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Changes in Occupational Tasks and the Costs of Job Loss*

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Preliminary draft, comments and suggestions are welcome!
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Abstract

Over the past decades, the workplace tasks of many occupations have changed substantially. This paper studies how individual workers are affected if they lose their jobs after such a period of task restructuring. Using a novel task dataset and individual social security records from Germany, I find that workers who are laid off after occupational task restructuring have up to -4,400 EUR (90%) higher average annual earnings losses than workers whose prior occupation remained unchanged. This penalty is persistent and about half of it is explained by a lower re-employment probability of more exposed workers. Occupation switchers and older workers with a potentially more outdated skill set suffer the highest earnings losses. To establish causality, I use plant closures and a Triple-Differences strategy to account for unobserved differences between more or less exposed workers. The results suggest that many individuals are slow to acquire new skills when occupational tasks change and that a layoff severely disrupts this process.

Keywords: tasks, occupations, job loss, plant closures, earnings losses
JEL-Codes: J24, J62, J63

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1 Introduction

"There is nothing permanent except change." This 2,500 year old quote from ancient philosopher Heraclitus certainly applies to the history of human labor. In Heraclitus' days, the introduction of papyrus and ink revolutionized the work of Greek scribes by replacing the wax coated tablet (Roemer, 2007). As a more recent example, the spread of ATMs redefined the job of bank tellers (Bessen, 2015). Looking forward, artificial intelligence will alter the tasks of many more occupations (Brynjolfsson et al., 2018).

This constant change challenges human adaptability: workers must trade off the costs of investing in new skills against potential productivity and wage losses. During this process, learning-by-doing and employee training likely play an important role for skill acquisition (Battisti et al., 2022). Unexpected career breaks, in turn, may preclude workers from acquiring new skills on the job and therefore provide an important obstacle to successful adjustment. This has implications for individual welfare, but also for aggregate skill supply and the rate of technology diffusion and innovation (Acemoglu, 1998). And yet, there is little empirical evidence about how individuals adjust to occupational task restructuring.

In this paper, I study the role of job loss during this process: Do workers experience greater earnings losses if they are laid off after a period of task restructuring? If such a task change penalty exists, is it permanent? And how is it related to age and occupational mobility?

To answer these questions, I use a newly available dataset that traces the task composition of occupations over three and a half decades. Taking this information to administrative social security records allows me to follow individual worker careers. I focus on layoffs during plant closures, because such separations are arguably unexpected, involuntary and unrelated to individual skills. I then compare the earnings losses of workers who were exposed to different levels of task change before job displacement. However, these workers may also differ in characteristics other than task change itself. In order to neutralize this bias, I employ a Triple-Differences estimator that uses non-displaced workers with similar task changes as an additional control group.

My results provide three novel empirical facts about how changes in occupational tasks affect the costs of subsequent job loss: First, workers in the top-quartile of task change experience about 4,400 Euros – or 90% – higher average annual earnings losses than workers in the bottom quartile. About half of this penalty is explained by a lower re-employment rate of more exposed workers.

Second, workers who are exposed to strong changes in occupational tasks are almost twice as likely to switch occupations after displacement. These switchers have much

higher earnings losses than those who acquire a new job in the same occupation. This suggests that many occupation switchers did not update their skills to qualify for a new job in their prior occupation. Hence, they are forced to accept lower-paying job offers in a different occupation.

Third, the earnings losses of older workers depend much more on pre-displacement changes in tasks. This is mainly driven by a lower re-employment rate. If older workers return to employment, they are more than twice as likely to switch occupations.

I conclude that changes in occupational tasks have a strong impact on the individual costs of job loss. Not all workers adapt equally fast when the task structure of their occupation changes. Especially older workers face higher learning costs and lower expected returns (Picchio, 2021). When workers with an outdated skill set are suddenly discharged, they are forced to switch occupations and accept lower wages or leave the labor force altogether. My results suggest that studying exogenous displacement during periods of occupational task restructuring is informative about unobserved individual skill updating. Such unexpected separations likely preclude workers from gradual on-the-job learning – or a smooth phase-out of older workers with higher adjustment costs.

This highlights the importance of 'life-long' learning as an insurance against sudden career interruptions in a dynamically changing environment. In the future, digitization will rapidly alter the skill requirements of many jobs, while population aging increases the adjustment costs. Hence, there may be a case for welfare-improving policy interventions. Especially for older workers, public training subsidies may foster skill investments and prevent early labor market exits after an unexpected career break, e.g., in case of job loss or when nursing family members.

In what follows, section 2 will relate my paper to the previous literature and discuss its contributions. Sections 3 and 4 introduce the data and empirical strategy. Section 5 presents the results and section 6 concludes.

2 Related Literature and Contribution

Earnings Losses of Displaced Workers The focus on job loss relates my paper to a large literature about the costs of job displacement during plant closures or mass layoffs. This literature consistently documents that displaced workers suffer large and persistent earnings losses (see e.g., Jacobson et al., 1993; Huttunen et al., 2011; Schmieder et al., 2022 or Bertheau et al., 2022).[1] A few recent papers have started exploring the role of technological change and changes in the demand for certain tasks. These papers fix the

[1] Carrington and Fallick (2017) provide a review of the empirical literature and theoretical explanations.

task structure of occupations in a base period. They generally conclude that workers who are displaced from initially more routine-intensive occupations experience larger earnings losses (Goos et al., 2020; Blien et al., 2021; Yakymovych, 2022). Arntz et al. (2022) show that this routine task penalty strongly depends on regional labor market conditions.

As a novelty, Braxton and Taska (2021) explicitly study how *changes* in the computer-intensity of occupations during the 2010's affect the earnings losses of displaced workers in the US. They find that an increasing computer-intensity is associated to greater occupational mobility and larger earnings reductions after job loss. Braxton and Taska's main contribution is a theoretical model that rationalizes these stylized facts and informs the optimal policy response.

I complement their findings by providing causal evidence about how changes in occupational tasks and job loss interplay to shape worker outcomes. Using a novel German task dataset, I track changes in the overall task composition of occupations over 35 years, rather than focusing on a single skill in the past decade. Moreover, using administrative data allows me to follow individual workers over a decade around job displacement. To the best of my knowledge, this is the first paper to estimate the causal effect of within-occupation task change on the costs of job loss.

Task Change within Occupations My results therefore also complement an emerging literature that studies task restructuring within occupations. Atalay et al. (2020) use news paper job ads to show that most of the overall change the task structure of US employment between 1950 and 2000 occurred within narrowly defined job titles. Spitz-Oener (2006) suggests that computerization is an important driver of increasing complexity and skill intensity of occupations. Hershbein and Kahn (2018) provide evidence that the Great Recession accelerated this process. Cortes et al. (2021) show that also social skills have become more important and that this contributed to the self-selection of women into high-paying occupations. Ross (2017) and Bachmann et al. (2022) document that occupations with an increasing non-routine cognitive task intensity generate substantially higher wage growth over time. Fedorets (2018) shows that incumbents who stay in a changing occupation experience wage increases beyond a pure tenure effect.

I add to this literature, by providing causal evidence about the role of job loss during individual adjustment to changes in occupational tasks. For that, I rely on a novel survey dataset that traces occupational tasks since the early 1970's. In comparison to previous studies, this data is more frequent, more consistent and based on much larger samples, which enables me to study more disaggregated occupations. This is important, because even within groups of similar occupations, the magnitude and timing of task changes

varies substantially. Moreover, I use plant closures as an exogenous shock to account for the endogeneity between task shifts, unobserved skills and job separation.

Skill Demand or Supply Shocks My paper is also related to a small literature that studies shocks on the demand or supply of particular skills or occupations. Horton et al. (2020) show that after the sudden abolition of Adobe Flash, many programmers left the market for 'Flash jobs' such that wages remained almost unchanged. Janssen and Mohrenweiser (2018) show that even young incumbents suffered long-lasting earnings losses when the IT skill requirements of a particular manufacturing occupation were suddenly raised. The specificity of these shocks makes the identification strategy of these papers very credible, but it also limits the generalizability of their results. Here, my paper adds a more general view on task change and worker adjustment: I study gradual changes in the overall task composition of occupations and use job loss as a relatively common individual-level shock during adjustment.

In this regard, my paper is closely related to Edin et al. (2019). Using Swedish data, they show that incumbent workers in declining occupations only experience small cumulative earnings losses. I provide similar evidence for Germany, but I also show that involuntary separations substantially increase the adjustment costs for workers.

3 Measuring Individual Exposure to Changes in Occupational Tasks

In this section, I will briefly introduce the merits of my novel occupation-level task data and how I measure changes in the task composition of a worker's occupations before job loss.

3.1 Occupational Tasks Data

Data The *Occupational Panel on Tasks and Education* (OPTE) is a dataset with yearly occupational-level information on work tasks and education investments between 1973 and 2011.[2] It is derived from 16 waves of the German Microcensus, a representative cross-sectional survey of one percent of the German population (see Maier, 2021 for details). About every two or three years respondents were asked to choose their most important work place activity from a list of tasks. The OPTE aggregates this

[2]Occupational Panel on Tasks and Education (OPTE) for Western Germany from 1973 to 2011, Version 1.0.0, SowiDataNet|datorium of the GESIS Leibniz Institute for Social Sciences, DOI: https://doi.org/10.7802/2126.

information to the level of 179 consistent occupations with at least 30 observations in every wave.[3] Each occupation o is characterized by an 11-dimensional task vector $q_{ot} = (q_{1ot}, \ldots, q_{jot}, \ldots, q_{11ot})$, where the entries q_{jot} measure the share of workers with main task $j = 1, \ldots, 11$ in year t.

This focus on the main activity likely underestimates the complexity of occupations, especially when the majority of workers in an occupation carry out the same main task. For example, in every survey year more than 90% of 'Educators and child care professionals' report 'Teaching/educating/publishing' as their main task (see right panel in Figure B.1 in Appendix B). Despite the apparent importance of teaching, most educators likely carry out some other tasks as well. But since these are not considered the main activity, their importance in a typical educator's job is likely understated. Hence, I only detect task changes that are 'severe' enough to substantially shift the distribution of main tasks across workers. My estimates of the effect of task change on the costs of job loss are therefore a lower bound.

To ease exposition, I follow the literature and classify the 11 tasks into five groups (e.g., Autor et al., 2003, Spitz-Oener, 2006): routine manual tasks, non-routine manual tasks, cognitive tasks, and interactive tasks.[4] For some descriptive analyses, I group occupations into the broad categories 'Manufacturing', 'High-wage Services' and 'Low-/Mid-wage Services'. This grouping is based on KldB1988 1-digit codes and West German occupational mean wages in 1990 as kindly provided by Dauth (2014).

Restrictions The OPTE is restricted to persons living in Western Germany with at least one working hour per week. I drop agricultural and mining occupations (based on KldB1988 1-digit codes), because they are subject to very particular structural changes in Western Germany and only represent a small fraction of overall employment.[5] I use the task information from workers in social security employment to match the sample restrictions of the administrative data I use for individuals.

[3] Smaller occupations were combined with others that feature a similar task focus (Maier, 2021).

[4] Unlike earlier studies I do not distinguish routine and non-routine cognitive tasks. In practical terms, this means I do not classify 'typewriting/calculating' tasks as routine cognitive, because the actual routine intensity of these tasks may differ between occupations and change over time. Consistently, recent studies find no general reduction in returns to supposedly routine cognitive tasks in Western Germany (see e.g., Wang, 2020; Bachmann et al., 2022).

[5] Note that soldiers, people in community service or living in collective accommodation, as well as respondents with incomplete occupation or task information are also excluded (see Maier, 2021). I further exclude occupations that are usually carried out by public servants, such as judges, prison staff or firefighters (occupation codes 801, 802, 811, 813, 814 in the OPTE classification), because such jobs are not covered by my administrative data.

Comparison to other Task Data Sets There are only few data sets that allow observing occupational tasks over a long time horizon. Many previous studies have used the *'German Qualifications and Career Surveys'* (GQCS) to describe differences in tasks *between* occupations at a given point in time (see e.g., Antonczyk et al., 2009; Gathmann and Schönberg, 2010). However, some features of the GQCS complicate its use for studying changes *within* occupations over time: The inconsistency of the task definitions across the waves make harmonization a challenging and discretionary exercise and deriving a time-consistent set of occupations is restricted by the sample size (Rohrbach-Schmidt and Tiemann, 2013).

In comparison, the OPTE has several advantages: As the primary data source, the Microcensus features much more frequent and consistent task definitions, which facilitates a credible harmonization of tasks over time.[6] Moreover, its larger sample sizes (at least 179,000 as in 1973) allow for a much more disaggregated set of occupations. As I will show below, further aggregation would blur variation in the level and timing of task changes between similar occupations.

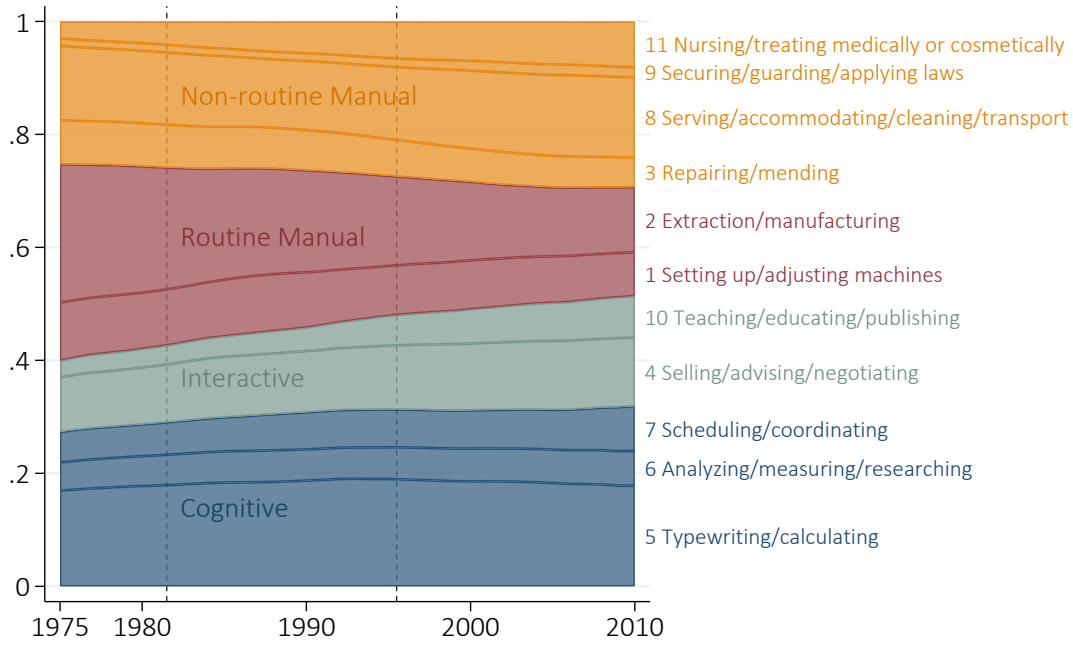
As an alternative, expert databases provide coherent and accurate task information for very disaggregated occupations. However, they are either only available for recent years (e.g., *Berufenet* for Germany) or were not updated regularly in the past (e.g., *Dictionary of Occupational Titles* for the US).

Apart from the job ads data of Atalay et al. (2020), the OPTE provides the only dataset for outside the US that allows for credibly measuring changes in the task composition of occupations over a long time horizon.

Descriptives Figure 1 shows how the worker shares of the 11 main tasks in the OPTE develop between 1975 and 2010. Overall, the prevalence of routine manual tasks are in decreases, while non-routine manual, interactive and cognitive tasks grow in importance. This is in line with previous research about the task-bias of technological change: automation replaces humans in more easily codifiable manual activities, while labor reallocates to complementary non-routine tasks (Autor et al., 2003, Acemoglu and Restrepo, 2018).

[6]The OPTE covers Microcensus waves 1973, 1976, 1978, 1980, 1982, 1985, 1987, 1989, 1991, 1993, 1995, 1996, 2000, 2004, 2007 and 2011. The gaps are filled by a +/- 3 years moving average. Over the entire survey period, the task items were modified twice (between 1980/82 and 1995/96). After harmonization across these intervals (see Maier, 2021 for details), there are no visible breaks in the task shares (see dashed vertical lines in Figure 1).

Figure 1: Main Task Composition of Employment in OPTE Data, 1975-2010



Notes: The figure shows how the share of workers (in employment subject to social security contributions) with a given main task evolves in Western Germany. The plot is based on population-level estimates of occupational employment provided in the OPTE data. The dashed vertical lines mark changes in the task definitions of the Microcensus, which is the underlying microdata source of the OPTE. There are no visible breaks around these years. The classification of tasks follows a usual approach in the literature (see e.g., Autor et al., 2003, Spitz-Oener, 2006): *Routine-manual* tasks subsume production activities that are deemed repetitive and well codifiable and thus susceptible to automation. *Non-routine* tasks are carried out in dynamic environments or involve exchange with humans, which is not easily taken over by machines. *Cognitive* and *interactive* tasks are considered complementary to technology, because technology supports these activities and makes workers more productive.

Data: OPTE.

3.2 Measuring Changes in the Task Composition of Occupations

Distance Measure To measure how the task content of an occupation o changes over time, I compute the Angular Separation between its task vectors q_o at two points in time t and t':

$$\mathcal{D}\left(o,t,t'\right) = 1 - \frac{\sum_{j=1}^{11} q_{jot} \times q_{jot'}}{\sqrt{\sum_{j=1}^{11} q_{jot}^2 \times \sum_j q_{jot'}^2}} \,. \tag{1}$$

This scalar measure describes how far an occupation has 'moved' from its initial task composition over a given time: It is zero if the task vector remains unchanged and takes the value of one if it turns into the orthogonal direction.[7] I will refer to $\mathcal{D}\left(o,t,t'\right)$ as the 'within-distance'.

In previous studies, similar measures have been used to describe the task distance between occupations at a given point in time (see e.g., Poletaev and Robinson, 2008, Gathmann and Schönberg, 2010 or Macaluso, 2019). To the best of my knowledge, Fedorets (2018) is the only other paper that uses a distance measure to study inter-temporal task changes.

Descriptives Figure 2 plots the within-distance of all occupations in the OPTE as compared to their initial composition in 1975. The colored lines highlight three example occupations, as well as the mean within-distance across all occupations in a given year t'. Many occupations only change moderately over the observation period, resulting in a relatively low mean (red line).[8] To take up the example from above, the within-distance of '864 Educators and Child Care Professionals' (orange line) stays close to zero, because almost all workers name '10 teaching/educating/publishing' as their main task in every year.

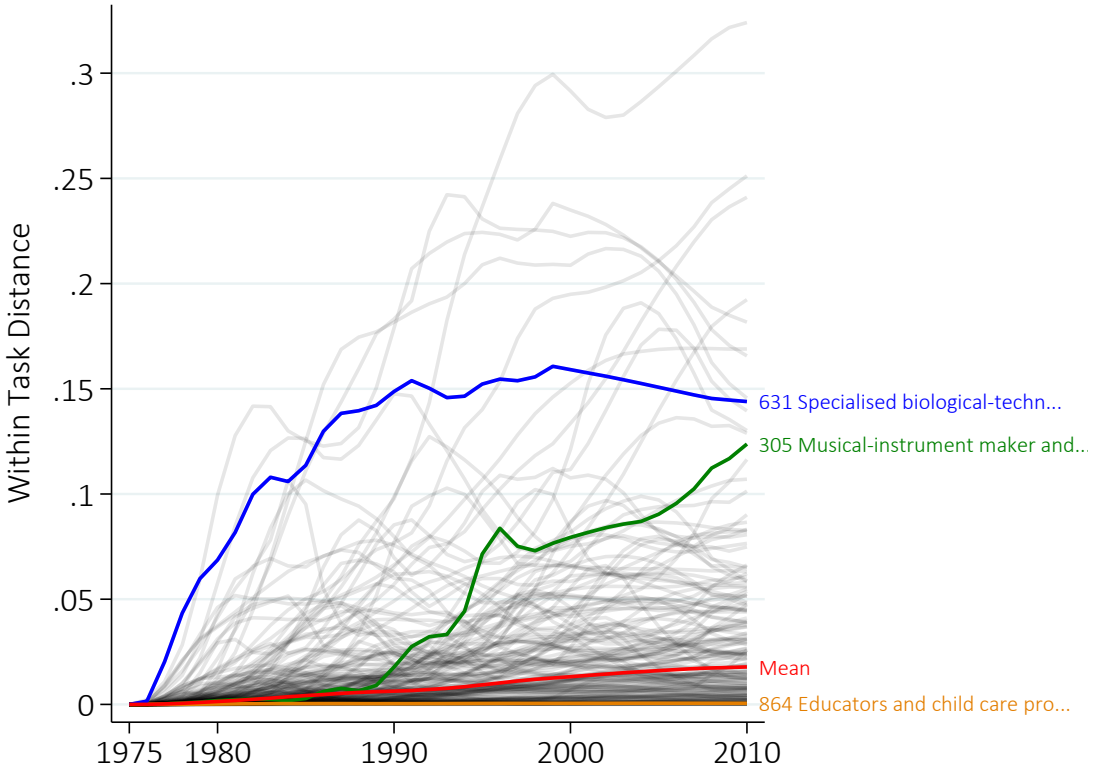
On the other hand, there is a lot of variation both across occupations and over time. For example, occupation 631 ('Specialised biological-technical workers', blue line) changes substantially between 1975 the 1990, but remains relatively constant thereafter. For occupation 305 ('Musical-instrument makers and other precision mechanics', green line) the time pattern is just the other way around.

Individual Task-Change Before Job Loss and Definition of Exposure Groups My goal is to estimate whether workers suffer higher earnings losses if they lose their jobs

[7] Figure B.1 in Appendix B illustrates how changes in the task composition translate into the distance measure for three example occupations.

[8] This general pattern also holds within manufacturing, high wage service occupation and low/mid wage service occupations (see Figure B.2 in Appendix B).

Figure 2: Changes in Occupational Task Compositions after 1975



Notes: The figure plots the within-distance of all occupations o in the OPTE between 1975 and all consecutive years t', $D\left(o, 1975, t'\right)$ (see equation (1)). The colored lines mark example occupations 305 'Musical-instrument makers and precision mechanics' (green), 631 'Specialised biological-technical workers' (blue), 864 'Educators and child care professionals' (orange) and the employment-weighted mean across all occupations in a given year (red). The mean uses the OPTE's population-level estimates of occupational employment as weights.

Data: OPTE.

during a period of task restructuring. For that purpose, I compute an individual-specific version of the within-distance in equation (1): $\mathcal{D}_i(o,e,c)$ measures how strongly the task composition of worker i's occupation o has changed between her year of entry e and the year before displacement c.◆

Explain idea of this measure; why between e and d? Theory part!

I then split the distribution of observed changes into quartiles and define three exposure groups: The first quartile represents the 'zero' exposure group (E_0), for whom occupational tasks hardly changed. The second and third quartile are combined into the 'low' exposure group (E_1). The fourth quartile is exposed to much larger levels of task change and is therefore classified as the 'high' exposure group (E_2).[9]

4 Estimating the Effect of Exposure to Task Change on the Individual Costs of Job Loss

4.1 Individual Employment Biographies and Plant Closures

Data As my individual-level data source I use the *Sample of Integrated Employment Biographies* (SIAB).[10] The SIAB is a two percent random sample of all individuals who ever contributed to the German social security system at least once since 1975. It originates from administrative process data of the German social security system. These records track spells of employment subject to social security contributions or benefit receipt with daily precision. Periods of self-employment, civil and military service or pension receipt are not covered. The data contains no information on working hours, but reports daily wages that are top-coded at the eligibility ceiling of the social security system. I closely follow the guidelines of Dauth and Eppelsheimer (2020) for preparing the data and imputing top-coded wages.

The weakly anonymised SIAB version also includes the ID of each worker's establishment. This allows me to merge employer characteristics such as the industry code, workforce size, median wages and estimated individual and establishment wage premia ('AKM' fixed effects).[11]

[9] Figure B.3 in Appendix B illustrates how the within-distance varies across and within the exposure groups. My results are very similar when using a tercile, quartile or decile grouping.

[10] Weakly anonymised Version of the Sample of Integrated Employment Biographies (SIAB) - Version 7519 v1. Research Data Center of the Federal Employment Agency (BA) at the Institute of Employment Research (IAB). DOI: 10.5164/IAB.SIAB7519.de.en.v1. For a description of the data see Frodermann et al. (2021).

[11] The estimates of the individual and establishment premia are based on the method pioneered by Abowd et al. (1999). They are estimated and directly provided by the IAB for linkage to the SIAB (for details see Bellmann et al., 2020). Note that I always use AKM effects that were estimated on a time window preceding the plant closures, so they are not contaminated by the displacement events themselves.

Identification of Plant Closures Job loss is not a random shock. Especially in presence of task changes, it might be related to unobserved individual skills and productivity, which by themselves affect worker outcomes. I therefore focus on layoffs during plant closures, because when the entire workforce of an establishment is discharged, job loss is reasonably independent an individuals relative productivity.

Plant closures can only be inferred from plant IDs that disappear from the administrative records between June 30 of two consecutive years (see Dauth and Eppelsheimer, 2020). This may also happen for other reasons like restructurings, mergers or ownership changes. In order to avoid falsely classifying such events as closures, I follow Hethey-Maier and Schmieder (2013) and exclude cases where more than 30 percent of the workforce jointly move to the same new establishment ID.

I label the last year before a plant disappears as an individual's baseyear c. For non-displaced workers, I mark all years in which they fulfill the same sample restrictions as applied on displaced workers and then pick a random year as the baseyear c.

Restrictions and Construction of Panel I apply a number of restrictions to displaced and non-displaced workers' baseyear characteristics. These restrictions are meant to assure that workers were employed in a stable job that would likely have persisted in absence of the closure: I only keep full-time workers in employment subject to social security contributions with at least two years of establishment and occupation tenure and restrict to workers between age 24 and 59 in the baseyear. Younger or older workers could either still be in education or become eligible to early retirement and therefore be less attached to the labor market. For the same reason, I exclude workers who were not observed in the administrative data at least once over the past four years, which could be due to inactivity. Moreover, I drop workers in agricultural and mining occupations, because they represent a very small share of the labor force that is concentrated in declining industries.[12] Individuals who were employed in Eastern Germany during the four years preceding the baseyear are removed to match the OPTE's restriction to Western Germany. In addition, I also drop workers from establishments with more than 500 employees, because these are very rare in the plant closure sample.[13]

I then construct an individual level panel dataset that covers $t = -4$ to $t = +6$ years around the individual baseyear c. This panel measures individual outcomes like the employment status or occupation changes on June 30 of each year. It also includes annual

[12] Like in the OPTE, I also exclude occupations that would usually be employed as public servants and should not be covered by the SIAB under normal circumstances (see footnote 5).

[13] As a robustness check, I keep these observations in the sample and explicitly match displaced and non-displaced workers in the same establishment size class (for details see section 5.5.)

aggregates like days employed and labor earnings, which cover the entire calendar year around June 30.

The resulting sample consists of 634,002 workers with about 15,000 to 40,000 individuals per baseyear. It includes 14,527 workers who were displaced in plant closures between 1979 and 2010, with roughly 200 to 700 individuals per baseyear.

4.2 Research Design and Estimation Specification

The basic idea of my empirical approach is to compare whether displaced workers with a greater exposure to task change, i.e., the high and low exposure groups E_1 and E_2, experience greater earnings losses than workers in the 'zero' exposure control group E_0.

Non-parallel Trends between Exposure Groups However, these exposure groups do not only differ in task change, but also in other characteristics that are related to earnings. Table 1 shows that a higher exposure is related to a lower share of females and a higher share of workers without a professional degree. Higher exposure workers are more likely employed in manufacturing occupations or industries and in larger establishments with higher median wages before job loss.

They are also older, have more labor market experience, job and occupation tenure and higher AKM fixed effects, daily wages and annual earnings. This is not surprising, because early career workers have simply spent less time in their occupation and are thus less likely to have experienced strong changes in tasks. At the same time, they typically experience steeper earnings growth as they build up specific human capital and obtain better job matches. This, however, also implies that workers in different exposure groups would likely have experienced different post-displacement earnings losses also in absence of any changes in occupational tasks.

A Difference-in-Differences (DD) comparison between the low or high exposure group and the zero exposure control group would therefore be contaminated by non-parallel trends bias (Callaway et al., 2021).

The Triple-Differences Estimator To account for this bias, I use non-displaced workers as an additional control group in a Triple-Differences (DDD) design. While these workers remain in a stable job in a given baseyear, they are still exposed to similar changes in tasks. Hence, also the non-parallel trends bias between the exposure groups should be similar as in the displaced worker sample. If this so-called Bias Stability assumption is fulfilled, taking the third difference between displaced and non-displaced

Table 1: Baseyear Characteristics of Displaced Workers By Exposure Group

	(1) Zero Exposure (E_0)	(2) Low Exposure (E_1)	(3) High Exposure (E_2)
Person:			
Female	.607	.368	.281
Age	39.262	41.781	43.678
German	.928	.908	.896
No professional training	.107	.144	.193
Vocational training	.852	.812	.741
Academic degree	.04	.045	.066
Experience	10.084	12.197	15.145
Job tenure	5.258	7.318	9.368
No of benefit receipts	1.321	1.279	1.174
No of n-spells	1.279	.993	.923
AKM person FE	4.181	4.284	4.347
Occupation:			
Within-distance since entry	0	.001	.013
Occupation tenure	7.226	10.462	13.816
Agriculture	.	.	.
Mining	.	.	.
Manufacturing	.112	.44	.649
Mid/High Wage Services (>=p25)	/	/	/
Low Wage Services (<p25)	.885	.512	.244
wGR baseyear occupation (1980-2010)	.006	.002	-.002
Industry:			
Agriculture/Fishing/Mining	/	/	/
Manufacturing/Energy/Construction	.292	.536	.664
Trade/Hospitality/Traffic/Communication	.551	.321	.21
Credit/Real estate/Public Sector	.092	.089	.083
Education/Health/Other services	.06	.046	.036
Establishment:			
Establishment size	43.567	53.511	64.064
<10	.284	.233	.19
10-50	.486	.467	.445
51-100	.122	.147	.169
101-250	.079	.116	.146
251-500	.029	.037	.051
>500	.	.	.
Median Daily Wage	62.781	65.647	72.609
AKM establishment FE	.064	.114	.145
Outcomes:			
Labor earnings per Year	28417.624	34124.762	37530.723
Employed	1	1	1
Days employed per year	362.015	360.193	360.906
Switch occupation	0	0	0
Log real daily wage	4.235	4.436	4.532
min(N)	1618	3702	2801
max(N)	2868	7033	4192

Notes: Columns (1) to (4) show the mean baseyear characteristics of displaced workers in the low (E_1, first quartile), medium (E_1, second and third quartile) and high (E_4, fourth quartile) exposure group. The sample size varies because of missing values in some characteristics. The AKM fixed effects are only available for about half of the sample. '.' marks cells that are empty by restriction, '/' mark cells that contain less than 20 observations and must be censored in accordance with data protection regulations of the IAB.
Data: SIAB, OPTE.

workers will cancel out the non-parallel trends bias between the exposure groups that contaminates the DD estimate (Olden and Møen, 2022).

Empirical Specification I estimate the following Triple-Differences specification to obtain the effect of a higher task change exposure on the costs of job loss:

$$
\begin{aligned}
Y_{ioect} = & \sum_{k=1}^{2} \beta_{1k} E_k \cdot Post_t \cdot Disp_{ic} \\
& + \sum_{k=1}^{2} \beta_{2k} E_k \cdot Post_t + \sum_{k=1}^{2} \beta_{3k} Disp_i \cdot E_k + \beta_4 Disp_{ic} \cdot Post_t \\
& + \sum_{k=1}^{2} \beta_{5k} E_k + \beta_6 Post_t + \beta_7 Disp_{ic} \\
& + X_{ic}\phi + \gamma(s,b,o,c) + \alpha + \epsilon_{ioect} \,,
\end{aligned}
\tag{2}
$$

where Y_{ioect} is the outcome of worker i, who enters occupation o in year e and is displaced in baseyear c. The main outcome of interest is labor earnings per year, but I will also consider days employed per year and the probability of re-employment and switching out of the baseyear occupation. $Disp_i$ marks displaced workers and $Post_t$ marks the post-displacement periods $t \geq 0$.

E_k is an indicator for workers in the low ($k = 1$) and high ($k = 2$) exposure groups. The parameters of interest are the β_{1k} coefficients of the three-way interactions. They identify how the post-displacement earnings losses of exposure group E_k differ compared to the zero exposure control group E_0. The remaining interaction terms account for differences in the outcome levels and time-trends between the exposure groups or displaced and non-displaced workers.

X_{ic} is a set of baseyear control variables to account for observable differences, including person characteristics like education, experience, job and occupation tenure, as well as two lags of individual wages, the baseyear occupations' aggregate long-term employment growth rate as well as industry and establishment size fixed effects (see table A.1 in Appendix A for a list and description of all variables). As a robustness check, I also add AKM worker and establishment fixed effect.[14] $\gamma(s,b,o,c)$ is a set of fixed effects for baseyear industry s, establishment size class b, occupation o and the calendar baseyear c. α is the intercept and ϵ_{ioect} is the idiosyncratic error term.

[14] I do not include the AKM effects in the main specification, because this reduces the sample size by about half while substantially altering the results.

Additional Specifications I also estimate a fully interacted event study model to explore how the task change penalty evolves over time. For this purpose, I replace the *Post* indicator in equation (2) by a set of time-period t dummies, excluding $t = -1$ as the reference period.[15] To study effect heterogeneity across groups, I fully interact the model in (2) with an indicator for different subgroups of workers, e.g., women, older persons or occupation switchers. All models are estimated with OLS and stadard errors are clustered at the individual level.

Differential Timing A stream of recent papers has shown that OLS estimates of Difference-in-Differences models can be biased if the treatment timing varies across units (see Roth et al., 2022 for a review). Goodman-Bacon (2021) shows that this bias arises, because the OLS estimator involves comparisons of earlier and later treated units that may even flip the sign of the estimated average treatment effect. To avoid these 'sinful' comparisons, I transform the data into a balanced panel where time is defined relative to the displacement baseyear. This 'stacked' regression approach assures that the OLS estimator is a weighted average of the baseyear-specific average treatment effects with strictly positive weights (Gardner, 2022).[16]

4.3 Discussion of Assumptions

No Anticipation and No Spillovers Workers should not anticipate the plant closing and adjust their behavior in a way that affects their outcomes in advance. Moreover, non-displaced workers' outcomes should not be affected in any way, e.g., by spillovers or market adjustments.

Following a common approach in the displacement literature, I only consider job loss during plant closures and focus on stable job matches. When all workers are discharged simultaneously, then job loss is likely unrelated to relative individual productivity. I exclude workers who leave the plant within two years before closure, because early leavers may be positively selected and bias the estimated costs of job loss downwards. This and the other stable match restrictions imply that workers are reasonably attached to their

[15] Note that the annual earnings and days employed in the baseyear ($t = 0$) may already be affected by the plant closure, because some plants close down between June 30 and December 31 of the baseyear.

[16] Other estimators for the differential timing setting are available (e.g., Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). But they typically require a fully balanced panel, where all units are observed for the same time interval during which treatment occurs in different periods. In my setting, I would have to observe all workers over the entire observation period between 1975 and 2010. Clearly, many workers retire or drop-out of the labor force over a period this long. So, to apply these estimators, I would have to impose strong restrictions on the data. The stacking approach taken here also requires setting a time window around the baseyear, but – in my view – this is more transparent in my application. Moreover, this approach has been commonly used in the previous displacement literature.

jobs and would not have quit in absence of plant closure. From the individuals' point of view, displacement can thus be considered an unexpected and exogenous shock. Consistently, there are no signs of anticipation before the baseyear for annual earnings, the employment probability, days worked per year or occupational mobility (see panel a in Figures B.6 to B.9 in Appendix B).[17]

The focus on complete plant closures also precludes any spillovers on workers remaining in the establishment. The relatively small average size of closing plants (see Table A.2 an Appendix A) suggests that local spillovers or general equilibrium effects (see e.g., Gathmann et al., 2020) are not a concern.

Bias Stability The Bias Stability assumption requires that the unobserved heterogeneity between the exposure groups is the same in the displaced and non-displaced worker sample.

Figure 3 shows how the time trends in annual earnings of the low (E_1, left panel) and high exposure group (E_2, right panel) differ relative to the zero exposure control group (E_0, represented by the zero line). In both panels, the reference year is $t = -1$ and the solid line represents displaced workers, the dashed line non-displaced workers.[18] Indeed, the pre-trends of both the low and hig exposure group divert substantially from the zero exposure group – hence the violation of the parallel-trends assumption. However, comparing the solid and the dashed lines reveals that this deviation is almost identical in the displaced and non-displaced sample. This suggest that non-displaced workers indeed provide a valid additional control group to account for the non-parallel trends bias between the exposure groups.

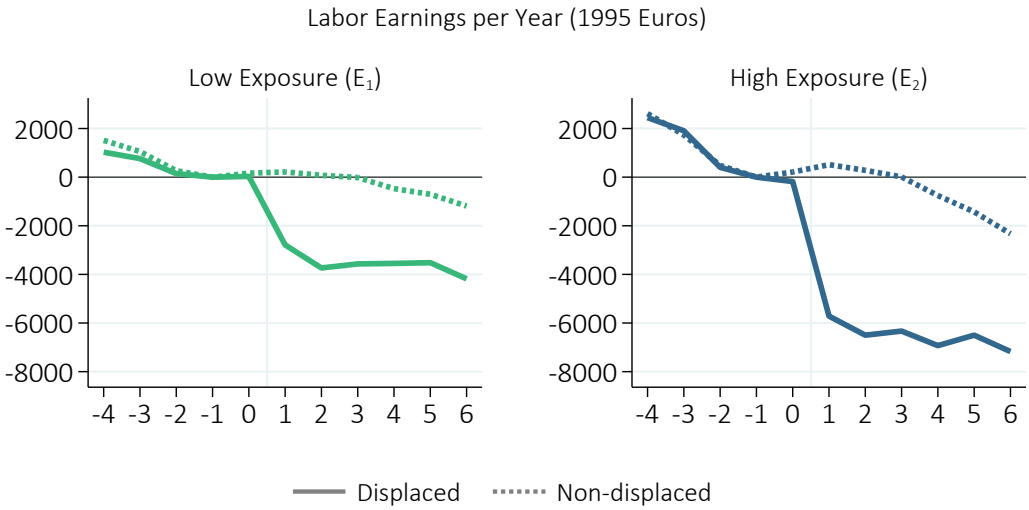
Nevertheless, there are some observed differences between displaced and non-displaced workers. Notably, non-displaced workers are less likely to work in manufacturing occupations or industries and they are employed in larger establishments (see Table A.2 in Appendix A).[19] Especially firm size is a predictor of technology adoption, firm survival (Acemoglu et al., 2020; Koch et al., 2021) and on-the-job training (Oi and Idson, 1999). Workers in 'non-displacing' plants may therefore develop new skills more quickly and have better outside options in case of job loss. Such a bias may result in an overestimation of the effect of task change exposure on worker outcomes.

[17] Panel b in in Figures B.6 to B.9 in in Appendix B) show the mean outcomes of non-displaced workers. The gradual reduction in non-displaced workers' earnings after the baseyear is a consequence of lifting the stable match restriction, which allows workers in the sample to leave employment or switch occupations.

[18] The corresponding plots for the employment probability, days worked per year and occupational mobility are given in Figures B.10 to B.12 in Appendix B.

[19] These differences between displaced and non-displaced workers also hold within exposure groups (see Table A.4 in Appendix A).

Figure 3: Deviation from Parallel Trends in Earnings between Exposure Groups for Displaced and Non-Displaced Workers



Notes: The figure plots the unconditional event studies for the earnings of lowly and highly exposed workers in comparison to the zero exposure group, separately for displaced and non-displaced workers. Time trends are relative to the reference period $t = -1$. The plots support the validity of the Bias Stability assumption for the pre-displacement period, i.e., that the non-parallel trends bias for the low/high exposure group is almost identical in the displaced and non-displaced worker sample.
Data: SIAB, OPTE.

I will therefore control for baseyear occupation tenure and person characteristics as well as two lags of individual wages and other observed differences. Moreover, I successively add establishment size, industry, occupation and baseyear fixed effects to account for unobserved confounders that are constant within subgroups.

I do not observe individual skills or plant-level technology. Instead, I include AKM worker and plant fixed effects in a robustness check. These fixed effects serve as proxies for unobserved wage components like worker ability, plant productivity or rent sharing. In a further robustness check, I explicitly match displaced and non-displaced workers in the same exposure and establishment size group – and with a similar displacement propensity – to eliminate all imbalances in observables ex-ante and re-estimate the results.

No Selection into Exposure The previous two assumptions identify the causal effect of a low or high exposure as compared to the zero exposure group. However, the difference between these estimates only reveals the true effect of exposure itself under an additional assumption: Individuals should not select into exposure groups based on expected 'gains' (Callaway et al., 2021).

In my application, workers should not strategically enter or leave occupations based

on expected changes in tasks *and* the resulting additional costs of job loss. To warrant this assumption, I only include workers who have stayed in their occupation for at least two years before job loss. This excludes workers who recently entered or left the occupation in response to task changes or to obviate displacement. In my sample, the average occupation tenure of displaced workers with a non-zero exposure ranges between 10.4 and 13.8 years (see Table A.4 in Appendix A). Arguably, for many occupations it is difficult to predict how tasks will change over more than a decade. Moreover, the risk and timing of job loss are uncertain. It therefore seems unlikely that workers mainly chose their baseyear occupation, because they anticipated how future task changes would alter the costs of job loss.

Nevertheless, I do control for observed differences between the exposure groups that may be related to outside options and unobserved determinants of occupational mobility. This includes baseyear characteristics, as well as pre-displacement wages and industry, establishment size class, occupation and baseyear fixed effects. In a robustness check, I add AKM person and establishment fixed effects to account for unobserved wage components that may correlate with occupation choice.

5 Results

5.1 Descriptive Results

Columns 1 and 2 of Table 2 provide the outcome means of displaced workers in different exposure groups before and after job loss. Column 3 reports the before/after change of each exposure group. Columns 4 and 5 contrast the change in outcomes of the low and high exposure group to the change of the zero exposure group.

More exposed workers generally have higher pre-displacement earnings, more stable employment relationships and they switch occupations less often. As mentioned earlier, this is because more exposed workers tend to be more advanced in their careers and therefore better matched. Column 3 shows that a greater exposure to task change before job loss is associated with substantially larger earnings and employment losses after displacement and a greater likelihood to switch occupations. As compared to the zero exposure group, highly exposed workers experience 144% higher earnings losses and an additional penalty of almost 30% on the employment probability and days worked per year. Conditional on re-employment, they are 82% more likely to switch occupations than the zero exposure group.

However, given the association between career progress and task change these values cannot be interpreted as a pure consequence of exposure itself. The next sections will

Table 2: Mean Outcomes of Displaced Workers Before and After Job Loss by Exposure to Pre-Displacement Task Change

		(1)	(2)	(3)	(4)	(5)
		Mean		Change	Diff to Zero Exposure	
	Exposure	Pre	Post	Absolute	Absolute	In %
Labor Earnings per Year (1995 Euros)	Zero	26,957.43	22,173.78	-4,783.65	.	.
	Low	33,568.40	25,361.53	-8,206.87	-3,423.23	-72%
	High	38,319.63	26,630.38	-11,689.26	-6,905.61	-144%
Employed	Zero	0.97	0.75	-0.23	.	.
	Low	0.98	0.72	-0.26	-0.03	-14%
	High	0.99	0.70	-0.29	-0.06	-27%
Days Employed per Year	Zero	349.46	263.50	-85.96	.	.
	Low	354.41	254.98	-99.43	-13.46	-16%
	High	358.54	247.98	-110.56	-24.60	-29%
Switch Occupation (rel. to baseyear)	Zero	0.10	0.30	+0.20	.	.
	Low	0.05	0.33	+0.28	+0.09	+44%
	High	0.02	0.37	+0.35	+0.16	+82%

Notes: The table shows the mean outcomes of displaced workers in different exposure groups over the pre- and post-displacement period (columns 1 and 2). The exposure groups represent different intensities of task changes between individual occupation entry and displacement (see 4). Column 3 reports the change in mean outcomes after job loss for each exposure group. Columns 4 and 5 contrast the change in outcomes of the low/high exposure group with the change of the zero exposure group.
Data: SIAB, OPTE.

therefore discuss the results of the Triple-Differences estimator, which purges the values in column 4 of Table 2 of the non-parallel trends bias.

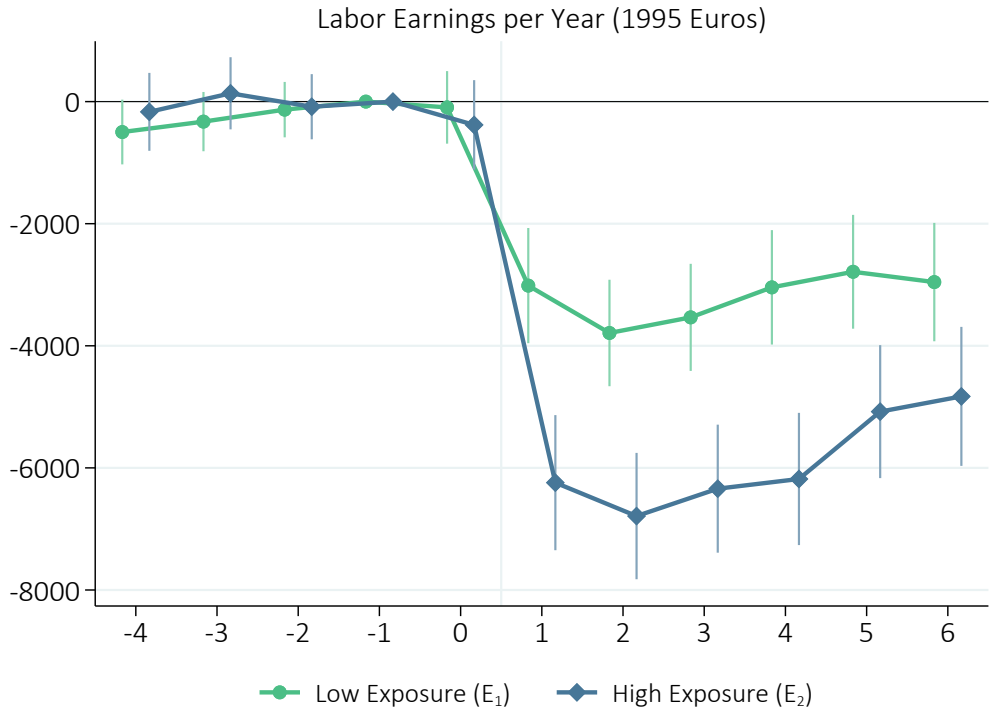
5.2 The Task Change Penalty on Post-Displacement Earnings

Triple-Differences Event Study Figure 4 plots the Triple-Differences equivalent of an event study plot for annual earnings.[20] The estimates originate from a model that fully interacts equation (2) with a set of time dummies. The specification controls for baseyear characteristics as well as baseyear industry, establishment size class, occupation and calendar baseyear fixed effects.

First, the pre-trends are close to zero for both exposure groups. Hence, the DDD estimator indeed eliminates the non-parallel pre-trends introduced in Figure B.6. For the low exposure group there is a slight deviation from zero, but it is insignificant and small. After displacement, the earnings losses strongly increase with prior exposure to task change. Even though there is some recovery, these additional losses are highly persistent.

[20]The corresponding plots for the employment probability, days employed per year and occupational mobility are provided in Figures B.13, B.14 and B.15 in Appendix B.

Figure 4: Triple-Differences Event Study Estimates of Penalty for Exposure to Task Change on Labor Earnings per Year



Notes: The plot shows the estimates for labor earnings per year from a fully interacted version of the Triple-Differences specification in equation (2), where the *Post* indicator has been replaced by a set of indicators for each relative time period $t = -4, \ldots, +6$, with $t = -1$ as the omitted reference period. The specification controls for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects. The coefficients represent the average additional penalty over six post-displacement years for displaced workers in exposure groups E_1 (low) and E_2 (high) relative to the zero exposure group E_0. The vertical line illustrates that the plant closure occurs between $t = 0$ and $t = 1$.

Data: SIAB, OPTE.

Average Post-Displacement Effect Table 3 provides the average earnings penalty of the two exposure groups over the entire post-displacement period of six years. Low exposed workers experience about 2,100 Euros greater annual earnings losses than workers in the zero exposure group. Highly exposed workers have about 4,400 Euros higher earnings losses than zero exposure workers. Relative to the losses in the zero exposure group, this corresponds to an additional penalty of about 44% for lowly exposed workers and 91% for highly exposed workers.

These estimates are considerably lower than the unconditional penalty in column 4 of Table 2, which highlights the importance of controlling for differences in pre-trends between the exposure groups. However, the earnings losses are still strongly increasing with exposure to task change and this gradient is robust to adding control variables or different sets of fixed effects. This implies that the effect of exposure is not explained by observed differences between displaced and non-displaced workers or exposure groups. Adding AKM fixed effects as proxies for unobserved wage determinants raises the estimates and reduces the gradient, but the earnings losses are still clearly increasing in exposure.

5.3 Re-Employment Prospects and Occupational Mobility

Re-Employment Prospects Table 4 provides the DDD estimates for the probability of being employed (column 1), days worked per year (column 2) and the annual labor earnings of re-employed individuals (column 3). Each model controls for baseyear characteristics and industry, establishment size class, occupation and calendar baseyear fixed effects.

The re-employment probability is decreasing with exposure to pre-displacement task change. After job displacement, low exposure workers are about 3 percentage points less likely employed and work 13 days less per year than zero exposure workers. This is equivalent to an additional penalty of 12% on the employment probability and 15% on days worked as compared to the average losses of the zero exposure group. For highly exposed workers, the penalty decreases to -7 percentage points on the employment probability and -27 days employed per year, which corresponds to a relative penalty of 30% and 32% on top of the average reduction in the zero exposure group.

As column 3 shows, the earnings losses are substantially lower when conditioning on re-employment. About half of the overall earnings penalty of more exposed workers in Table 3 is explained by a lower re-employment probability. This is consistent with the idea that changes in occupational tasks depreciate worker skills, resulting in worse outside options and lower re-employment prospects after job loss.

Table 3: Effect of Exposure to Task Change on Labor Earnings per Year (1995 Euros)

Labor Earnings per Year	(1)	(2)	(3)	(4)
Low Exposure (E_1)	-2124.03***	-2083.125***	-2083.125***	-3007.264***
	(321.753)	(323.811)	(323.817)	(478.33)
High Exposure (E_2)	-4456.263***	-4441.491***	-4441.491***	-4927.887***
	(376.843)	(379.204)	(379.212)	(524.156)
Baseyear Control Variables		✓	✓	✓
Industry FE		✓	✓	✓
Estab. Size Category FE		✓	✓	✓
Occupation Tenur (+sq)		✓	✓	✓
Occupation FE			✓	✓
Baseyear FE			✓	✓
AKM Estab. & Person FE				✓
N	5151036	5068316	5068316	2404699
Adj. R^2	.03	.44	.46	.47

Notes: The table provides the Triple-Differences coefficient estimates for the three-way interactions of the exposure groups in equation (2). The columns show the estimates from specifications with a growing set of baseyear control variables and fixed effects (see Table A.1 in Appendix A for a list and description). ***/**/* mark statistical significance at the 1/5/10% level.
Data: SIAB, OPTE.

Table 4: Effect of Exposure to Task Change on Employment and Contribution to Losses in Labor Earnings per Year (1995 Euros)

	(1) **Employment Prob.**	(2) **Days Employed per Year**	(3) **Labor Earnings per Year**
Conditional on:	All	All	Re-employed
Low Exposure (E_1)	-.028***	-12.843***	-657.260***
	(.007)	(2.497)	(252.517)
High Exposure (E_2)	-.070***	-27.117***	-1,859.134***
	(.007)	(2.756)	(291.887)
Baseyear Control Variables	✓	✓	✓
Industry FE	✓	✓	✓
Estab. Size Category FE	✓	✓	✓
Years since Occ. Entry (+sq)	✓	✓	✓
Occupation FE	✓	✓	✓
Baseyear FE	✓	✓	✓
N	5068316	5068316	4355059
Adj. R^2	0.09	0.11	0.61

Notes: The table provides the Triple-Differences coefficient estimates for the three-way interactions of the exposure groups in equation (2). Columns (1) show the estimates show the estimates for the probability of being employed on June 30 of a given panel year, column (2) shows the results for the number of days employed per year. Column (3) shows the estimates for annual labor earnings conditional on being employed. All specifications controls for baseyear characteristics (see Table A.1 in Appendix A for a list and description) and industry, occupation and calendar baseyear fixed effects. ***/**/* mark statistical significance at the 1/5/10% level.
Data: SIAB, OPTE.

Occupational Mobility Table 5 shows the estimated effect of task change on the probability of switching to a different occupation after job loss and the associated earnings penalties. Columns 2 and 3 are obtained from fully interacting equation (2) with an indicator for occupation switching. This decomposes the earnings penalty of all re-employed workers (column 3 of Table 4) into a separate effect for occupation stayers and switchers. Each model controls for baseyear characteristics, industry fixed effects, establishment size class, occupation and calendar baseyear fixed effects. Note that occupations are only observed for employed workers, such that the estimates are subject to self-selection into re-employment and should be interpreted as descriptive rather than causal.

The probability of switching occupations increases substantially with exposure to task change (column 1). Low exposed workers are about 4.7 percentage points – or 24% – more likely to switch occupations after job loss than zero exposure workers. Highly exposed workers are about 9 percentage points more likely to switch occupations than the zero exposure group, which corresponds to a 46% higher switching probability.

Among both low and high exposure workers, occupation switchers experience a substantially higher earnings penalty than workers who return to the same occupation (compare columns 2 and 3 of Table 5). The estimates for switchers are very close to the average earnings penalty for all re-employed workers (see column 3 in Table 4). This implies that the overall earnings losses of re-employed workers are mainly driven by occupation switchers. At the same time, the point estimates of switchers also varies a lot. The top panel of Figure 5 shows that for highly exposed occupation switchers, the 95% confidence interval for earnings ranges from below -4,000 up to about +750 Euros per year. This means, that some switchers experience no larger earnings reductions after job loss than workers in the zero exposure group.

Also the earnings reductions of occupation stayers increase with the previous exposure to task change, but for them the penalty is much lower than for switchers (see column 2 of Table 5). Highly exposed occupation stayers yield a penalty of 840 Euros pear year as compared to zero exposure workers. For occupation switchers, the penalty increases to -1,700 Euros. This indicates that workers who manage to return to the same occupation have at least partially updated their skills to the new requirements. Hence, they can transfer more specific human capital and suffer lower earnings losses.

Among highly exposed workers, both occupation switchers and stayers have slightly less days employed than the zero exposure group (see top panel of Figure 5). However, with -3 and -7 days per year on average over a six year period the penalty is small in absolute terms.

Table 5: Effect of Exposure to Task Change on Occupational Mobility and Contribution to Earnings Losses (1995 Euros)

	(1)	(2)	(3)
	Switch Occupation	**Labor Earnings per Year**	
Conditional on:	Re-employed	Occupation Stayers	Occupation Switchers
Low Exposure (E_1)	.047***	-437.501*	-981.805
	(.009)	(251.597)	(962.631)
High Exposure (E_2)	.092***	-840.209***	-1,746.741
	(.009)	(292.807)	(1,273.357)
Baseyear Control Variables	✓	✓	✓
Industry FE	✓	✓	✓
Estab. Size Category FE	✓	✓	✓
Occupation Tenure (+sq)	✓	✓	✓
Occupation FE	✓	✓	✓
Baseyear FE	✓	✓	✓
N	4305163	4305163	
Adj. R^2	.09	0.61	

The table provides the Triple-Differences coefficient estimates for the three-way interactions of the exposure groups in equation (2). Columns (1) shows the estimates for the probability switching occupations conditional on re-employment. Columns (2) and (3) shows the estimates for annual labor earnings conditional on switching occupations or returning to the same occupation. All specifications controls for baseyear characteristics (see Table A.1 in Appendix A for a list and description) and industry, occupation and calendar baseyear fixed effects. ***/**/* mark statistical significance at the 1/5/10% level.
Data: SIAB, OPTE.

5.4 Effect Heterogeneity

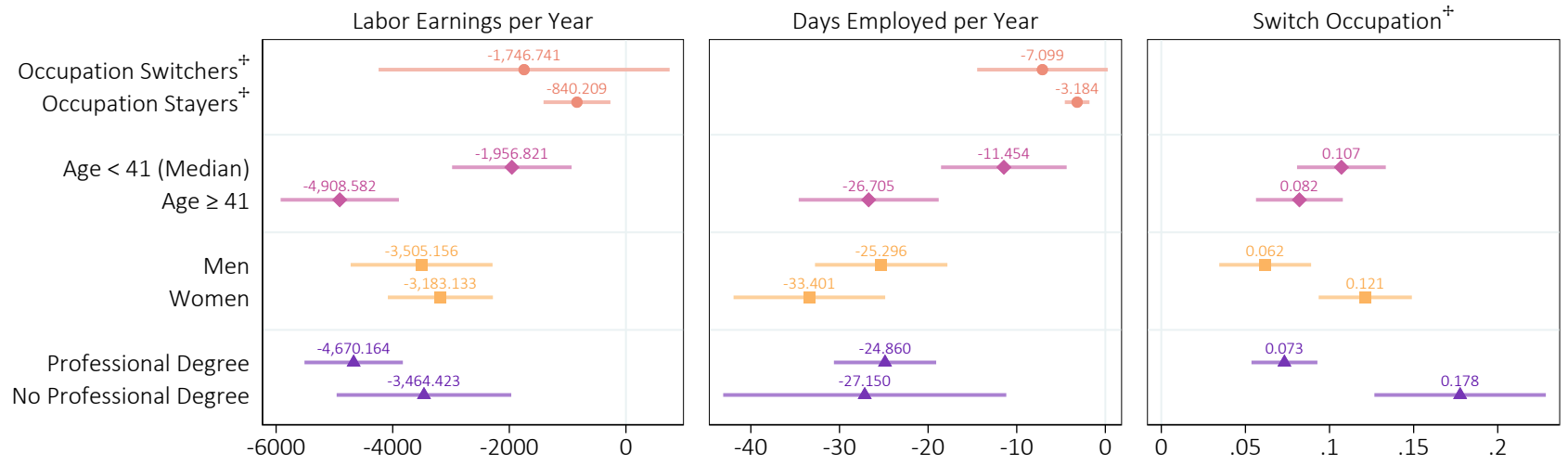
Figure 5 provides the estimates of the four-way interaction model that further decomposes the exposure penalty into different subgroups. For ease of display, the plots only show the decomposition for the high exposure group's penalty.[21] Again, the model controls for baseyear characteristics, industry, establishment size class, occupation and baseyear fixed effects.

Age Highly exposed workers above the median age of 41 experience much larger earnings losses than younger workers. In fact, their losses almost coincide with the average penalty of the entire high exposure group (see Table 3). The same holds for the effect on the employment probability and days employed (see Table 4). In contrast, conditional on re-employment older workers are less likely to switch occupations. These results suggest that changes in occupational tasks devalue the skills of older workers more, such that they qualify less for a new job in their previous occupations. At the same time, it is more costly for older individuals to start all over again in a new occupation, such that more workers remain unemployed.

Gender Recent studies have shown that women often suffer substantially larger earnings losses after job displacement than men, because mothers with young children accept part-time jobs with lower wages more often (Frodermann and Müller, 2019; Illing et al., 2021). I find that for women a high exposure to task change has a greater effect on the probability to stay unemployed and to switch occupations. The resulting earnings penalty, however, is only slightly more negative than for men. This suggest that for a given exposure to task change, women make more beneficial matches when switching occupations. It would be an interesting avenue for further research to explore how changes in tasks affect the self-selection of women who return to work and the role of motherhood.

[21] Note that the decomposition results for the high exposure group do not necessarily carry over to the low exposure group. For the sake of brevity, I spared the heterogeneity results for the employment probability, as they are very similar to days employed. They can be found in Figure B.16 in Appendix B.

Figure 5: Heterogeneity in the Earnings Penalty of the High Exposure Group



+ Conditional on re-employment

Notes: The Figure shows a decomposition of the Triple-Differences effect on labor earnings per year for the high exposure group (E_2) into separate estimates for different sub groups of workers. The three panels in the columns represent different outcomes, the rows represent the different subgroups. These estimates are derived from a four-way-interaction model, i.e., equation (2) is fully interacted with indicator variables for the sub groups. All models control for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects.
Data: SIAB, OPTE.

Professional Degree The high-exposure earnings penalty is lower for workers without a professional degree, but it also varies more as the confidence interval reveals. The same applies to the effect on days employed. Conditional on re-employment, workers without a degree are much more likely to switch occupations. One explanation could be that individuals without a degree tend to work in occupations that require more general skills and pay lower average wages. As a consequence, these workers may find it easier to transfer their skills to a different occupation that pays a similar wage.

5.5 Robustness Checks

Matched Sample As I have discussed above, displaced and non-displaced workers differ in some characteristics that may be related to the relative earnings trajectories of the exposure groups. If this was related to different non-parallel trends biases in the displaced versus the non-displaced sample, then the Bias Stability assumption of the Triple-Differences design could be violated.

Even though Bias Stability seems to be satisfied without any control variables (see Figure 3), especially the difference in occupation tenure and establishment size may be a matter of concern. I therefore control for these and other observed differences in baseyear characteristics in most specifications. Such a control variables approach requires sufficient overlap between the groups – otherwise, explicitly matching each displaced worker with a similar non-displaced control may be more effective. For the two most apparent confounders, occupation tenure and establishment size, the boxplots in Figures B.4 and B.5 suggest that there is sufficient common support for a control variables approach.

Nevertheless, I also construct a matched sample as a robustness check. I first use the set of control variables to predict the individual propensity of displacement for each worker in the sample. Then I exactly match displaced and non-displaced workers with the same baseyear, exposure group and establishment size class. Within these cells, I pick each displaced worker's nearest neighbor in terms of the propensity score as the control unit. The resulting matched sample is clean of any significant imbalances (see Table A.5 in Appendix A).

I use the matched sample to re-estimate the triple-differences model in equation (2). Again, I add control variables to account for differences between the exposure groups. Table A.6 reports the results of this exercise. Reassuringly, they are very similar to the ones obtained from the unmatched sample.

Task Change over a Fixed Ten Year Time Window For my main analyses, I measure within-occupation task changes between each worker's individual year of occupation en-

try and job loss (or the baseyear for non-displaced workers). This creates an additional source of identifying variation: Even for workers with the same occupation who are displaced in the same year, the exposure to task change differs by entry years. However, this approach also contributes to the systematic relationship between exposure and occupation tenure, because entering an occupation earlier and staying longer mechanically increases the chance of experiencing task changes. But then, changes that happened many years ago may not really affect outcomes today. Moreover, individuals who endure task changes over many years might be selected in terms of unobserved ability or other relevant characteristics. In this case, the estimated exposure penalty could be confounded by unobservables that are jointly related to task change, occupation tenure and earnings.

To address this concern, I fix the time window for changes in tasks to ten years before the baseyear c and compute the within distance of worker i's occupation o since then, i.e. $\mathcal{D}_i(o, c-10, c)$ as in equation (1). I then define exposure groups in the same way as before: the low quartile is classified as the zero exposure group, the second and third quartile are combined into the low exposure group and the fourth quartile is the high exposure group. The groups are then used to re-estimate the DDD model in equation (2).

Table A.7 in Appendix A shows the results. For earnings, the results are qualitatively similar to the main analyses: a greater exposure leads to higher earnings losses as compared to the zero exposure group, but the penalty is lower in absolute terms. Also the probability to switch occupations is still increasing with exposure, even to a slightly higher degree than in the main analyses. Only for employment, the exposure gradient basically vanishes; the low exposure group now has a significantly higher employment probability (+1.5 percentage points) and more days worked (about +4 days per year) than the zero exposure group – but the effects are very small in absolute terms. For the high exposure group, the outcomes do not differ significantly from the zero group.

Note that the entry-year specific distance measure of the main-analyses and the fixed ten-year distance measure are not perfectly correlated ($\rho = 0.63$) such that the assignment of displaced workers to exposure groups somewhat differs. Therefore, the results may not be perfectly comparable to the main analyses.

6 Discussion and Conclusion

This paper shows that changes in occupational tasks have a strong impact on the individual costs of job loss. To establish this result, I employ a novel data set that allows

tracing the task content of occupations over three decades and merge it to individual social security records. Since job loss is not an exogenous shock, I focus on layoffs during plant closures, where displacement can be considered independent of individual skills or productivity. I then split the sample of displaced workers into three groups, who were either exposed to a high, low or zero changes in occupational tasks before job loss. These groups do not only differ in terms of exposure to task change, but also in characteristics that may determine earnings and employment prospects. The eliminate the resulting bias, I use non-displaced workers with a similar exposure to task changes as an additional control group in a Triple-Differences design.

On average, a high exposure to task change before job loss inreases the post-displacement earnings losses by about 4,400 Euros per year, or 90%, as compared to workers with a zero exposure. This task change penalty largely persists over six years and about half of it is explained by a lower re-employment probability. If highly exposed workers return to employment, they are almost twice as likely to switch occupations than workers whose previous occupation remained unchanged. Such switches often involve substantial reductions in earnings.

My result suggest that not all workers are equally quick to adjust their skill set when the task content of their occupation changes. Especially older workers suffer large reductions in the re-employment probability and earnings when being displaced during a period of task restructuring. Job loss seems to interrupt on-the-job adjustment, e.g., via learning-by-doing or job training, leading to worse outside options, more involuntary occupation switches and higher earnings losses. However, there are also workers who leave a changing occupation without additional earnings losses. For these workers, a layoff may provide an unexpected opportunity to find a better match after having successfully acquired new skills.

I contribute to a growing literature that links the costs of job loss to technological change and task restructuring. Most of these papers fix occupational tasks in a baseyear and then compare the outcomes of workers in initially more or less routine intensive occupations. However, recent theoretical and empirical advances highlight the importance of task restructuring *within* occupations (see e.g., Acemoglu and Restrepo, 2018; Atalay et al., 2020). This paper is the first to provide causal evidence about how such within-changes affect the costs of job loss. An interesting avenue for future research would be to study self-selection into 'involuntary' and 'voluntary' occupational mobility in response to task changes and the role of specific tasks in more detail. Another natural follow-up questions regards the role of firms, training and knowledge spillovers between colleagues for individual adjustment to changes in workplace tasks.

Overall, my results highlight the importance of continuous training and 'lifelong learning'. Digitization will profoundly change the skill requirements of many jobs, while population ageing increases the adjustment costs. Targeted policy interventions like training subsidies could foster the skill acquisition of groups with higher learning costs and lower returns. This could be especially relevant to avoid early labor market exits after sudden career breaks, e.g., in case of job loss or domestic caring obligations. Such policy interventions could be welfare-improving, if the joint risk of future task changes and career interruptions is hard to predict when workers make long-lasting occupation choices early in their career (Cunha and Heckman, 2016).

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Appendix

A Supplementary Tables

Table A.1: List of Variables

Variable Group	Description
Outcomes:	
	Employed
	Labor earnings per year (1995 Euros)
	Days employed per year
	Switching out of baseyear occupation
	Female (0/1)
Baseyear Control Variables Main Specification:	
Person	Age (years)
	German (0/1)
	No professional degree (1/0, omitted reference category)
	Vocational training (0/1)
	Academic degree (0/1)
	No of benefit receipts
	No of n-spells
	Labor market experience (days)
	Labor market experience squared (days)
	Job tenure (days)
	Job tenure squared (days)
	Occupation tenure (years)
	Occupation tenure squared (years)
	Weighted growth rate of baseyear occupation (Western Germany, 1980-2010)
	Log real daily wage in $c-1$ (1995 Euros)
	Log real daily wage in $c-2$ (1995 Euros)
Industry (0/1)	Agriculture/forestry (omitted reference category)
	Pisciculture/fishery
	Mining/mineral extraction
	Manufacturing
	Energy/water supply
	Construction
	Retail, maintenance and repair of cars and durables
	Hospitality
	Transportation/communication
	Credit/insurance
	Real estate/renting of movable goods/business-services
	Public administration/defense/social insurance
	Education
	Health/veterinary/social Care
	Other services
	Private households
Establishment Size (0/1)	<10 (omitted reference category)
	10-50
	51-100
	101-250
	251-500
	>500
Additional Baseyear Control Variables:	
AKM Fixed Effects (logs)	Person
	Establishment

Data: SIAB, † Dauth (2014).

Table A.2: Baseyear Characteristics of Displaced and Non-displaced Workers

	(1) Displaced	(2) Non-Displaced	(3) Diff. (1)-(2)	
Person:				
Female	.393	.48	-.087	+
Age	41.834	40.018	1.816	+
German	.908	.928	-.02	
No professional training	.152	.141	.011	
Vocational training	.798	.771	.028	
Academic degree	.05	.088	-.038	+
Experience	12.63	9.882	2.748	++
Job tenure	7.501	5.927	1.574	++
No of benefit receipts	1.259	1.139	.12	
No of n-spells	1.031	1.383	-.352	+
AKM person FE	4.284	4.308	-.024	
Occupation:				
Within-distance since entry	.004	.003	.001	
Occupation tenure	10.786	8.6	2.186	++
Agriculture	.	.	.	
Mining	.	.	.	
Manufacturing	.434	.287	.147	++
Mid/High Wage Services (>=p25)	.056	.058	-.002	
Low Wage Services (<p25)	.51	.655	-.145	++
wGR baseyear occupation (1980-2010)	.002	.004	-.002	+
Industry:				
Agriculture/Fishing/Mining	.004	.006	-.002	
Manufacturing/Energy/Construction	.523	.346	.177	++
Trade/Hospitality/Traffic/Communication	.336	.277	.059	+
Credit/Real estate/Public Sector	.088	.194	-.107	++
Education/Health/Other services	.047	.172	-.125	++
Establishment:				
Establishment size	54.584	108.208	-53.624	++
<10	.23	.198	.032	
10-50	.465	.295	.17	++
51-100	.148	.147	.001	
101-250	.117	.206	-.089	+
251-500	.039	.153	-.114	++
>500	.	.	.	
Median Daily Wage	67.082	72.891	-5.809	+
AKM establishment FE	.113	.112	.002	
Outcomes:				
Labor earnings per Year	33923.408	34618.6	-695.192	
Employed	1	1	0	
Days employed per year	360.727	361.512	-.786	
Switch occupation	0	0	0	
Log real daily wage	4.422	4.408	.014	
min(N)	8149	224403		
max(N)	14141	457693		

Notes: Columns (1) and (2) show the mean baseyear characteristics of displaced and non-displaced workers. Column (3) provides the difference between both groups and its significance in terms of the absolute value of the standardized difference: $^{+}$ marks 'marginal' differences between 0.1 and 0.25; $^{++}$ marks 'significant' differences above 0.25 (Imbens and Wooldridge, 2009; Austin, 2011). In contrast to the usual *t*-statistic, this measure does not mechanically increase in large samples. The sample size varies because of missing values. The AKM fixed effects are only available for about half of the sample. '.' marks cells that are empty by restriction.
Data: SIAB.

Table A.3: Baseyear Characteristics of Displaced and Non-Displaced Workers By Exposure Group

	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
		E_0				E_1				E_2		
	Disp.	Non-Disp.	Diff		Disp.	Non-Disp.	Diff		Disp.	Non-Disp.	Diff	
Person:												
Female	.607	.67	-.062	+	.368	.446	-.078	+	.281	.31	-.029	
Age	39.262	37.474	1.788	+	41.781	40.471	1.31	+	43.678	41.931	1.746	+
German	.928	.935	-.007		.908	.925	-.018		.896	.926	-.031	+
No professional training	.107	.116	-.009		.144	.149	-.005		.193	.143	.05	+
Vocational training	.852	.811	.041	+	.812	.763	.049	+	.741	.747	-.006	
Academic degree	.04	.073	-.032	+	.045	.088	-.043	+	.066	.11	-.044	+
Experience	10.084	7.654	2.43	++	12.197	9.874	2.323	++	15.145	12.608	2.537	++
Job tenure	5.258	4.2	1.058	++	7.318	5.987	1.331	++	9.368	7.877	1.491	+
No of benefit receipts	1.321	1.209	.112		1.279	1.136	.143		1.174	1.056	.118	
No of n-spells	1.279	1.408	-.129		.993	1.369	-.376	+	.923	1.364	-.441	+
AKM person FE	4.181	4.224	-.043	+	4.284	4.308	-.024		4.347	4.4	-.053	+
Occupation:												
Within-distance since entry	0	0	0	+	.001	.001	0		.013	.013	0	
Occupation tenure	7.226	5.676	1.55	++	10.462	8.761	1.702	+	13.816	11.813	2.003	++
Agriculture	.	.	.		.	.	.		.	.	.	
Mining	.	.	.		.	.	.		.	.	.	
Manufacturing	.112	.073	.039	+	.44	.331	.109	+	.649	.457	.193	++
Mid/High Wage Services (>=p25)	/	/	/		/	/	/		/	/	/	
Low Wage Services (<p25)	.885	.921	-.036	+	.512	.612	-.1	+	.244	.418	-.174	++
wGR baseyear occupation (1980-2010)	.006	.009	-.003	+	.002	.004	-.001	+	-.002	-.001	-.002	++
Industry:												
Agriculture/Fishing/Mining	/	/	/		/	/	/		/	/	/	
Manufacturing/Energy/Construction	.292	.205	.087	+	.536	.368	.168	++	.664	.477	.187	++
Trade/Hospitality/Traffic/Communication	.551	.384	.167	++	.321	.255	.066	+	.21	.198	.013	
Credit/Real estate/Public Sector	.092	.191	-.099	++	.089	.194	-.105	++	.083	.204	-.121	++
Education/Health/Other services	.06	.212	-.151	++	.046	.172	-.127	++	.036	.112	-.076	++
Establishment:												
Establishment size	43.567	97.954	-54.388	++	53.511	108.247	-54.736	++	64.064	121.15	-57.086	++
<10	.284	.221	.063	+	.233	.196	.037		.19	.173	.017	
10-50	.486	.311	.175	++	.467	.295	.172	++	.445	.278	.167	++
51-100	.122	.145	-.023		.147	.149	-.002		.169	.143	.026	
101-250	.079	.191	-.112	++	.116	.207	-.091	++	.146	.224	-.078	+

(continued on next page)

	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
		E_0				E_1				E_2		
	Disp.	Non-Disp.	Diff		Disp.	Non-Disp.	Diff		Disp.	Non-Disp.	Diff	
(continued)												
251-500	.029	.132	-.103	++	.037	.152	-.116	++	.051	.182	-.131	++
>500	.	.	.		.	.	.		.	.	.	
Median Daily Wage	62.781	70.502	-7.721	++	65.647	71.231	-5.585	+	72.609	79.865	-7.255	+
AKM establishment FE	.064	.083	-.018		.114	.111	.003		.145	.15	-.005	
Outcomes:												
Labor earnings per Year	28417.624	29291.881	-874.257		34124.762	34934.058	-809.296		37530.723	40862.859	-3332.136	+
Employed	1	1	0		1	1	0		1	1	0	
Days employed per year	362.015	361.667	.348		360.193	361.285	-1.092		360.906	361.885	-.979	
Switch occupation	0	0	0		0	0	0		0	0	0	
Log real daily wage	4.235	4.248	-.013		4.436	4.425	.011		4.532	4.581	-.049	+
min(N)	1618	59756			3702	103807			2801	59706		
max(N)	2868	124233			7033	226271			4192	103679		

Notes: The table shows the mean baseyear characteristics of displaced (Disp.) and non-displaced (Non-Disp.) workers in dosage groups zero (E_0), low (E_1) and the exposure high (E_1) group (for the classification of exposure groups see 4). The sample size varies because off missing values. The AKM fixed effects are only available for about half of the sample. '.' marks cells that are empty by restriction, '/' mark cells that contain less than 20 observations and must be censored in accordance with data protection regulations of the IAB.

Data: SIAB, OPTE.

Table A.5: Balancing in the Matched Sample

	(1) Displaced	(2) Non-Displaced	(3) Diff. (1)-(2)
Person:			
Female	.395	.403	-.008
Age	41.751	41.666	.085
German	.915	.924	-.009
No professional training	.142	.138	.004
Vocational training	.81	.814	-.004
Academic degree	.048	.048	0
Experience	12.653	12.116	.538
Job tenure	7.457	7.295	.162
No of benefit receipts	1.3	1.23	.069
No of n-spells	1.059	1.027	.032
AKM person FE	4.283	4.285	-.002
Occupation:			
Within-distance since entry	.004	.004	0
Years since occupation entry	10.878	10.582	.296
Agriculture	.	.	.
Mining	.	.	.
Manufacturing	.429	.413	.016
Mid/High Wage Services (>=p25)	.054	.05	.004
Low Wage Services (<p25)	.518	.537	-.02
wGR baseyear occupation (1980-2010)	.002	.002	0
Industry:			
Agriculture/Fishing/Mining	.004	.01	-.006
Manufacturing/Energy/Construction	.509	.484	.025
Trade/Hospitality/Traffic/Communication	.351	.345	.006
Credit/Real estate/Public Sector	.086	.099	-.014
Education/Health/Other services	.049	.059	-.011
Establishment:			
Establishment size	36.758	38.608	-1.85
<10	.289	.289	0
10-50	.484	.484	0
51-100	.137	.137	0
101-250	.09	.09	0
251-500	.	.	.
>500	.	.	.
Median Daily Wage	66.281	67.546	-1.265
AKM establishment FE	.107	.094	.013
Outcomes:			
Employed	1	1	0
Labor earnings per Year	33540.376	33487.135	53.242
Days employed per year	360.689	360.671	.018
Switch occupation	0	0	0
Log real daily wage	4.412	4.387	.025
min(N)	8409	8099	
max(N)	13699	13699	

Notes: Columns (1) and (2) show the mean baseyear characteristics of displaced and non-displaced workers in the matched sample. Column (3) provides the difference between both groups and its significance in terms of the absolute value of the standardized difference: $^{+}$ marks 'marginal' differences between 0.1 and 0.25 by; $^{++}$ marks 'significant' differences above 0.25 (Imbens and Wooldridge, 2009; Austin, 2011). In contrast to the usual *t*-statistic, this measure does not mechanically increase in large samples. The sample size varies because of missing values. The AKM fixed effects are only available for about half of the sample. '.' marks cells that are empty by restriction.
Data: SIAB.

Table A.6: Triple-Differences Estimate for Average Penalty for Exposure to Task Change from Matched Sample

	(1)	(2)	(3)	(4)	(5)
Labor Earnings per Year					
Low Exposure (E_1)	-2186.54***	-2186.54***	-2186.54***	-3320.762***	-2160.532***
	(458.757)	(458.787)	(458.95)	(689.374)	(458.913)
High Exposure (E_2)	-4375.654***	-4375.654***	-4375.654***	-5302.03***	-4344.571***
	(532.957)	(532.992)	(533.18)	(748.219)	(532.634)
N	274406	274406	274406	147191	274197
Adj. R^2	.04	.38	.39	.39	.39
Employment Probability					
Low Exposure (E_1)	-.039***	-.039***	-.039***	-.049***	-.039***
	(.01)	(.01)	(.01)	(.013)	(.01)
High Exposure (E_2)	-.082***	-.082***	-.082***	-.077***	-.081***
	(.011)	(.011)	(.011)	(.014)	(.011)
N	274406	274406	274406	147191	274197
Adj. R^2	.08	.1	.11	.11	.11
Days Employed per Year					
Low Exposure (E_1)	-15.95***	-15.95***	-15.95***	-19.475***	-15.817***
	(3.563)	(3.563)	(3.564)	(4.862)	(3.565)
High Exposure (E_2)	-30.451***	-30.451***	-30.451***	-29.273***	-30.344***
	(3.92)	(3.921)	(3.922)	(5.14)	(3.923)
N	274406	274406	274406	147191	274197
Adj. R^2	.09	.12	.13	.13	.13
Switch Occupation					
Low Exposure (E_1)	.049***	.047***	.047***	.041**	.047***
	(.011)	(.011)	(.011)	(.016)	(.011)
High Exposure (E_2)	.098***	.097***	.096***	.096***	.096***
	(.012)	(.012)	(.012)	(.017)	(.012)
N	222727	222727	222727	121532	222585
Adj. R^2	.11	.14	.16	.16	.16
Baseyear Control Variables		✓	✓	✓	✓
Industry FE		✓	✓	✓	✓
Estab. Size Category FE		✓	✓	✓	✓
Occupation Tenur (+sq)		✓	✓	✓	✓
Occupation FE			✓	✓	✓
Baseyear FE			✓	✓	✓
AKM Estab. & Person FE				✓	
Excl. Large Estab. ($\geq$ 500)					✓

Notes: The table provides the Triple-Differences coefficient estimates for the three-way interactions of the exposure groups in equation (2) using the matched sample (see Section 5.5 for details about the matching procedure). The columns show the estimates from specifications with a growing set of baseyear control variables and fixed effects (see Table A.1 in Appendix A for a list and description). The horizontal panels show the estimates for labor earnings per year, the probability of being employed, days employed per year and the probability of switching out of the baseyear occupation as outcomes. ***/**/* mark statistical significance at the 1/5/10% level.
Data: SIAB, OPTE.

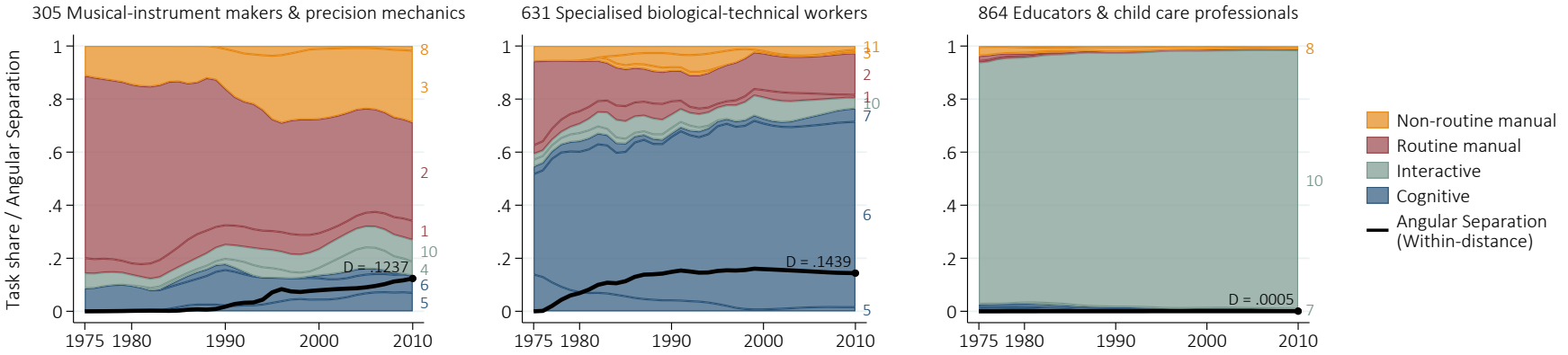
Table A.7: Triple-Differences Estimate for Average Penalty for Exposure to Task Change with Fixed Ten-Year Time Window for Task Change

	(1)	(2)	(3)	(4)	(5)
Labor Earnings per Year					
Low Exposure (E_1)	-915.89***	-932.822***	-932.822***	-2090.337***	-1850.375***
	(325.626)	(327.418)	(327.426)	(438.208)	(549.325)
High Exposure (E_2)	-1434.189***	-1445.005***	-1445.005***	-2132.143***	-2354.116***
	(416.389)	(418.896)	(418.905)	(553.435)	(724.348)
N	4454219	4391563	4391563	2404699	1071510
Adj. R^2	.02	.45	.47	.47	.5
Employment Probability					
Low Exposure (E_1)	.015**	.015**	.015**	-.007	.005
	(.007)	(.007)	(.007)	(.008)	(.011)
High Exposure (E_2)	.005	.005	.005	-.009	-.01
	(.008)	(.008)	(.008)	(.01)	(.013)
N	4454219	4391563	4391563	2404699	1071510
Adj. R^2	.04	.07	.08	.07	.08
Days Employed per Year					
Low Exposure (E_1)	4.79*	4.55*	4.55*	-3.604	2.138
	(2.467)	(2.471)	(2.471)	(3.129)	(3.993)
High Exposure (E_2)	.89	1.024	1.024	-4.617	-3.981
	(2.92)	(2.923)	(2.923)	(3.641)	(4.852)
N	4454219	4391563	4391563	2404699	1071510
Adj. R^2	.05	.08	.1	.09	.1
Switch Occupation					
Low Exposure (E_1)	.062***	.063***	.063***	.063***	.066***
	(.008)	(.008)	(.008)	(.01)	(.013)
High Exposure (E_2)	.139***	.139***	.139***	.134***	.138***
	(.009)	(.01)	(.01)	(.012)	(.016)
N	3825145	3776445	3776445	2107211	962066
Adj. R^2	.02	.07	.09	.09	.09
Baseyear Control Variables		✓	✓	✓	✓
Industry FE		✓	✓	✓	✓
Estab. Size Category FE		✓	✓	✓	✓
Occupation tenure (+sq)		✓	✓	✓	✓
Occupation FE			✓	✓	✓
Baseyear FE			✓	✓	✓
AKM Estab. & Person FE				✓	
Occupation Tenure $\geq$ 10 yrs					✓

Notes: The table provides the Triple-Differences coefficient estimates for the three-way interactions of the exposure groups in equation (2) using the matched sample (see Section 5.5 for details about the matching procedure). The classification of exposure groups is based on a fixed ten-year time window of occupational task change before the baseyear c for all workers, i.e., $D(o, c-10, c)$ (see equation (1) section 4). The columns show the estimates from specifications with a growing set of baseyear control variables and fixed effects (see Table A.1 in Appendix A for a list and description). The horizontal panels show the estimates for labor earnings per year, the probability of being employed, days employed per year and the probability of switching out of the baseyear occupation as outcomes. ***/**/* mark statistical significance at the 1/5/10% level.
Data: SIAB, OPTE.

B Supplementary Figures

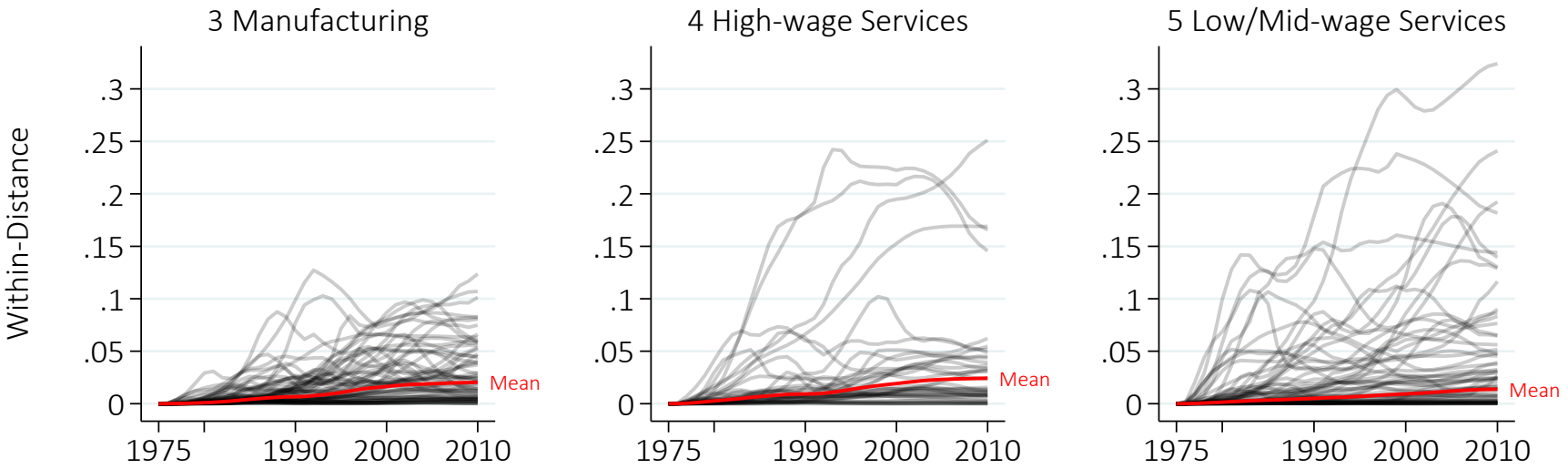
Figure B.1: Occupational Task Compositions and Within-Distance as a Measure of Change, Example Occupations



Notes: The figure plots the share of workers with a given main task (colored areas) in three example occupations and how they translate into the Angular-Separation $\mathcal{D}(o, 1975, t)$ ('within-distance', see equation (1)) as a scalar measure of changes in composition relative to 1975 (thick black line). The labels on the right margin of the subplots mark the main tasks: 1 Setting up/adjusting machines, 2 Extraction/manufacturing, 3 Repairing/mending, 4 Selling/advising/negotiating, 5 Typewriting/calculating, 6 Analyzing/measuring/researching, 7 Scheduling/coordinating, 8 Serving/accommodating/cleaning/transport, 9 Securing/guarding/applying laws, 10 Teaching/educating/publishing, 11 Nursing/treating medically or cosmetically. The labels of tasks with very small or zero shares have been omitted.

Data: OPTE.

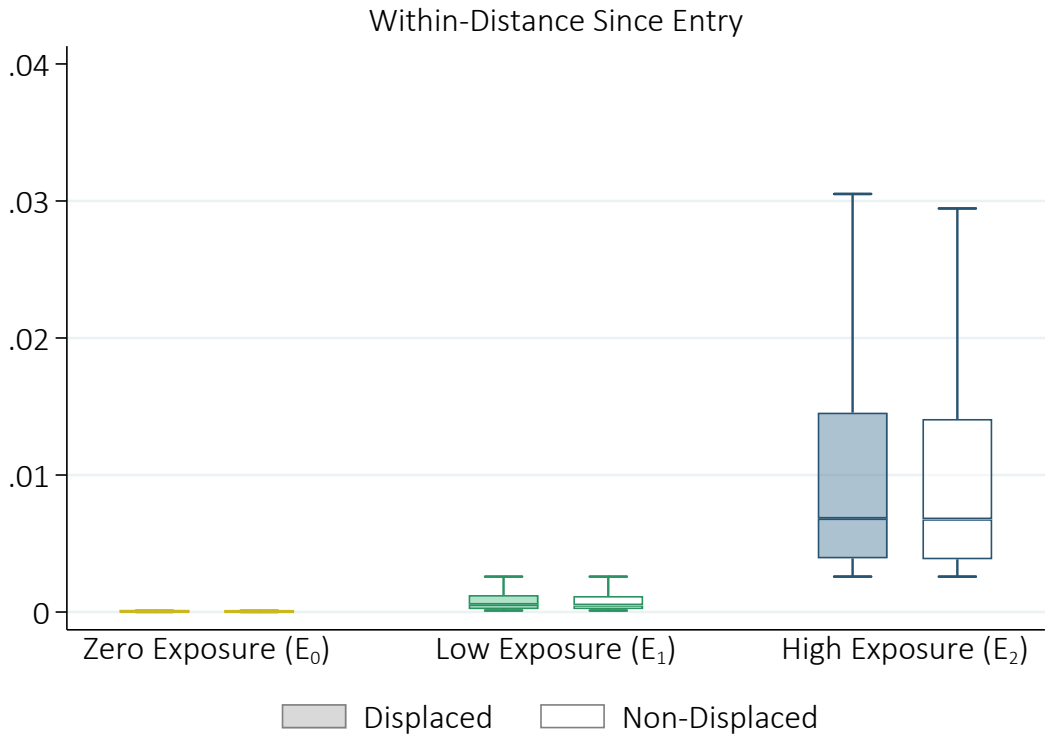
Figure B.2: Within-Distance as a Measure of Changes in Occupational Tasks, by Occupation Type



Notes: The figure plots the within-distance of occupations between 1975 and all consecutive years $D(o, 1975, t)$ (see equation (1)) for three broad occupation groups. The classification of occupations is based on KldB1988 1-digit codes and occupational mean wages in Western Germany as kindly provided by Dauth (2014). The thick red line provides the employment-weighted mean across all occupations in a given grouping group and given year. The mean uses the OPTE's population-level estimates of occupational employment as weights.

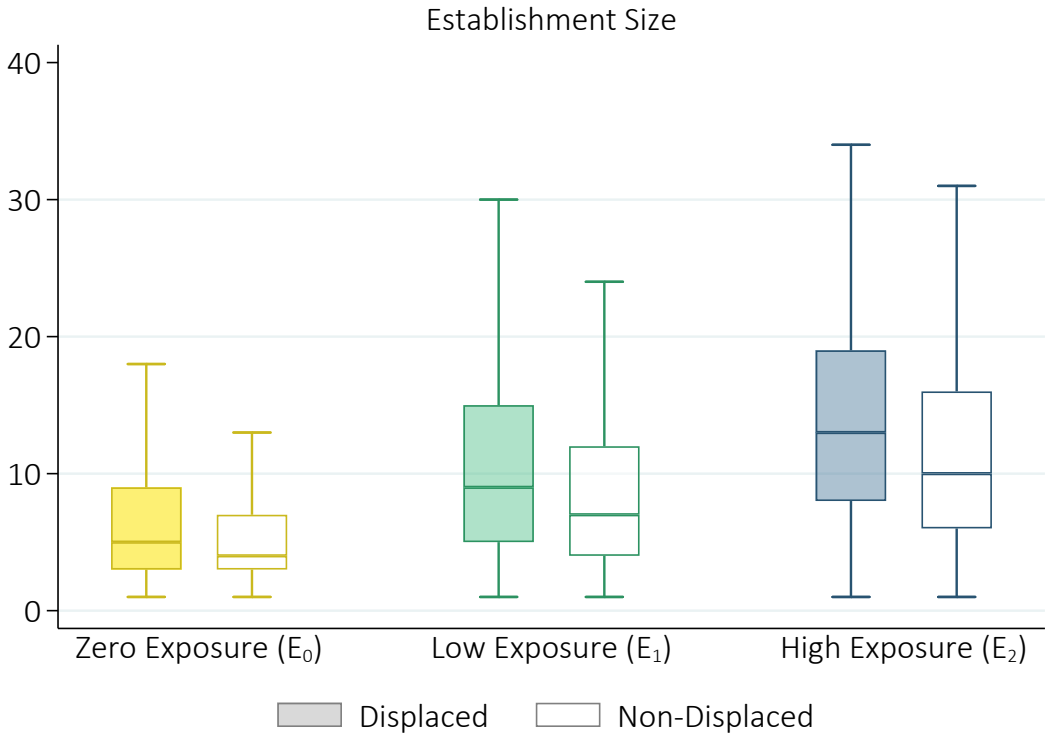
Data: OPTE, Dauth (2014).

Figure B.3: Variation in Occupation Tenure across Groups



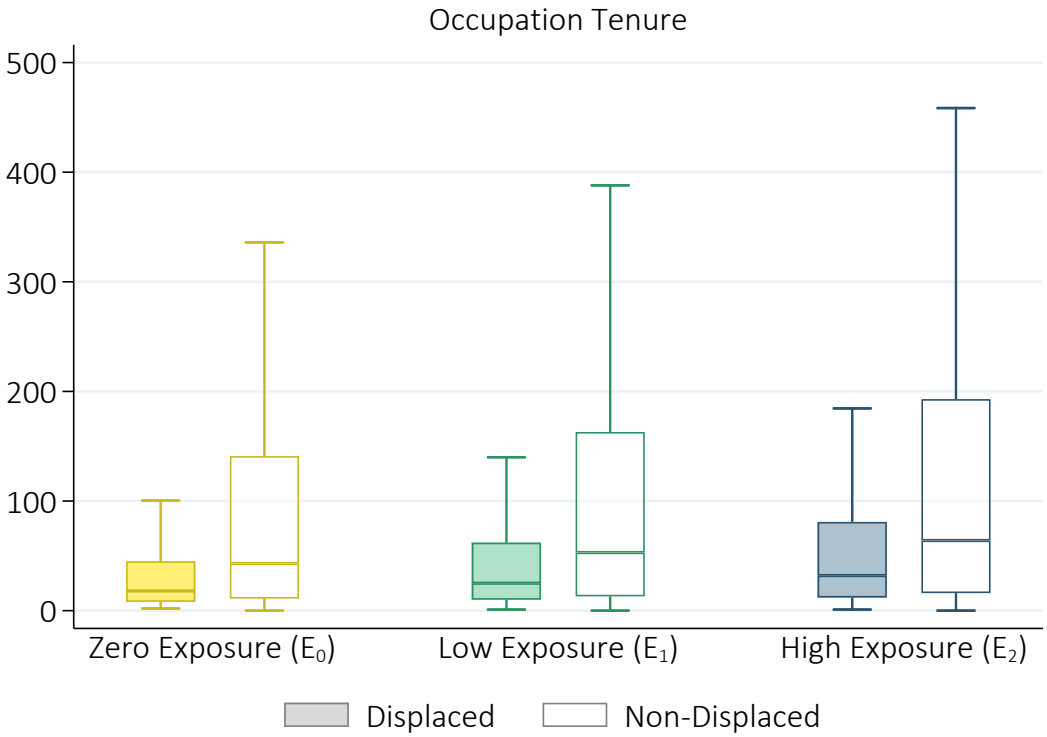
Notes: The boxplot illustrates how the within-distance varies within exposure groups and between the displaced and non-displaced worker sample. The within distance measures the composition change in occupational tasks between individual entry into occupation o in year e and the displacement baseyear c, i.e., $D(o,e,c)$ (see equation 1). The line in the middle of the box is the median, the top and bottom margin of the box mark the bottom and top quartiles. The whiskers mark the interquartile range.
Data: SIAB, OPTE.

Figure B.4: Variation in Occupation Tenure across Groups



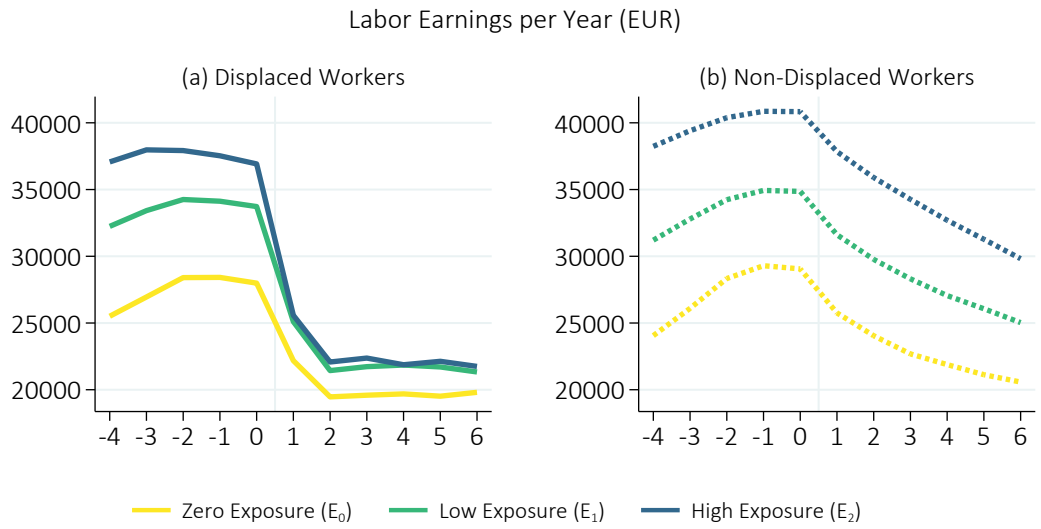
Notes: The boxplot illustrates how the baseyear occupation tenure varies within exposure groups and between the displaced and non-displaced worker sample. The line in the middle of the box is the median, the top and bottom margin of the box mark the bottom and top quartiles. The whiskers mark the interquartile range.
Data: SIAB, OPTE.

Figure B.5: Variation in Establishment Size across Groups



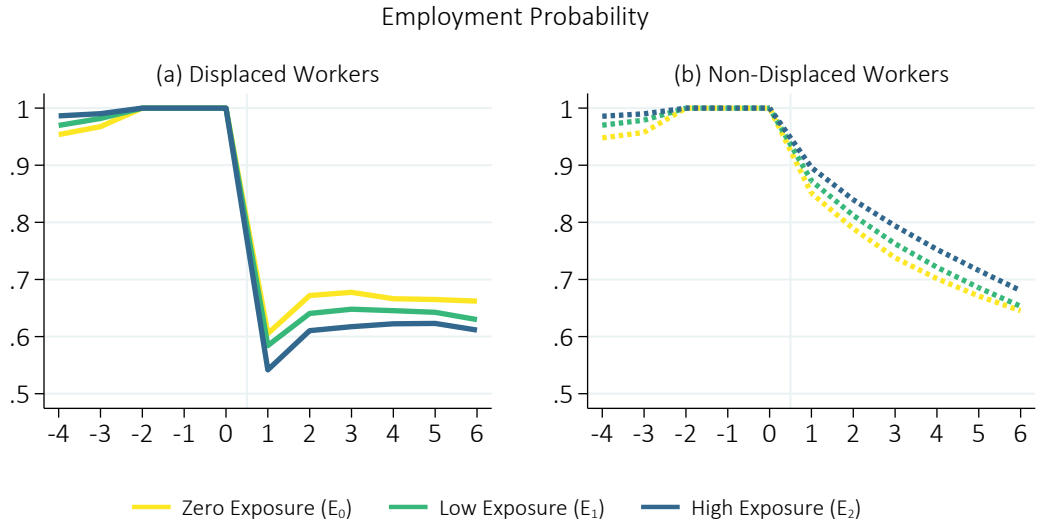
Notes: The boxplot illustrates how the baseyear establishment size varies within exposure groups and between the displaced and non-displaced worker sample. The line in the middle of the box is the median, the top and bottom margin of the box mark the bottom and top quartiles. The whiskers mark the interquartile range.
Data: SIAB, OPTE.

Figure B.6: Mean Labor Earnings per Year by Displacement Status and Exposure Group



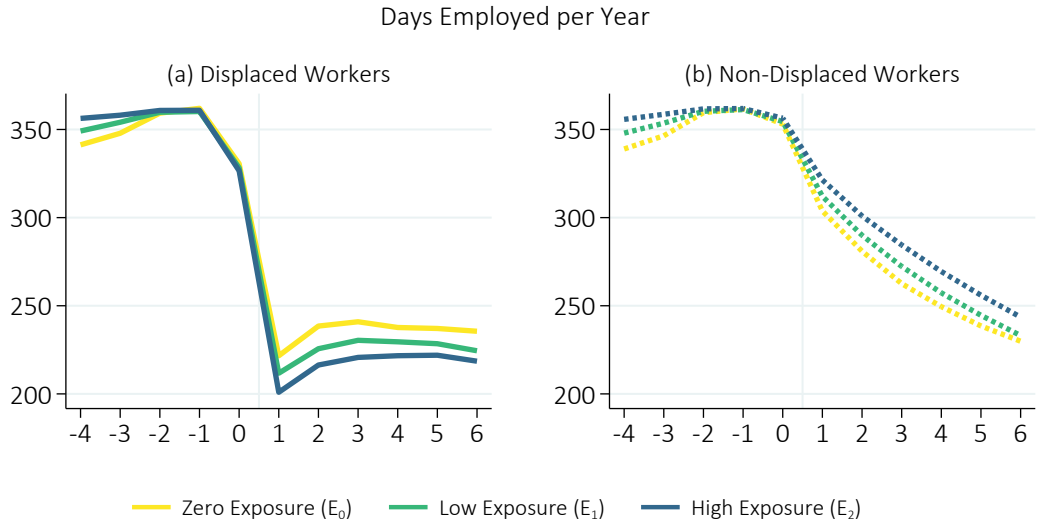
Notes: The figure plots the unconditional mean labor earnings per year for the zero (E_0), low (E_1) and high exposure (E_23, see 4.2 for how exposure groups are classified). Panel (a) shows the mean for displaced workers, panel (b) for non-displaced workers.
Data: SIAB, OPTE.

Figure B.7: Share of Employed Workers by Displacement Status and Exposure Group



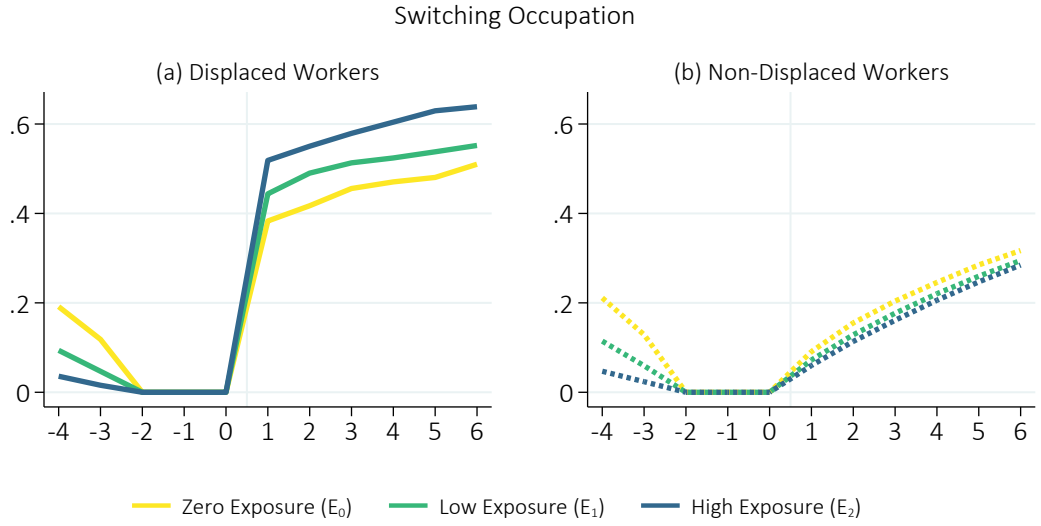
Notes: The figure plots the share of employed workers for the zero (E_0), low (E_1) and high exposure (E_23, see 4.2 for how exposure groups are classified). Panel (a) shows the mean for displaced workers, panel (b) for non-displaced workers.
Data: SIAB, OPTE.

Figure B.8: Mean Days Employed per Year by Displacement Status and Exposure Group



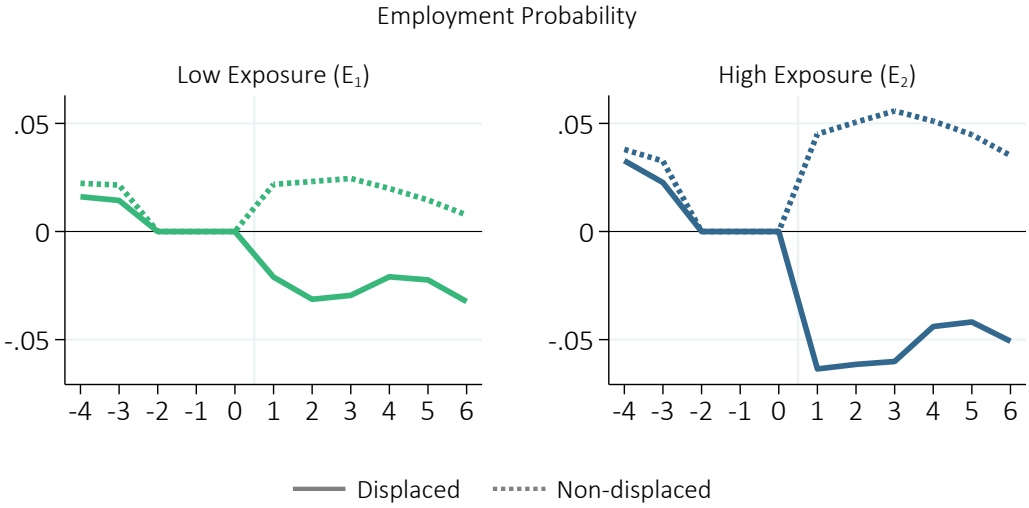
Notes: The figure plots the unconditional mean days employed per year for the zero (E_0), low (E_1) and high exposure ($E_2$3, see 4.2 for how exposure groups are classified). Panel (a) shows the mean for displaced workers, panel (b) for non-displaced workers.
Data: SIAB, OPTE.

Figure B.9: Share of Employed Workers in an Occupation other than in the Baseyear by Displacement Status and Exposure Group



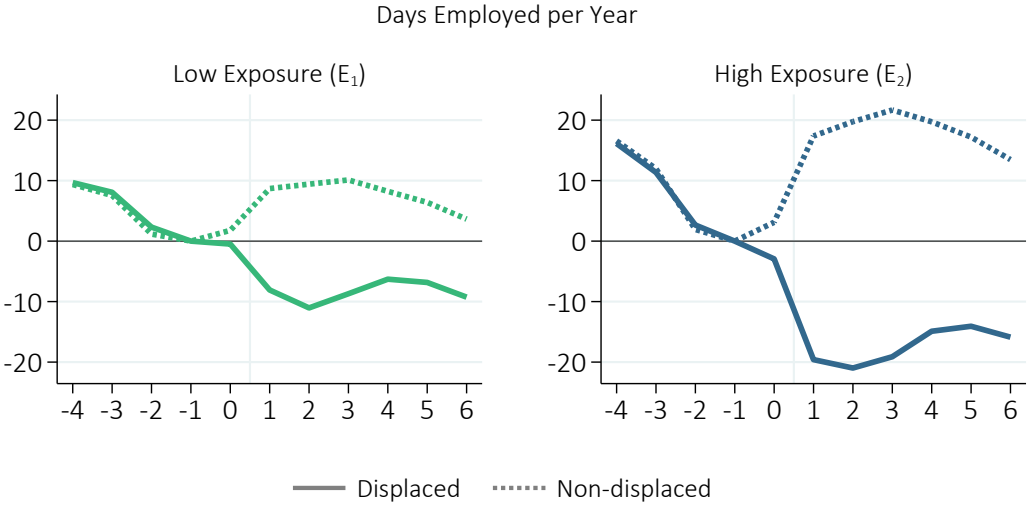
Notes: The figure plots the share of workers in an occupation other than in the baseyear for the zero (E_0), low (E_1) and high exposure ($E_2$3, see 4.2 for how exposure groups are classified). Panel (a) shows the mean for displaced workers, panel (b) for non-displaced workers.
Data: SIAB.

Figure B.10: Deviation from Parallel Trends in the Employment Probability between Exposure Groups for Displaced and Non-Displaced Workers



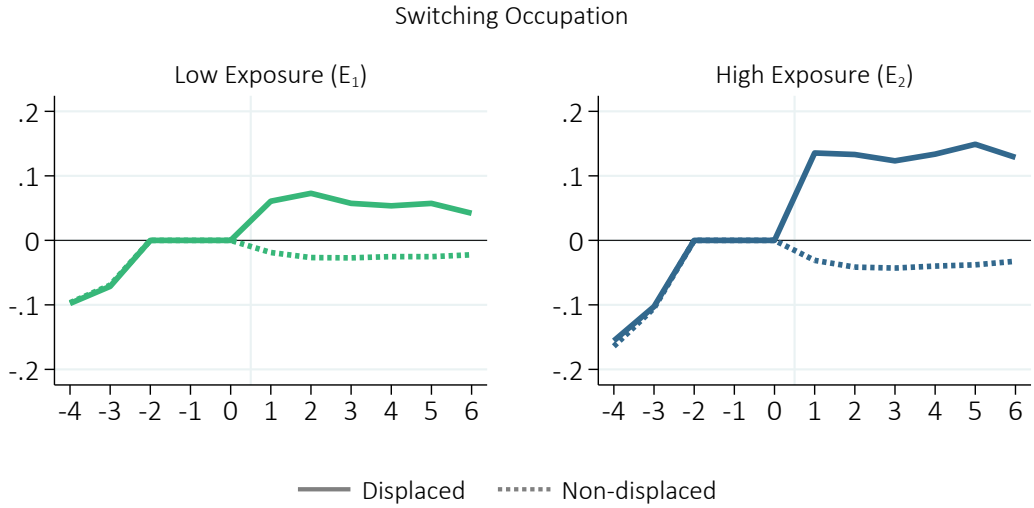
Notes: The figure plots the unconditional event studies for the employment probability of lowly and highly exposed workers in comparison to the zero exposure group, separately for displaced and non-displaced workers. Time trends are relative to the reference period $t = -1$. The plots support the validity of the Bias Stability assumption for the pre-displacement period, i.e., that the non-parallel trends bias for the low/high exposure group is almost identical in the displaced and non-displaced worker sample.
Data: SIAB, OPTE.

Figure B.11: Deviation from Parallel Trends in Days Employed per Year between Exposure Groups for Displaced and Non-Displaced Workers



Notes: The figure plots the unconditional event studies for days employed per year of lowly and highly exposed workers in comparison to the zero exposure group, separately for displaced and non-displaced workers. Time trends are relative to the reference period $t = -1$. The plots support the validity of the Bias Stability assumption for the pre-displacement period, i.e., that the non-parallel trends bias for the low/high exposure group is almost identical in the displaced and non-displaced worker sample.
Data: SIAB, OPTE.

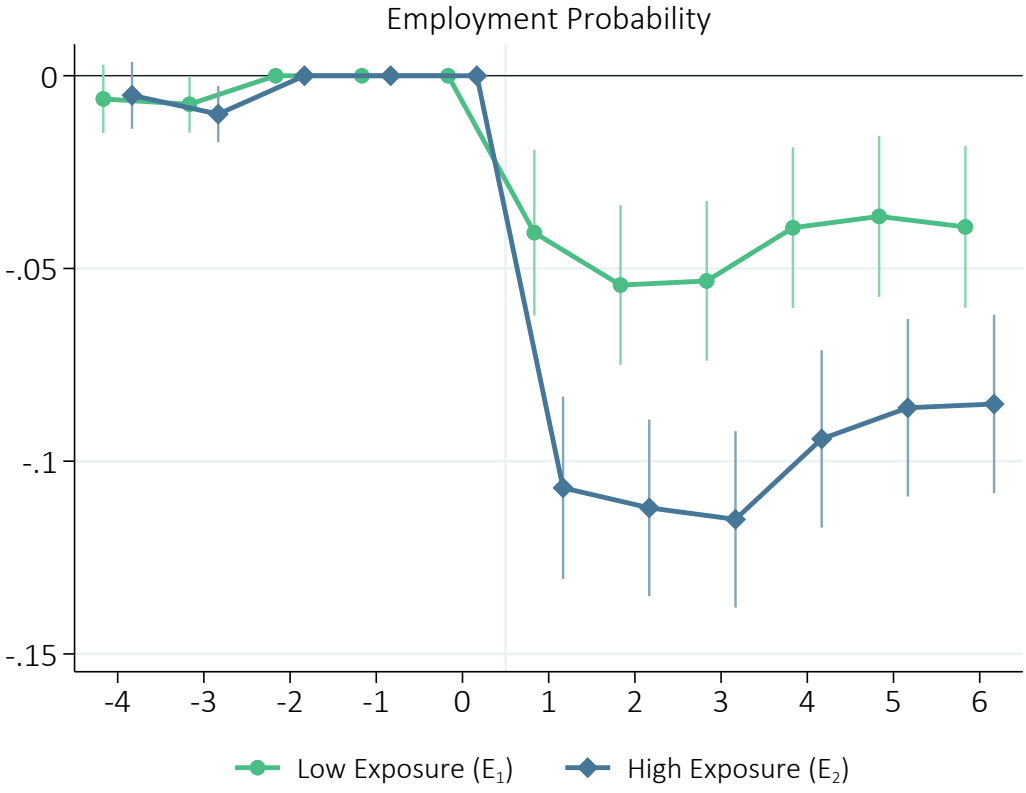
Figure B.12: Deviation from Parallel Trends in Occupational Mobility per Year between Exposure Groups for Displaced and Non-Displaced Workers



Notes: The figure plots the unconditional event studies for probability of working in an occupation other than in the baseyear of lowly and highly exposed workers in comparison to the zero exposure group, separately for displaced and non-displaced workers. Time trends are relative to the reference period $t = -1$. The plots support the validity of the Bias Stability assumption for the pre-displacement period, i.e., that the non-parallel trends bias for the low/high exposure group is almost identical in the displaced and non-displaced worker sample.

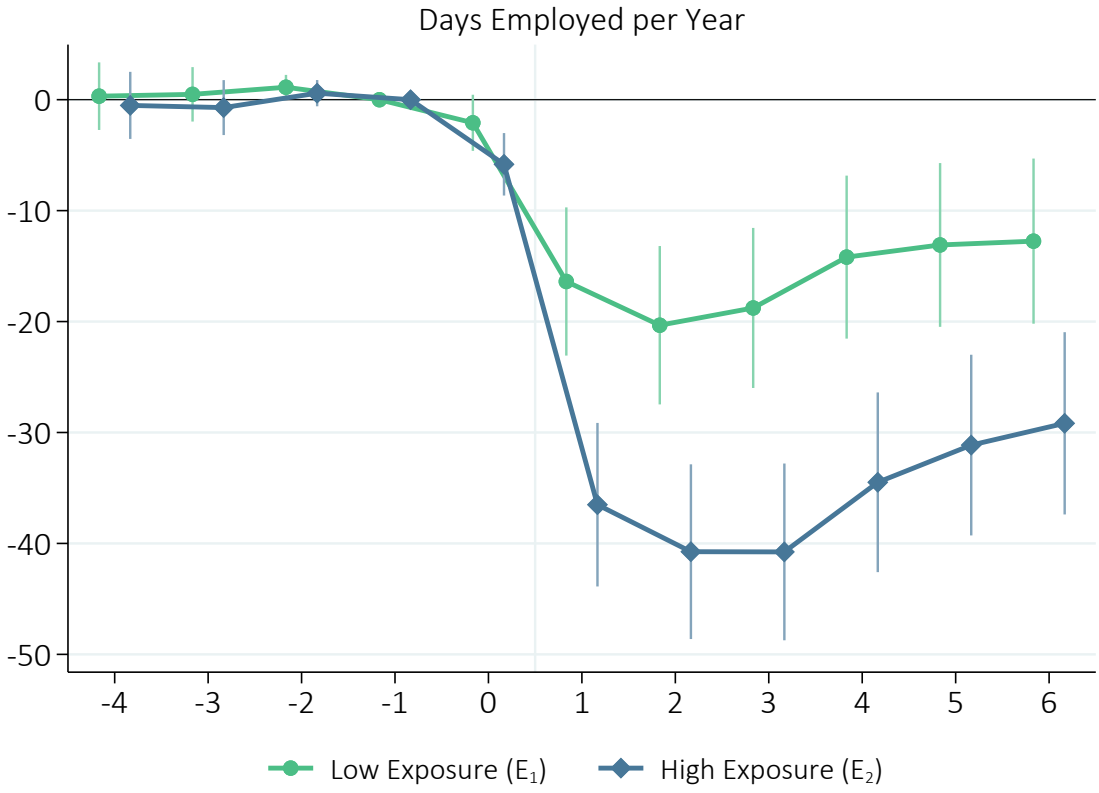
Data: SIAB, OPTE.

Figure B.13: Triple-Differences Event Study Estimates of Penalty for Exposure to Task Change on the Employment Probability



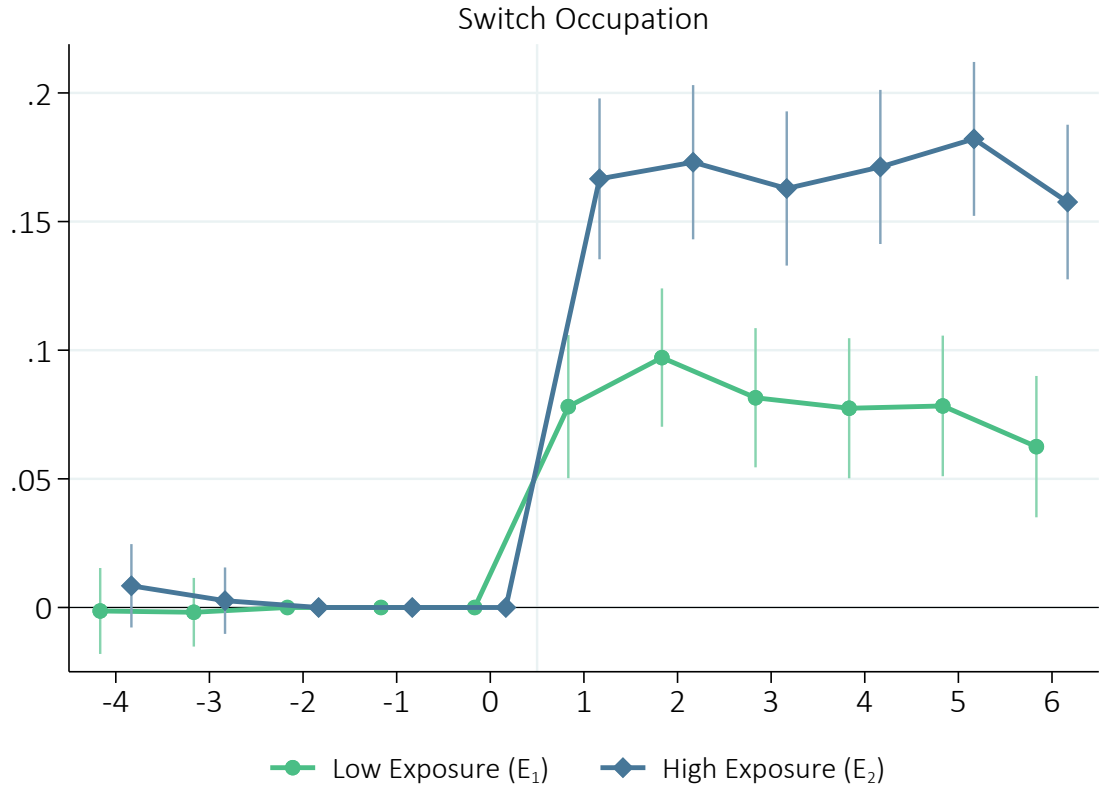
Notes: The plot shows the estimates for the employment probability per year from a fully interacted version of the Triple-Differences specification in equation (2), where the *Post* indicator has been replaced by a set of indicators for each relative time period $t = -4, \ldots, +6$, with $t = -1$ as the omitted reference period. The specification controls for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects. The coefficients represent the average additional penalty over six post-displacement years for displaced workers in exposure groups E_1 (low) and E_2 (high) relative to the zero exposure group E_0. The vertical line illustrates that the plant closure occurs between $t = 0$ and $t = 1$.

Figure B.14: Triple-Differences Event Study Estimates of Penalty for Exposure to Task Change on Days Employed per Year



Notes: The plot shows the estimates for days worked per year from a fully interacted version of the Triple-Differences specification in equation (2), where the *Post* indicator has been replaced by a set of indicators for each relative time period $t = -4, \ldots, +6$, with $t = -1$ as the omitted reference period. The specification controls for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects. The coefficients represent the average additional penalty over six post-displacement years for displaced workers in exposure groups E_1 (low) and E_2 (high) relative to the zero exposure group E_0. The vertical line illustrates that the plant closure occurs between $t = 0$ and $t = 1$.

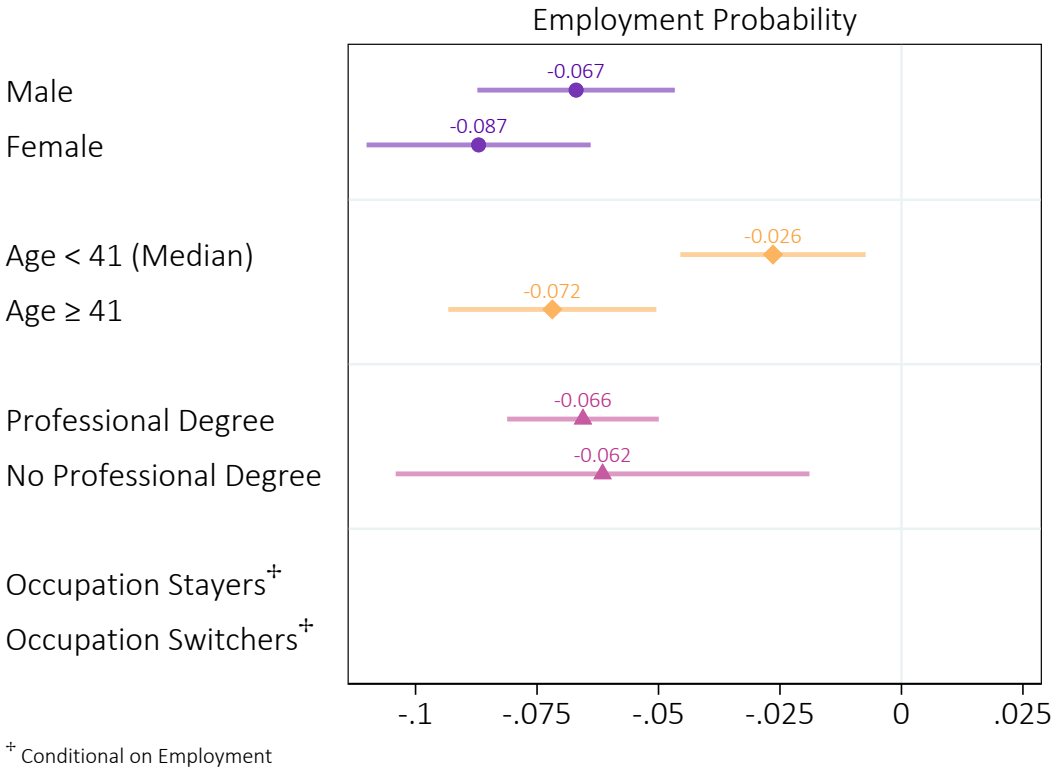
Figure B.15: Triple-Differences Event Study Estimates of Penalty for Exposure to Task Change on the Probability working in an Occupation other than in the Baseyear



Notes: The plot shows the estimates for the probability of working in an occupation other than in the baseyear from a fully interacted version of the Triple-Differences specification in equation (2), where the *Post* indicator has been replaced by a set of indicators for each relative time period $t = -4, \ldots, +6$, with $t = -1$ as the omitted reference period. The specification controls for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects. The coefficients represent the average additional penalty over six post-displacement years for displaced workers in exposure groups E_1 (low) and E_2 (high) relative to the zero exposure group E_0. The vertical line illustrates that the plant closure occurs between $t = 0$ and $t = 1$.

Data: SIAB, OPTE.

Figure B.16: Heterogeneity in the Earnings Penalty of the High Exposure Group on the Employment Probability



Notes: The Figure shows a decomposition of the Triple-Differences effect on the employment probability for the high exposure group (E_2) into separate estimates for different sub groups of workers. These estimates are derived from a four-way-interaction model, i.e., equation (2) is fully interacted with indicator variables for the sub groups. All models control for baseyear characteristics (see Table A.1 in Appendix A), occupation fixed effects and calendar baseyear fixed effects. There is no estimate for occupation switchers/stayers, because occupational mobility is conditional on re-employment and thus collinear to being employed as an outcome.
Data: SIAB, OPTE.