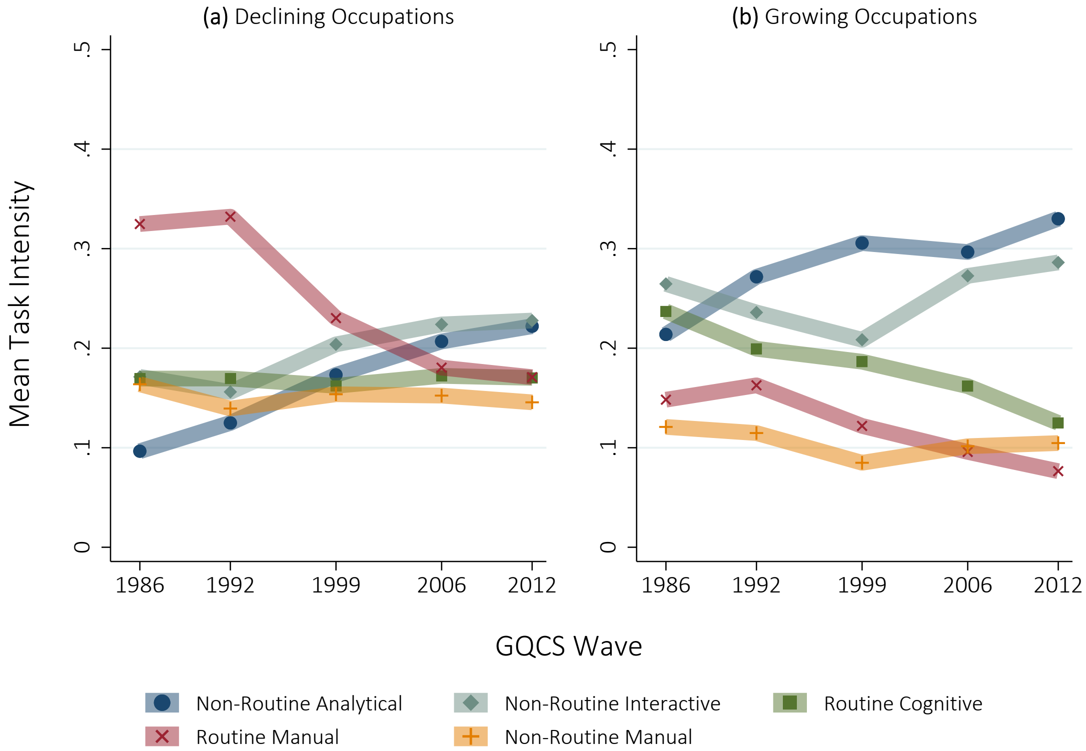


Notes: RM = Occupations with mainly routine manual tasks, Other = Occupations with other main tasks (GQCS 1986). Growth rates are weighted with the occupations' initial employment share in 1990 (see the formula for $grRM_r^{LR}$ in Appendix A.2.1 where r is set to the West German aggregate). These weighted growth rates can be interpreted as each occupation's contribution to overall employment growth. The horizontal line at rank 30 marks the occupation with just slightly above zero growth.
Data: BeH, GQCS.

The shift away from RM tasks did not only take place between, but also within occupations. Figure 2 plots how the average task composition (weighted by 1990 employment shares) of growing and declining occupations changed over time. Growing occupations reduced their intensity in RM and routine cognitive tasks and intensified their initial focus on non-routine analytical and interactive tasks. Declining occupations evolved from a strong specialization in RM tasks to a more diverse task composition with an increasing focus on analytical and interactive tasks.

We conclude that structural change in West Germany was mainly biased against RM tasks rather than routine tasks per se. The demand for RM tasks declined both within and between occupations resulting in potentially worse career prospects for workers specialized in these tasks. By contrast, workers specialized in other main tasks have either seen stable or an increasing demand for their task-specific skills. We will therefore focus on workers from initially RM-intensive occupations and compare them to workers from

Figure 2: Task Content of Declining and Growing Occupations 1986-2012



Notes: The figure plots shifts in the average task intensity of declining and growing occupations (below/above rank 30 in Figure 1). Averages are weighted by occupational employment in the year of the respective GQCS wave.
Data: GQCS, BeH.

occupations with other main tasks.

2.3 Regional Heterogeneity in RM-biased Structural Change

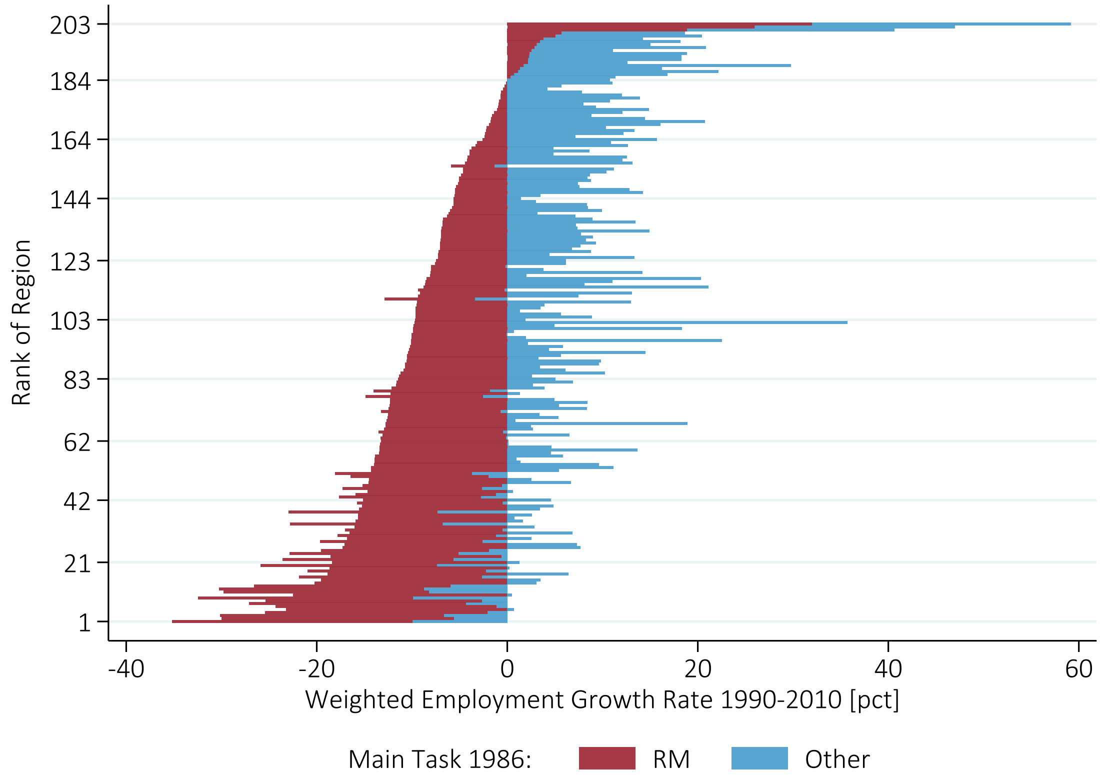
Figure 3 demonstrates that RM-biased structural change was far from uniform across West German regions. For each of the 203 West German local labor market regions, the figure shows the local growth rate of RM occupations (red bars) and all other types of occupations (blue bars) between 1990 and 2010, ranked by the red bars. We take the red bars as a measure of the intensity of long-run **RM**-**B**iased **S**tructural **C**hange across regions and we will refer to the corresponding distribution as the RMBSC distribution.

Regions at the lower end of the RMBSC distribution experienced a strong decline in RM occupations, but only limited growth in other occupations. Overall job creation, which corresponds to the sum of both bars, was mostly negative or low.[7] Moving up

[7]This is because growth rates are weighted by the occupations' initial employment shares in 1990. At the West German aggregate, social security employment in full-time equivalents decreased by 2%

the distribution, job decline in RM occupations becomes less severe and tends to be compensated by job growth in other occupations. At the very top, RM occupations even grew along with the other occupations. Hence, structural shifts and overall job growth are closely related (correlation $\rho = 0.93$), a finding that is in line with other studies of structural change and regional development (e.g. Glaeser, 2005, Duranton, 2007, Findeisen and Suedekum, 2008, Dauth and Suedekum, 2016).

Figure 3: Occupational Change across West German Regions 1990-2010



Notes: RM = Occupations with mainly routine manual tasks, Other = Occupations with other main tasks (GQCS 1986). The red and blue bars represent the weighted employment growth rates of RM and other occupations between 1990 and 2010 in local labor market regions. Growth rates are weighted with the occupations' initial employment share in 1990 (see the formula for $grRM_r^{LR}$ in Appendix A.2.1).
Data: BeH, GQCS.

To illustrate how regions differ along the RMBSC distribution, the top row of Figure 4 shows the initial (1990) industry and establishment size structure for the deciles of the distribution. The bottom row shows the corresponding growth rates between 1990 and 2010 (weighted by the 1990 shares). Regions with the strongest decline in RM jobs, i.e. the lower deciles of the RMSBC distribution, started out with a larger

between 1990 and 2010 (based on our BeH sample). In headcounts, social security employment grew by about 4.7% over this period (estimate based on data of the Statistical Office of the Federal Employment Agency).

metal/machinery/automotive sector and a much higher share of employment in large establishments with more than 250 employees. Over time, however, these regions also experienced strong employment losses in large companies and in manufacturing. For regions ranked higher in the RMBSC distribution, both the initial share and the subsequent employment decrease in the manufacturing sector and in large establishments were lower, while employment in services and retail grew more strongly. Note, however, that the initial share of RM occupations was quite similar along the RMBSC distribution (see Figure B.2(c) in Appendix B.2). We also find that RM job losses were more pronounced in urban areas with a higher initial labor productivity (see Figure B.2(a) and (b)). In contrast, regions at the top of the distribution were more rural and less productive in 1990, but also experienced stronger productivity and population growth in the two subsequent decades.

These stylized facts suggest that, in Western Germany, many of the RM jobs were lost in former industrial centres, where large manufacturing establishments dominated the local economy. New jobs were created in rising, innovative and more rural areas with a higher share of small and medium-sized establishments.[8] This pattern is in line with Findeisen and Suedekum (2008) who show that growing regions in West Germany rapidly transformed towards a modern industry structure, while turnover in declining regions was often driven by the disappearance of old industries. Consistent with this, a region's initial industry structure and corresponding exposure to import competition has been identified to affect regional transformation Dauth and Suedekum, 2016. Technological change may have been another contributor to this development. Firms may have had a stronger incentive to substitute labor with automation machinery if import-exposure raised cost pressures. New tasks and jobs, on the other hand, may have been created in regions where investments were guided towards developing new products and services, rather than realizing cost savings.[9]

[8] A map of West German labor market regions distinguished by deciles of the RM and other occupation growth rate can be found in Figure B.1 in the Appendix.

[9] Acemoglu and Restrepo (2018) discuss that technologies may have a replacing or reinstating, i.e. task- and job-creating effect. Autor et al. (2021) pick up this idea and show that job creation is strong in occupations with new augmentation technologies, while job growth is weak in occupations with innovations in automation technologies. Empirical evidence to what extent there may be regional differences in automation and augmentation innovations is missing yet, but could be an additional driver of regional structural change.

Figure 4: Initial Industry and Establishment Size Structure and Growth over Time

(a) Industries: (b) Establishment Size:

Notes: wGR = Growth rate weighted by initial employment share in 1990; Agric/mining = Agriculture, mining; Raw mat/goods/energy = Raw material, goods, energy; Metal/machinery/auto = Metal, machinery, automotive; Cons/food = Consumption goods, food; Constr = Construction; Wholes/retail = Wholesale, retail; Busi/priv/publ serv = Business, private, public services. Residual category "Other industries" omitted from the graph for ease of display. The x-axis refers to the deciles of the regional distribution of weighted growth rates in RM occupations between 1990 and 2010 (i.e. the 'red bars' in Figure 3, see also the formula for $grRM_r^{LR}$ in Appendix A.2.1).

Data: BeH, GQCS.

Overall, we thus find strong differences in RMBSC between West German regions. Although RMBSC is closely related to overall job growth, the RM task bias underlying these differential growth patterns implies that workers specialized in RM tasks should be affected differently than other workers. In the subsequent analysis, we will therefore focus on how the exposure to structural change affects RM and other workers by estimating post-displacement effects along the RMBSC distribution.

3 Displacement Sample and Empirical Strategy

Our analysis aims to identify the causal effect of job loss along the regional RMBSC distribution for different types of workers. This requires several conditions:

First, displaced workers should not be selected on characteristics that would influence their employment and earnings prospects also in absence of job loss, like e.g. individual productivity. For that purpose, we consider only workers who were laid off during mass-layoffs or plant closures and who had stable employment relationships preceding these events. During such events a large fraction or the entire workforce of a plant is laid off such that those affected are unlikely selected on unobservables. Conditioning on stable employment relationships ensures that workers were attached to their original plant and would probably not have left soon anyway. Second, we need to find non-displaced control workers to approximate the counterfactual situation of keeping one's job. In particular, displaced workers and otherwise similar control individuals should have the same pre-displacement occupation type and should be exposed to similar levels of RMBSC. Third, the displacement should not only be exogenous to the individual, but also exogenous to regional structural change. Otherwise, post-displacement outcomes may not be comparable between regions. For this requirement to hold, the probability of displacement should be independent of regional structural change. In addition, the composition of displaced workers should not differ systematically along the regional RMBSC distribution. The subsequent sections discuss how our empirical strategy takes account of these conditions.

3.1 Identification of Displacement Events

In order to construct a sample of displaced workers, we first need to identify establishments in which a displacement event occurs. For that purpose, we use data from the IAB Establishment History Panel (BHP) for the period of 1990 to 2010.[10] The BHP contains

[10]Data set version BHP 7514 v1. For further information on the data and on data access see the website of the Research Data Center of the Institute for Employment Research: http://fdz.iab.de/.

administrative employment data for the universe of all German establishments on June 30 of each year. To ensure that our results are comparable to other studies, we closely follow the definition of displacement events suggested by Hethey-Maier and Schmieder (2013). We only consider establishments with more than 10 employees in order to exclude small firms that may largely rely on the productivity of individual workers. In such cases, being laid off during a displacement event cannot be considered unrelated to individual productivity.

According to our definition, a displacement event occurs if either a plant closes permanently or a mass layoff takes place. A plant closure occurs when an establishment identifier that was present in previous years disappears from the BHP between two consecutive years. For the definition of a mass layoff, we require that establishments had at least 100 employees in the year prior to the event. A mass layoff occurs when plant-level employment decreases by at least 30%, or at least 500 employees, between June 30 of two consecutive years (see e.g. Gathmann et al., 2020 for a comparable definition). We restrict the sample to event establishments with a stable pre-event workforce by excluding establishments with employment fluctuations of more than 10% over the previous three years. We also exclude event establishments that fully recover within the following three years. Cases where a substantial share (>30%) of the work force moves to the same new establishment ID are also excluded to rule out misidentifying other events like ownership changes or outsourcing (Hethey-Maier and Schmieder, 2013).

3.2 Matching Displaced Workers and Control Individuals

Sample of Displaced Workers and Potential Controls. We identify workers who lost their jobs during a displacement event in the Integrated Employment Biographies (IEB).[11] This data set contains spells of dependent employment, registered unemployment, job-search and benefit receipt for all dependent employees that contributed to the social security system at least once since 1975.[12] Since employment records also include the establishment ID of the employer, we can merge employer characteristics from the BHP such as the industry code, the size of the workforce, median wages as well as individual and establishment wage premia ('AKM' fixed effects).[13] Moreover, we can

[11] IAB Integrierte Erwerbsbiografien (IEB) V13.00.00, Nuremberg 2017. For a description of the IEB see Oberschachtsiek et al. (2009).

[12] It does not contain spells of self-employment, military or civil service or pension receipt.

[13] BHP and IEB do not contain a firm identifier that would allow linking affiliated establishments (see also Hethey-Maier and Schmieder, 2013). The individual and establishment wage premia are based on the method pioneered by Abowd et al. (1999) and provided by the IAB. We use AKM effects that were estimated on pre-displacement years, so they are not contaminated by the displacement events themselves. For a detailed description about the estimation of the AKM effects see Bellmann et al. (2020).

identify all workers who were employed in an establishment on June 30 of the year preceding the event and who leave the establishment in the subsequent year. We denote the year prior to the event the 'base year' c. By this definition, the displacement event takes place between June 30 of base year c and June 30 of the following year $c+1$. This results in a total sample of 87,934 displaced workers, with about 3,000 to 4,000 individuals per baseline year and up to 7,000 displaced individuals in some years.

Our sample is restricted to individuals who work full-time in the baseline year at a West German establishment, who are between 24 and 50 years old[14], have at least three years of establishment tenure and one year of county tenure in order to make sure that workers are leaving a stable job that most likely would have persisted in absence of displacement.[15]

The sample of non-displaced potential control individuals is a 15% random sample of individuals working in West German establishments with at least 10 employees and for whom the same age and employment restrictions apply as for the displaced workers on June 30 of a given base year c. Not-yet-displaced workers remain potential controls until they actually experience their first displacement event. For the subsequent analysis, we construct a yearly individual-level panel data set, which is centered around the base year c and contains information on employment states and job characteristics observed on June 30 of the four preceding and six subsequent years.

Matching Procedure. We identify a control person for each displaced worker by adapting the two-stage matching procedure of Schmieder et al. (2020) to our setting. In a first step, we exactly match displaced workers and potential controls on the baseline year c, the worker's occupation type (1986 main-task: RM vs. other main task) and region type R1, R2, R3. These region types indicate the terciles of the weighted local RM occupation growth rate between 1990 an 2010 (see Figure 3 and Appendix A.2.1 for details). R1 refers to regions in the lowest tercile, i.e. with the strongest RM employment decline, R2 and R3 refer to the middle and upper tercile, respectively.[16] Exactly matching on these region types ensures that displaced and control workers start out in regions with a broadly comparable long-run structural change pattern. In the second

[14]We do so as workers below 24 years of age may not have fully entered the labor force and workers older than 50 years might be generally less attached to the labor force, e.g. because of access to partial retirement programs.

[15]Specifically, we exclude interns, trainees, part-time workers and workers who are in part-time retirement schemes. We also exclude individuals who are employed in the sectors of mining, public administration, defense, activities of private households and extra-territorial organizations as well as those who have agricultural, mining or unspecified occupations.

[16]The average long-run growth rate in RM employment is -17.0% in R1, -9.7% in R2 and -0.7% in R3.

step, we use nearest neighbor propensity score matching to select the most comparable control person from the set of potential control persons defined in step one.[17] We use a comprehensive set of pre-displacement worker, establishment and region characteristics as predictors of the propensity score. This set also contains the local weighted growth rate of RM occupations over the last ten years preceding base year c (see definition of $grRM_r^{c-10}$ in Appendix A.2.2) to ensure, that within region types R1 to R3, displaced and control workers originate from regions with similar medium-run structural change.

Table 1 compares the averages of these variables for displaced RM workers, a set of randomly chosen control individuals and the control individuals selected by our matching procedure. Columns (4) and (5) report the standardized differences Δ_X between displaced workers and either set of control workers as a scale-free measure of balancing.[18] Since there is no universally agreed criterion for how small the standardized difference must be to provide balance, we lean on two rules of thumb provided in the literature[19] and a similar notation as typically used for significance levels: We mark absolute values above 0.25 by $^{++}$, absolute values between 0.1 and 0.25 by $^{+}$ and absolute values below 0.1 are left blank to indicate close-to-perfect balancing for the respective variable.

Already the random controls are very similar to the displaced worker sample, as most standardized differences are insubstantial and only two exceed the threshold of 0.25. Most notably, displaced workers earn lower pre-treatment wages, are less common in large establishments and in the metal, machinery and automotive industry and have lower AKM establishment fixed effects. Even before matching, there are no substantial imbalances with respect to regional characteristics such as population density, unemployment rate or the growth rate of RM occupations over the past decade, supporting the notion that displacement is unrelated to regional conditions. After matching, any differences vanish – expect for a minor imbalance with respect to the metal, machinery and automotive industry share that hardly passes the lower threshold. Note that we deliberately do not include AKM person and establishment fixed effects in the propensity score estimation, in order to be able to check the quality of the matching ex-post.[20] In

[17]We use matching with replacement such that the same non-displaced worker can be a control individual for several displaced workers, but this only concerns about 2.5% of the matches. 2% of the displaced workers serve as control persons before they experience their first displacement event.

[18]The standardized difference is defined as $\Delta_X = \left(\bar{X}_1 - \bar{X}_0\right) / \left((S_1^2 + S_0^2)/2\right)^{0.5}$, where $\bar{X}_w$ is the sample mean of displaced ($w = 1$) or control ($w = 0$) individuals and S_w^2 are the respective sample variances (Austin, 2011). The advantage of Δ_X over the usual t-statistic is that it does not mechanically increase with the sample size and therefore avoids exaggerating small imbalances that would still appear significant in a t-test.

[19]The criterion for balance of $\Delta_X < |0.25|$ is suggested by Imbens and Wooldridge (2009), the stricter criterion of $\Delta_X < |0.1|$ is suggested by Austin (2011).

[20]Instead we chose to include the individual pre-treatment wage in $c-1$ and $c-2$ as well as the median establishment wage, which are highly collinear to the AKM fixed effects.

Table 1: Base Year Characteristics of Displaced Workers and Control Individuals

	(1)	(2)	(3)	(4)		(5)	
		Controls		Std. Diff. (Disp. - Contr.)			
	Displaced	Random	Matched	Random		Matched	
PS matching variables:							
Worker:							
Log real wage in $c-1$	4.67	4.74	4.66	-0.15	+	0.01	
Log real wage in $c-2$	4.65	4.71	4.64	-0.14	+	0.01	
Female	0.28	0.27	0.28	0.03		0.00	
Age	37.79	37.86	37.89	-0.01		-0.01	
Low-skilled	0.12	0.11	0.12	0.02		0.00	
Medium-skilled	0.77	0.76	0.77	0.01		0.00	
High-skilled	0.11	0.12	0.11	-0.03		0.00	
Experience	15.77	15.95	15.75	-0.03		0.00	
Establishment tenure	9.98	10.42	9.91	-0.07		0.01	
Occupation:							
Production, crafts	0.37	0.39	0.37	-0.03		0.00	
Senior office occupations	0.13	0.17	0.13	-0.12	+	0.00	
Sales occupations	0.07	0.04	0.07	0.12	+	-0.01	
Office occupations	0.28	0.26	0.28	0.05		0.01	
Service occupations	0.15	0.14	0.15	0.01		-0.01	
Establishment:							
10-49 employees	0.26	0.20	0.25	0.13	+	0.01	
50-99 employees	0.18	0.11	0.19	0.20	+	-0.02	
100-249 employees	0.26	0.16	0.27	0.24	+	-0.01	
> 249 employees	0.30	0.53	0.29	-0.47	++	0.02	
Establishment age	39.17	38.94	39.32	0.06		-0.04	
Median wage	89.85	91.62	90.55	-0.05		-0.02	
Industry:							
Raw Materials and Goods	0.07	0.10	0.09	-0.09		-0.07	
Metal, Machinery, Automotive	0.18	0.31	0.15	-0.29	++	0.10	+
Consumption Goods	0.12	0.11	0.12	0.02		0.00	
Construction	0.09	0.06	0.09	0.12	+	-0.01	
Wholesale, Retail	0.19	0.12	0.20	0.17	+	-0.02	
Business Services, Transport	0.23	0.18	0.24	0.13	+	-0.01	
Priv. Services, Educ., Social Sector	0.11	0.11	0.11	-0.01		0.00	
Region:							
Active population [1k] †	420.61	425.04	422.26	-0.01		0.00	
Population density [pop/km^2] †	562.90	550.78	561.57	0.02		0.00	
UE rate [pct] ‡	0.08	0.08	0.08	0.04		-0.01	
wGR RM occ. $(c, c-10)$ [pct]	-4.55	-4.59	-4.55	0.01		0.00	
Not in PS matching:							
AKM worker FE [log points] ¶	4.37	4.39	4.37	-0.06		0.00	
AKM establishment FE [log points] §	0.20	0.23	0.19	-0.20	+	0.04	
Observations	87,934	87,934	87,934				

Notes: PS = Propensity Score; UE = Unemployment; wGR = Growth rate weighted by initial employment share in 1990; FE = Fixed Effect; RM occ. = Occupations with mainly routine manual tasks; Std. Diff. = standardized difference. The table compares the mean base year c characteristics of displaced workers to a set of random and matched non-displaced control individuals. For the displaced, c is the year prior to job loss; control individuals are required to fulfill the sampling restrictions and to be not (yet) displaced in year c. Displaced and control individuals are exactly matched on the base year c, long-run local RMBSC as given by region types (R1/R2/R3), and the main-task of their pre-displacement occupation (RM/Other as defined by GQCS wave 1986). Establishment characteristics are measured in $c-1$. AKM FE in the most recent time period available before year c. For a description of AKM fixed effects see Section 3.4.2 and Bellmann et al. (2020).

$^{+}$ marks standardized differences between |0.1| and |0.25|, $^{++}$ marks standardized differences > |0.25|.

Varying observation numbers because of missing values: ¶ 84,197-84,647, § 86,170-87,244.

Data: BHP, IEB, GQCS, † The European Regional Database (EUI, 2021), ‡ Statistical Office of the Federal Employment Agency.

fact, there are no notable differences in pre-displacement worker or firm wage premia after matching. Hence, our matching approach may also capture differences in unobserved wage determinants that were not directly account for. Overall, these results suggest that our matched control group represents a valid counterfactual for the sample of displaced workers.

3.3 Exogeneity of Displacements to Regional Structural Change

Our aim is to compare the estimated effects of displacement between workers who lost their jobs in regions with differential exposure to RMBSC. Therefore, the estimated displacement effects for different regions need to be comparable. This requirement could be threatened if plant closures and mass-layoffs were systematically more likely in regions that are strongly exposed to RMBSC. Reassuringly, this is not the case. If at all, the overall displacement rate is slightly positively correlated to RM job growth, but the relation's significance depends on a few outlier regions with exceptionally many displaced workers or strong positive RM occupation growth (see Figure B.3(a) in the Appendix). The same holds for the displacement rate for RM workers (see Figure B.3(b)). Hence, displacement events are not concentrated in specific regions. This can also be seen in Figure B.4 in the Appendix which shows maps with the spatial distribution of the overall displacement rate as well as the displacement rate for RM workers across West German local labor market regions. We conclude that the displacement risk is not higher in regions with strong RMBSC. Albeit this may be surprising at first sight, it is well in line with the finding that the decline in routine occupations is mainly driven by reduced inflow rates, rather than rising outflows into unemployment (Cortes et al., 2020). For the subsequent analysis, we thus assume that displacement events exogenously expose displaced workers to different degrees of RM-biased structural change.

Another threat to the comparability of post-displacement outcomes between regions would be differences in the composition of displaced workers. Indeed, Table B.2 in Appendix B.1 shows that there are some differences in the pre-displacement characteristics of displaced RM workers between region types. These differences are mostly small. Nonetheless, we will explicitly account for them in the matched DiD approach that we discuss in the next section.

3.4 Estimation Approach

In this section, we will introduce two different estimation approaches to identify the effect of routine-biased structural change on individual workers' careers after job displacement.

3.4.1 Event Study Design for Evolution of Displacement Effects over Time

We first follow the general approach in the displacement literature and employ an event study design to study the effects of job loss within occupation-region type cells over time. This approach compares the change in displaced workers' outcomes at various points in time after the event to the corresponding changes in outcomes of similar workers who were not displaced. We estimate the following model:

$$y_{ict} = \sum_{k=-4}^{6} \delta_k \, D_i \times I(t=k) + \sum_{k=-4}^{6} \gamma_k \, I(t=k) + \pi_c + \epsilon_{ict} \ , \tag{1}$$

where y_{ict} represents the employment status for an individual i in year $t = \{-4, \dots, +6\}$ before or after a displacement in base year c. $I(t = k)$ indicates the years around the baseline year, D_i distinguishes displaced and control workers. π_c are baseline calendar year fixed-effects that account for year-specific displacement effects unrelated to local structural change, like the current business cycle. ϵ_{ict} is the idiosyncratic error term. δ_k are the coefficients of interest, i.e. the effect of displacement in year k before or after the event relative to non-displaced control workers.[21]

We split the sample by worker i's pre-displacement occupation type (RM vs. other main task) and region type R={R1, R2, R3} (i.e. the tercile of the region r in the distribution of long-term RMBSC as shown in Figure 3) and estimate equation (1) separately within occupation-region type cells. Standard errors are clustered at the individual level.

The event study estimates provide a first impression about how displacement effects differ for workers laid off in regions with broadly different long-run patterns of structural change. They may also be indicative of potentially problematic pre-trends and allow for an easy comparison of the post-displacement evolution of outcomes of RM and other workers within region types. Moreover, they are readily comparable to the existing displacement literature. However, further controlling for compositional differences between workers across regions would necessitate to introduce multiple interactions between region type, worker type, displacement indicator and event time, resulting in a computationally demanding specification. For this reason, we use a matched DiD approach which gives equivalent results[22], but is both easier to implement and interpret (see also Schmieder et al., 2020). The next section introduces the matched DiD method in more detail.

[21] Since our matching procedure yields treatment and control workers with very similar baseline characteristics (see Table 1), the inclusion of further control variables or individual and establishment fixed effects hardly affects the estimates.

[22] See Figure B.6 in the Appendix.

Moreover, the event study approach, uses an arguably arbitrary and time-constant aggregation of regions (R1/R2/R3). As an alternative, we use a time-varying measure of local structural change that measures the growth in RM-employment in the ten years prior to the displacement event, $grRM_r^{c-10}$. This has the advantage of avoiding (1) the arbitrary classification of regions and (2) to model displacement effects based on structural change measured partly after the displacement event.

3.4.2 Matched DiD Design for Identifying the Structural Change Effect

To study how structural change affects post-displacement outcomes, we exploit the heterogeneity along the RMBSC distribution and implement a matched DiD approach in the spirit of Schmieder et al. (2020). Since each displaced worker is matched to a statistical twin, we can compute an 'individual Diff-in-Diff' for each displaced worker i at time t as follows:

$$\Delta_{dd} y_{iocrt} = \Delta_d y_{iocrt} - \Delta_{nd} y_{iocrt} \ , \tag{2}$$

where $\Delta_{\{d,nd\}} y_{iocrt}$ measures the individual i's change in outcomes between the pre-displacement base year c and the post-displacement year t for each displaced worker ($\Delta_d y_{icrt}$) and her non-displaced matched control individual ($\Delta_{nd} y_{icrt}$). The indices o and r mark the pre-displacement occupation and region in base year c. In addition to employment, we also examine wages and mobility in terms of occupational or regional switches as outcomes.

Effect of Exposure to RMBSC. In order to explicitly study how the exposure to RMBSC affects job loss while controlling for differences in the worker composition, we use the 'individual DiD' as the dependent variable and the time-varying indicator $grRM_r^{c-10}$, the weighted growth rate of RM occupations in the worker's pre-displacement region r over the decade preceding base year c, as the measure of RMBSC exposure:

$$\begin{aligned} \Delta_{dd} y_{iocrt} = \omega\, grRM_r^{c-10} &+ \phi\, I\left(RM_o^c\right) \\ &+ \beta\, grRM_r^{c-10} \times I\left(RM_o^c\right) \\ &+ X_{ic}\theta + \pi_c + \alpha + v_{iocrt} \ , \end{aligned} \tag{3}$$

$$\Delta_{dd} y_{iocrt} = \omega\, grRM_r^{c-10} + \phi\, I\left(RM_o^c\right) + \quad \beta\, grRM_r^{c-10} \times I\left(RM_o^c\right) + X_{ic}\theta + \pi_c + \alpha + v_{iocrt} \ , \tag{4}$$

where $I(RM_o^c)$ is an indicator for the type of the worker's pre-displacement occupation o (= 1 if RM, = 0 if other main task). The interaction term $grRM_r^{c-10} \times I\left(RM_o^c\right)$ thus allows the displacement effect to vary with RMBSC in a linear fashion. Since $grRM_r^{c-10}$ ranges from -16% at the bottom to $+16\%$ at the top of the distribution, we will later present the average marginal effects of displacement for RM workers as well as other workers types over this range.[23] X_{ic} contains individual pre-displacement characteristics (gender, skill level, age, tenure, experience, AKM worker fixed effects). π_c are base year fixed-effects, α is a constant and v_{iocrt} is the idiosyncratic error term. The model is estimated separately for each post-displacement year t but jointly across displaced workers in all regions r.

All in all, this approach provides a parsimonious and easily interpretable way of modeling how structural change affects outcomes after job loss for different workers types while controlling for compositional differences.

4 Employment and Wage Effects of Job Displacement

4.1 Event Study Estimates by Region and Occupation Type

Figure 5(a) displays the results of the event study models for the employment probability as the dependent variable – separately estimated for RM and other workers within region types R1 to R3. The plot provides no indication of an obvious violation of the parallel trends assumption, as the pre-treatment outcomes of all subgroups are close to zero and precisely estimated. After displacement, both RM and workers from other occupations face substantial drops in the employment probability.[24] One year after displacement, the re-employment probability of displaced workers from other occupations is between 10 to 12pp lower as compared to control persons, with little variation between region types. After partial recovery, displacement still leads to a 6 to 7pp lower probability of being employed in year six after the event. Even in R3 regions with strong job growth in other occupations, displacement still comes with persistent negative employment effects.

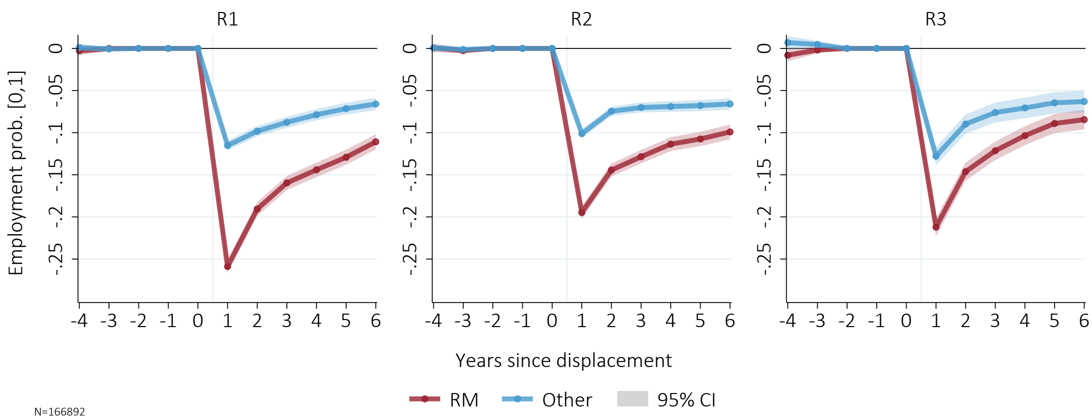
Compared to workers displaced from other occupations, RM workers generally expe-

[23] We will provide a robustness check using a more flexible specification and argue in favor of this functional form assumption.

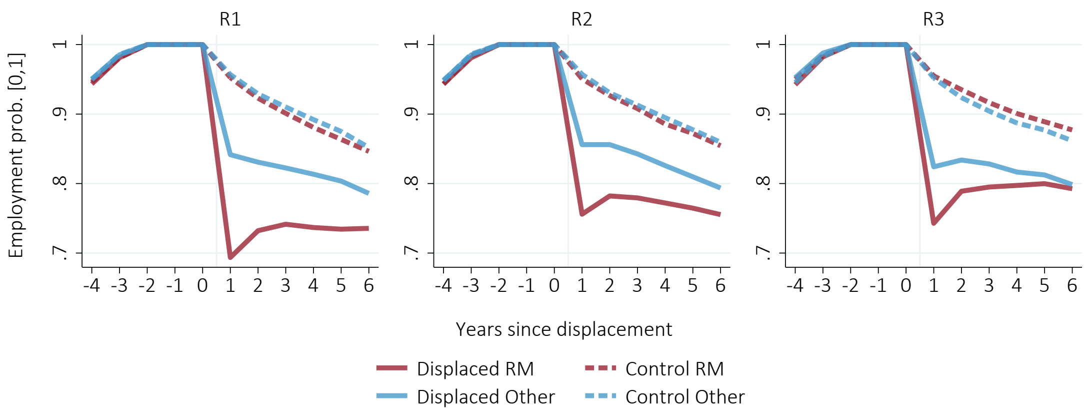
[24] On average, across both worker types and regions, displacement decreases employment by about -16pp after one year and -8pp after six years (see Figure B.5 in the Appendix). These results are in a comparable order of magnitude as in previous studies for Germany and other European countries (see e.g. Eliason and Storrie, 2006; Huttunen et al., 2011; Gulyas and Pytka, 2019; Schmieder et al., 2020; Blien et al., 2021; Goos et al., 2020 Fackler et al., 2021; Gathmann et al., 2020; Helm et al., 2022; Bertheau et al., 2022;). Differences to these studies may result from different institutional settings, time frames and sample restrictions (we include women, study both small firm closures and large mass layoffs and we match on region and occupation types).

Figure 5: Displacement Effects by Region Type and Main Task

(a) Employment Effects of Displacement (Event Study)



(b) Displacement vs. Counterfactual Employment (Means)



Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Plot (a) shows coefficient estimates and confidence intervals from the event study model (see equation (1)), estimated separately by occupation type (RM/Other) and region type (R1/R2/R3). Standard errors are clustered at the individual level. Plot (b) shows the unconditional means, i.e. the employment share of displaced and non-displaced RM/Other workers by region type (R1/R2/R3). Region type refers to the tercile of the regional distribution of weighted employment growth rates of RM occupations between 1990-2010 (see Figure 3 and Appendix A.2.1); Average within region types: R1=−17.0%, R2=−9.7%, R3=−0.7%.
Data: BHP, IEB, BeH, GQCS.

rience stronger employment penalties in every region type. This is in line with findings of Blien et al. (2021) and Goos et al. (2020), who study how the costs of job displacement vary with routine intensity at the occupation level. Our results suggest that the regional context matters: While workers from other occupations have similar employment probabilities in all region types, the losses of RM workers are highest in regions with the strongest decline in RM occupations. In R1 regions, their employment probability drops by -27pp, as compared to about -20pp in R2 and R3 regions. In addition, in R1 regions RM workers do not catch up as much with other workers: After six years, they are still about 6pp less likely employed than workers from other occupations in R1 regions. In region types R2 and R3 this gap narrows to about -3pp and turns insignificant in R3.

Our findings suggest that RM workers' employment prospects after job loss are more sensitive to structural change, resulting in a stronger and more persistent drop in their re-employment probabilities in more exposed regions. Therefore, this group has a higher risk of long-term unemployment and labor force exit in regions with strong RM biased structural change.

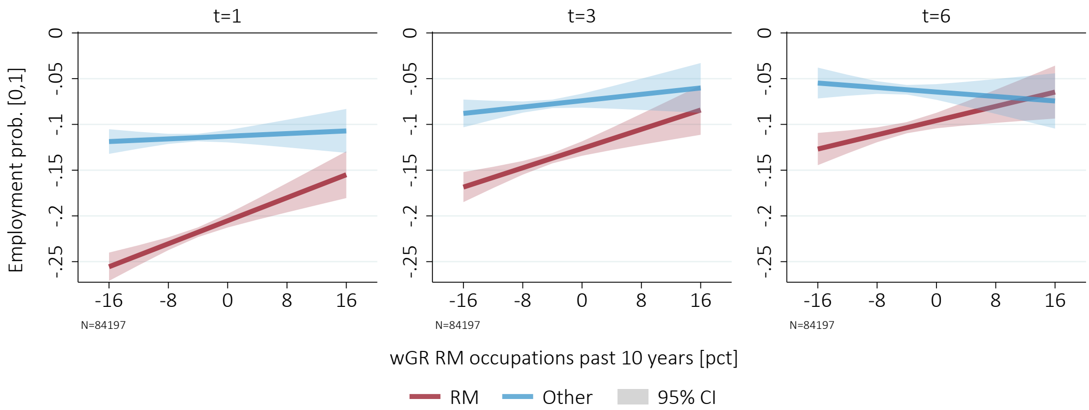
Figure 5(b) plots the unconditional employment share for displaced workers and their non-displaced controls. Since control individuals are matched on the initial region and occupation type and a comprehensive set of other characteristics, they provide a counterfactual for what would have happened to RM workers in absence of displacement. Strikingly, the employment trajectories of non-displaced control workers do not differ much by occupation or region type. Even in regions hit hardest by structural change, non-displaced RM and other workers experience very similar employment trajectories. Hence, RM workers seem to cope fairly well with structural change unless an unexpected lay-off forces them to look for a new job.

4.2 Matched DiD Estimates along the RMBSC Distribution

In this section we introduce the results of the matched DiD approach using the time-varying indicator of the RMBSC distribution.

Employment Effects along the RMBSC Distribution. Figure 6 shows the results from the matched DiD model (4) that incorporates linear RM occupation growth as a continuous measure and its interaction with the RM occupation indicator. The plots shows how the average marginal effect of displacement on employment for RM and other workers (vertical axis) varies with the local growth rate of RM occupation in the past ten years (horizontal axis). The three panels provide the effects for one, three and six years after job loss. As regards workers from other occupations, the initial employment losses do not significantly differ with local structural change. By contrast, for RM workers there is a strong positive gradient with RMBSC. At the bottom of the RMBSC distribution, where RM occupations strongly decline, displaced RM workers are about 25pp less likely employed after one year than their non-displaced controls. At the other end of the spectrum, where RM occupations grow, employment losses of RM workers are almost 10pp lower. Again, we observe some convergence between worker types over time and a flattening of the regional gradient for RM workers. However, at the bottom of the RMBSC distribution, RM workers are significantly less likely employed than other workers even after six years. At the upper end of the regional distribution, the difference between both worker types has vanished by then.

Figure 6: Employment Effects along the Structural Change Distribution
(matched DiD with ind. controls, t=1,3,6)



Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2. The x-axis refers to the weighted regional growth rate in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level.
Data: BHP, IEB, BeH, GQCS.

Robustness. We run several checks to test the robustness of these findings. First, we document that the inclusion of individual control variables hardly affects the estimates, such that differences in worker composition between regions or occupation types are of minor importance (compare panel (a) and (b) in Figure B.7 in the Appendix). Estimates are also robust to the exclusion of outlier regions with unusually severe displacement events. Hence, the gradient is not driven by a few singular events in a certain part of the RMBSC distribution (see Figure B.7(c)).[25] We then relax the linearity assumption

[25] Outliers are defined as labor market regions with average treatment effects below the 1%-ile or above the 99%-ile.

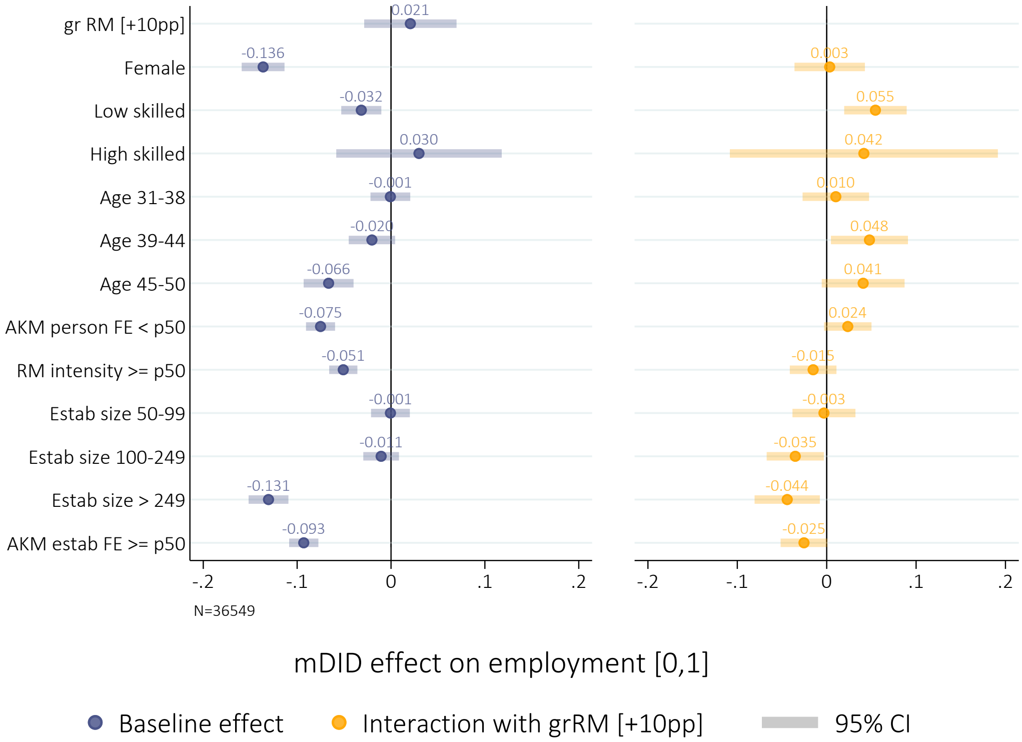
in model (4) by replacing the linear interaction term with a separate interaction term for each quintile of the $grRM_r^{c-10}$ distribution. The results in Figure B.8 show that also in this more flexible specification, the RMBSC gradient is very close to a linear trend. In a further check, we exclude the *Ruhrgebiet*, an old industrialized rust belt type of region in the west of Germany that has seen a major economic decline since the 1980s. Again, excluding these regions yields almost identical estimates as our baseline specification (compare panel (a) and (b) in Figure B.9).

In another specification, we examine the employment probability of displaced routine cognitive rather than RM workers and compare their outcomes to those of all workers with a different non-routine main task (i.e. non-routine analytical, non-routine interactive or non-routine manual). The rationale is that much of the literature focuses on routine intensity per se, rather than comparing RM workers to all others (see e.g. Autor et al., 2008). The results suggest that routine cognitive workers are indeed more similar to other non-routine workers than to RM workers, as their employment probability lies in between both groups but much closer to all other non-routine workers (see Figure B.9(c)).

Heterogeneity by Worker Characteristics. Having established that RM workers' employment prospects are highly sensitive to regional conditions, we now analyze which sub groups of RM workers are more or less vulnerable to structural change. For this, we re-estimate equation (4) in Section 3.4.2 for the sample of RM workers only and interact individual characteristics with the local growth rate of RM employment in the past ten years. The left panel in Figure 7 provides the base coefficients for each X-variable, which reflect its effect on the re-employment probability independent of local structural change conditions. The right panel shows the coefficient of the interaction with regional RM growth ($grRM \times X$). The interaction effects are scaled to measure how the employment probability of a person with characteristic X changes when $grRM$ increases by 10pp. A positive interaction effect means that a worker with characteristic X has a lower employment probability in regions with a stronger decline of RM jobs (i.e. a 10pp lower value of $grRM$) and *vice versa*.

First of all, the left hand side implies that women, workers between 45-50 years, low-skilled workers and workers with a pre-displacement RM task intensity above the median are generally less likely to be re-employed one year after displacement. The same holds for less productive workers, i.e. workers with an AKM person fixed effect below the median, as well as workers previously employed in large establishments or establishment with higher wage premiums, i.e. above median AKM establishment fixed effects. In line with much of the displacement literature, this suggests that older workers

Figure 7: Employment Effects along the Structural Change Distribution by Individual Characteristics
(RM workers, matched DiD with ind. controls, t=1)



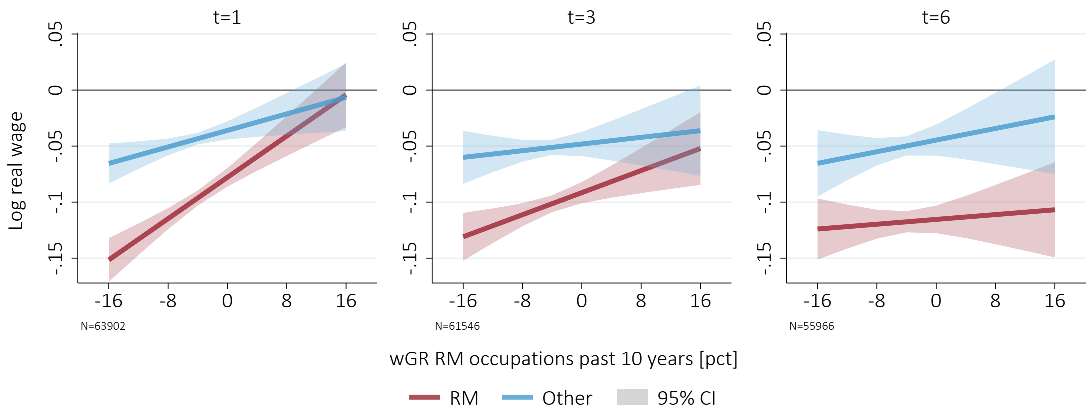
Notes: RM = Workers in occupations with mainly routine manual tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where $I(RM)$ is replaced by individual characteristics X and their interaction with $grRM$. The sample is restricted to RM workers. The left panel shows the estimated baseline effect of X, the right panel shows the estimated effect of its interaction with $grRM$, the weighted regional growth in RM occupations over the decade preceding the base year c (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Standard errors are clustered at the individual level.

Data: BHP, IEB, BeH, GQCS.

with less and more outdated skills are generally more at risk of poor post-displacement outcomes.

The interaction coefficients on the right-hand side of Figure 7 imply that older, low-skilled and low-productive workers are significantly more vulnerable to local RMBSC. For example, a low-skilled worker's re-employment probability would increase by 5.5pp if being displaced in a region with a 10pp higher RM occupation growth rate. Such an improvement in regional conditions would more than compensate the base line penalty of -3.2pp for low-skilled workers.[26] By contrast, the employment probability of workers who were displaced from large well-paying firms is higher in strongly exposed regions where RM occupations decline more. Moreover, women's re-employment chances are generally lower, but do not significantly depend on local structural change conditions.

Figure 8: Wage Effects along the Structural Change Distribution
(matched DiD with ind. controls, cond. on re-employment, t=1,3,6)



Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level.
Data: BHP, IEB, BeH, GQCS.

Wage Effects. Conditional on re-employment, displacement effects on wages differ substantially with exposure to structural change, as can be seen in Figure 8. For both worker types, wage losses are larger at the lower end of the local RMBSC distribution, but for RM workers they are roughly twice as large. In these regions, RM workers exhibit wage losses of about 14% in year one (-0.15 log points). In regions at the top of the

[26] A 10pp difference corresponds to about one third of the range of $grRM$ observed in our data (-16 and +16%).

distribution, where RM and total employment grow, the wage penalty from job loss is small and not significantly different from zero for both RM and other workers. This suggests that the average wage losses that are typically found for displaced workers in the literature differ markedly across space. The more exposed a region is to RM-biased structural change, the higher are resulting wage losses, especially for RM workers. The regional gradient for RM workers flattens over time, but their wage losses are highly persistent. Even after six years, they still amount to about -12% in bottom regions.

5 Occupational and Regional Mobility

In order to examine whether regional and occupational mobility serve as an adjustment mechanism to regional structural change, we first analyze the probability of working in a different occupation type or a different labor market region one year after displacement – conditional on re-employment at that time. We then examine the potential costs of moving. Since re-employment and mobility after displacement are subject to individual self-selection, these results should be interpreted as descriptive rather than causal. We do, however, control for differences in observable pre-displacement characteristics in all specifications.

5.1 Switching Probabilities

Figure 9 shows the switching probabilities for occupational mobility (panel (a)) and regional mobility (panel (b)) one year after displacement.[27] There are three main takeaways: First, occupational mobility is low compared to regional mobility. Conditional on re-employment, only 5 to 10% of displaced workers have switched the occupation type after one year. By contrast, the probability to work in a different labor market region ranges between 10 to 30%.[28]

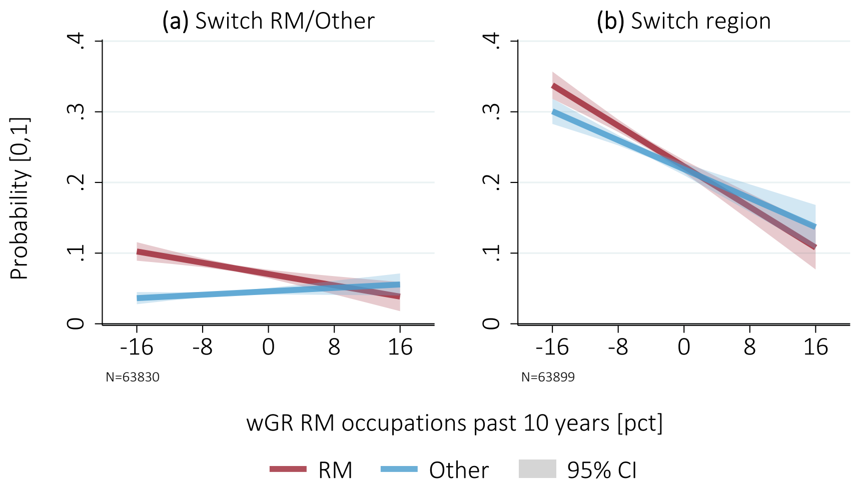
Second, there is a clear regional gradient for both worker types in regional mobility. This indicates that poorer job growth in the bottom part of the distribution incentivizes not only RM workers, but also other worker types to extend their search radius. For RM workers, regional mobility seems to be slightly more responsive to local structural change than for other worker types.

[27] For these estimates, we replace the dependent variable in the matched DiD specification (4) by indicator variables for individuals that switch from RM to other occupations or *vice versa*, or who take up a job in a different labor market region at time t. Results for years three and six after displacement are provided in Figure B.10 in the Appendix. The general mobility patterns do not change much over the six post-displacement years.

[28] This encompasses both re-location and commuting.

Third, occupational switching occurs mainly among displaced RM workers in regions hit hardest by structural change. The share of workers from other occupations who switch to an RM-occupation is small and only slightly increasing along the RMBSC distribution. By contrast, the probability for RM workers to switch to an other occupation type is around 10% in the bottom part of the distribution, but declines to about 4% in the upper part, which is similar to the share of displaced workers from other occupations. Thus, occupational switching mainly occurs in regions where displaced RM workers compete for a declining number of RM jobs and is lower in regions with an abundant growth in other occupations. Put differently, occupational switching does not seem to be driven by opportunity, but rather by a lack of better alternatives.

Figure 9: Effects on Occupational and Regional Mobility along the Structural Change Distribution
(matched DiD with ind. controls, cond. on re-employment, t=1)

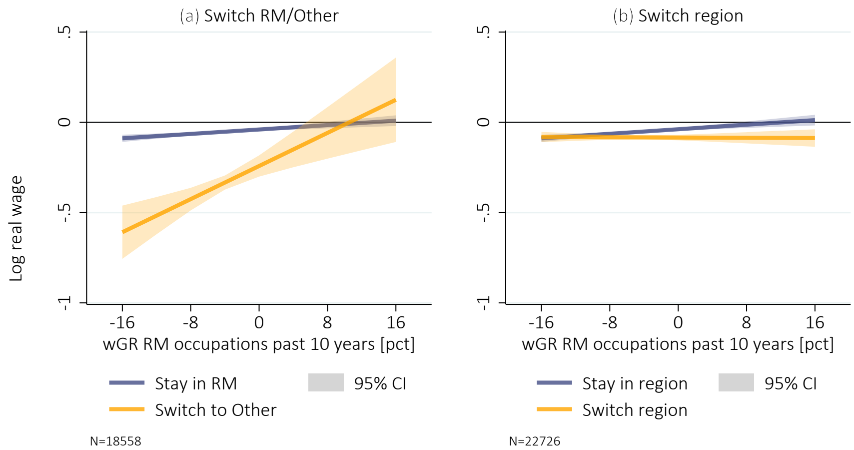


Notes: RM = Workers in occupation with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the probability of working in an occupation with a different main task as compared to the pre-displacement occupation (i.e. switching from RM to Other or *vice versa*). Panel (b) shows the probability of working in a local labor market other than the one in which displacement took place.
Data: BHP, IEB, BeH, GQCS.

5.2 Mobility Costs

If RM workers in bottom regions mainly switch occupations to avoid unemployment, we expect that they are also willing to accept lower wage offers than comparable workers in top regions. To shed light on this, we now focus on RM workers and examine how their post-displacement wages differ by their mobility status one year after displacement.[29] We focus on RM workers who either switch regions or the occupation type, but not both. By that, we avoid mixing the effects of regional and occupational mobility. Moreover, worker who switch along both dimensions are arguably a special selection of few highly flexible individuals.[30] The results are plotted in Figure 10 and we will discuss occupational (panel (a)) and regional mobility (panel (b)) one after another.

Figure 10: Wage Effects along the Structural Change Distribution by Mobility Choices (RM workers, matched DiD with ind. controls, cond. on re-employment, t=1)



Notes: RM = Workers in occupation with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where $I(RM)$ is replaced by an indicator variable for switchers. The sample is restricted to RM workers. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the wage losses of workers displaced from an RM occupation by whether they are re-employed in an RM or other occupation. Panel (b) shows the wage losses of workers displaced from an RM occupation by whether they are re-employed in the same labor market region or in a different region.
Data: BHP, IEB, BeH, GQCS.

Occupational Mobility and Wages. For RM workers in regions that are most exposed to RMBSC, occupational mobility is associated with substantial wage losses. One year after displacement, these workers earn almost half the wage (-0.6 log points) of their non-displaced peers. Even after six years, the wage penalty still amounts to around 18% (-0.2 log points, see Figure B.11(a) in the Appendix). In contrast, workers who enter a RM job again incur relatively small initial losses of -7% (-0.07 log points) that vanish over time. In the upper part of the RMBSC distribution, occupational switchers do not

[29] For that purpose, we replace the indicator for RM-occupations in equation (4) by an indicator for occupation type or region switching and restrict the sample to RM workers.
[30] This pertains to 3.8% of all RM workers that are employed after one year.

experience significant wage penalties – they even experience insignificant gains from switching occupation types after displacement.

Hence, the average wage losses of RM workers at the bottom of the RMBSC distribution that we document in Figure 8 are mainly driven by occupation type switchers. These higher switching costs in bottom regions are not explained by higher losses in task-specific human capital that could occur if switchers took up more dissimilar jobs. To the contrary, the task distance of RM to other task switchers in bottom regions is substantially smaller than in the upper part of the regional distribution (see Figure B.12(a) in the Appendix).[31] However, in bottom regions, RM to other task switchers incur substantially larger losses in establishment wage premia than RM stayers, while in the upper part of the region distribution, the change in wage premia is insignificant for both RM to other task switchers and RM stayers (see Figure B.12(b)).

To sum up, in regions where RM occupations strongly decline, more RM workers switch occupation type despite of large and persistent wage losses – suggesting that these switches mainly occur because of a lack of better alternatives. These workers resort to the most similar jobs available to them, but still bear high costs – partly because of higher losses in establishment wage premia. This might reflect the link between RM-biased structural shifts and concurring shifts in the establishment structure that we discussed in Section 2.3: Employment losses in these regions were concentrated in initially large and highly productive manufacturing establishments. As a result, leaving an RM occupation in these regions, on average, coincides with switching to lower-paying firms and thus comes at high costs. Consistently, RM workers only incur low and temporary losses in overall wages and establishment premia if they return to an RM occupation in a bottom region.

In regions with relatively strong job growth in RM occupations and even higher job growth in other occupations, the story likely differs. Here, a rather small share of RM workers gain from taking advantage of job opportunities in other occupations and benefit from higher wages in the medium-run despite larger task distances.

Regional Mobility and Wages. Since the vast majority of individuals who take up a job in a different labor market region stick to RM jobs (86% of all regional movers), regional mobility seems to mainly serve as a strategy to keep an RM occupation that is locally no longer available. The task distances involved in these moves are small (see

[31] In bottom (top) regions we estimate an average task distance of about 0.4 (0.6) for switchers. Given the 1986 task structure, this would for example correspond to switching from '06 Metal Production and Processing' to '42 Janitors' ('26 Technical Specialists'). See Appendix A.1.2 for details about our measure of task distance.

Figure B.13(a) in the Appendix).[32] However, RM workers who leave a bottom region experience wage losses of -10%. A substantial part of these wage losses, again, reflects losses in wage premia (see Figure B.13(b)). Similar to occupational switchers, regional switchers from regions in the bottom part of the distribution, tend to leave well-paying jobs in large establishments such that regional moves incur lower firm premia, on average. As a result, related wage losses are no less compared to those who are re-employed in a local RM job. Put differently, movers are not compensated for the monetary and non-monetary costs of moving. This could be one of the reasons why regional mobility for RM workers is only marginally more responsive to regional conditions than for other types of workers (see Figure 9).

Finally, workers who are displaced in one of the top regions and return to a local RM job do not experience any wage losses. These workers take up similar jobs as before, both in terms of tasks and wage premia (see Figure B.13 (a) and (b)). Leaving these top regions comes with small wage losses, but these are not explained by higher task distances or losses in establishment wage premia.

6 Discussion and Conclusion

In this paper, we show that regional differences in the exposure to routine-biased structural change have important implications for the individual employment trajectories of displaced workers. By exploiting the regional heterogeneity in how local employment shifts are biased against routine manual (RM) occupations, we compare post-displacement outcomes across regions for workers specialized in RM or other types of tasks. In our empirical analysis, we focus on workers displaced during mass-layoffs or plant closures and apply a matched difference-in-differences (DiD) approach to identify causal effects that are comparable between regions. We thereby add a number of novel empirical insights.

First of all, we find that, even in the most exposed regions, workers specialized in RM tasks are shielded from the disruptions associated with structural change as long as they remain on the job. It is only upon displacement that structural change starts to matter. Our findings suggest that the disruptive consequences of displacement are amplified for workers in regions that underwent a stronger decline in task-related employment. One year after job loss, RM workers who got displaced in regions with the strongest long-run decline in RM jobs have a 10pp lower re-employment probability and 14pp greater wage

[32] The average estimated task distance both for region stayers and switchers is about 0.05, which would correspond to switching between '06 Metal Production and Processing' and '04 Chemistry and Plastics Production'.

losses than comparable workers in regions where RM occupations grow the most. This regional gap narrows over time but still persists after six years.

Secondly, related wage losses are closely linked to occupational switching. While the 90% of RM workers who are re-employed after one year in an RM occupation suffer only small and temporary wage losses, those who switch occupations suffer wage losses of almost 50% after one year and 15% after 6 years. Moreover, a substantial share of these wage losses comes from lower post-displacement firm wage premia, reflecting that regions hit hardest by structural change were initially dominated by large, highly productive manufacturing firms that experienced a subsequent decline. Hence, the costs of occupational mobility in these most exposed regions are particularly high. Regional mobility, on the other hand, provides a remedy only for workers with low moving costs because such moves do not yield a wage premium that would compensate workers for any related costs. As a result, low-skilled, low-productive, and older workers are put at the end of the local queue for a declining number of RM jobs, while neither regional nor occupational mobility is a feasible adjustment strategy for them. For example, for a low-skilled worker the risk of being unemployed after one year is 17.6pp higher in regions most exposed to structural change as compared to the least exposed regions.[33]

From a policy perspective, our paper calls for a place-sensitive approach to reduce risks that structural change may pose to individual workers. However, there is likely no easy way out as our results suggest severe barriers to occupational and regional mobility. Most importantly therefore, supportive measures should be directed to reducing related costs for the most vulnerable groups in declining regions. For this, a successful strategy likely necessitates a bundle of measures. While re-training measures should aim at facilitating occupational mobility, a temporary wage subsidy for occupational movers may reduce barriers related to the corresponding loss of firm wage premia. In addition, mobility subsidies that cover not only actual monetary moving costs, but also pay an additional compensation for non-monetary costs might help boosting regional mobility. Although these measures are costly, the costs of not addressing the disruptive character of displacement in declining regions may even be worse in a longer run, as this may be a source for the rise in discontent, anti-establishment sentiments, and populism that has been found particularly among low-skilled workers in lagging regions hit by local economic and industrial decline (Rodríguez-Pose, 2020, Dijkstra et al., 2020).

[33] These numbers are derived from Figure 7 by multiplying the regional gradient for low-skilled workers (that captures a 10% increase in RM employment growth) by a factor of 3.2 (reflecting the difference between a region with RM employment growth -16 as compared to +16%.

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Appendix

A Details of Data Preparation

A.1 Occupational Tasks

A.1.1 German Qualifications and Career Surveys (GQCS)

In order to characterize the task content of occupations, we use the 1979, 1985/86, 1991/92, 1998/99, 2006 and 2012 waves of the GQCS (see Rohrbach-Schmidt and Tiemann, 2013 for a detailed description of the data set). The GQCS are repeated cross-sectional surveys of about 20,000 to 30,000 individuals per wave. We restrict the sample to regularly employed workers between 15 and 65 years of age and exclude agriculture and mining occupations as well as trainees, interns, individuals still in education and retirees. All waves classify occupations by KldB-1988 3 digit codes, which we aggregate to the 52 occupation fields used in our main analysis (see Tiemann et al., 2008 for the mapping between classifications). This step assures sufficient observation numbers for each occupation to compute mean task intensities and allows us to merge them to our other data sets.

A.1.2 Occupational Task Intensities

Among many other things, the GQCS contain information about the tasks individuals carry out at work and the tools they use. One of the great merits of the data is the long time span it covers, that allows us to study long-term shifts in the task structure of occupations. The downside is that the task definitions, the item scales and the survey populations differ across waves, such that using the data requires careful harmonization and, in some cases, imputation in order to avoid mechanical trends or breaks. Following Rohrbach-Schmidt and Tiemann (2013), we condense a set of 22 binary task indicators that are consistently available in most of the waves. We then impute missing tasks at the individual level by using skill requirements or work tools that are available across several waves to predict whether a person likely carries at a certain task.[34]

We then follow the common practice in the task literature and categorize each task as either non-routine abstract, non-routine interactive, routine cognitive, routine manual or non-routine manual (see Table 4, column 3 in Rohrbach-Schmidt and Tiemann, 2013).

[34]For example, in the 1986 and 1992 wave the missing task 'measuring' is set to 1 if individuals use measuring devices as a main work tool. We validate this approach by checking for sufficient correlations in waves where both variables are present. For the previous example the correlation is 0.8 in 1999.

The data only tell us whether or not an individual carries out a given task, but not the time spent on doing so. To proxy the share of working time spent on each task, we follow the approach of Antonczyk et al. (2009) and compute task intensities. For example, if an individual carries out 4 tasks, then each task is assumed to take up 1/4 of the total working time. The same holds for the intensity of task categories: if 3 of these 4 tasks are routine manual (RM), the RM task intensity would be 3/4. We define the main task to be the task category with the highest intensity. In the previous example, the main task would thus be RM.

We then average the task intensities over all individuals in each occupation and wave and close remaining gaps for some tasks and waves by linear extrapolation.[35] This provides us with a vector of 22 average task intensities, and alternatively, a vector of the 5 broad task category-intensities, for each of the 52 occupations and most of the GQCS waves.

In order to arrive at an occupation-year panel, we expand the data and linearly interpolate the average occupational task intensities between the survey waves. This implicitly assumes that changes in tasks occur gradually between survey waves. The final data set allows us to merge the task content of occupations to our regional and individual level data via occupation-year cells.

A.1.3 Bilateral Task Distances between Occupations

We use the detailed vectors of 22 occupational task intensities to compute bilateral task distances $d_t^{o,o'}$ between all occupation pairs (o, o') in every year t. Following Gathmann and Schoenberg (2010), we measure distance in terms of the angular separation, which describes the angle between two vectors, i.e. the difference in their orientation in the task space:

$$AngSep_t^{o,o'} = \frac{\sum_j q_{jo} \times q_{jo'}}{[(\sum_j q_{jo}^2) \times (\sum_j q_{jo'}^2)]^{0.5}} ,$$

where q_{jo} and $q_{jo'}$ is the average task-'j'-intensity of any two occupations o and o', i.e. the 22 elements of each occupation's task vector as described above.

If two task vectors point in the exact same direction, their angular separation is 1; if they are orthogonal it is 0. [36] We therefore use $d_t^{o,o'} = 1 - AngSep_t^{o,o'}$ as our task distance measure, which has been shown to be a strong predictor of worker transitions

[35] We account for differences in the total number of tasks surveyed in each wave such that the imputed task intensities still sum to one.

[36] In contrast to the Euclidean distance, the angular separation disregards the task vectors' distance to the origin. In our application this is not relevant, because the task intensities always sum to 1 by definition, such that each occupation's task vector has unit length.

between occupations and wage growth (Gathmann and Schoenberg, 2010).

Since the task distances $d_t^{o,o'}$ are year-specific, they change over time as occupations shift their task contents. For example, in 1986 the occupation pair with the minimum task distance of 0.01 is '28 Wholesale/Retail Dealers' and '30 Other Mercantile Occupations (excl. Retail/Wholesale/Banking)', the pair with the maximum distance of 0.96 are '20 Laborers' and '49 Social Occupations'. Until 2012, the minimum and maximum task distances decline to 0.03 ('04 Chemistry and Plastics Production' and '05 Paper Production and Processing, Printing') and 0.82 ('37 Finance, Accounting, Bookkeeping' and '14 Bakers, Confectioners, Candy Production'), respectively.

A.2 Indicators of Local Structural Change

A.2.1 Long-run Changes in Local Occupation Structures

In order to calculate long-run changes in local occupation structures, we use regional and occupational employment data based on the BeH at three points in time, i.e. 1990, 2000 and 2010. This data was aggregated from register data of the German social security system at the level of local labor market regions and KldB1988-3-digit occupations and provided by Dauth (2014). [37]

Our first use of this data is to characterize the RM-bias of structural change in each West German local labor market region. In Section 2.2 we justified classifying occupations by their initial main task in 1986, i.e RM and Other, because specialization with respect to these tasks is strongly related to either occupational decline or growth at the West German aggregate. To characterize regional differences in the exposure to long-run RM-biased structural change, we compute the weighted employment growth rates of RM occupation types in each local labor market region between 1990 and 2010 (this is the observation period for which we observe displacement events):

$$grRM_r^{LR} = \frac{E_{r,1990}^{RM}}{E_{r,1990}} \cdot \frac{E_{r,2010}^{RM} - E_{r,1990}^{RM}}{E_{r,1990}^{RM}} .$$

where $E^RM_{r,t}$ is the sum of employment in all occupations o of type RM in region r and $E_{r,t}$ is total employment in region r at time $t = \{1990, 2010\}$. The first term on the right-hand side is the occupation type's initial employment share. This weighting

[37] For further information about underlying micro data see Section 2.1. A detailed description of the sample restrictions and the aggregation procedure is given in the Appendix of Dauth (2014). The regional level of aggregation are local labor market regions, which basically reflect commuting zones (BBSR, 2021). We further aggregate the data from KldB1988-3-digit occupations to 52 occupation fields (as defined by Tiemann et al., 2008).

factor avoids overstating the impact of initially small occupations on long-term growth. The weighted growth rates can be interpreted as the contribution of RM occupations to overall local employment growth between 1990 and 2010. Using the same formula, we also compute the weighted long-term growth rate for occupations with a main task other than RM. By definition, $grRM_r^{LR}$ and $grOther_r^{LR}$ sum up to the local growth rate of total employment between 1990 and 2010.

We plot these growth rates in Figure 3 to illustrate regional heterogeneity with respect to structural change. We then classify regions into types R=$\{$R1, R2, R3$\}$ that indicate a region's tercile in the distribution of $\Delta_{LR} E_r^{RM}$. These region types enter our matching procedure, i.e. we directly match displaced workers and control individuals from the same tercile of long-run local RM-Biased Structural Change (RMBSC) distribution and use these region types to study effect heterogeneity in our event study models (see Section 4.1).

A.2.2 RM-Biased Structural Change Preceding Displacement Base Years

In addition to long-run structural change at the local level, we compute a time-varying measure of RMBSC for each labor market region and potential base year c which covers the time span 1990 to 2010. In order to merge region and individual level data, we expand the regional employment data to a region-occupation-year panel and fill the gaps between decades by linear interpolation.

Next, we compute the weighted growth rate of RM occupations for each local labor market and a ten year window preceding each potential base year c between 1990 and 2010:

$$grRM_r^{c-10} = \frac{E_{r,c-10}^{RM}}{E_{r,c-10}} \cdot \frac{E_{r,c}^{RM} - E_{r,c-10}^{RM}}{E_{r,c-10}^{RM}} \, .$$

In our propensity score estimation, this measure accounts for differences with respect to structural change within region types R1 to R3 in the decade before the displacement event. Moreover, we explicitly use this base year c-specific measure in our matched DiD analyses to analyze how the effects of displacement vary along the distribution of regional RMBSC (see variable $grRM_r^{c-10}$ in equation (4) in Section 3.4.2).

B Supplementary Material

B.1 Supplementary Tables

Table B.1: Characteristics of Declining and Growing Occupations

Rank	Occupation	(1) Category	(2) Wage 1990	(3) Share 1990 [pct]	(4) wGR 1990-2010 [pct]	(5) Task Intensity 1986 / 2012 NRA [pct]	(6) NRI [pct]	(7) RC [pct]	(8) RM [pct]	(9) NRM [pct]
Growing Occupations:										
52	48 Health Occ.s without Approbation	Serv.	Mid	4.17	1.73	14.0 / 27.3	28.2 / 25.6	16.2 / 13.2	4.9 / 6.1	33.4 / 20.5
51	39 Commercial Office Occ.s	Serv.	Mid	11.90	1.53	26.7 / 42.9	23.9 / 27.9	42.5 / 14.6	4.8 / 3.7	1.7 / 2.2
50	20 Laborers	Manuf.	Low	1.04	1.45	2.1 / 21.5	2.3 / 17.3	4.4 / 12.2	74.0 / 10.6	14.2 / 30.0
49	38 IT Core Occ.s	Techn.	High	1.15	1.27	55.3 / 45.5	17.5 / 25.0	12.3 / 13.0	11.9 / 6.4	2.3 / 5.3
48	21 Engineers	Techn.	High	2.39	0.73	41.9 / 37.3	23.5 / 33.4	19.7 / 15.3	5.9 / 3.8	3.9 / 2.9
47	35 Management, Auditing and Business Consulting	Serv.	High	2.20	0.50	31.9 / 34.4	42.8 / 41.9	17.9 / 9.0	4.0 / 2.9	2.5 / 2.0
46	47 Health Occ.s with Approbation	Serv.	High	0.63	0.37	23.4 / 30.9	26.0 / 34.2	13.7 / 7.3	4.5 / 4.5	27.5 / 13.3
45	50 Teachers	Serv.	High	0.69	0.32	19.0 / 39.1	63.9 / 37.2	12.3 / 9.4	1.6 / 1.8	1.9 / 5.9
44	49 Social Occ.s	Serv.	Low	0.50	0.31	11.1 / 26.9	65.9 / 34.2	7.6 / 12.8	0.9 / 0.9	14.0 / 17.2
43	28 Wholesale/Retail Dealers	Serv.	Mid	1.93	0.25	13.7 / 32.8	48.9 / 47.0	26.0 / 3.4	8.0 / 5.5	2.7 / 3.9
42	31 Advertising Specialists	Serv.	High	0.18	0.25	29.9 / 35.5	45.7 / 39.8	17.1 / 16.0	4.0 / 2.4	1.8 / 1.3
41	53 Hotel, Restaurant and Housekeeping Occ.s	Serv.	Low	1.41	0.20	5.7 / 17.7	32.0 / 36.7	10.4 / 10.0	7.0 / 7.2	44.4 / 20.7
40	16 Cooks	Serv.	Low	1.19	0.17	4.6 / 12.4	14.1 / 22.4	7.0 / 12.3	36.8 / 19.1	35.1 / 27.2
39	36 Public Administration Occ.s	Serv.	High	0.16	0.16	42.3 / 41.1	31.2 / 32.9	22.1 / 11.8	2.3 / 0.8	1.5 / 1.2
38	22 Chemists, Phyisicists, Natural Scientists	Techn.	High	0.38	0.14	48.1 / 35.3	22.0 / 27.0	13.7 / 23.8	8.0 / 4.7	2.9 / 2.2
37	41 Personal Protection and Guarding	Serv.	Low	0.46	0.13	15.7 / 23.0	21.2 / 19.6	4.0 / 23.6	6.1 / 7.2	52.3 / 18.3
36	44 Legal Occ.s	Serv.	High	0.06	0.11	50.4 / 38.1	30.0 / 41.7	15.1 / 4.7	1.2 / 1.2	3.2 / 1.4
35	51 Publication, Library, Translation and related Scientific Occ.s	Serv.	High	0.38	0.10	29.7 / 39.5	48.9 / 31.2	18.5 / 19.8	2.0 / 2.8	0.9 / 1.3
34	45 Artists and Musicians	Serv.	Mid	0.21	0.05	9.1 / 32.7	55.0 / 38.8	9.8 / 5.3	16.1 / 6.6	6.6 / 8.8
33	32 Traffic Occ.s	Serv.	Low	3.52	0.04	4.1 / 15.7	10.2 / 14.5	6.3 / 8.3	62.9 / 34.4	15.5 / 20.1
32	42 Janitors	Serv.	Mid	0.40	0.03	3.3 / 22.5	8.8 / 15.7	18.0 / 10.0	16.6 / 16.1	44.1 / 32.1
31	43 Security	Serv.	High	0.06	0.01	42.1 / 34.3	18.4 / 27.8	16.0 / 9.4	5.3 / 4.3	16.7 / 11.8
30	25 Surveyors	Techn.	Mid	0.07	0.00	48.3 / 23.1	11.0 / 23.4	24.8 / 42.2	6.6 / 3.5	2.9 / 0.6
Sum/Average†		-	-	35.07	9.85	21.4 / 33.0	26.5 / 28.6	23.7 / 12.5	14.8 / 7.6	12.1 / 10.5
Declining Occupations:										
29	46 Designers, Fotographers, Promoters	Serv.	Mid	0.30	0.00	31.4 / 38.6	29.7 / 38.4	16.0 / 11.5	12.0 / 6.5	6.6 / 1.5
28	33 Aviation and Seafaring Occ.s	Serv.	High	0.20	-0.04	11.9 / 18.2	17.3 / 18.6	12.8 / 36.3	30.8 / 13.6	21.8 / 5.1
27	40 Office assistants, telephonists	Serv.	Mid	0.94	-0.06	28.1 / 50.0	12.9 / 17.6	35.4 / 11.5	18.8 / 10.7	4.1 / 2.8
26	10 Precision Mechanics	Manuf.	Mid	0.70	-0.07	10.4 / 19.9	11.7 / 22.0	19.0 / 20.5	27.1 / 19.6	19.7 / 14.4
25	29 Banking/Insurance Professionals	Serv.	High	3.52	-0.09	18.4 / 28.6	46.3 / 36.8	31.5 / 26.3	3.2 / 1.1	0.6 / 1.2
24	34 Packager, Warehouse and Transport Workers	Serv.	Low	4.13	-0.09	5.9 / 22.2	11.1 / 17.5	12.3 / 9.3	60.6 / 32.4	8.2 / 10.5
23	52 Personal and Body Care Occ.s	Serv.	Low	0.63	-0.11	6.1 / 21.9	42.0 / 40.6	7.2 / 3.8	7.0 / 5.3	37.0 / 18.8
22	26 Technical Specialists	Techn.	High	0.62	-0.11	35.4 / 43.9	9.3 / 8.8	25.6 / 20.2	12.8 / 14.7	3.9 / 10.2
21	14 Bakers, Confectioners, Candy Prod.	Manuf.	Low	0.59	-0.12	6.4 / 8.0	19.4 / 19.3	7.9 / 14.8	60.1 / 27.9	3.5 / 24.6
20	30 Other Mercantile Occ.s (excl. Retail/Wholesale/Banking)	Serv.	Mid	2.01	-0.12	14.2 / 27.2	50.6 / 40.4	22.1 / 16.1	9.2 / 6.4	2.8 / 4.2
19	17 Beverage, Luxury Foods and Other Food Prod.	Manuf.	Low	0.45	-0.15	10.9 / 14.5	13.3 / 14.1	12.8 / 10.9	46.9 / 28.5	11.5 / 23.8
18	24 Technical Drawers	Techn.	Mid	0.68	-0.16	61.1 / 60.1	5.3 / 13.2	24.2 / 19.1	3.4 / 3.2	0.7 / 1.5
17	15 Butchers	Manuf.	Low	0.54	-0.16	8.0 / 15.1	21.4 / 18.9	9.2 / 26.3	52.3 / 24.5	5.3 / 10.4
16	54 Cleaning and Disposal	Serv.	Low	2.56	-0.21	4.5 / 14.4	6.6 / 17.2	3.8 / 12.8	19.1 / 11.4	64.2 / 36.6
15	03 Stone, Constr. Material, Ceramics/Glas Prod. and Processing	Manuf.	Low	0.46	-0.26	5.4 / 11.3	5.8 / 11.1	13.8 / 14.7	48.8 / 42.5	16.7 / 15.3
14	27 Salespersons (Retail)	Serv.	Low	5.88	-0.29	4.1 / 19.5	65.2 / 44.5	12.3 / 7.9	14.4 / 8.8	3.1 / 11.9
13	37 Finance, Accounting, Bookkeeping	Serv.	High	1.13	-0.31	31.5 / 41.0	14.5 / 22.1	51.8 / 25.6	2.1 / 0.9	0.1 / 1.6
12	23 Technicians	Techn.	High	4.06	-0.32	28.6 / 26.9	18.5 / 21.9	20.8 / 30.7	13.6 / 7.9	9.7 / 6.9
11	09 Vehicle and Aircraft Constr. and Maintenance	Manuf.	Low	1.89	-0.36	4.4 / 21.9	10.8 / 16.8	19.3 / 14.7	20.3 / 17.0	32.4 / 24.9
10	12 Spinners, Textile Prod. and Refinement	Manuf.	Low	0.54	-0.40	2.0 / 25.2	7.4 / 8.7	4.4 / 19.4	68.1 / 23.5	15.1 / 18.1
9	11 Electrics Occ.s	Manuf.	Mid	3.20	-0.65	7.0 / 24.1	7.8 / 16.4	20.8 / 21.2	25.2 / 12.2	24.9 / 21.0
8	05 Paper Prod. and Processing, Printing	Manuf.	Mid	1.63	-0.74	12.6 / 25.4	10.8 / 17.2	14.6 / 12.5	48.6 / 25.5	8.6 / 12.6
7	19 Goods inspection, Preparation for Shipment	Manuf.	Mid	2.26	-0.74	12.0 / 35.0	4.8 / 14.9	14.1 / 23.9	57.0 / 12.9	3.8 / 7.0
6	08 Industrial Mechanics and Tool Makers	Manuf.	Mid	4.09	-0.94	5.4 / 18.3	5.5 / 12.7	19.4 / 15.2	36.2 / 27.5	19.3 / 19.9
5	04 Chemistry and Plastics Prod.	Manuf.	Mid	2.88	-0.96	10.8 / 22.8	4.7 / 11.6	10.8 / 15.8	55.4 / 29.8	11.6 / 14.2
4	13 Textile Processing and Leather Prod.	Manuf.	Low	1.22	-0.97	4.7 / 12.8	9.7 / 22.0	3.2 / 12.7	58.3 / 34.0	23.3 / 13.2
3	07 Metal, Plant and Sheet Metal Constr., Installation and Assembly	Manuf.	Mid	6.44	-1.74	3.7 / 13.1	5.7 / 15.8	17.5 / 19.4	34.0 / 24.5	25.9 / 21.5
2	06 Metal Prod. and Processing	Manuf.	Mid	4.08	-1.82	3.3 / 18.5	3.3 / 10.0	15.0 / 18.3	51.0 / 32.6	15.3 / 15.4
1	18 Constr. and Wood/Plastics Processing	Constr.	Low	7.31	-2.87	3.8 / 13.3	7.9 / 23.0	15.8 / 15.1	37.0 / 19.2	24.1 / 21.9
Sum/Average†		-	-	64.93	-14.86	9.6 / 22.2	17.1 / 22.8	16.9 / 17.0	32.5 / 17.1	16.4 / 14.6

Notes: Share = employment share, wGR = employment growth rate weighted by 1990 employment share, Manuf. = Manufacturing, Constr. = Construction, Techn. = Technical, Serv. = Service. NRA = Non-routine analytical, NRI = non-routine interactive, RC = routine cognitive, RM = routine manual, NRM = non-routine manual. Underlined figures mark the occupations' main task in 1986/2012, i.e. the task category with the largest intensity. Mean task intensities are weighted by occupational employment. Occupation categories are based on KldB1988 1-digit codes (*Berufsbereiche*). The categorization of wages is based on the terciles of the West German distribution of occupational mean wages in 1990, as provided by Dauth (2014). † This line provides the column sum for the 1990 employment share and weighted employment growth rate of 1990-2010, as well as the column average for the task intensities in the GQCS waves of 1986/2012.

Source: BeH, GQCS.

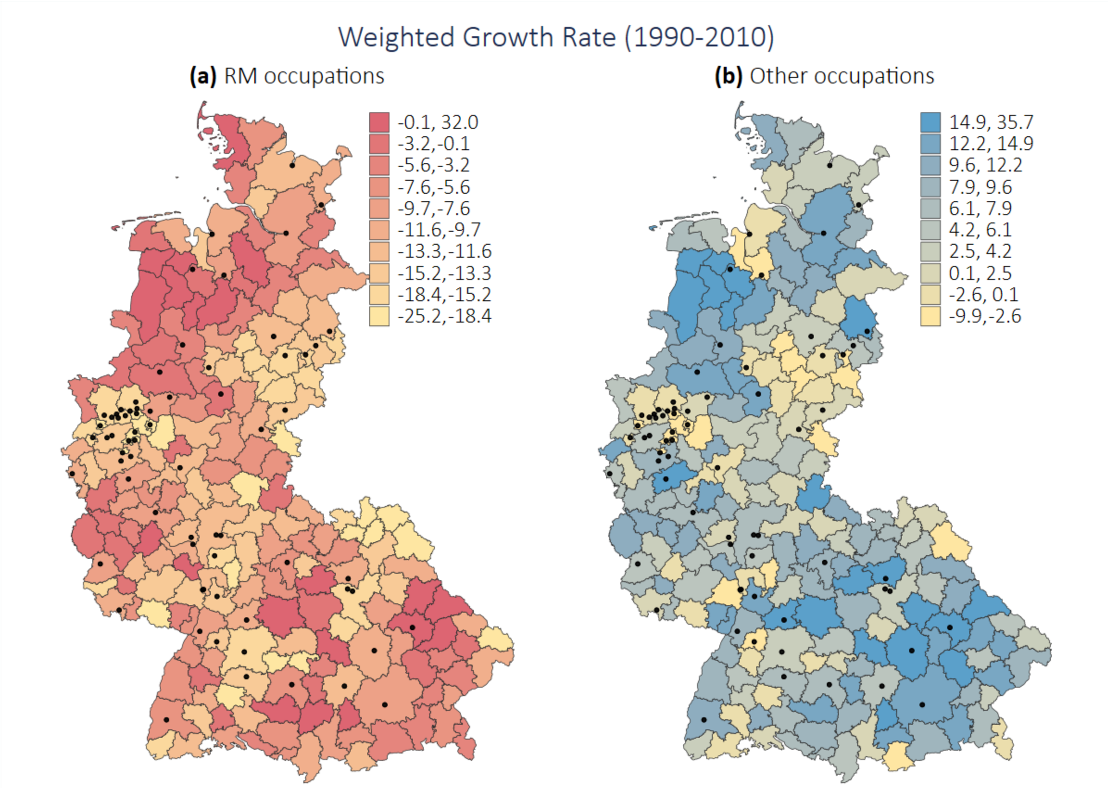
Table B.2: Base Year Characteristics of Displaced RM Workers by Region Type

	(1)	(2)	(3)	(4)		(5)	
	Region Type			Difference			
	R1	R2	R3	R1 - R2		R1 - R3	
PS matching variables:							
Worker:							
Log real wage in $c-1$	4.51	4.51	4.46	-0.01		0.05	**
Log real wage in $c-2$	4.52	4.52	4.48	-0.01		0.04	
Female	0.14	0.13	0.15	0.01		-0.01	
Age	38.06	37.68	37.81	0.38	**	0.25	
Low-skilled	0.24	0.16	0.14	0.07	***	0.09	***
Medium-skilled	0.75	0.82	0.84	-0.07	***	-0.10	***
High-skilled	0.01	0.01	0.01	0.00		0.00	
Experience	15.89	15.72	16.50	0.17		-0.61	**
Establishment tenure	10.41	10.38	10.38	0.04		0.04	
Displacement year	1998.89	1998.45	2000.70	0.44		-1.81	**
Occupation:							
Production, crafts	0.83	0.77	0.83	0.06	***	0.00	
Service occupations	0.17	0.23	0.17	-0.06	***	0.00	
Establishment:							
10-49 employees	0.29	0.27	0.30	0.02		-0.01	
50-99 employees	0.19	0.17	0.23	0.02		-0.04	
100-249 employees	0.26	0.24	0.25	0.02		0.01	
> 249 employees	0.26	0.32	0.22	-0.06		0.04	
Establishment age	40.27	39.31	38.93	0.97	***	1.34	***
Median wage	78.93	78.37	77.64	0.55		1.29	
Industry:							
Raw Materials and Goods	0.10	0.11	0.09	-0.01		0.01	
Metal, Machinery, Automotive	0.28	0.23	0.24	0.05		0.03	
Consumption Goods	0.19	0.16	0.26	0.04		-0.07	*
Construction	0.18	0.17	0.15	0.01		0.03	
Wholesale, Retail	0.11	0.11	0.10	0.00		0.01	
Business Services, Transport	0.09	0.16	0.11	-0.07	***	-0.02	
Priv. Services, Educ., Social Sector	0.05	0.07	0.04	-0.02		0.01	
Region:							
Active population (1k) †	441.51	375.76	130.57	65.75	**	310.94	***
Population density (pop/km^2) †	834.56	425.45	169.68	409.11	***	664.88	***
UE rate ‡	0.08	0.09	0.07	-0.01	***	0.02	***
wGR RM occ. $[c, c-10]$ (percent) #	-6.89	-4.17	0.58	-2.72	***	-7.47	***
Not in PS matching:							
AKM worker FE ¶	4.26	4.27	4.29	-0.01		-0.03	*
AKM establishment FE §	0.20	0.19	0.16	0.01		0.04	**
Observations	15,036	15,248	7,586				

Notes: PS = Propensity Score; UE = Unemployment; wGR = Growth rate weighted by initial employment share in 1990; FE = Fixed Effect; RM occ. = Occupations with mainly routine manual tasks. The table compares the mean base year c characteristics of displaced workers in different region types (as defined in Section 2.3). Establishment characteristics are measured in $c-1$. AKM FE in the most recent time period available before year c. For a description of AKM fixed effects see Section 3.4.2 and Bellmann et al. (2020). ***/**/* mark significant differences at the 1/5/10% significance level. # The weighted growth rate of RM occupations differs between region types by definition. ¶ Lower observation numbers because of missing values: 15,180 in R1; 14,248 in R2; 8,052 in R3. § Lower observation numbers because of missing values: R1: 15,504; R2: 14,539; R3: 8,262.
Data: BHP, IEB, BeH, GQCS, † The European Regional Database (EUI, 2021), ‡ Statistical Office of the Federal Employment Agency.

B.2 Supplementary Figures

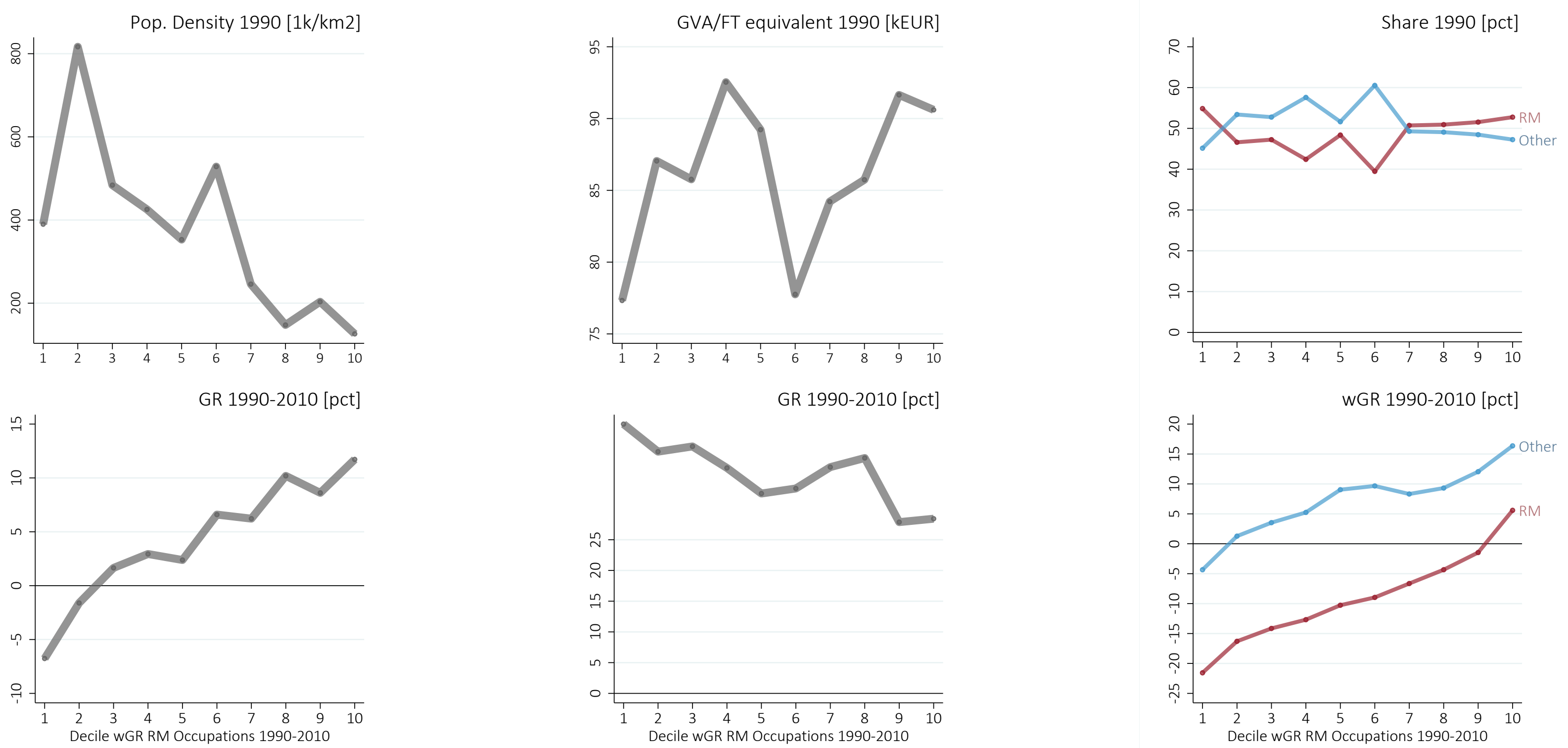
Figure B.1: Spatial Distribution of Task-Biased Structural Change across West German Local Labor Market Regions, 1990-2010



Notes: The maps plot the weighted regional growth in RM (a) and other (b) occupations between 1990 and 2010. Growth rates are weighted with the initial employment share in 1990 (see the formula for $\Delta_{LR} E_r^{RM}$ in Appendix A.2.1). The legend scale represents the deciles of the growth rates. Compare also to the spatial distribution of the weighted growth rate of RM and Other occupations in Figure B.1. Boundaries mark West German Local Labor Market Regions as defined by BBSR (2021). Black dots mark cities with 100,000 inhabitants or more.
Data: BeH, GQCS.

Figure B.2: Initial Region Characteristics and Change over Time

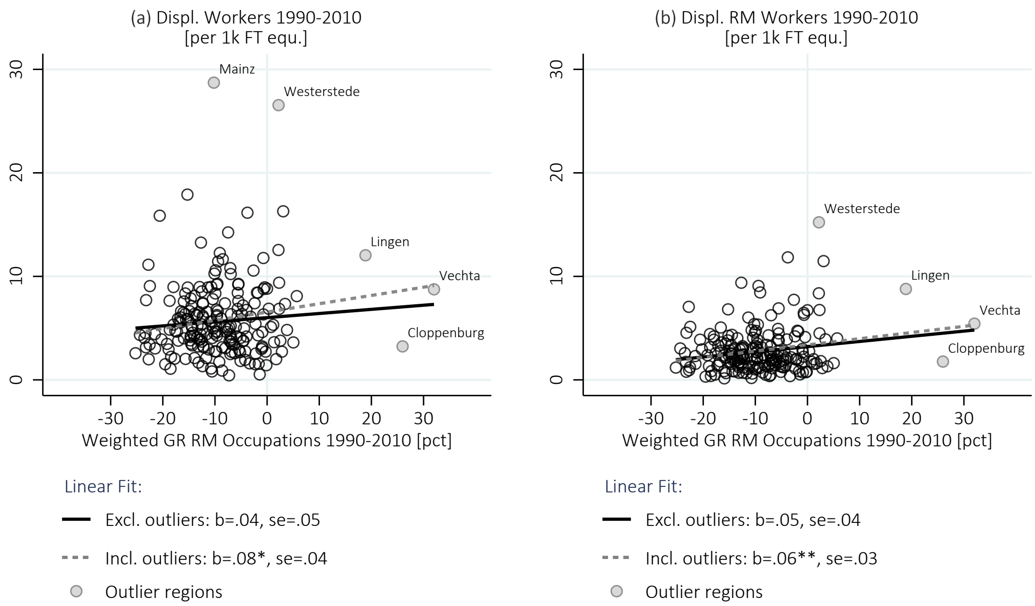
(a) Population Density (b) Labor Productivity (c) RM/Other Occupations



Notes: GR = Growth rate, wGR = Growth rate weighted by initial employment share, GVA = Gross value added, FTequ = Full-time equivalent.
Residual category "Other industries" omitted from the graph for ease of display. The x-axis refers to the deciles of the regional distribution of weighted growth rates in RM occupations between 1990 and 2010 (i.e. the ‘red bars’ in Figure 3, see also the formula for $\Delta_{LR} E_r^{RM}$ in Appendix A.2.1). Growth rates are weighted with the initial employment share in 1990. The growth rates of RM/Other occupations within these deciles plotted in the lower panel are computed in the same way. For population density and labor productivity growth rates are unweighted. Region definitions (and thus a region’s area) are time-invariant, such that increases in population density imply absolute population growth.

Data: European Regional Database (EUI, 2021), BeH, GQCS.

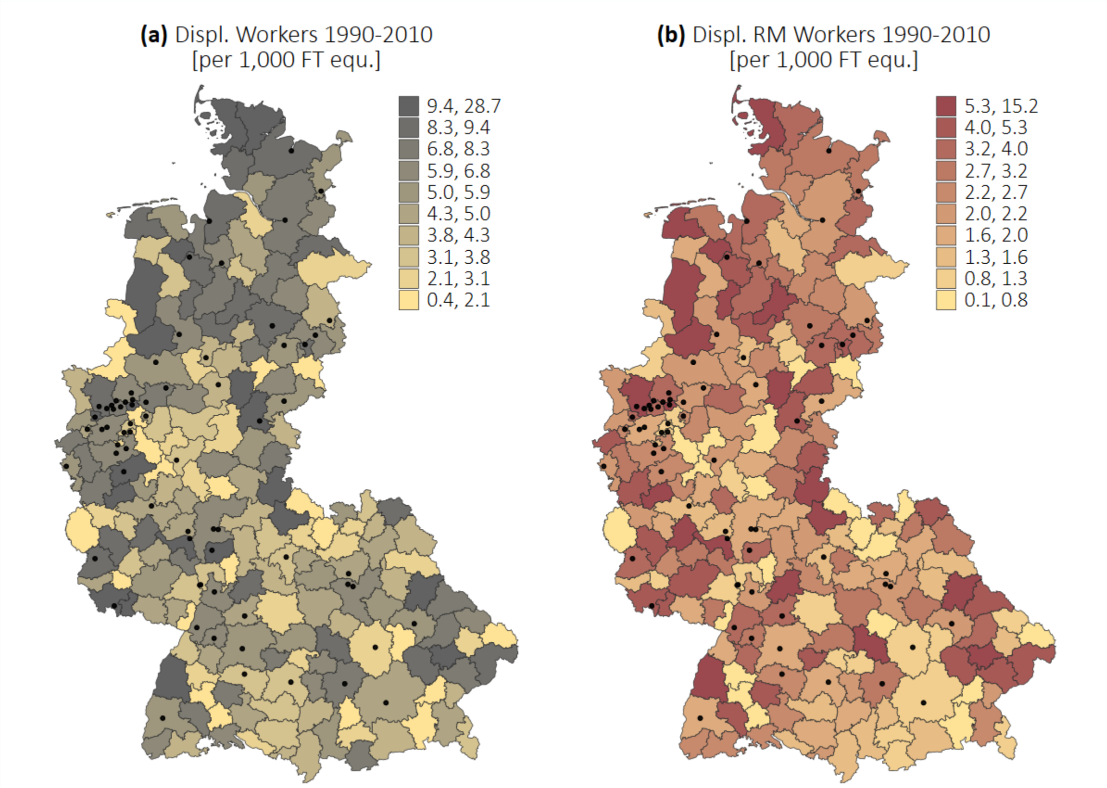
Figure B.3: Local Incidence RM-biased Structural Change and Displacement, 1990-2010



Notes: Displ. = Displaced, GR = Growth rate, equ. = equivalents. The vertical axis represents the number of workers displaced in events as defined in Section 3.1 over the number of full-time equivalent employment in 1990 (to scale for size differences of regions). The horizontal refers to the weighted regional growth in RM occupations between 1990 and 2010. Growth rates are weighted with the initial employment share in 1990 (see the formula for $\Delta_{LR} E_r^{RM}$ in Appendix A.2.1). The labelled dots represent outliers with an exceptionally high number of displaced workers or exceptionally strong GR of RM occupations. The dashed (solid) regression line includes (excludes) these outliers. The fitted lines are derived from linear regressions that control for initial regional characteristics in 1990 (population density, GVA, GVA per full-time equivalent employment, industry and establishment size structure of employment). The legend provides the coefficient estimate *b* and its standard error *se* from the linear model including/excluding the outlier regions. ***/**/* mark significant differences at the 1/5/10% significance level.

Data: BHP, IEB, BeH, GQCS.

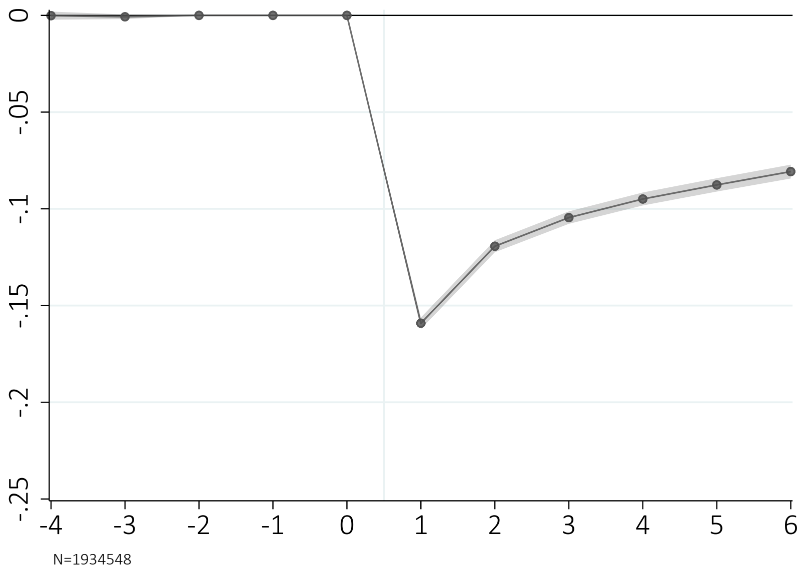
Figure B.4: Spatial Distribution of Routine Manual Biased Structural Change and Displacement across West German Local Labor Market Regions, 1990-2010



Notes: Disp. = Displaced, RM = Routine manual, FT equ. = FT equivalents. Map (a) plot the total number of displaced workers (between 1990 and 2010) per 1,000 FT equivalents (as of 1990), (b) plots the number of workers displaced from RM occupations (between 1990 and 2010) per 1,000 1,000 FT equivalents (as of 1990). Boundaries mark West German Local Labor Market Regions as defined by BBSR (2021). Black dots mark cities with 100,000 inhabitants or more.

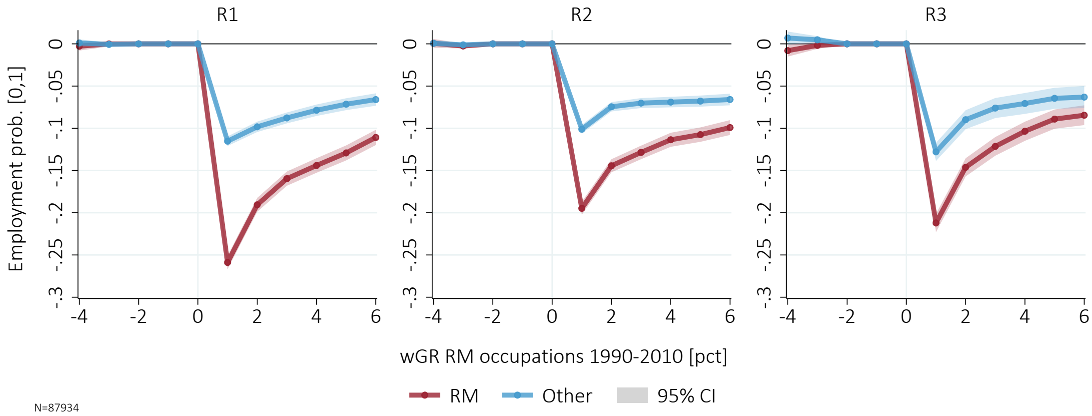
Data: IEB, BHP, BeH, GQCS.

Figure B.5: Average Employment Effects of Displacement
(All Workers, Event Study)



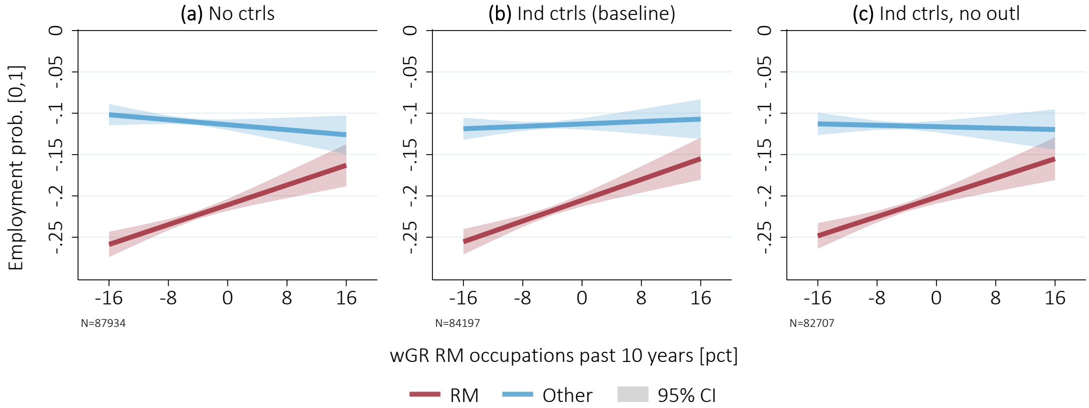
Notes: CI = Confidence interval. The plot shows coefficient estimates (dots) and 99% confidence intervals (shaded area) from the event study model (1) with additionally controlling for base year occupation (RM/Other) and region type (R1/R2/R3) based on the full sample of treated and control individuals. Standard errors are clustered at the individual level.
Data: BHP, IEB, BeH.

Figure B.6: Reproducing the Event Study Estimates by Region Type and Main-task with Matched DiD



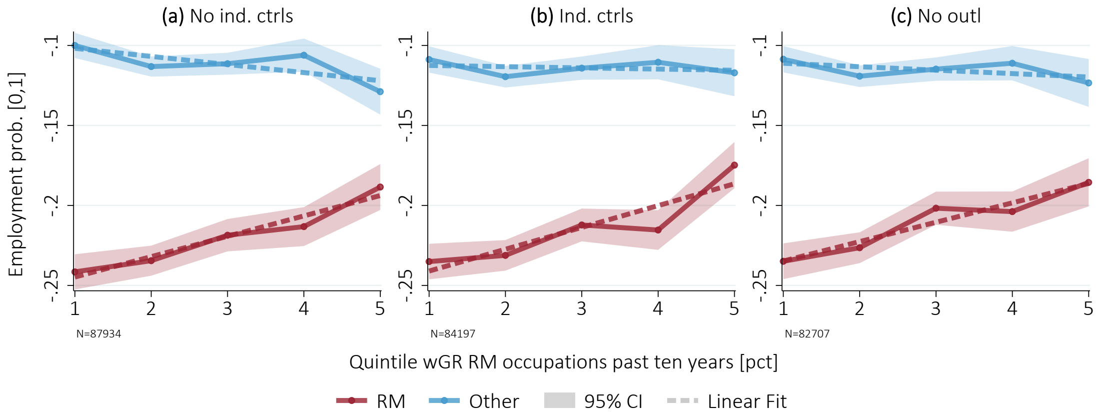
Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. The figures are based on the matched DiD specification in equation (equation 4 in Section 3.4.2), where $grRM^{c-10}$ is replaced by dummies for region types R1/R2/R3. The plot shows the estimated employment effect from a matched DiD model that was specified to reproduce the event study model in equation 1. For this purpose, the continuous measure of structural change $grRM_r^{c-10}$ was replaced by region type indicators for R1/R2/R3 and their interaction with the worker type indicator $I\left(RM_o^c\right)$ and omits further control variables as in the original event study model. Standard errors are clustered at the individual level.
Data: BHP, IEB, BeH, GQCS.

Figure B.7: Employment Effects along the Structural Change Distribution, Robustness Checks I
(matched DiD, various specifications, t=1)



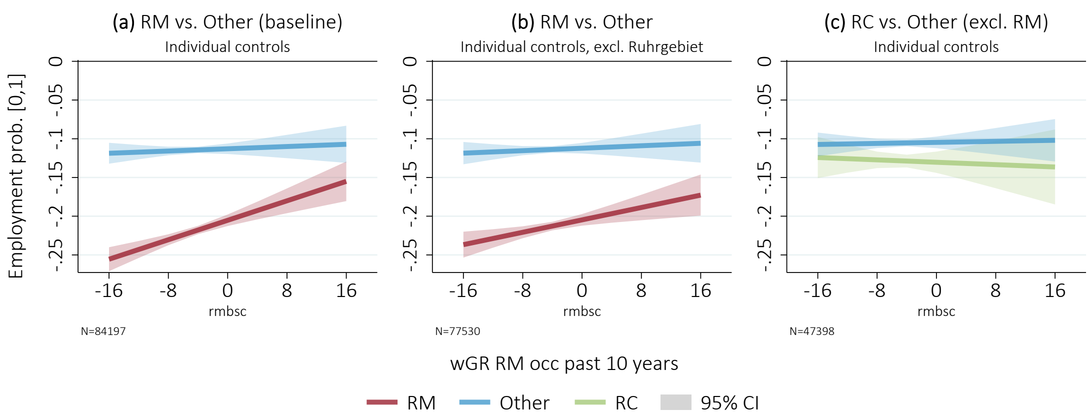
Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, Ind ctrls = individual control variables, Outl = outliers, CI = Confidence interval. Based on equation (4) in Section 3.4.2. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Outliers are defined as labor market regions with average treatment effects below the 1%-ile or above the 99%-ile.
Data: BHP, IEB, BeH, GQCS.

Figure B.8: Employment Effects by Quintiles of the Structural Change Distribution, Robustness Checks II
(matched DiD, various specifications, t=1)



Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, Ind ctrls = individual control variables, Outl = outliers, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where continuous $grRM$ is replaced with indicator variables for the quintiles of the $grRM$ distribution and their interaction with $I(RM)$. Quintiles are computed from the distribution of the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Outliers are defined as labor market regions with average treatment effects below the 1%-ile or above the 99%-ile.
Data: BHP, IEB, BeH, GQCS.

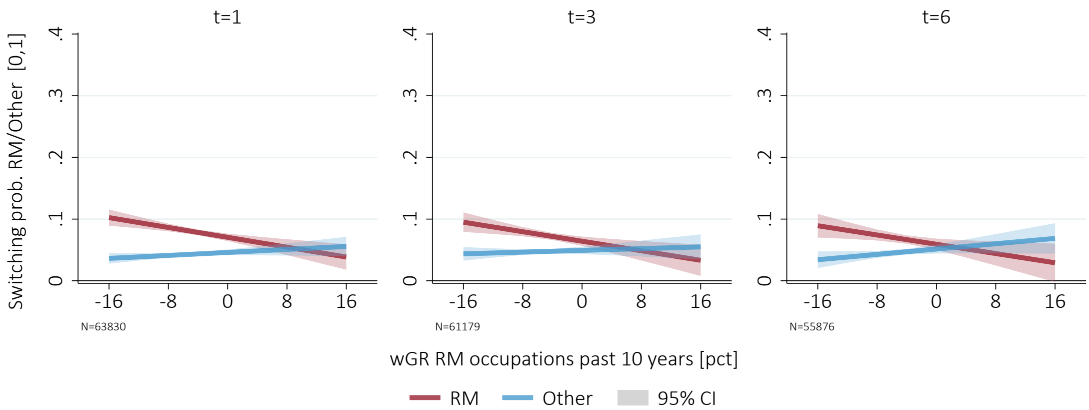
Figure B.9: Employment Effects along the Structural Change Distribution, Robustness Checks III
(matched DiD with ind. controls, various specifications, t=1)



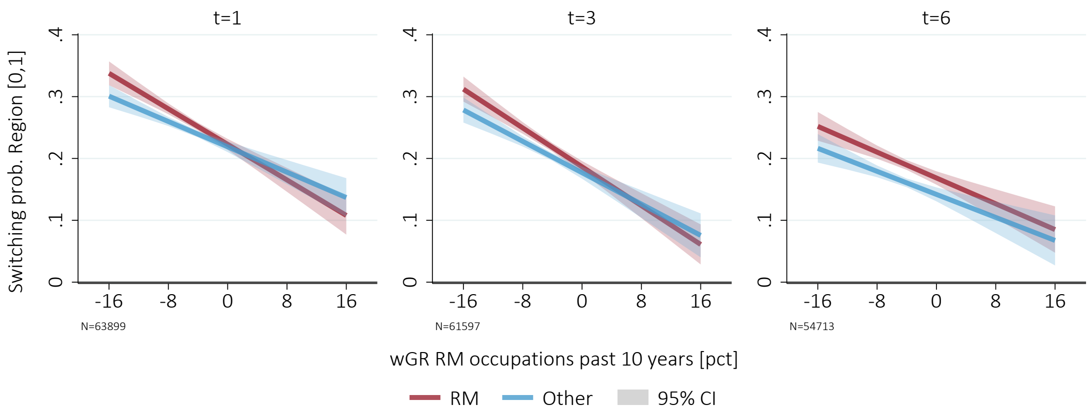
Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see Appendix A.2.2). Individual controls include gender, skill level, age, experience, tenure, AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (b) shows effects based on a sample that excludes labor market regions in the *Ruhrgebiet*, which is a densely populated area that underwent specific structural changes due to a gradual decline of the coal mining industry. Panel (c) shows the effects for routine cognitive (RC) occupations (as defined by their 1986 main task) and compares them to occupations with a task focus other than that (i.e. non-routine abstract, non-routine interactive or non-routine manual).
Data: BHP, IEB, BeH, GQCS.

Figure B.10: Effects on Occupational and Regional Mobility along the Structural Change Distribution
(matched DiD with ind. controls, cond. on re-employment, t=1,3,6)

(a) Switch RM/Other



(b) Switch Region

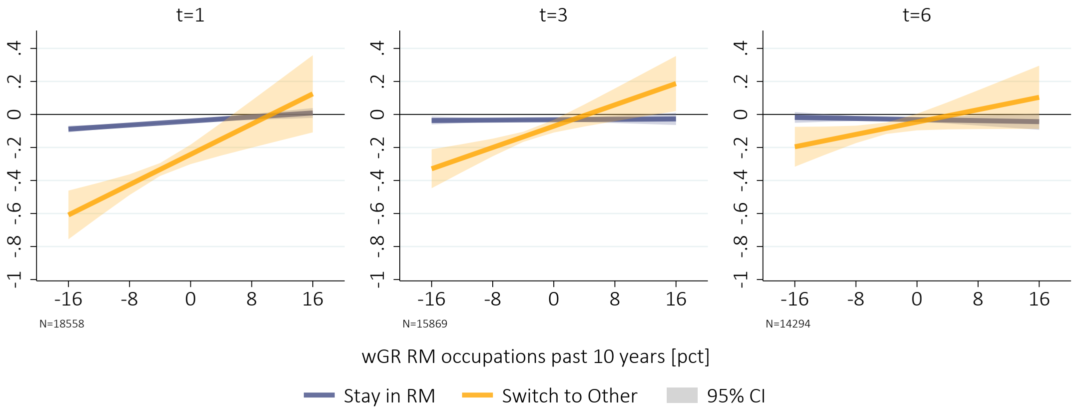


Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the probability of working in an occupation with a different main task as compared to the pre-displacement occupation (i.e. switching from RM to Other or *vice versa*). Panel (b) shows the probability of working in a local labor market other than the one in which displacement took place.

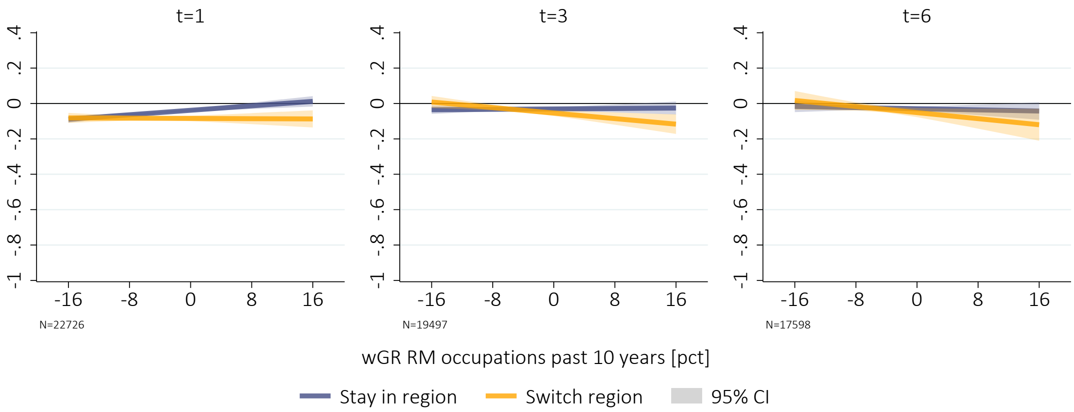
Data: BHP, IEB, BeH, GQCS.

Figure B.11: Wage Effects along the Structural Change Distribution by Mobility Choices
(RM workers, matched DiD with ind. controls, cond. on re-employment, t=1,3,6)

(a) RM Occupation Stayers vs. Switchers



(b) Region Stayers vs. Switchers

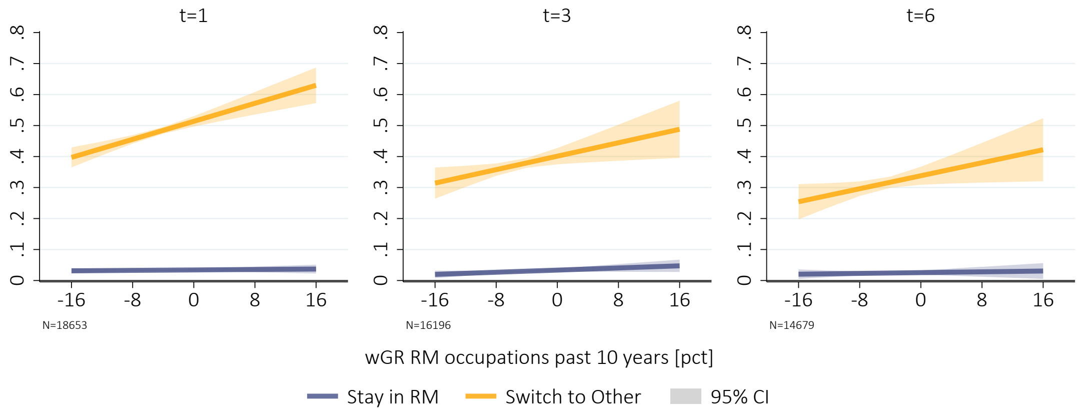


Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where $I(RM)$ is replaced by an indicator variable for switchers. The sample is restricted to RM workers. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the wage losses of workers displaced from an RM occupation by whether they are re-employed in an RM or other occupation. Panel (b) shows the wage losses of workers displaced from an RM occupation by whether they are re-employed in the same labor market region or a different region.

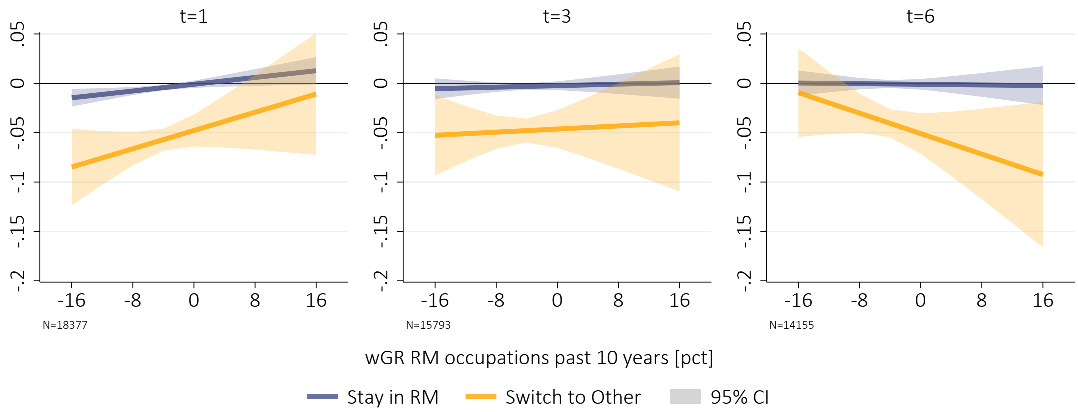
Data: BHP, IEB, BeH, GQCS.

Figure B.12: Effects on Task Distance and AKM Establishment Fixed Effects along the Structural Change Distribution, by occupational mobility
(RM workers, matched DiD with ind. controls, cond. on re-employment, t=1,3,6)

(a) Task Distance of RM Stayers vs. Switchers



(b) AKM Establishment FE of RM Stayers vs. Switchers

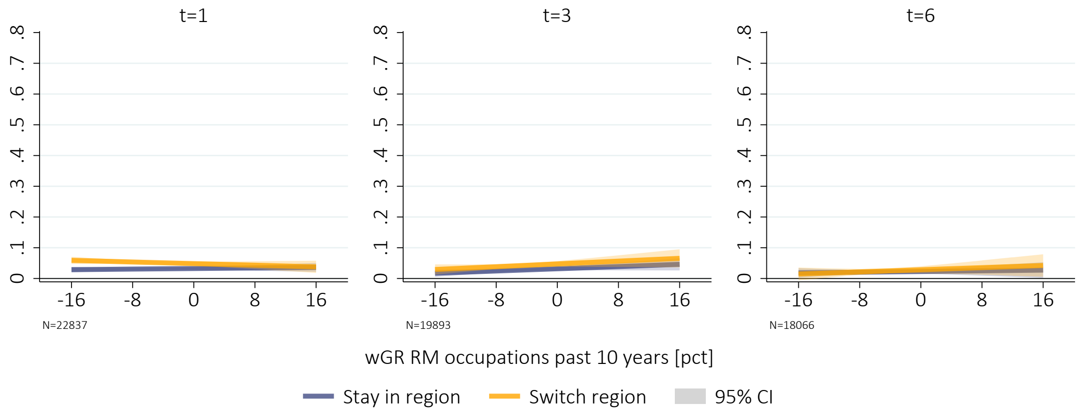


Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where $I(RM)$ is replaced by an indicator variable for switchers. The sample is restricted to RM workers. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the estimated task distance as a measure of occupational dissimilarity (see Section A.1.3 in the Appendix). Panel (b) shows the estimated losses of AKM establishment fixed effects as a measure of establishment wage premia (see Section 3.2).

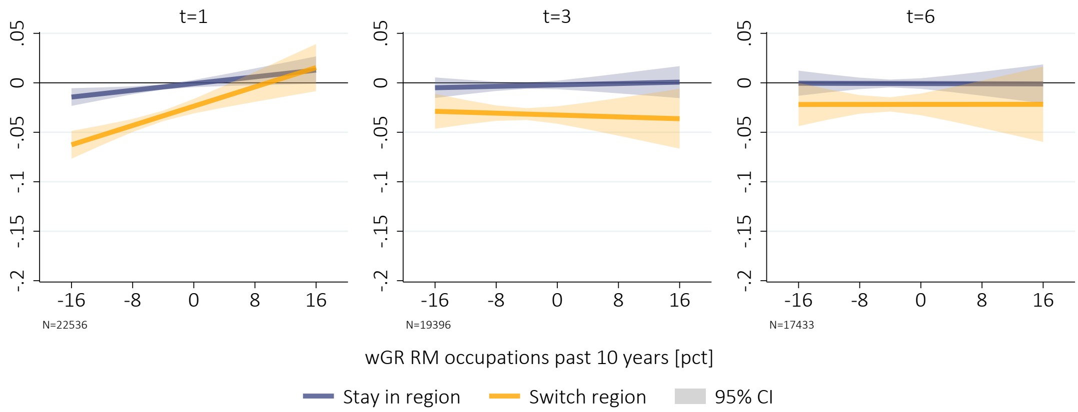
Data: BHP, IEB, BeH, GQCS.

Figure B.13: Effects on Task Distance and AKM Establishment Fixed Effects along the Structural Change Distribution, by regional mobility
(RM workers, matched DiD with ind. controls, cond. on re-employment, t=1,3,6)

(a) Task Distance of Region Stayers vs. Switchers



(b) AKM Establishment FE of Region Stayers vs. Switchers



Notes: RM = Workers in occupations with mainly routine manual tasks, Other = Workers in occupations with other main tasks, CI = Confidence interval. Based on equation (4) in Section 3.4.2, where $I(RM)$ is replaced by an indicator variable for switchers. The sample is restricted to RM workers. Estimated on the subsample of displaced workers who are re-employed. The x-axis refers to the weighted regional growth in RM occupations over the decade preceding the base year c. Growth rates are weighted with the initial employment share in $c-10$ (see the formula for $grRM_r^{c-10}$ in Appendix A.2.2). Individual control variables include gender, skill level, age, experience, tenure and AKM worker fixed effects. Standard errors are clustered at the individual level. Panel (a) shows the estimated task distance as a measure of occupational dissimilarity (see Section A.1.3 in the Appendix). Panel (b) shows the estimated losses of AKM establishment fixed effects as a measure of establishment wage premia (see Section 3.2).

Data: BHP, IEB, BeH, GQCS.

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